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Michigan Justice Statistics Center

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About the Authors

Jason Rydberg is an assistant professor of criminology and justice studies at the University of Massachusetts Lowell, where he is also co-director of the Center for Program Evaluation. His research interests concern the evaluation of criminal justice program and policies, particularly in the areas of prisoner reentry, community supervision, and sex offender policy. His research has recently appeared in the *Journal of Quantitative Criminology*, the *Journal of Experimental Criminology*, and *Sexual Abuse*.

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Christine C. Kwiatkowski is a dual PhD student between the School of Criminal Justice and Neuroscience Program at Michigan State University. Her research focuses on the biological aspects of aggressive behavior and how environmental factors influence individual physiology to increase risk for aggression. Her work has appeared in *Violence and Gender, Neuroscience,* and *Homicide Studies.*

Executive Summary

This report provides an analysis of illegal drug activity in the State of Michigan, focusing on opioid-related incidents between 2013 and 2017. Data from a number of sources are combined, including incident-based crime data from the Michigan Incident Crime Reports (MICR), opioid-related mortality data from the Michigan Department of Health and Human Services (MDHHS), prescription monitoring data from the Centers for Disease Control and Centers for Medicare & Medicaid Services, and socio-ecological data from a variety of sources. Key results can be summarized as follows:

- Between 2013 and 2017 **opioids consistently appeared in 13-14% of illegal drug-related crime incidents**, making them the second most prevalent drug category next to marijuana (appearing in 57-65% of incidents).

- Patterns of **opioid-related illegal activities** known to law enforcement (e.g., buying/selling, possession, distribution) **remained relatively stable year-to-year**, suggesting no meaningful shifts in such activities over the 2013-2017 period.

- Relative to other types of drugs, offenders involved in opioid-related incidents in the MICR data were **typically between 25 and 34, male, and white**. When **adjusting for prevalence in the population**, rates of opioid-related offending were **highest among those 25 to 34, male, and African American**.

- Between 2013 and 2017 there were **approximately 6,960 deaths attributable to opioids** in the State of Michigan, at an average of 1,392 per year. Of those deaths, **3,048 (43.8%) were attributable to synthetic opioids**. For context, these totals are compared to approximately 2,904 homicides over the same period.

- Between 2013 and 2017 the county-level **rate of opioid-related deaths increased 127%**, and **deaths attributable to synthetic opioids increased 1,243%** - a rate of increase consistent with national trends. These increases occurred despite decreases in opioid prescription rates, and stable trends in arrests and seizures.

- Opioid- and synthetic-opioid related mortality rates were highest in metropolitan area counties.

- County-level variation in law enforcement factors such as **seizures, police officers per 10,000 residents, and opioid-related arrests** were associated with **lower rates of opioid- or synthetic-opioid related deaths**. Higher rates of **retail and Medicare opioid prescriptions** were associated with **higher rates of opioid-related arrest**.

Recommendations

- Although the MICR drug categories are relatively detailed, more granular definitions would enhance the capability of the data to track emergent substances in illegal drug activity. For instance, it is currently difficult to disentangle opioids like heroin and morphine from synthetic opioids like fentanyl in the MICR data. This creates difficulties when trying to examine illegal activity pertaining to these emerging substances, as well as inconsistencies with how substances are classified by other agencies (e.g., MDHHS, CDC). The Michigan State Police should explore how additional detail can be built into the drug categories in the property segment file so as to improve monitoring of these substances.

- Although this analysis found that higher levels of opioid seizures, arrests, and law enforcement personnel were associated with decreases in the rate of opioid-related deaths, it is important to recognize that law enforcement efforts are only one component of the response to the opioid crisis. Justice-involved individuals have been found to have heightened risk of opioid-related deaths, particularly within a short period following release from correctional facilities. Interventions which focus solely on law enforcement goals may not be as impactful on public health-related goals as those that combine law enforcement and public health-related efforts.

- Promising practices from other areas of the US include decriminalization of possession of non-prescribed buprenorphine, and training and equipping officers with overdose-reversing drugs such as naloxone.

Purpose of this Research

Many areas of the United States are experiencing an epidemic of drug overdose deaths, often involving opioids. In 2017, there were 70,237 drug overdose deaths in the United States, a rate 9.6% higher than 2016. 47,600 of these deaths involved an opioid (National Institute on Drug Abuse [NIDA], 2019). The opioid overdose epidemic has been described as a series of "waves." The first wave began with increased prescribing of opioid analgesics in the 1990s driving an increase in prescription opioid overdose deaths. The second wave, starting around 2010, was characterized by a rapid increase in overdose deaths involving heroin. Beginning in 2013 and continuing today, many areas of the country are experiencing the "third wave" of the epidemic, characterized by a significant increase in overdose deaths involving synthetic opioids like fentanyl (Centers for Disease Control [CDC], 2018). Some experts have indicated that a coming "fourth wave" may be characterized by overdose deaths related to polysubstance use including opioids, cocaine, and psychostimulants (e.g. methamphetamine).

Beyond these general trends, research shows that the nature of the overdose epidemic is region-specific. It could be said that there is not one overdose epidemic, but many epidemics that vary substantially by a region's economic and demographic characteristics. This "geography of the U.S. opioid overdose crisis" was recently mapped by Shannon Monnat and colleagues (2019), who found that overall drug mortality rates are higher in counties characterized by more economic disadvantage, more blue-collar and service employment, and higher opioid-prescribing rates. Specifically, Michigan shows a pattern of increasing heroin-involved deaths in the west and south-west areas of the state, a mixture of emerging heroin, prescription opioids, and "synthetic+" (synthetic opioids alone or in combination with other opioids) in the rural north, and a "syndemic" (all types of opioids and combinations) in the southeast. In the Upper Peninsula, we see high and emerging heroin counties along the Wisconsin border, and synthetic+ counties along the peninsula's eastern tip. These patterns map to economic and demographic patterns across Michigan. "Urban professional" areas are related to rapidly rising probability of "syndemic" classification (e.g. the greater Detroit area). Blue-collar worker presence is associated with the emerging heroin and syndemic classes, and service economy areas (e.g. the north half of the state) are associated with rising probability of membership in all five opioid classes (high prescription opioid, emerging heroin, high heroin, synthetic+, and syndemic). The prescription opioid class counties are more likely to be rural, economically disadvantaged, and have high scores on blue-collar and service economy indices.

These results make it clear that there is no single solution to the overdose crisis. To understand and, importantly, to effectively respond to the crisis and reduce opioid-related mortality, we must have an in-depth understanding of the crisis in *Michigan*, both from the perspective of public health and of law enforcement. This research draws on data from a number of different sources to triangulate a comprehensive picture of illegal drug activity in the State of Michigan. These sources are leveraged to combine information gathered from law enforcement sources, prescription monitoring, mortality and vital statistics, and community demographics.

Data Sources and Definitions

Law Enforcement Data Sources

The **Michigan Incident Crime Reporting System (MICR)** is an incident-level crime database maintained by the Michigan State Police. The MICR system represents Michigan's contribution to the National Incident Based Reporting System (NIBRS), containing information on victims, offenders, arrestees and offense circumstances across crime incidents. For this analysis, the MICR system was used to identify incidents reported to law enforcement that involved illegal drug activity, and then to subsequently describe the nature of that activity, the substances involved, and the associated offenders.

