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# THE OPIOID CRISIS AND ECONOMIC OPPORTUNITY: GEOGRAPHIC AND ECONOMIC TRENDS

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This study examines relationships between indicators of economic opportunity and the prevalence of prescription opioids and substance use in the United States. Overall, areas with lower economic opportunity are disproportionately affected by the opioid crisis. However, the extent of that relationship varies regionally.

(1) The prevalence of drug overdose deaths and opioid prescriptions has risen unevenly across the county, with rural areas more heavily affected. Specific geographic areas, such as Appalachia, parts of the West and the Midwest, and New England, have seen higher prevalence than other areas.

(2) Poverty, unemployment rates, and the employment-to-population ratio are highly correlated with the prevalence of prescription opioids and with substance use measures. On average, counties with worse economic prospects are more likely to have higher rates of opioid prescriptions, opioid-related hospitalizations, and drug overdose deaths.

(3) Some high-poverty regions of the country were relatively isolated from the opioid epidemic, as shown by our substance use measures, as of 2016.

## INTRODUCTION

Opioid use disorder has reached epidemic levels in the United States, with a 200 percent increase in overdose deaths from opioid and heroin use between 2000 and 2014.[1] The Centers for Disease Control and Prevention (CDC) estimated that over 60,000 drug overdose deaths occurred in 2016, with overdose death rates three times the rate of 1999.[2] Overdose death rates involving opioids have risen dramatically, with deaths due to synthetic opioids other than methadone doubling from 2015 to 2016.[2]

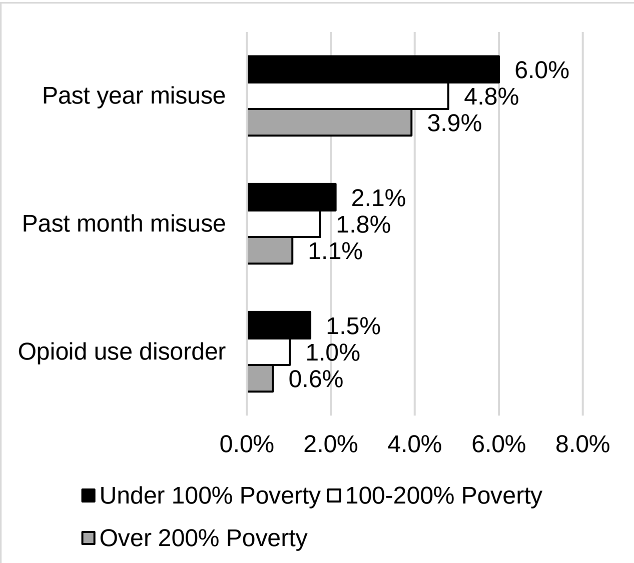
Lower-income individuals, including those on Medicaid and the uninsured, are more likely to misuse opioids[i] and have opioid use disorder than the general U.S. population.[3–5] As shown in Figure 1, in 2016, individuals under the poverty line were 2.1 percentage points more likely to have misused opioids in the past twelve months than individuals above 200 percent of the poverty level. They were over twice as likely to have has an opioid use disorder. In fact, even as rates of nonmedical use of opioids among the low-income population decreased from the 2003-2005 period to the 2012-2014 period, rates of dependency rose by over 50 percent.[3] In 2012, the CDC issued a report stating that “Medicaid recipients and other low-income populations are at high risk for prescription drug overdose.”[6]

While the individual-level relationship is clear, the relationship between community prevalence of opioid use disorder and economic conditions has not been fully studied. This relationship is important for decision-makers at the federal, state, and local levels to understand as they consider policy and budgetary proposals to address the crisis. The opioid crisis has not affected the nation uniformly. The extent to which it may be concentrated in areas with higher poverty and fewer employment opportunities may exacerbate

[i] Throughout this brief the terms *opioids*, *opioid misuse*, and *opioid use disorder* include the use of prescription opioids as well as heroin and synthetic opioids.

disparities in access to health care and treatment options in such communities.

**Figure 1. Past Year Opioid Misuse and Use Disorder by Poverty Status, 2016**




**Source:** 2016 National Survey on Drug Use and Health.
**Note:** Includes nonmedical use of prescription painkillers or use of heroin. $N$ = 56,897. All differences across poverty status within each category are statistically significant at $p < 0.001$.

One recent study found that increases in county unemployment rates predict increases in opioid death rates and that macroeconomic shocks drive the overall drug death rate.[7] Another study found that per capita opioid-related hospital stays and emergency department visits are higher, and have increased at higher rates, in low-income communities than in higher income communities.[8] In addition, labor force participation has fallen by a greater percentage in areas where relatively more opioid pain medication is prescribed.[9] Finally, a recent study from the Federal Reserve found that "adults who have been personally exposed to the opioid epidemic have somewhat less favorable assessments of economic conditions than those who have not been exposed."[10]

To explore how a county's economic conditions relate to the opioid crisis, we examine geographic and statistical relationships between indicators of economic opportunity, substance use, and prescription opioid prevalence. We analyze data from 2006 through 2016 for most counties in the U.S. We use four separate measures that serve as proxies for different aspects of the opioid crisis, including retail opioid sales, Medicare Part D opioid prescriptions, opioid-related hospitalizations, and drug overdose deaths. These indicators do not directly measure opioid misuse or opioid use disorder, however currently no local measures exist that are nationally representative.

Measures of prescription opioid prevalence include retail opioid sales, measured in volume of medical morphine equivalents, and Medicare Part D opioid prescriptions. Opioid-related hospitalizations are measured as the number of unique hospital stays or emergency department visits for which the use of any opioid (prescription, synthetic, or heroin) was listed as a cause of the stay. Our measure of drug overdose deaths includes deaths due to any substance (excluding alcohol and tobacco). Unfortunately, we did not have access to data on county-level opioid-related overdose deaths. All data are measured as rates per 100,000 people.

Our measures of economic opportunity include poverty rates, unemployment rates, and the employment-to-population ratio. The latter measures the number of individuals employed relative to a county's entire population. For simplicity, we present descriptive trends for poverty and unemployment rates, and include the employment-to-population ratio only in statistical models. More details on the data and methods can be found in the Appendix.