Specifically, for this analysis we parsed MICR data pertaining to the years 2013 to 2017 using a file linking strategy described by Rydberg (2016). Across each year, we narrowed the data down to two specific offense codes pertaining to illegal drug activity:

Table 1. MICR Offense Codes and Labels for Illegal Drug Activity

MICR Code	Offense Label
35001	Violation of Controlled Substance
35002	Narcotics Equipment Violations

As an incident-level file, each incident can contain a number of offenses, each with a number of offenders, who may or may not be arrested. In order to avoid counting duplicate records within each of these levels of analysis (e.g., double counting offenders within an incident because each one committed multiple offenses), we used the dplyr package in R (Wickham, Francois, Henry, & Muller, 2019) to systematically identify unique entities within each incident. Across the 2013 to 2017 period, Table 2 identifies counts for unique entities. In total, the MICR data identify 233,703 unique incidents involving illegal drug activity. Within the MICR data, incidents are defined as "one or more offenses committed by the same person or group of persons acting in concert, at the same time and place" (MSP, 2014). These incidents involved 296,453 unique offenders, who committed 258,016 unique offenses, leading to 199,156 unique arrests. From year to year, totals for these observed entities remains relatively stable.

Table 2. Unique Incidents, Offenders, Offenses, and Arrests in MICR Drug Activity Data, 2013-2017

Reporting Year	Incidents Frequency (%)	Offenders Frequency (%)	Offenses Frequency (%)	Arrests Frequency (%)
2013	46,578 (19.9)	60,123 (20.3)	50,928 (19.7)	34,306 (17.2)
2014	45,529 (19.5)	58,868 (19.9)	49,881 (19.3)	41,126 (20.7)
2015	46,744 (20.0)	59,236 (20.0)	51,494 (20.0)	41,999 (21.1)
2016	47,977 (20.5)	59,988 (20.2)	52,843 (20.5)	42,139 (21.2)
2017	46,875 (20.1)	58,242 (19.6)	52,870 (20.5)	39,590 (19.9)
Total	233,703	296,453	258,016	199,156

Note: Percentages reflect column percentages for year to year trends.

Identifying Opioid-Related Incidents

The MICR data include information to distinguish the nature of the illegal substance(s) involved in the incident. These drugs – identified by the variable MICR9_DRUG_TYPE – are identified by one of 20 unique codes (Table 3). In this analysis, **opioid-involved** incidents are those that included the drugs heroin, morphine, opium, or other narcotics (categories 4, 6, 7, and 8). It is important to note that these existing categories do not make it possible to systematically distinguish naturally occurring opiates (e.g., heroin) from synthetic opioids (e.g., Fentanyl). The reason for this is that the "Other Narcotics" category includes both naturally occurring and synthetic opioids, and yet this category is the closest approximation for identifying synthetic opioid-related incidents within the MICR data, and NIBRS more broadly. To this extent, certain analyses in this report will examine these incidents in isolation, but with the understanding that the definition used in the data may be more inclusive than what is typically considered a synthetic opioid.

Law Enforcement Personnel

County-level information on the number of sworn law enforcement personnel was derived from the Law Enforcement Officers Killed and Assaulted (LEOKA) data sets maintained by the FBI. These data were retained for the 2013-2017 period in order to whether variation in opioid arrests or overdose deaths were attributable to the density of law enforcement officers.

Opioid Prescription Monitoring Data

County-level data on opioid pain reliever prescription monitoring was derived from a number of data sources. Prescriptions for these drugs were tracked in two ways. Annual data on **retail opioid prescriptions** were obtained from the Centers for Disease Control (CDC).[1] Additionally, annual data on **Medicare Part D opioid prescriptions** were obtained from the Centers for Medicare & Medicaid Services (CMS).[2] Regardless of the source, these represent legal prescriptions to natural, semisynthetic, and synthetic opioids, including buprenorphine, codeine, fentanyl, hydrocodone, hydromorphone, methadone, morphine, oxycodone, oxymorphone, propoxyphene, tapentadol, and tramadol. Prescriptions are defined as written and submitted to be filled.

Each of these measures allows for the calculation of opioid prescribing rates, but differentiating prescriptions that are paid for by Medicare, and thus more likely to reflect prescriptions to individuals over the age of 65 and those in rural communities (Kimmel, Fwu, Abbott, Ratner, & Eggers, 2016). Differentiating these sources of opioid prescriptions is important because of research suggesting the association between Medicare Part D utilization and substance abuse by the elderly population (Lichtenberg & Sun, 2007). Because the CDC retail prescription data includes Medicare Part D prescriptions, the **non-Medicare retail**

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[1] https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html

[2] https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/OpioidMap.html

prescriptions were calculated by subtracting the Medicare Part D prescription rate from the total prescription rate per 10,000 population.

Table 3. MICR Drug Type Codes

MICR Drug Category Code	Description	Analysis Category
1	"Crack" Cocaine	Stimulants
2	Cocaine (all forms except "Crack")	Stimulants
3	Hashish	Marijuana / Hashish
4*	**Heroin**	**Opioids**
5	Marijuana	Marijuana / Hashish
6*	**Morphine**	**Opioids**
7*	**Opium**	**Opioids**
8*	**Other Narcotics: Codeine, Demerol, Dihydromorphinone or Dilaudid, Hydrocodone, or Percodan, Methadone, etc.**	**Opioids**
9	LSD	Hallucinogens
10	PCP	Hallucinogens
11	Other Hallucinogens: K2, BMDA, DMT, MDA, MDMA, Mescaline, etc.	Hallucinogens
12	Amphetamines	Stimulants
13	Other Stimulants: Adipex, Fastine, Ionamin, Benzedrine, Didrex, Ritalin, Tenuate, etc.	Stimulants
14	Barbiturates	Depressants / Sedatives
15	Other Depressants: Glutethimide, Methqualone, Pentazocine, etc.	Depressants / Sedatives
16	Other Drugs: Antidepressants, Aromatic Hydrocarbons, Tranquilizers, etc.	Other Drugs
17	Methamphetamines	Methamphetamines
18	GHB (Date Rape Drug)	Depressants / Sedatives
77	Over three (3) drug types	Over 3 drug types
99	Unknown	Unknown

Note: * Categorized as opioids

Mortality and Vital Statistics

Data to measure deaths attributable to opioids were obtained from a number of sources. Primarily, county-level counts of **opioid-involved deaths** were obtained for the 2013-2017 period from the Michigan Department of Health and Human Services, Division for Vital Records and Health Statistics. Opioid-related deaths were identified based on ICD-10 (International Classification of Diseases) underlying cause of death codes related to drug poisoning deaths, with contributing cause codes in the T.40 series, which includes heroin, semi-synthetic opioids, and synthetic opioids.[3] Because these contributing cause codes enable disaggregating **deaths attributable to synthetic opioids** with the T40.4 (Other Synthetic Narcotics) category, it will be possible to separately consider trends related to these specific drugs in a manner that is not possible with the classifications used in MICR.

Community Demographics

In order to examine the extent to which community demographics, economic factors, and health environment are associated with opioid-related deaths and illegal drug activity, this report draws on data from a number of sources. These sources include the American Community Survey, the US Department of Housing and Urban Development, and the Robert Wood Johnson Foundation county health rankings. Specific measures derived from these sources will be described in detail later in the report.

Analysis Plan

The following will first consider a descriptive analysis of the **prevalence and nature of illegal drug activity** in Michigan as described in the MICR data for 2013-2017. These analyses will contextualize the extent of opioid-related illegal activity, relative to other drug types. The analysis will then consider the individuals involved with and subsequently arrested for the offenses. The analysis will then shift to a descriptive analysis of **county-level** data to describe **trends** in illegal opioid activity, prescriptions, and opioid-involved deaths. These analyses will consider broad trends over time, as well as geographic differences across counties. The final set of analyses will examine the **county-level associations** between community-level factors, law enforcement activity, prescriptions, and opioid-involved deaths. This analysis will leverage the longitudinal nature of the data to consider the impact of differences in these factors between counties, as well as variation within counties over time.