# TRENDS IN ECONOMIC OPPORTUNITY, OPIOID PRESCRIPTIONS, AND SUBSTANCE USE MEASURES

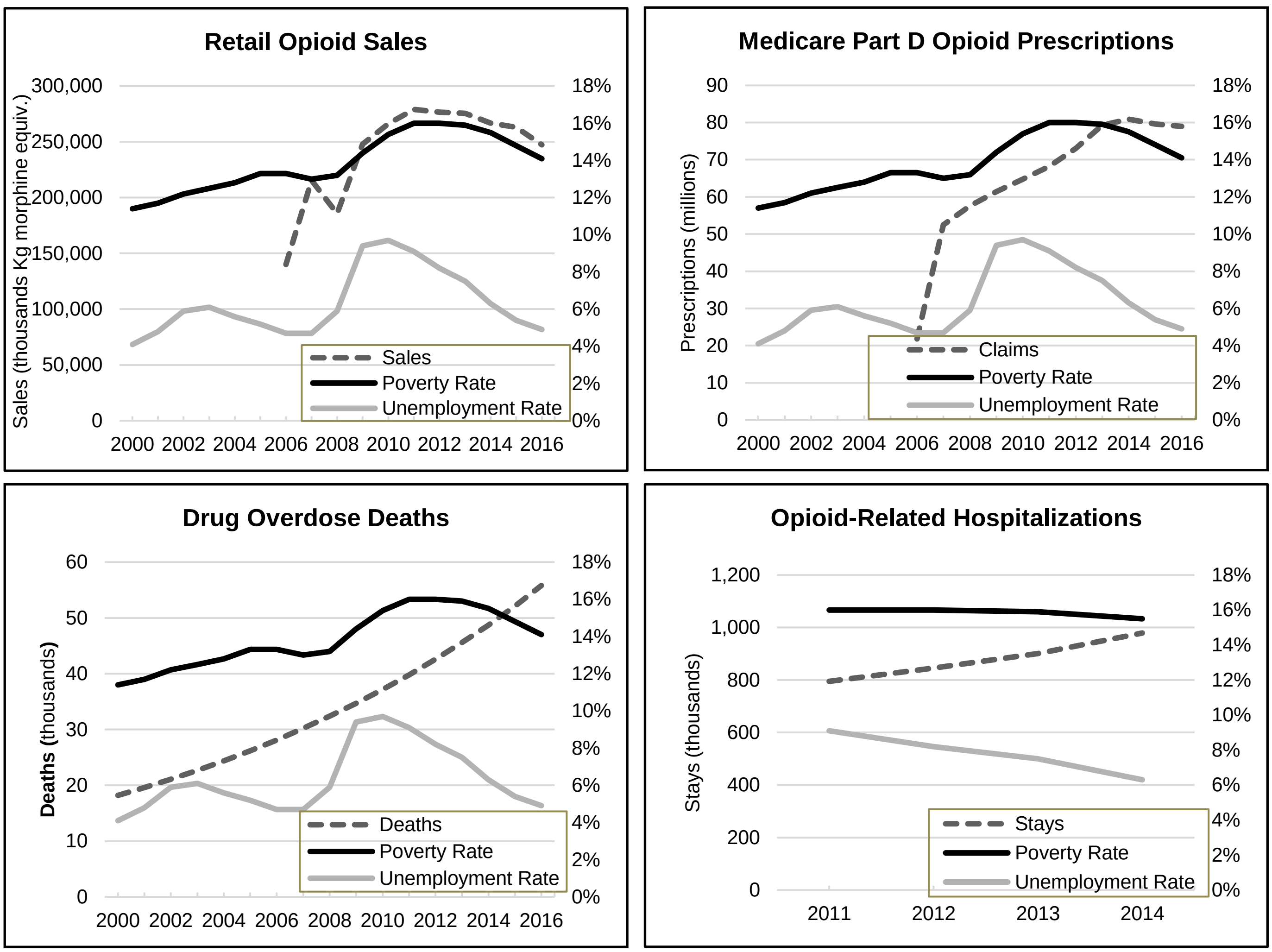
National measures of opioid prescribing and substance use have been consistently rising since the early 2000s. Part of this rise corresponded with economic declines; however, rates continued to rise even after economic indicators showed improvement. The increase at the national level masks variation in rates across the country.

### National Trends

Indicators of substance use and opioid prevalence have risen substantially over the past 15 years. Figure 2 shows the relationship between two measures of economic opportunity and aggregate levels of retail opioid sales, Medicare Part D opioid prescriptions, opioid-related hospitalizations, and drug overdose deaths.

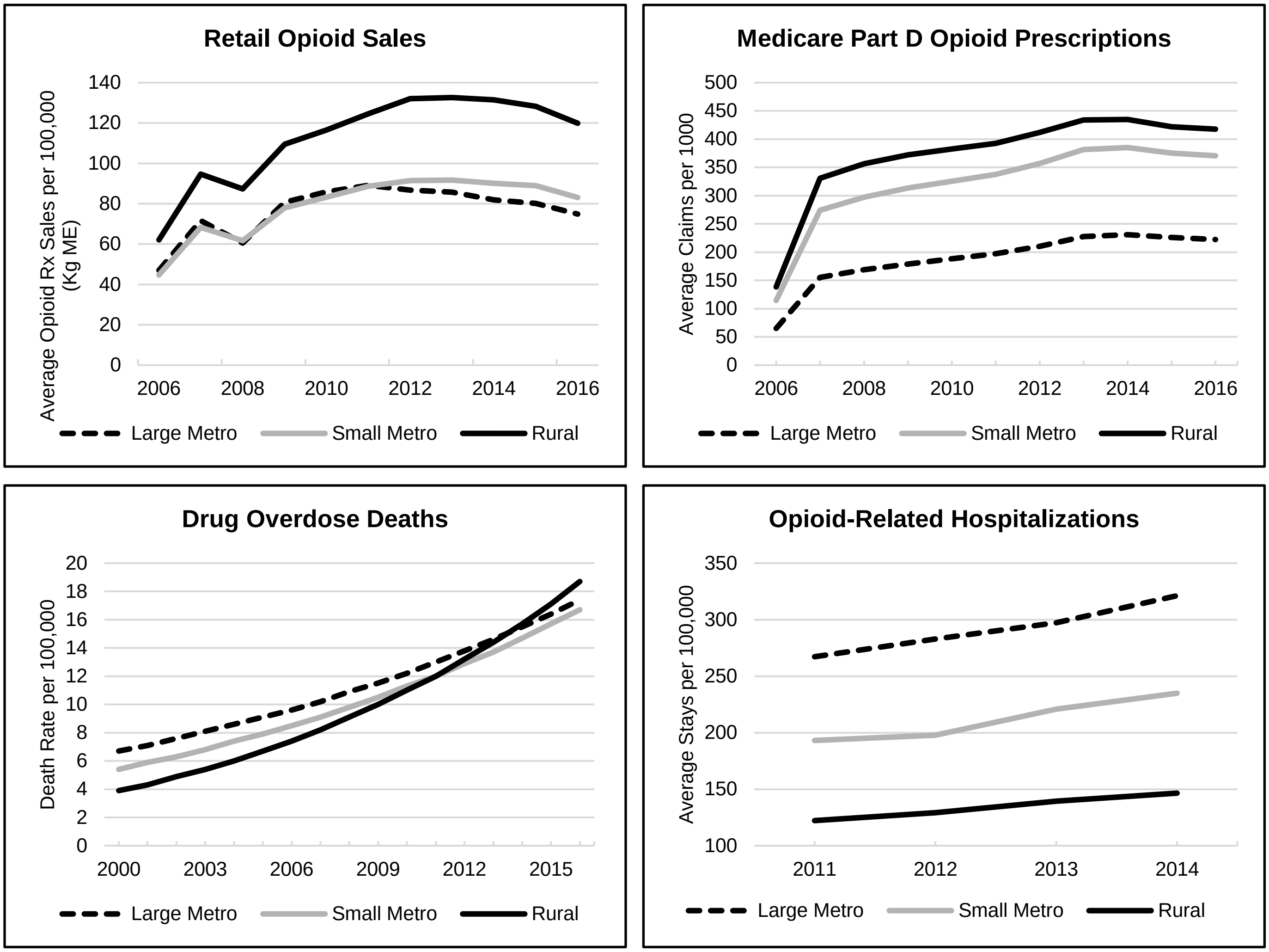
Unemployment and poverty rates increased during the Great Recession. More specifically, unemployment rates peaked in 2010 at a rate of nearly 10 percent, while poverty rates increased slowly throughout the early 2000s, increased markedly between 2008 and 2011, and then declined through 2016.

**Figure 2. National Trends in Unemployment, Poverty, and Measures of Substance Use and Opioid Prevalence**




**Sources:** Poverty: U.S. Census Bureau Small Area Income and Poverty Estimates. Unemployment: Bureau of Labor Statistics. Prescription opioid sales: Drug Enforcement Administration (DEA) Automation of Reports and Consolidated Orders System (ARCOS), measured in kilograms of medical morphine equivalence per 100,000. Medicare Part D Prescriptions: Centers for Medicare & Medicaid Services (CMS) Prescription Drug Event File. Drug overdose deaths: CDC Small Area Estimates. Hospitalizations: Healthcare Cost and Utilization Project (HCUP) State Inpatient Databases and State Emergency Department

**Figure 3. Measures of Substance Use and Opioid Prevalence, by Urbanicity**




**Sources:** Retail prescription opioid sales: DEA Automation of Reports and Consolidated Orders System (ARCOS), measured in kilograms of morphine equivalence per 100,000. Medicare Part D Prescriptions: CMS Prescription Drug Event File. Drug overdose deaths: CDC Small Area Estimates. Hospitalizations: HCUP State Inpatient Databases and State Emergency Department Databases.

All measures of substance use and opioid prevalence increased relative to those in the initial reporting period, though prescribing rates are now on the decline. Our data on retail opioid sales began to decline in 2012 after nearly doubling from 2006 to 2011. Other sources of data on opioid sales indicate a peak in 2011 rather than 2012.[11] Medicare Part D prescriptions follow a similar trend, although they did not decline as substantially in the more recent period. Opioid-related hospitalizations increased by over 20 percent from 2011 to 2014, the last year for which data are available.