[3] Specifically, drug overdose deaths are identified using the underlying cause of death codes X40-X44, X60-X64, X85, and Y10-Y14. Opioid-related deaths are identified using contributing case of death codes T40.0 (Opium), T40.1 (Heroin), T40.2 (Other Opioids), T40.3 (Methadone), T40.4 (Other Synthetic Narcotics), and T40.6 (Unspecified Narcotics).

Prevalence and Nature of Illegal Drug Activity

Drug Presence at Incidents

The first set of analyses (Tables 4 and 5) consider the prevalence of each drug type at incidents identified in the MICR data. By a wide margin, Marijuana was the most prevalent drug, appearing in 57% to 65% of incidents across 2013-2017, followed by opioids, which appeared in 13% to 14% of incidents. Concerning opioids in particular, their relative prevalence in crime incidents followed a curvilinear pattern, increasing between 2013 and 2015, and then decreasing back to 2013 levels by 2017. Of the drug types considered in Table 3, methamphetamines demonstrated the largest relative increase during the 2013-2017 period. In that time, the number of incidents involving methamphetamine increased 156%, from 946 in 2013 to 2,246 in 2017.

Table 4. Presence of Specific Drugs across Unique Drug Activity Incidents, 2013-2017

Drug Category	2013 Frequency (%)	2014 Frequency (%)	2015 Frequency (%)	2016 Frequency (%)	2017 Frequency (%)
Depressants / Sedatives	433 (0.8)	447 (0.9)	525 (1.0)	593 (1.1)	722 (1.3)
Hallucinogens	406 (0.8)	425 (0.8)	456 (0.9)	496 (0.9)	539 (1.0)
Marijuana	33,951 (64.9)	32,787 (63.9)	32,225 (62.3)	33,446 (60.0)	31,317 (57.0)
Methamphetamines	946 (1.8)	1,023 (2.0)	1,385 (2.6)	1,828 (3.3)	2,426 (4.4)
Opioids	6,778 (13.0)	7,127 (13.9)	7,626 (14.3)	7,717 (13.8)	7,130 (13.0)
Stimulants	5,761 (11.0)	5,462 (10.6)	6,101 (11.4)	6,525 (11.7)	7,946 (14.5)
Other Drugs	2,189 (4.2)	2,295 (4.5)	2,398 (4.5)	3,336 (6.0)	3,010 (5.5)
Over 3 Drug Types	83 (0.2)	445 (0.9)	123 (0.2)	239 (0.4)	179 (0.3)
Substance Unknown	1,730 (3.3)	1,338 (2.6)	1,523 (2.9)	1,542 (2.8)	1,720 (3.1)
Total (Incidents)	52,277	51,349	53,362	55,722	54,989

Note: Percentages reflect column percentages for year to year trends.

Table 5 breaks opioids down into two categories, distinguishing heroin, morphine, and opium from "synthetic opioids." [4] In each year of the 2013-2017 period, heroin, morphine, and

[4] Note that "synthetic" is offered in quotes because this category of "Other Narcotics" is the category most likely to contain synthetic narcotics such as fentanyl, but may also include some natural and semi-synthetic opioids as well.

opium were more prevalent than synthetic opioids in MICR incidents by roughly a 2 to 1 margin. The presence of synthetic opioids remained relatively stable over this period, while the prevalence of heroin, morphine, and opium increased between by 32% between 2013 and 2016, before decreasing in 2017.

Table 5. Presence of Opioids across Unique Drug Activity Incidents, 2013-2017

Drug Category	2013 Frequency (%)	2014 Frequency (%)	2015 Frequency (%)	2016 Frequency (%)	2017 Frequency (%)
Heroin, Morphine, Opium	4,105 (8.4)	4,519 (9.4)	5,092 (10.3)	5,407 (10.6)	4,899 (9.8)
"Synthetic" Opioids	2,851 (5.8)	2,796 (5.8)	2,733 (5.6)	2,515 (4.9)	2,499 (4.9)
All Other Drugs	41,999 (85.8)	40,717 (84.8)	41,702 (84.1)	43,008 (84.4)	42,532 (85.3)
Total (Incidents)	48,955	48,032	49,567	50,930	49,880

Note: Percentages reflect column percentages for year to year trends.

Drug Activities undertaken by Offenders

In the MICR data, each identified offender is recorded as engaging in one or more illegal drug activity within each incident. These activities can include buying or receiving a given drug, distribution, or possession, among others. For all illegal drug activity, the prevalence of these activities across offenders within the MICR data is displayed in Table 6. Possession or concealment of an illegal substance was the most prevalent activity by offenders in the data, with approximately three-quarters of offenders engaging in such activity between 2013-2017. Distribution / selling was the next most prevalent activity, with 13% to 16% of offenders each year.

Table 7 considers drug activities engaged by offenders in incidents that specifically involved opioids. As with overall drug activities, possession and concealment was the most prevalent activity, occurring among 62% to 64% of offenders. Relative to patterns with drugs in general, distribution and selling of opioids was a relatively more common activity, occurring among 25% to 29% of offenders. These patterns were largely stable over time, with no sizable shifts in relative percentages between 2013 and 2017.

Table 6. Drug Activities among Offenders, 2013-2017

Drug Activity	2013 Frequency (%)	2014 Frequency (%)	2015 Frequency (%)	2016 Frequency (%)	2017 Frequency (%)
Buying/Receiving	645 (1.0)	856 (1.4)	883 (1.4)	727 (1.1)	775 (1.2)
Cultivating / Manufacturing	2,497 (3.9)	2,407 (3.8)	2,255 (3.5)	2,098 (3.2)	1,692 (2.7)
Distribution / Selling	10,236 (16.1)	9,733 (15.6)	8,718 (13.7)	8,255 (12.7)	8,325 (13.3)
Exploiting Children	8 (> 0.0)	26 (> 0.0)	2 (> 0.0)	22 (> 0.0)	5 (> 0.0)
Operating / Promoting / Assisting	321 (0.5)	276 (0.4)	347 (0.5)	337 (0.5)	242 (0.4)
Possessing / Concealing	45,398 (71.3)	44,384 (71.0)	46,091 (72.5)	47,684 (73.5)	46,353 (74.1)
Transporting / Importing	1,059 (1.7)	1,507 (2.4)	1,839 (2.9)	1,960 (3.0)	1,283 (2.1)
Using / Consuming	3,490 (5.5)	3,355 (5.4)	3,430 (5.4)	3,808 (5.9)	3,849 (6.2)
Total (Offenders)	63,654	62,544	63,565	64,891	62,524

Note: Percentages reflect column percentages for year to year trends.

Table 7. Opioid Drug Activities among Offenders, 2013-2017

Drug Activity	2013 Frequency (%)	2014 Frequency (%)	2015 Frequency (%)	2016 Frequency (%)	2017 Frequency (%)
Buying/Receiving	233 (2.4)	255 (2.5)	260 (2.3)	191 (1.8)	192 (1.9)
Cultivating / Manufacturing	177 (1.8)	136 (1.3)	201 (1.8)	178 (1.6)	152 (1.5)
Distribution / Selling	2,793 (28.8)	2,843 (27.8)	2,816 (25.4)	2,676 (24.5)	2,536 (25.2)
Exploiting Children	1 (> 0.0)	4 (> 0.0)	0 (> 0.0)	3 (> 0.0)	0 (> 0.0)
Operating / Promoting / Assisting	33 (0.3)	29 (0.3)	44 (0.4)	40 (0.4)	41 (0.4)
Possessing / Concealing	5,974 (61.5)	6,388 (62.4)	7,047 (63.5)	6,921 (63.4)	6,441 (63.9)
Transporting / Importing	103 (1.1)	170 (1.7)	182 (1.6)	176 (1.6)	165 (1.6)
Using / Consuming	400 (4.1)	416 (4.1)	551 (5.0)	728 (6.7)	551 (5.5)
Total (Offenders)	9,714	10,241	11,101	10,913	10,078

Note: Percentages reflect column percentages for year to year trends.