Finally, accidental drug overdose deaths have increased considerably: at the start of the analysis period, there were roughly 18,000 deaths per year in the United States. This figure rose to 28,000 deaths in 2006 and then continued to rise to over 50,000 deaths in 2016. Stated another way, the number of accidental overdose deaths was nearly three times higher in 2016 than in 2000. While not all drug overdose deaths are caused solely by opioids, the opioid epidemic is linked to the vast majority of these deaths.

### Rural Areas Had Higher Prevalence of Opioids and Greater Increases in Substance Use Than Other Areas

Overdose deaths, opioid-related hospitalizations, and prescription opioids are not uniformly present in communities across the United States. As Figure 3 indicates, rural counties have historically had higher rates of per capita retail opioid sales and Medicare opioid prescriptions. In 2016, retail opioid sales per capita were around 50 percent higher in rural areas than in small and large metropolitan counties.

Although metropolitan counties have historically had higher drug overdose death rates and opioid-related hospitalization rates, rural counties had a higher growth rate of these two measures.[8] In 2016, the drug overdose death rate in rural areas surpassed that of other types of counties, with an estimated 18.7 deaths per 100,000 persons. The overdose death rate in rural counties was 4.8 times larger in 2016 than it was in 2000.

## GEOGRAPHIC ASSOCIATION BETWEEN ECONOMIC OPPORTUNITY, SUBSTANCE USE AND OPIOID PRESCRIBING

Counties with higher poverty and unemployment rates generally had higher rates of retail opioid sales and Medicare opioid prescriptions, as well as drug overdose deaths and opioid-related hospitalizations. This relationship was clustered in specific areas of the country. Despite the strong relationship, some counties had high poverty and unemployment rates but did not have relatively high substance use and opioid prevalence indicators as of 2016.

### Economic Opportunity and Indicators of Opioid Prevalence Vary Markedly across Geographic Regions

Indicators of economic opportunity and the opioid epidemic were not homogeneous across the country. Figure 4 shows the quintiles of poverty and unemployment rates for 2016. Poverty and unemployment rates were clearly geographically concentrated in certain parts of the country. Statistical measures show that both of these measures had a high degree of spatial clustering (see Appendix for more details).[ii] Poverty rates were much lower in the Midwestern states than in other areas. In fact, the average poverty rate for a Midwestern county was 13.2 percent in 2016, versus 17.3 percent for all other areas combined. Additionally, poverty and unemployment rates were particularly pronounced and clustered in Appalachia, the South, and the West. Moreover, the poverty rates were high in some areas: while the average poverty rate was 15.8 percent in 2016, over 250 counties in the U.S. had a poverty rate greater than 25 percent.

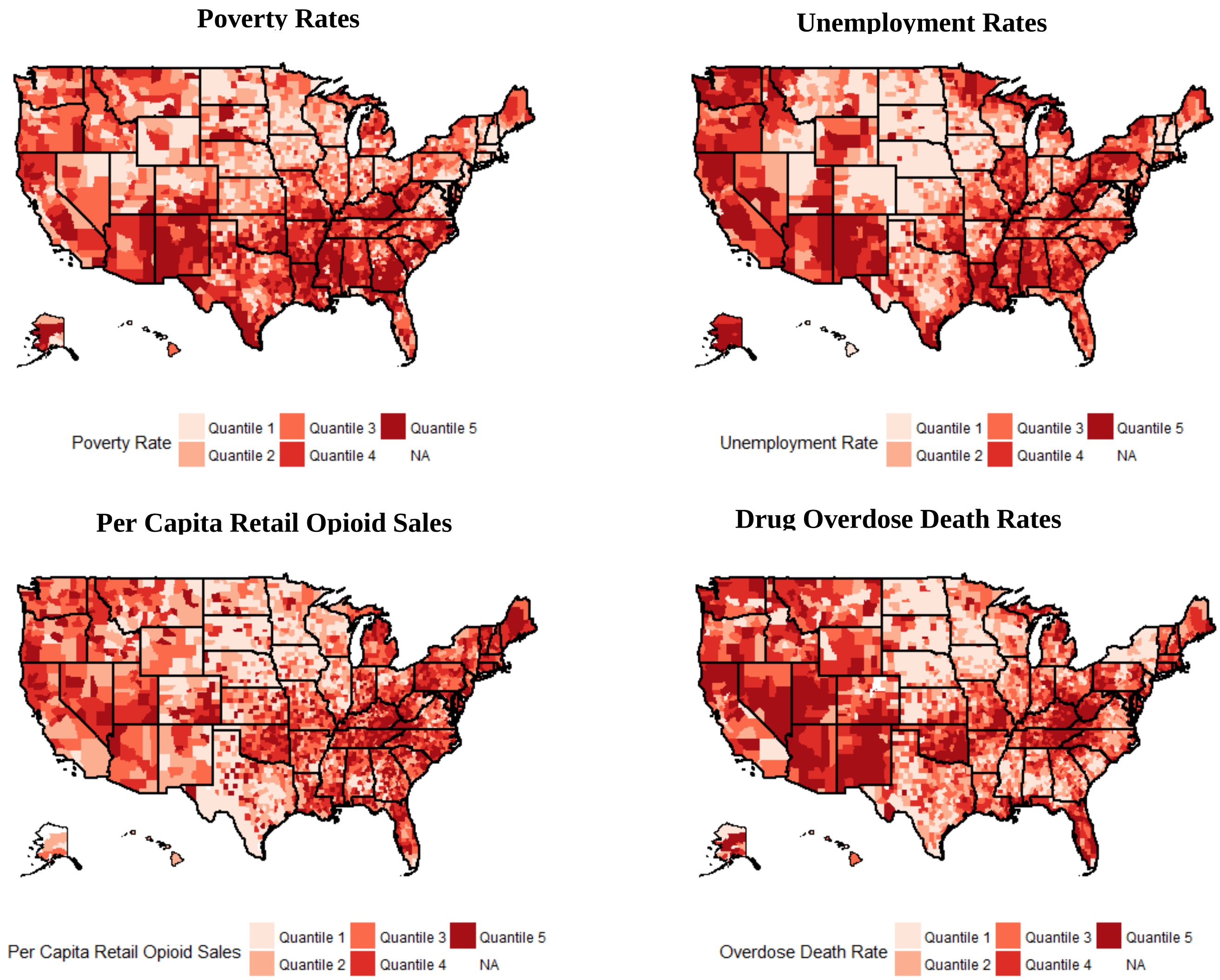
Similarly, all four measures of the opioid epidemic show spatial clustering as well, consistent with other research.[12] The bottom two maps in Figure 4 show quintiles of per capita retail opioid sales and overdose death rates across the country. Though not shown, per capita Medicare opioid prescriptions and opioid-related hospitalizations had similar geographic patterns.

### Economic Indicators Were Strongly Related to Rates of Prescription Opioid Sales and Drug Overdose Deaths in Certain Geographic Areas

Figures 5 and 6 show the geographic relationships between poverty rates and per capita retail opioid sales, and between poverty rates and drug overdose deaths, respectively; they reveal a strong relationship

[ii] Moran's I, a metric of spatial clustering, was 0.58 ($p < 0.001$) for poverty and was 0.61 ($p < 0.001$) for unemployment. Moran's I is measured on a scale from −1 to 1, where positive values mean that counties near one another tend to have similar values.

**Figure 4. County Poverty Rates, Unemployment Rates, Per Capita Retail Opioid Sales, and Drug Overdose Death Rates, 2016**



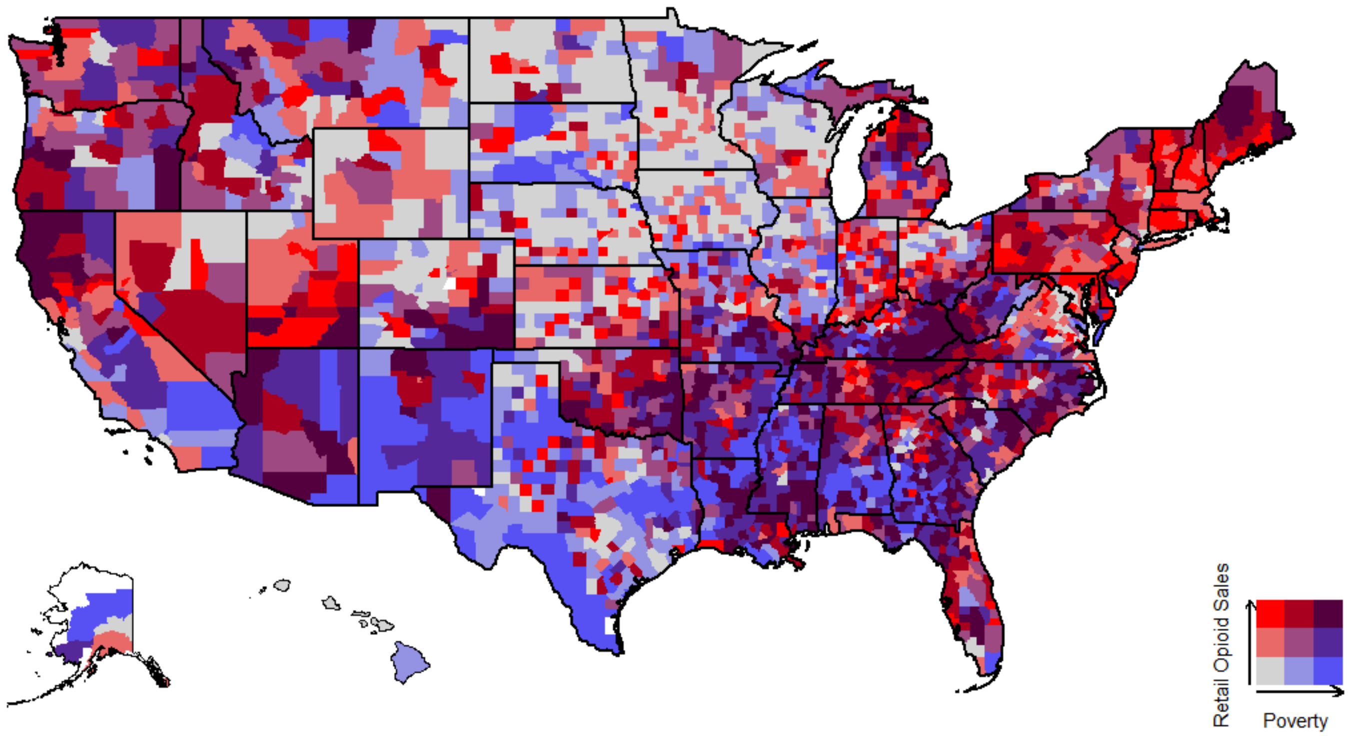

**Sources:** Poverty Rates: U.S. Census Bureau Small Area Income and Poverty Estimates. Unemployment Rates: Bureau of Labor Statistics. Opioid Sales: DEA Automation of Reports and Consolidated Orders System. Overdose Deaths: CDC Small Area Estimates of Drug Mortality.

between these variables. Counties with higher per capita opioid sales are colored in red, and areas of higher poverty rates are displayed in blue. These colors combine in areas that have high rates of poverty and high rates of opioid sales.

In 2016, counties with higher poverty and higher per capita retail opioid sales, as well as higher overdose death rates, were concentrated in several geographic areas. These areas include parts of the west coast; including northern California and southwestern Oregon; Appalachia; and portions of the Midwest and South, including Missouri, Arkansas, Oklahoma, Louisiana, and Alabama. In other parts of the country the relationship is more scattered, particularly across the two drug measures. New England, for example, had relatively high rates of opioid sales and overdose deaths without a consistently higher poverty rate.

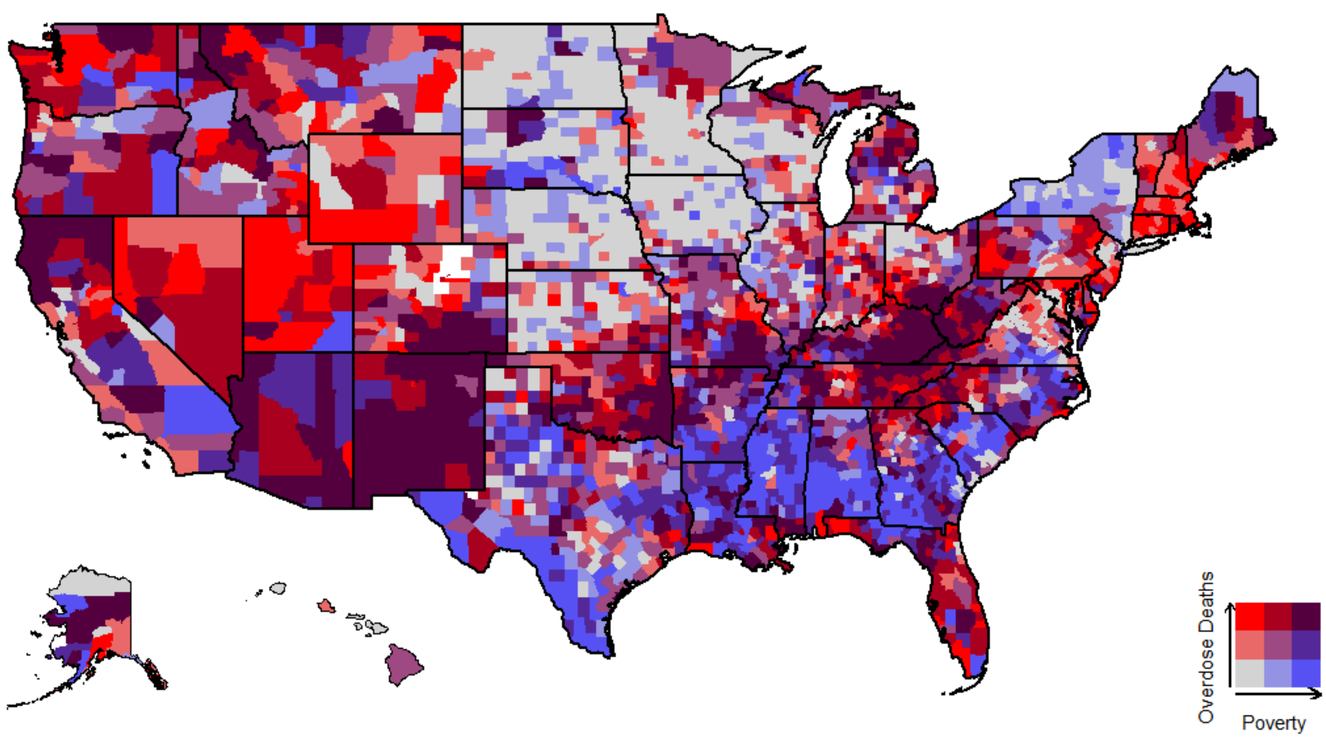
Appendix Figures B1 and B2 present the same results for unemployment rates. The relationships are similar, with counties clustered in the same identified regions having high rates of unemployment as well as high drug overdose death rates and prescription opioid sales.

**Figure 5. Poverty Rates and Per Capita Retail Opioid Sales, 2016**




**Sources:** U.S. Census Bureau Small Area Income and Poverty Estimates, DEA Automation of Reports and Consolidated Orders System.
**Note:** Each variable is split into tertiles.

**Figure 6. Poverty Rates and Drug Overdose Death Rates, 2016**




**Sources:** U.S. Census Bureau Small Area Income and Poverty Estimates, CDC Small Area Estimates of Drug Mortality.
**Note:** Each variable is split into tertiles.

**Some Counties with Less Economic Opportunity Are Insulated from the Substance Use and Opioid Epidemic**

Figures 5 and 6 display areas of the country where the relationships between poverty and unemployment, and between per capita retail opioid sales and overdose death rates, are not as systematic as previously described. A fraction of U.S. counties had relatively higher rates of drug measures yet low poverty and unemployment rates. In these counties, poorer economic conditions do not predict as strongly, if at all, the prevalence of retail opioid sales and overdose deaths, suggesting the presence of other contributing factors. These counties were more likely to be in New England and the Mid-Atlantic, as well as parts of the West.