Offenders Arrested for Illegal Drug Activities

Among offenders detailed in each MICR incident, not all are ultimately arrested by law enforcement. The likelihood of arrest in these data are based on both officer discretion and whether the offender is apprehended (Drave, Thomas, & Walker, 2014). The percentage of offenders who were arrested for each drug category is displayed in Table 8. Overall, approximately 70 percent of offenders are arrested for illegal drug-involved offenses, and this percentage is relatively stable from year to year. However, there is considerable variation in the likelihood of arrest across drug categories, both within and between years.

Specifically, offenders involved in incidents with more than 3 drug types tended to be the most likely to be arrested, but this likelihood ranged from 63.9 percent in 2014, to 87 percent in 2017. The percentage of offenders arrested for marijuana-based offenses were the most consistent, ranging from 71 percent to 73 percent across years. Offenders involved in incidents with methamphetamines and when the substance was unknown were consistently the least likely to be arrested.

Considering opioids in particular, in 2013 70.6 percent of offenders in opioid-involved incidents were arrested. This percentage decreases to 62.3 percent in 2017.

Table 8. Percent of Offenders Arrested by Drug Category, 2013-2017

Drug Category	2013 Arrests (%)	2014 Arrests (%)	2015 Arrests (%)	2016 Arrests (%)	2017 Arrests (%)
Depressants / Sedatives	73.5	67.9	71.7	65.3	61.4
Hallucinogens	66.3	64.2	62.8	58.7	59.9
Marijuana	72.6	72.5	73.3	73.3	71.1
Methamphetamines	58.2	52.4	56.7	59.1	57.9
Opioids	70.6	68.0	68.0	63.9	62.3
Stimulants	71.5	69.5	70.8	71.8	67.4
Other Drugs	65.0	60.5	65.5	70.9	71.5
Over 3 Drug Types	78.6	63.9	69.1	78.0	87.4
Substance Unknown	55.0	51.9	54.7	57.3	52.8
Overall	70.9	69.7	70.7	70.5	68.0

Note: Percentages calculated as unique arrestees divided by unique offenders.

Table 9 details the likelihood of arrest across all drugs, but based on the type of drug activity the offender was engaged in. Across all years, offenders involved in transporting or importing drugs were the most likely to be arrested, with approximately 80 percent of offenders being arrested for such activities.[5] For other activities, the likelihood of arrest changed over the 2013 to 2017 timeframe. For instance, in 2013 56.1 percent offenders engaging in operating, promoting, and assisting activities were arrested, and this percentage increased to more than 71 percent in 2016 and 2017.

[5] This excludes the "exploiting children" category, which contained a relatively small number of offenders across all years.

Table 9. Percent of Offenders Arrested by Drug Activity, 2013-2017

Drug Category	2013 Arrests (%)	2014 Arrests (%)	2015 Arrests (%)	2016 Arrests (%)	2017 Arrests (%)
Buying/Receiving	59.5	48.5	49.8	45.5	44.5
Cultivating / Manufacturing	48.7	43.0	46.8	48.8	48.1
Distribution / Selling	57.8	51.9	54.3	55.4	54.4
Exploiting Children	75.0	11.5	100	63.6	40.0
Operating / Promoting / Assisting	56.1	54.0	65.7	71.2	71.5
Possessing / Concealing	75.3	75.9	75.5	74.3	71.8
Transporting / Importing	80.4	78.3	82.2	82.0	80.7
Using / Consuming	66.9	65.4	67.8	64.2	66.8
Overall	70.8	69.9	71.0	70.4	68.3

Note: Percentages calculated as unique arrestees divided by unique offenders.

Table 10 presents a similar breakdown of the likelihood of arrest for offenders engaging in drug activities, but specifically for opioids. As with the pattern in Table 8 above, the likelihood of offenders being arrested for opioid-related activities decreased from 2013 to 2017, shifting from 71 percent to 63 percent. This same pattern is evident across several specific types of illegal drug activities involving opioids, where the likelihood of arrest for possession, using / consuming, distribution / selling all decreased over time.

Table 10. Percent of Offenders Arrested for Opioid Related Activities, 2013-2017

Drug Category	2013 Arrests (%)	2014 Arrests (%)	2015 Arrests (%)	2016 Arrests (%)	2017 Arrests (%)
Buying/Receiving	61.4	48.6	48.1	37.2	39.1
Cultivating / Manufacturing	58.2	50.0	53.7	62.4	58.6
Distribution / Selling	57.5	53.0	54.2	51.9	50.7
Exploiting Children	100	25.0	0	66.7	
Operating / Promoting / Assisting	66.7	72.4	79.5	75.0	65.9
Possessing / Concealing	78.8	77.1	75.5	70.9	69.2
Transporting / Importing	73.8	65.3	75.3	78.4	72.7
Using / Consuming	57.5	55.0	52.3	43.1	49.7
Overall	70.9	68.2	68.0	63.8	62.8

Note: Percentages calculated as unique arrestees divided by unique offenders.

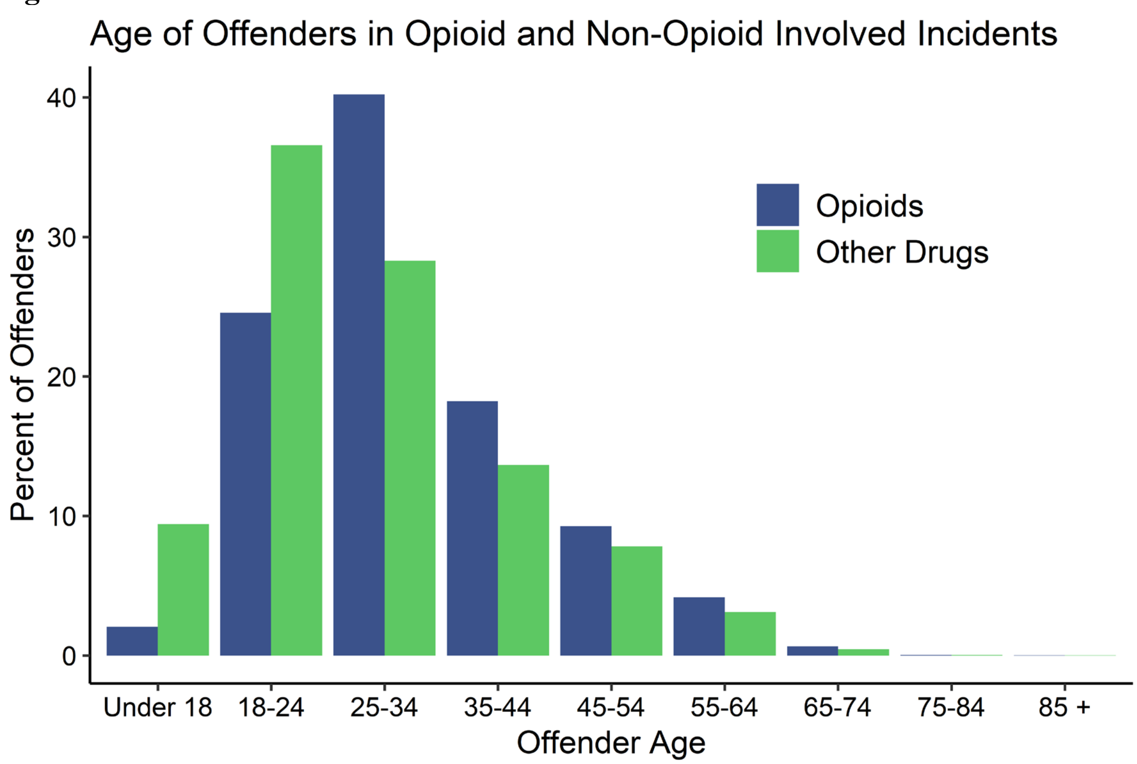
Characteristics of Offenders in Opioid-Involved Incidents