A second set of counties had higher relative poverty and unemployment rates, while having lower rates of overdose deaths and opioid prescriptions. In these counties, despite worse economic conditions, opioid sales and overdose death rates were relatively low. To the extent that these two indicators reflect the ongoing epidemic of substance and opioid use, they may indicate that other factors protected these counties. These counties were more likely to be in the South, and further analysis revealed that these counties were more likely to have a larger minority population and to have had improvements in unemployment or poverty rates, compared with other counties.

# ASSOCIATION OF ECONOMIC OPPORTUNITY WITH SUBSTANCE USE AND OPIOID MEASURES

We have identified geographic diversity in the relationship between economic opportunity, substance use and opioid prevalence measures. Counties differ in their economic, demographic, cultural, and political contexts, all of which may account for this diversity. These factors can also confound the underlying relationship between economic opportunity and the opioid epidemic. By adjusting for some of these variables in statistical models, we can better identify how unemployment and poverty relate to the four measures of opioid prescribing and substance use.

On average, there is a strong statistical link between county poverty and unemployment rates and measures of the opioid crisis. Table 1 shows results from statistical models that adjust for several county-

**Table 1. Change in Opioid and Substance Use Measures Associated with a One-Point Increase in Economic Measures**

| | Retail Opioid Sales, Per Capita | Medicare Part D Opioid Prescriptions, Per Capita | Opioid-Related Hospitalization Rates | Drug Overdose Death Rates |
|---|---|---|---|---|
| Poverty rate | 1.4%* | 3.3%* | 2.4%* | 1.7%* |
| Unemployment rate | 3.8%* | 1.9%* | 5.1%* | 4.6%* |
| Employment-to-population ratio | −0.5%* | −0.5%* | −0.3% | 0.5%* |

**Notes:** *N* ranges from 30,220 to 34,405 for models of retail opioid sales, Medicare part D opioid prescriptions, and overdose deaths. *N* ranges from 5,820 to 5,831 for models of hospitalizations. Data are from 2006 through 2016 for retail opioid sales, Medicare prescriptions, and overdose deaths and from 2011 through 2014 for hospitalizations.
* statistically significant at $p < 0.05$. Results are from statistical models adjusting for various factors. For details on sample sizes and results, see Tables A4 and A5 in the Appendix.

level demographic factors, such as population size, race/ethnicity, and urbanicity. From 2006 through 2016, on average, an increase of 1 percentage point in a county's poverty rate was associated with a 1.4 percent increase in per capital retail opioid sales, a 3.3 percent increase in the Medicare Part D opioid prescription rate, and a 1.7 percent increase in the overdose death rate. From 2011 through 2014, on average, an increase of 1 percentage point in a county's poverty rate was associated with a 2.4 percent increase in the rate of opioid-related hospitalizations.

Similarly, measures of employment were associated with higher overdose death rates. Table 1 shows that an increase of 1 percentage point in a county's unemployment rate was associated with a 3.8 percent increase in per capita opioid sales, a 1.9 percent increase in per capita Medicare Part D opioid prescriptions, and a 4.6 percent increase in the overdose death rate, in the period from 2006 to 2016. Even more dramatic, from 2011 through 2014, an increase of 1 percentage point in a county's unemployment rate was associated with a 5.1 percent increase in the opioid-related hospitalization rate.

Using the employment-to-population ratio provides somewhat more mixed results. For this variable, higher values mean higher levels of employment. An increase of 1 percentage point in this ratio corresponds with a decrease of 0.5 percent in per capita opioid sales and Medicare Part D opioid prescriptions. No significant relationship with opioid-related hospitalization rates was identified. The relationship with drug overdose death rates is the opposite of what was expected: an increase of 1 percentage point in the employment-to-population ratio corresponds with an *increase* of 0.5 percent in drug overdose death rates.

# DISCUSSION

This research demonstrates that economically disadvantaged counties tend to be affected more deeply by substance use and the opioid crisis than counties that have stronger economic conditions. Across four different measures of opioid prescribing and substance use, and using three different measures of economic opportunity, we generally find a negative correlation between the crisis and economic opportunities.

Higher poverty and unemployment rates are associated with higher rates of retail opioid sales, Medicare Part D opioid prescriptions, opioid-related hospitalizations, and drug overdose deaths. The employment-to-population ratio is negatively associated with these indicators, with the exception of overdose death rates, where the relationship was positive.

On average, counties with worse economic prospects are more likely to have higher prevalence of substance use and opioid prescriptions. However, our geographic analysis finds some areas with relatively high poverty and unemployment that were relatively isolated from the indicators of the opioid epidemic as of 2016.

This analysis has several limitations. First, it does not identify a causal relationship between the indicators, nor does it address the direction of any possible causal link. It is possible that economic conditions both affect and are affected by substance use. It may also be that something else drives the connection between the two; for example, traumatic experiences and other behavioral health issues may affect both economic self-sufficiency and substance use. In fact, two recent studies suggest that poor economic conditions may not be major factors in the rapid rise in drug overdose deaths and opioid prescribing.[13,14] These hypotheses are not mutually exclusive, and it is possible that the causal relationships differ in different parts of the country.

A second important limitation is that the measures used do not perfectly identify opioid misuse or opioid use disorder in particular, or substance use generally. We do not have a good measure of county-level opioid misuse or opioid use disorder. While this is an important limitation, the fact that we found comparable results using four distinct indicators, collected through separate mechanisms, suggests that they are good proxies for the epidemic.

As decision-makers at the federal, state, and local levels consider approaches to address the opioid epidemic, these results shine light on where these efforts could be targeted. The challenges facing impoverished areas coping with the opioid crisis may be exacerbated to the extent that these areas face shortages of primary care providers, substance use and mental health treatment providers, and other important support services.

Over the past few years, greater attention has been paid to increasing access to treatment services, particularly among more vulnerable populations. For example, the Centers for Medicare and Medicaid Services (CMS) is encouraging states to expand the availability of medication-assisted treatment for opioid use disorder for Medicaid recipients through mechanisms such as 1115 waivers. The 21st Century Cures Act of 2017 dedicated $1 billion to fighting the opioid epidemic, with much of the funds going to treatment and recovery services. The 2018 Consolidated Appropriations Act provided over $3 billion in additional funding, including $1 billion for State Targeted Response to the Opioid Crisis Grants through the Substance Abuse and Mental Health Services Administration and over $400 million for the Health Resources and Services Administration to improve access to addiction treatment in rural and underserved areas.

In addition, the Department of Health and Human Services is taking efforts to address other challenges faced by impoverished communities that have a high degree of substance use. Regional Partnership Grants are designed to identify child welfare practices that can mitigate the impact of parental substance use; funding for these grants recently increased by $100 million in the Bipartisan Budget Act of 2018.[iii] The Maternal, Infant, and Early Childhood Home Visiting Program is identifying interventions to prevent opioid use disorder among parents and its detrimental effects on children. The Administration for Children and Families is in the process of identifying interventions to increase economic self-sufficiency of individuals eligible for the Temporary Assistance for Needy Families program who are affected by opioid use disorder.

This study affirms the importance of these and other efforts at the federal and state levels to increase access to prevention, treatment, and other support services for individuals with opioid use disorder in impoverished areas. While more research is needed to better understand how economic opportunity and substance use interact at the community level, action to address the risks and consequences of the opioid epidemic in communities simultaneously facing economic challenges need not wait.

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[iii] For more information on Regional Partnership Grants, see https://ncsacw.samhsa.gov/technical/rpg-i.aspx.

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# APPENDIX A. DATA AND METHODS

## Data Sources

**Opioid Misuse and Use Disorder**

Data for Figure 1 come from the 2016 National Survey on Drug Use and Health, a nationally-representative survey sponsored by the Substance Abuse and Mental Health Services Administration. Past year opioid misuse is measured based on whether the respondent affirmed using heroin (survey item HERYR), or had non-medical use of a prescription painkiller (survey item PNRNMYR). Past year opioid use disorder is based on criteria from the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders, 4th edition (DSM-IV). Respondents were defined as having an opioid use disorder if they met criteria for either dependency or abuse. A respondent is coded as having a dependency if the respondent responded positively to three or more of the following criteria:

1. Spent a great deal of time over a period of a month getting, using, or getting over the effects of the substance.
2. Unable to keep set limits on substance use or used more often than intended.
3. Needed to use the substance more than before to get desired effects or noticed that using the same amount had less effect than before.
4. Unable to cut down or stop using the substance every time he or she tried or wanted to.
5. Continued to use substance even though it was causing problems with emotions, nerves, mental health, or physical problems.
6. Reduced or gave up participation in important activities due to substance use.

Respondents were defined as abusing a substance if they reported a positive response to one of four abuse criteria, including:

1. Having a serious problem due to substance use at home, work or school.
2. Using substance regularly and then did something where substance use might have put them in physical danger.
3. Substance use causing actions that repeatedly got them in trouble with the law.
4. Having problems caused by substance use with family or friends and continued to use a substance even though it was thought to be causing problems with family and friends.

Respondents were coded as having an opioid use disorder if they responded in the affirmative to survey items for dependency on prescription opioids (DEPNDPYRPNR) or heroin (DEPNDHER), or abuse of prescription opioids (UDPYPNR) or heroin (ABODHER).

**County Prevalence Measures**

Data for measures of county prevalence of prescription opioids and substance use come from four different sources.

**Retail Prescription Opioid Sales**

Data on retail prescription opioid sales come from the Drug Enforcement Administration's (DEA) Automation of Reports and Consolidated Orders System (ARCOS). Data are available for 2006 through

2016 for all counties in the United States. ARCOS reports are collected quarterly, and contain information on the inventories, acquisitions, and dispositions of certain controlled pharmaceuticals. Narcotics (including opioids) that are schedule III controlled substances are reported into ARCOS. Other data sources on retail opioid sales may provide more accurate estimates, but were not available for this analysis. These include commercial data from IQVIA, used by the CDC[11] and the Food and Drug Administration[15], and data from prescription drug monitoring programs. Aggregate national trends of ARCOS data and these data sources are comparable, though not exactly identical.

We selected commonly prescribed and misused opioids, and which have been consistently reported to ARCOS over the time period of study. These include dextropropoxyphene, dihydrocodeine, fentanyl, hydrocodone, hydromorphone, levorphanol, meperidine, morphine, oxycodone, oxymorphone, and tapentadol. Buprenorphine and methadone were excluded, as they are more commonly used to treat opioid use disorder, though both are prescribed for other purposes. ARCOS reports the weight of sales of each drug, and we converted those weights to morphine equivalents using conversion factors provided by FDA.

The DEA publishes ARCOS data for all three-digit zip codes (e.g. 209 would include zip codes 20902 and 20906). To convert to counties, the three digit zip codes were first converted to five-digit zip codes by distributing the share of opioid sales across the appropriate zip codes based on population proportions. This makes the assumption that the distribution of prescription opioids follows the same distribution as the population. Zip codes were then converted to counties using a zip code-county crosswalk provided by the Department of Housing and Urban Development. ARCOS data are reported as rates of morphine equivalent opioid transactions (called "sales" in this report) per 100,000 residents.

There are several important limitations to statistical use of ARCOS data. First, not all opioids are reported into ARCOS, particularly opioids that are not Schedule III. Second, being an administrative data collection, entries into ARCOS may not be consistent and may be correlated with the prevalence of opioid misuse. For example, an investigation by the DEA Inspector General[16] in 2002 found that ARCOS reports "are limited in their value…because of problems of completeness, accuracy, and timeliness." It is unclear to what extent data collection has improved since 2002. One study of psychostimulants found that ARCOS had a high reliability when compared to a state-run prescription drug monitoring program, suggesting that whatever the issues are with absolute measurement, the distribution of ARCOS data may be appropriate.[17] Finally, while research has found a correlation between legitimate use of opioids for therapy and opioid misuse[18], not all individuals that misuse opioids obtain their drugs through prescriptions. This measure will be biased to the extent that non-medical flows of opioids do not mirror prescription flows.

### Opioid-Related Hospitalizations

Data on hospital stays and emergency department visits related to opioids were drawn from the State Inpatient Databases (SID) and State Emergency Department Databases (SEDD), collected as part of the Healthcare Cost and Utilization Project from the Agency for Healthcare Quality and Research. States voluntarily submit patient data to the SID and SEDD, following ICD codes. Hospital inpatient stays and emergency department visits are non-duplicative: patients admitted to the hospital after visiting the ER are considered a hospital stay and removed from the ED visit. Data were available for 32 states, for the years 2011 through 2014.

Patient records were aggregated to the county of patient residence, and calculated as rate per 100,000 residents. Separate data are reported for several categories of substances. Table A1 reports the ICD-9 codes used in this report.

**Table A1. ICD-9 Codes for Hospital and Emergency Department Data**

| **ICD-9-CM diagnosis codes** | **Description** |
|---|---|
| 304.00–304.03 | Opioid type dependence |
| 304.70–304.73 | Combinations of opioids with any other |
| 305.50–305.53 | Nondependent opioid abuse |
| 760.72 | Narcotics affecting neonate |
| 965.00 | Poisoning by opium |
| 965.01 | Poisoning by heroin |
| 965.02 | Poisoning by methadone |
| 965.09 | Poisoning by other opiates and related narcotics |
| E850.0 | Heroin poisoning, accidental |
| E850.1 | Methadone poisoning, accidental |
| E850.2 | Other opiates and related narcotics poisoning, accidental |
| E935.0 | Heroin, adverse effects |

### Medicare Part D Opioid Prescriptions

Data on Medicare Part D opioid prescriptions come from the CMS Patient Drug Event (PDE) file, and are for all claims processed between January 1st 2006 through December 31st, 2016. The PDE file is an administrative data source, based on claims from beneficiaries enrolled in Medicare Part D. Data were tabulated by the address of the Medicare beneficiary. Prescriptions are included for all opioid-containing prescriptions. A complete list of medications is available upon request. Data were calculated as Medicare Part D opioid prescriptions per 100,000 population.

### Death Due to Accidental Drug Poisoning

Data on deaths due to accidental drug poisoning come from small area estimates produced by the CDC.[19] The data contain deaths due to any substances, excluding alcohol and tobacco. Details can be found here: https://www.cdc.gov/nchs/data-visualization/drug-poisoning-mortality/. Data were calculated as age-adjusted death rates per 100,000 population.

## Economic Measures

Poverty rates were drawn from U.S. Census Bureau's Small Area Income and Poverty Estimates (SAIPE), which use small area estimation techniques to augment data collected from the American

Community Survey. Unemployment rates were drawn from the Bureau of Labor Statistics. Data for the employment-to-population ratio were drawn from the Census Bureau’s County Business Patterns.

# Geospatial Analysis

To identify geographic clustering, also known as spatial dependency, we visually examined maps of the relevant variables. We also estimated Moran's I, a measure of spatial dependency. Moran's I is on a scale from -1 to 1. A value of -1 means a perfectly negative spatial relationship, meaning a county is likely to have the opposite value of its neighboring counties. A value of 0 means there is no spatial relationship, that is nearby counties have no relationship with one another on the specific variable. A value of 1 means there is a perfectly positive relationship, meaning a county is more likely to have a similar value as its neighbors. Table A3 reports the values for Moran's I for the measures used in this study.

**Table A3. Spatial Dependency, Moran's I**

| Variable | Moran's I |
|---|---|
| Poverty rate | 0.5843 |
| Unemployment rate | 0.6117 |
| Employment to population ratio | 0.1401 |
| Per capita retail opioid sales | 0.4303 |
| Per capita Medicare Part D opioid prescriptions | 0.2208 |
| Opioid-related hospitalization rate | 0.4594 |
| Drug overdose death rate | 0.4944 |

**Note:** All estimates are statistically significant, $p<0.001$. Estimates for Poverty rate, Unemployment rate, retail opioid sales, Medicare Part D opioid prescriptions are for 2016. The estimate for the employment-to-population ratio is for 2015. The estimate for opioid-related hospitalization rates is for 2014.

# Regression Analysis

To estimate the statistical relationship between the various indicators, we used a series of population-weighted linear regression models. We ran separate models for each opioid and substance use measure.