Next, the analysis considers the characteristics of individual offenders in opioid-involved incidents. The MICR data include a limited number of demographic characteristics to characterize offenders, including age, sex, and race.[6] In considering these characteristics, this analysis will display the relative distribution of offenders in both opioid and non-opioid involved incidents within MICR, and then display offending rates normalized by population counts from the 2017 American Community Survey.

Offender Age

The relative age of offenders in opioid and non-opioid involved incidents are displayed in Figure 1. Offenders in opioid involved incidents were most frequently between 25 and 35 years old, while offenders in non-opioid incidents were most frequently 18-24. These distributions suggest that, among offenders in the MICR data for 2013-2017, offenders in opioid incidents tended to be older than those in non-opioid incidents.

Figure 1



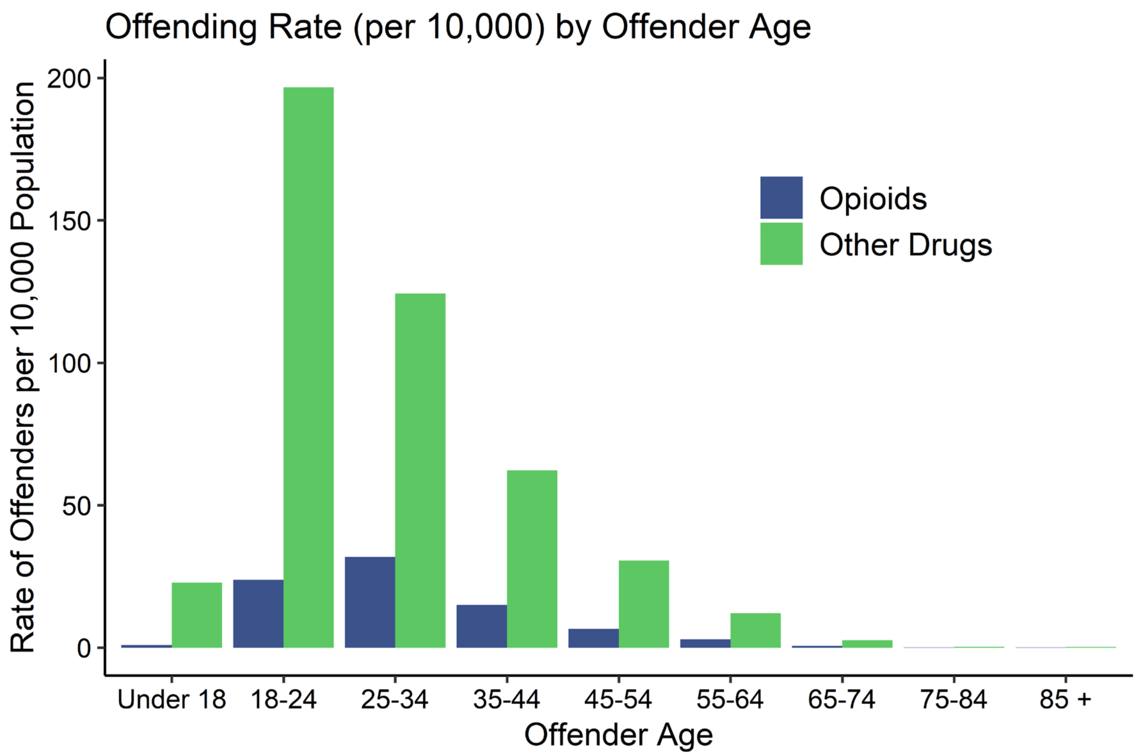
Although such a breakdown is useful for describing the characteristics of offenders within the MICR data, these totals do not speak to how prevalent such offenses are among the Michigan population as a whole. Using the offending totals from MICR over the 2013-2017

[6] Offender ethnicity is also included within the data, but is measured with less precision than the other demographic characteristics. Because of the degree of missing data in this measure, we do not include offender ethnicity as a characteristic here.

period, these counts were converted into rates per 10,000 population by dividing by the Michigan population (× 5, since there were 5 years of data) and multiplying by 10,000.

The offending rates (per 10,000 population) for offender age groups are displayed in Figure 2. This comparison suggests that although the rate of opioid involved offending is highest among 25-34 year olds (31.8 per 10,000), the difference in offending rates between 18-24 year olds and those 25-34 is not as stark as indicated in Figure 1. Further, involvement with opioids is still far outweighed by rates of offending with other drugs.

Figure 2



Offender Sex

Next, Figures 3 and 4 present similar distributions considering offender sex. As with patterns of criminal offending in general, offenders in illegal drug activity incidents are most commonly male. However, when considering opioid vs. non-opioid involved incidents in the MICR data (Figure 3), a larger proportion of offenders in opioid incidents are female (27.8% vs. 22.23%). When considering rates of offending per 10,000 population, Figure 4 highlights that rates of offending are higher for males, and that rates of non-opioid involved offending outweigh those involving opioids. However, highlighting the difference in the relative prevalence of females among opioid involved offenses in Figure 3, in Figure 4 the rate of opioid-involved offending for females is 37 percent that of the rate for males (5.34 vs. 14.3 per 10,000), compared to non-opioid drugs, in which the offending rate for females is 28 percent that of males (23.7 vs. 85.4 per 10,000).

Figure 3

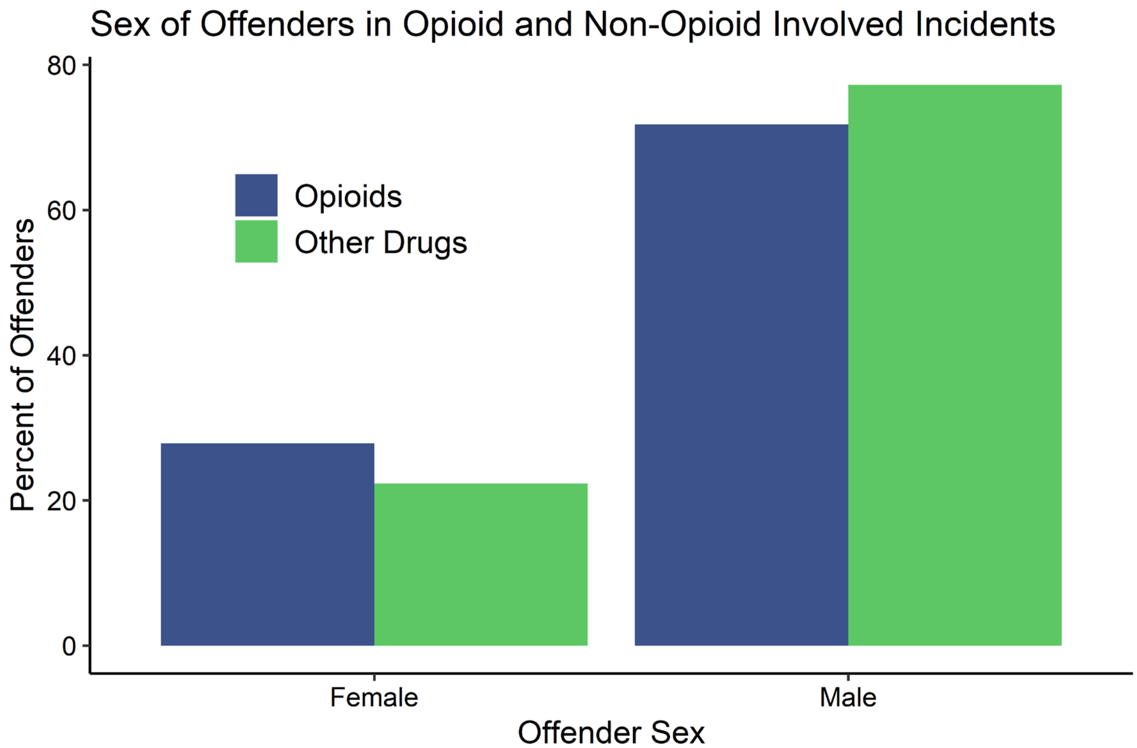
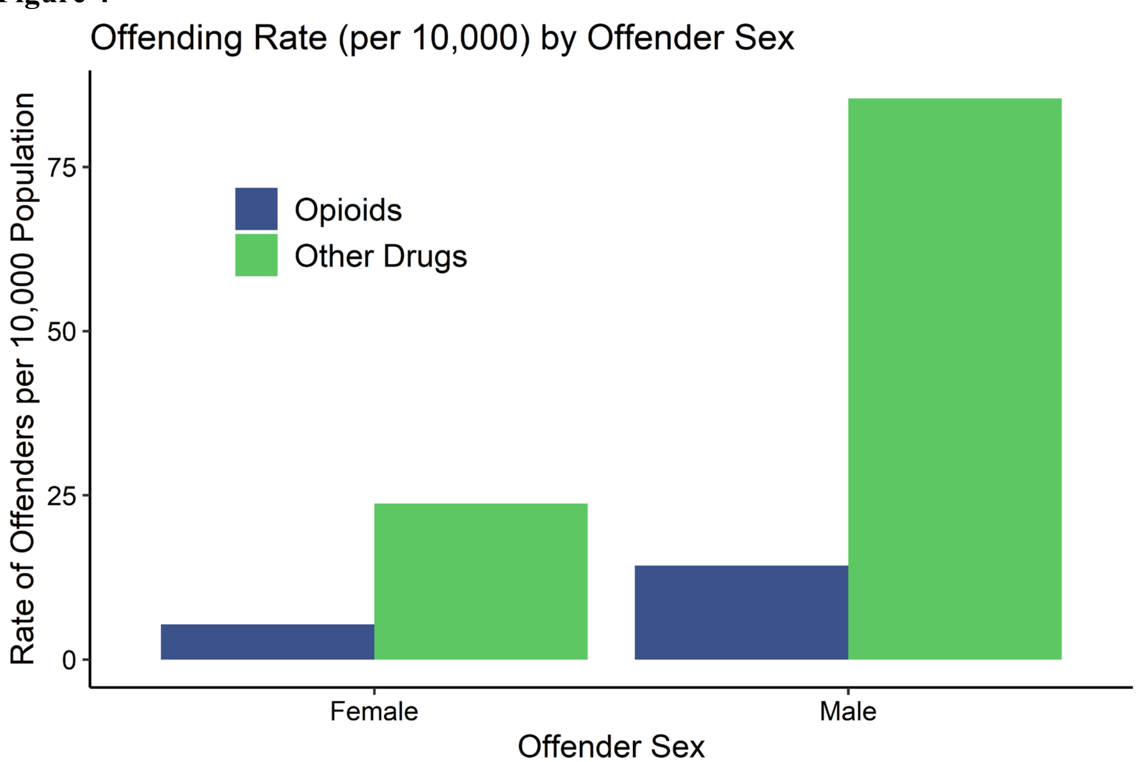