### Sample

The unit of analysis is the county-year. The years covered for each measure depended on the data availability. Data for all employment measures were available for 2000 through 2016, with the exception of the employment-to-population ratio, which was only available through 2015. For retail opioid sales and Medicare Part D opioid prescriptions, data were available from 2006 through 2016. For drug overdose deaths, data were available for all counties from 2000 through 2016.

For opioid-related hospitalizations, data were available from 2011 through 2014. The sample was restricted to all counties in the 32 states reporting to HCUP, where at least 1 opioid-related hospitalization was reported. This sample change was required to ensure the log of opioid hospitalization rate would be normally distributed, required for valid statistical inference in a linear model. Additionally, estimates including counties with no opioid-related hospitalizations resulted in estimates that were unrealistically large. For counties with few hospitalizations, small changes in rates are proportionally large, and can overly-influence the estimation. It is also possible that at least some counties not reporting any opioid-related hospitalizations have different reporting practices, which could bias the results. While limiting the counties to those reporting leads to more realistic estimates, this limitation should be taken into account. Counties not reporting opioid-related hospitalizations different substantively from those reporting on a number of important variables. They were more likely to have smaller non-Hispanic white populations (77.2% vs 79.1%), higher poverty rates (17.2% vs 17.1%), lower unemployment rates (6.7% vs 8.0%), and higher uninsured rates (18.5% vs 16.1%). Perhaps most importantly, rural counties were far more likely to not report opioid hospitalizations than micropolitan and metropolitan counties (55.4%, 20.1%, and 12.6%, respectively). The final sample for hospitalization models had 52% of its counties in non-metropolitan areas, relative to 64.5% of all counties in the U.S. over the time period.

No other changes were made to the samples. Sample sizes are reflected in the results Tables A4 and A5.

## Methods

We used population-weighted linear regression models with year, state, and state-year fixed effects. The results should be interpreted as changes in the outcome measure associated with a concomitant change in the independent variables, within state-years. The model therefore captures differences both across counties within a state, and over time within a state. The model removes all variation due to stable, cross-state differences, such as culture, geography, and long-term institutional structures, as well as uniform shocks occurring to all counties and states in the same year. The outcome variables are all transformed using the natural logarithm, leading to the interpretation of the model coefficients as a percentage change in the outcome variable associated with a change in the independent variable. The models do not identify causal effects and should not be interpreted as such.

The functional form of the models is:

$$\textbf{(1)}\ \begin{pmatrix} \boldsymbol{Outcome} \\ \boldsymbol{Measure} \end{pmatrix}_{\boldsymbol{cy}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1} \begin{pmatrix} \boldsymbol{Poverty} \\ \boldsymbol{Rate} \end{pmatrix}_{\boldsymbol{cy}} + \boldsymbol{\beta_2}(\boldsymbol{Employment\ Measure})_{\boldsymbol{cy}} +$$

$$\boldsymbol{\gamma X_c} + \boldsymbol{\delta_s} + \boldsymbol{\zeta_y} + \boldsymbol{\xi_{sy}} + \boldsymbol{\varepsilon_c}$$

where $c$ is a specific county in state $s$ in year $y$. **Outcome measures** include per capita retail opioid sales, Medicare Part D prescription rates, opioid-related hospitalization rates, and drug overdose death rates; **Poverty Rate** is the county-level poverty rate for county $c$ in year $y$. **Employment measure** is either the county-level unemployment rate or employment-to-population ratio for county $c$ in year $y$. Because the unemployment rate and employment-to-population ratio are highly collinear, we modeled them separately, though included poverty rate in both models. In the results reported in Table A4 and A5, models (A) include the unemployment rate and models (B) include the employment-to-population ratio.

$\boldsymbol{\delta_s}$, $\boldsymbol{\zeta_y}$, and $\boldsymbol{\xi_{sy}}$ are state, year, and state-year fixed effects, respectively. $\boldsymbol{\varepsilon_{scg}}$ is the error term, which is clustered at the county-level. The **X** vector contains county-level controls. All models included the same basic sets of controls, including percent of population that is white, black, and Hispanic, the percent of the population aged over 65, indicators for the metropolitan status. Metropolitan status is defined using Rural-Urban Continuum Codes, created by the Economic Research Service. Models of per capita Medicare Part D opioid prescriptions include the proportion of the population receiving Medicare benefits, and the total number of Medicare Part D prescriptions (including opioids and non-opioids). Models of opioid-related hospitalization rates include the total number of hospitalizations (emergency room visits and hospital stays).

### Model Results

Table A3 reports summary statistics for regression models. Tables A4 and A5 provide detailed regression results. Two models were run for each indicator that differed only in which employment indicator was included. Models (A) included unemployment rates, and Models (B) included the employment-to-population ratio. Because these two variables are highly collinear, they were modeled separately. Results reported in Table 1 in the text for poverty rates were drawn from Models (A) for simplicity.

**Table A3: Summary Statistics for Models**

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Retail opioids sales (Kg morphine equivalents per 100,000)* | 90.12 | 92.32 | 0.00 | 4574.09 |
| Medicare Part D opioid prescriptions, per 100,000* | 301.44 | 158.2 | 0.00 | 1573.89 |
| Opioid-related hospitalizations, per 100,000* | 171.63 | 204.12 | 0.00 | 2665.26 |
| Death Rate Due to Drug Poisoning (per 100,000)* | 9.67 | 6.71 | 0.01 | 81.65 |
| Poverty Rate | 15.45% | 6.27% | 1.7% | 62.00% |
| Unemployment Rate | 6.32% | 2.73% | 1.10% | 28.90% |
| Employment-Population Ratio | 0.27 | 0.13 | 0.01 | 0.67 |
| White Population | 79.72% | 19.71% | 2.09% | 99.80% |
| Black Population | 9.19% | 14.52% | 0.01% | 86.11% |
| Hispanic Population | 7.89% | 12.98% | 0.08% | 97.54% |
| Age over 65 | 15.94% | 4.40% | 1.68% | 56.31% |
| Medicare enrollees | 18.39% | 5.03% | 0.11% | 81.11% |
| Medicare Part D prescriptions per capita* | 507,686.80 | 210,730.1 | 11.31 | 2,370,968.00 |
| Total hospitalizations (any reason)* | 37,382.57 | 23,023.08 | 647.15 | 209,114.90 |

* Values reported are the raw values, but included in the model with a logarithmic transformation.

**Table A4: Detailed Regression Results, Models for Retail Opioid Sales and Medicare Part D Opioid Prescriptions**

| | Per Capita Retail Opioid Sales | | Per Capita Medicare Part D Opioid Prescriptions | |
|---|---|---|---|---|
| | (A) | (B) | (A) | (B) |
| Poverty | 0.014*** | 0.016*** | 0.033*** | 0.033*** |
| | (0.004) | (0.004) | (0.004) | (0.003) |
| Unemployment | 0.038*** | | 0.019*** | |
| | (0.013) | | (0.006) | |
| Emp-Population Ratio | | -0.005*** | | -0.005** |
| | | (0.002) | | (0.002) |
| White population | 3.292*** | 3.088*** | 1.245*** | 1.137*** |
| | (0.870) | (0.905) | (0.379) | (0.378) |
| Black population | 2.089** | 2.088** | 0.160 | 0.177 |
| | (0.852) | (0.877) | (0.328) | (0.341) |
| Hispanic population | 1.607* | 1.548* | 0.208 | 0.178 |
| | (0.837) | (0.866) | (0.303) | (0.316) |
| Age, over 65 | -0.055 | 0.022 | -1.807 | -2.125** |
| | (0.437) | (0.441) | (1.104) | (1.069) |
| Small metropolitan | -0.251*** | -0.242*** | 0.140*** | 0.162*** |
| | (0.033) | (0.032) | (0.046) | (0.054) |
| Rural | -0.147* | -0.177** | 0.229** | 0.227** |
| | (0.075) | (0.078) | (0.094) | (0.094) |
| Medicare population | | | 0.068*** | 0.072*** |
| | | | (0.008) | (0.008) |
| Total Medicare Part D Prescriptions | | | 0.180*** | 0.201*** |
| | | | (0.065) | (0.074) |
| Constant | 1.297 | 1.936** | 5.432*** | 5.535*** |
| | (0.826) | (0.879) | (1.161) | (1.159) |
| N | 34,405 | 30,955 | 33,570 | 30,220 |
| $R^2$ | 0.3819 | 0.3749 | 0.5589 | 0.5674 |
| Adj. $R^2$ | 0.3715 | 0.3643 | 0.5514 | 0.5600 |

**Note:** Models include state, year, and state-year fixed effects. Standard errors are clustered at the county-level and statistical significance is as follows: * p<0.1, ** p<0.05, *** p<0.01.