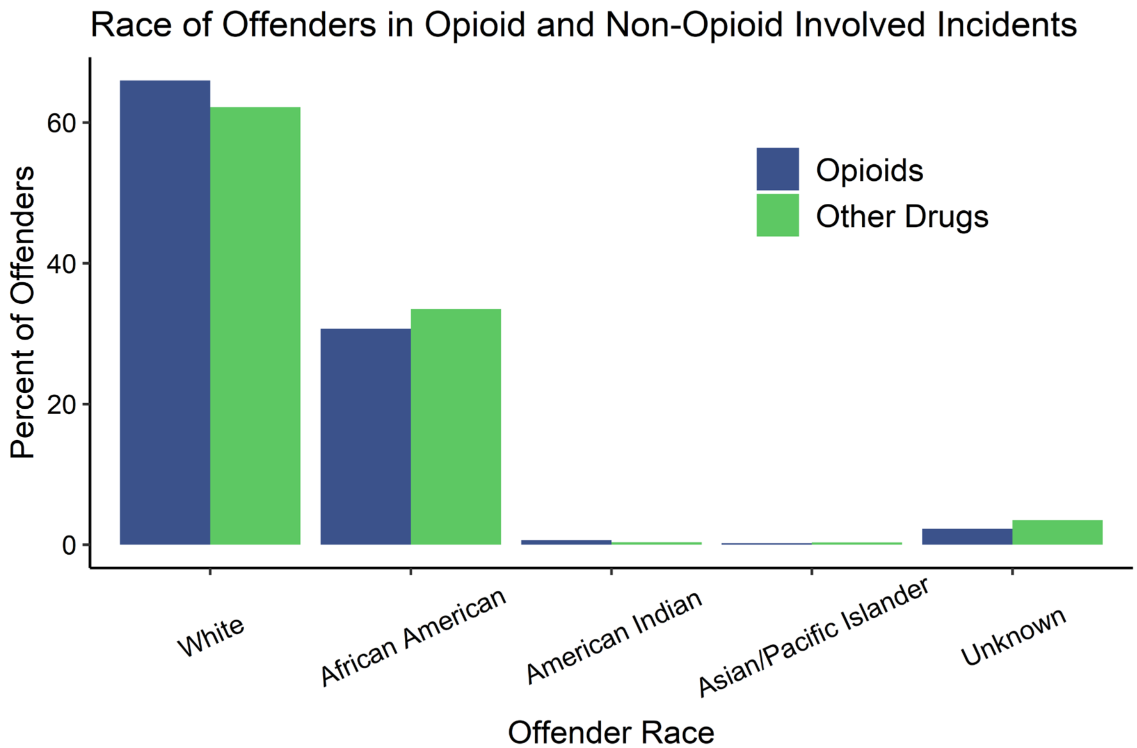
Figure 4



Offender Race

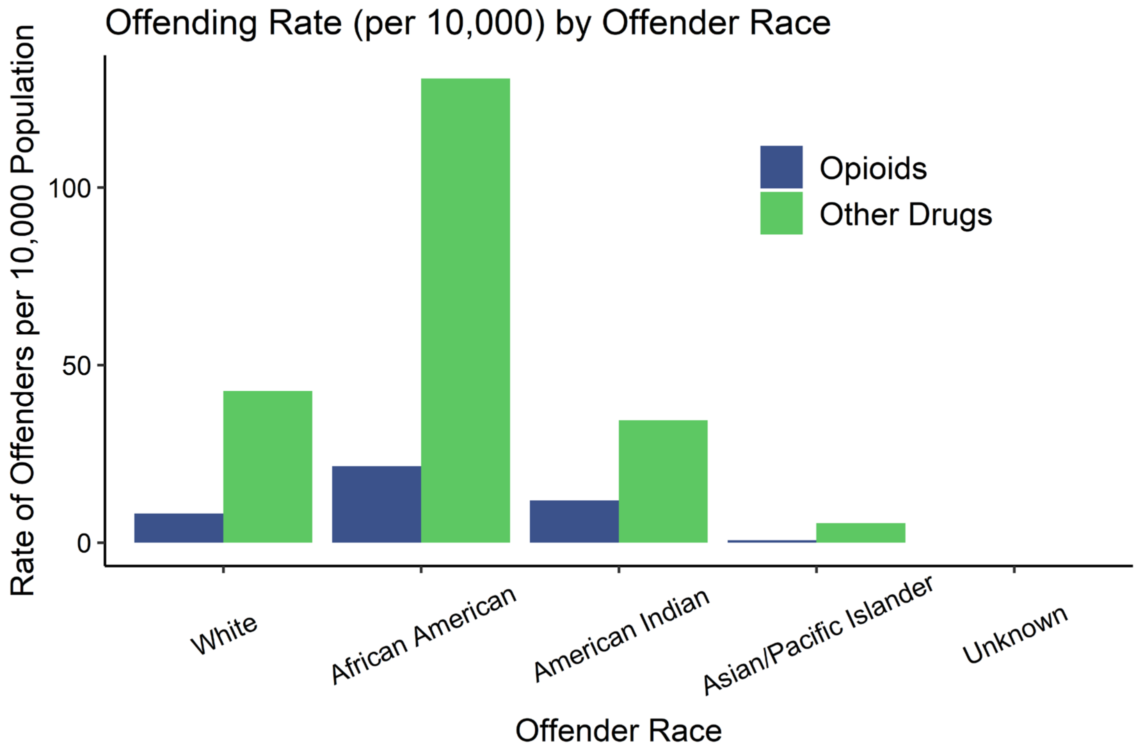
Figure 5 displays the prevalence of racial groups among MICR offenders in opioid and non-opioid involved incidents between 2013 and 2017. A comparison of these distributions suggests that most offenders in the data (~ 60%) are white, and slightly more opioid involved offenders are white compared to non-opioid involved offenders (66% vs. 62%). An opposite pattern is observed among Black offenders, in which a slightly larger percentage are involved with non-opioid drugs, as opposed to opioids (34% vs. 31%).

Figure 5



Although Figure 5 highlights that the majority of offenders in the MICR data are white, these totals are not normalized against the characteristics of the Michigan population. Figure 6 displays offending rates per 10,000 population. These results suggest that Black offenders are relatively more prevalent among both opioid and non-opioid offenses (21.6 and 131.0 offenses per 10,000 population, respectively). The rates also suggest that American Indians offenders are disproportionately represented among individuals in opioid involved offenses, with a rate of offending slightly higher than that of white individuals (11.9 vs 8.15 per 10,000).

Figure 6



Drug Seizures

For any given incident, the MICR data also include information on drugs that are seized by law enforcement. These records detail the suspected type of drug seized, and estimates of the quantity of drugs, measured in physical weight (kilograms), liquid volume (fluid liters), or physical units (e.g., pills, plants, syringes).[7] Table 11 details total sums of drugs seized each year, across the various drug categories in the MICR data. These totals vary considerably across drug types, and within drug categories over time. Concerning opioids in particular, these drugs are most often seized as physical units, and between 2013 and 2016 the amount seized was relatively stable at approximately 80,000 units per year, except for 2014 when 100,000 units were seized. In 2017, the number of units seized was relatively lower, at 51,000 units seized.

[7] Per the MICR Handbook, drug seizures are detailed when three conditions are met. First, one of the offenses listed in the incident is coded as 35001 Violation of Controlled Substance Act. Second, in the property file segment the property loss type is coded as seizures, and finally, the class of property detailed is a drug/narcotic.

Table 11. Drug Seizure Yearly Sums by Drug Category and Measurement Unit, 2013-2017

	2013	2014	2015	2016	2017
Total Weight (kg)					
Depressants / Sedatives	0.97	14.65	0.87	3.51	3.82
Hallucinogens	7.31	32.46	33.89	8.95	96.61
Marijuana	4,691.11	3,255.14	6,340.95	7,193.90	3,455.45
Methamphetamines	7.79	9.79	13.57	14.84	29.35
Opioids	181.60	31.14	1,062.11	74.73	35.67
Stimulants	107.16	120.58	192.94	106.88	137.42
Other Drugs	135.94	21.23	49.77	46.26	11.79
Substance Unknown	10.54	8.31	282.21	32.28	18.35
Total Fluid Liters					
Depressants / Sedatives	17.27	2.81	25.12	1.24	2.17
Hallucinogens	0.31	96.58	11.27	8.95	0.01
Marijuana	1,634.16	3,791.48	2,386.60	9,646.35	2,707.72
Methamphetamines	3.47	27.49	38.57	18.90	12.34
Opioids	95.47	87.82	108.84	56.77	53.71
Stimulants	310.95	29.48	31.53	7,365.23	178.09
Other Drugs	247.97	15.82	22.72	13.21	10.40
Substance Unknown	81.78	20.10	2.35	230.78	43.24
Total Units					
Depressants / Sedatives	8,279.83	9,428.45	11,469.0	10,460.2	14,938.2
Hallucinogens	5,590.02	5,531.10	9,228.75	16,220.5	9,650.75
Marijuana	78,602.8	73,206.48	73,264.6	62,117.1	66,038.8
Methamphetamines	2,249.39	5,326.98	896.05	1,013.78	868.08
Opioids	81,401.2	102,242.3	80,729.1	81,084.1	50,874.61
Stimulants	11,365.4	18,122.74	14,366.1	15,119.5	11,843.69
Other Drugs	59,231.7	66,987.9	70,443.8	79,718.8	93,304.6
Substance Unknown	14,683.8	12,081.78	13,257.8	12,565.5	9,296.84

Note: “Units” refers to physical units of the drug, such as joints or pills.

Table 12 breaks the opioid category down into heroin, opium, morphine, and “synthetic” opioids (as well as the MICR data are able to disaggregate these drugs). The patterning of the totals seized between these two groups largely mirrors that of overall opioids in Table 11 – physical units seized are relatively stable between 2013 and 2016 before decreasing in 2017. Among physical units, synthetic opioids make up the majority of units seized, ranging from 84 to 91% of opioids seized across years.

Table 12. Disaggregated Opioid Seizure Yearly Sums by Drug Category and Measurement Unit, 2013-2017

	2013	2014	2015	2016	2017
Total Weight (kg)					
Heroin, Morphine, Opium	43.98	19.83	1,047.9	47.92	22.09
"Synthetic" Opioids	137.62	11.31	14.24	26.82	13.59
Total Fluid Liters					
Heroin, Morphine, Opium	23.21	72.35	79.34	25.93	18.11
"Synthetic" Opioids	72.27	14.47	29.50	30.84	35.60
Total Units					
Heroin, Morphine, Opium	12,593.1	16,557.9	9,733.4	7,535.5	6,774.2
"Synthetic" Opioids	68,819.1	85,711.4	70,977.7	73,572.6	44,116.4

Note: "Units" refers to physical units of the drug, such as joints or pills.