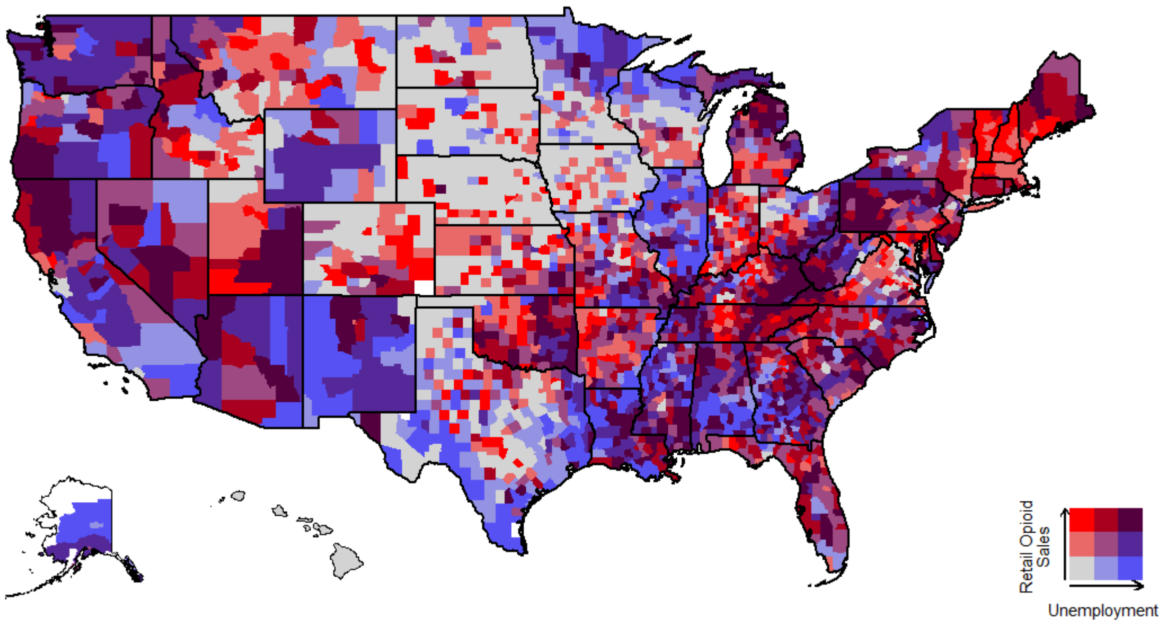
**Table A5: Detailed Regression Results, Models for Opioid-Related Hospitalizations and Drug Overdose Deaths**

| | Opioid-Related Hospitalization Rate | | Drug Overdose Death Rate | |
|---|---|---|---|---|
| | (A) | (B) | (A) | (B) |
| Poverty | 0.024*** | 0.031*** | 0.017*** | 0.027*** |
| | (0.004) | (0.003) | (0.002) | (0.002) |
| Unemployment | 0.051*** | | 0.046*** | |
| | (0.009) | | (0.005) | |
| Emp-Population Ratio | | -0.003* | | 0.005*** |
| | | (0.001) | | (0.001) |
| White population | 0.770* | 0.741* | -0.131 | -0.093 |
| | (0.409) | (0.378) | (0.185) | (0.197) |
| Black population | -0.846* | -0.727* | -1.468*** | -1.500*** |
| | (0.432) | (0.403) | (0.199) | (0.209) |
| Hispanic population | -0.707* | -0.588 | -1.030*** | -1.058*** |
| | (0.412) | (0.378) | (0.217) | (0.223) |
| Age, over 65 | 1.016** | 1.659*** | 0.566** | 1.096*** |
| | (0.439) | (0.449) | (0.261) | (0.264) |
| Small metropolitan | -0.055* | -0.046 | -0.161*** | -0.163*** |
| | (0.031) | (0.032) | (0.018) | (0.018) |
| Rural | 0.066 | 0.077 | -0.396*** | -0.365*** |
| | (0.063) | (0.063) | -0.161*** | -0.163*** |
| Total hospitalization rate (any reason) | 0.198*** | 0.202*** | | |
| | (0.015) | (0.017) | | |
| Constant | 1.832*** | 2.157*** | 1.832*** | 1.890*** |
| | (0.490) | (0.444) | (0.193) | (0.204) |
| N | 5831 | 5820 | 34,349 | 30,907 |
| $R^2$ | 0.5882 | 0.5786 | 0.5711 | 0.5650 |
| Adj. $R^2$ | 0.5787 | 0.5689 | 0.5639 | 0.5576 |

**Note:** Models include state, year, and state-year fixed effects. Standard errors are clustered at the county-level and statistical significance is as follows: * p<0.1, ** p<0.05, *** p<0.01.

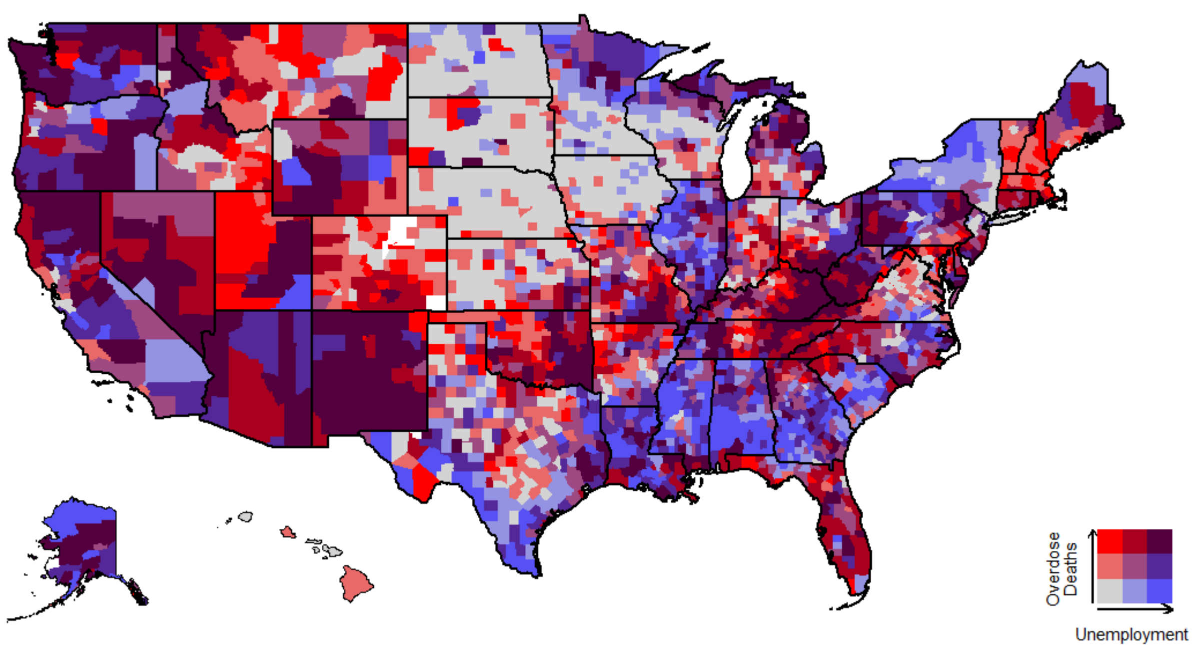
# APPENDIX B. SUPPLEMENTARY FIGURES

**Figure B1. Unemployment Rates and Per Capita Retail Opioid Sales, 2016**




Source: Bureau of Labor Statistics, DEA Automation of Reports and Consolidated Orders System.
Note: Each variable is split into tertiles.

**Figure B2. Unemployment Rates and Drug Overdose Death Rates, 2016**




Source: Bureau of Labor Statistics, CDC Small Area Estimates of Drug Mortality.
Note: Each variable is split into tertiles.