County-level Trends

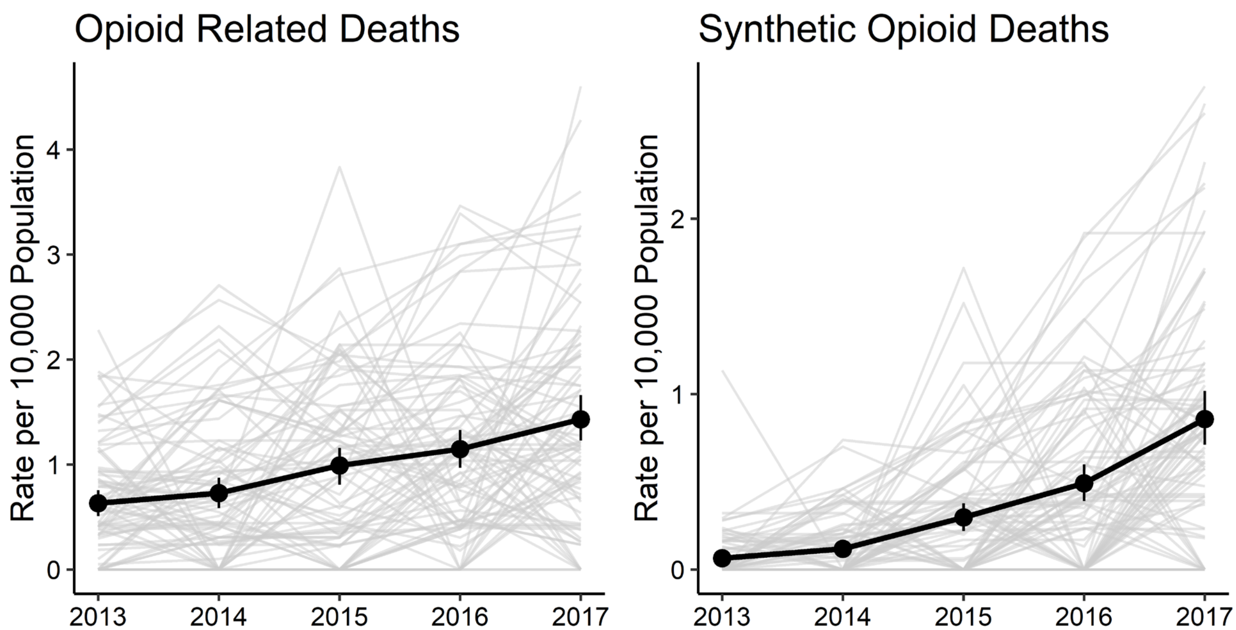
The next segment of the report will focus on a descriptive analysis of trends in outcomes and potential correlates of the opioid crisis, leveraging data from vital statistics, prescription monitoring, and MICR. Counties are used as the unit of analysis because they are simultaneously small enough to highlight meaningful regional variation in the State, but also large enough that it is possible to secure detailed and specific variables from a variety of sources (i.e., such linkages would not be possible with smaller units not quantified in the MICR data, such as census tracts).

Specifically, the following county-level trends will disaggregate counties by their rural-urban continuum designation, differentiating metro area, urban but non-metro, and rural counties from the USDA. Such a comparison is useful because of mixed findings in the health literature on rural-urban differences in prescription opioid misuse (Rigg & Monnat, 2015). For instance, although some research has been found to be particularly problematic in rural areas (Wunsch, Nakamoto, Behonick, & Massello, 2009), others have noted that opioid abuse is equally prevalent in metropolitan areas (Wang, Becker, & Fiellin, 2013).

Opioid-related Death Rates

The first set of trends uses vital statistics from the Michigan Department of Health and Human Services to estimate the number of opioid-related deaths, and then specifically the number of deaths attributable to synthetic opioids (see cause of death code definitions above). Figure 7 displays overall (mean) trends in the opioid and synthetic opioid-related death rates, as well as individual trajectories for each county. The results in Figure 7 indicate that the rate of opioid-related deaths increased every year between 2013 and 2017, increasing from 0.63 per 10,000 in 2013 to 1.43 deaths per 10,000 in 2017 – an increase of 127%. The rate of deaths attributable to synthetic opioids increased more sharply during the same time period, from 0.06 in 2013 to 0.86 deaths per 10,000 in 2017 - an increase of 1,243%. Although this rate of increase may seem incredible, it is consistent with nation wide trends. For instance, a recent report from the CDC found that synthetic opioid deaths among US women age 30-64 increased more than 1,600% between 1999 and 2017 (VanHouten, Rudd, Ballesteros, & Mack, 2019).

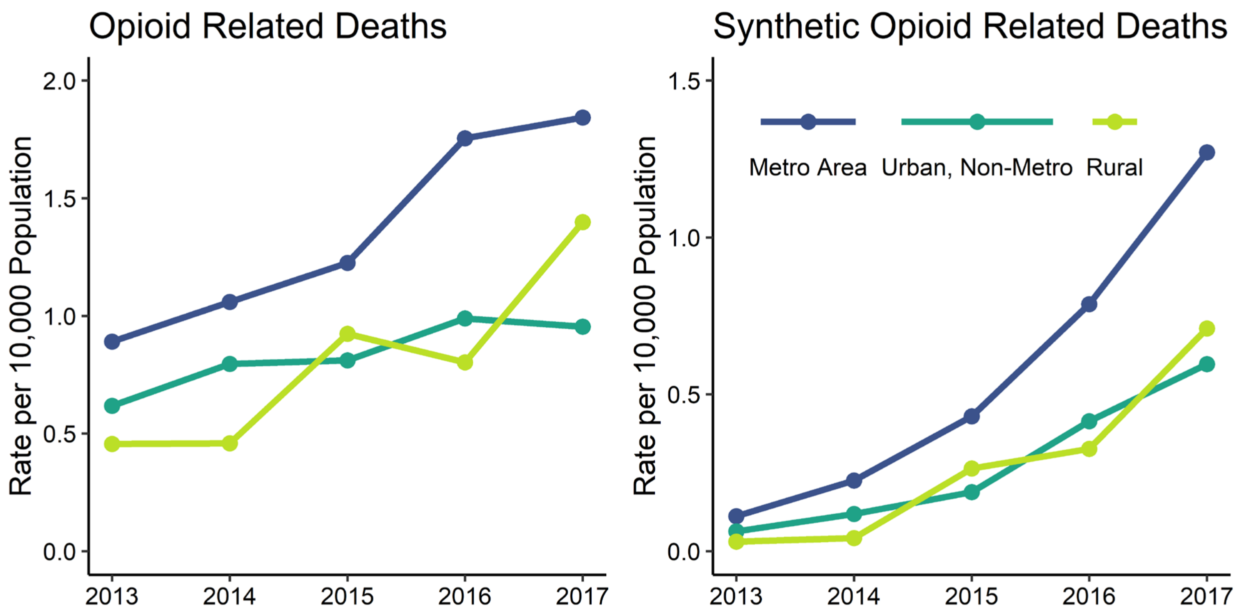
Figure 7. Trends in Opioid Prescriptions, Deaths, and Arrests in Michigan Counties, 2013-2017



Note: Black lines and points represent averages. Vertical black lines represent bootstrapped confidence intervals. Gray lines are individual trends for each county.

Figure 8 expands on these trends by disaggregating them by metro area, urban, and rural counties in Michigan. There are several points to take away from these panels. First, the rate of opioid- and synthetic opioid-related deaths increased in all types of counties, regardless of population density. However, even after accounting for differences in population, rates of death are higher in metro area counties, while urban and rural counties have approximately equal death rates and degrees of increase over time. Notably, the increase in synthetic opioid deaths in Michigan appears to be driven by trends in metro areas, which increased at a sharper rate than urban or rural counties.

Figure 8. Trends in Opioid-related Deaths in Michigan Counties by Rural Category, 2013-2017



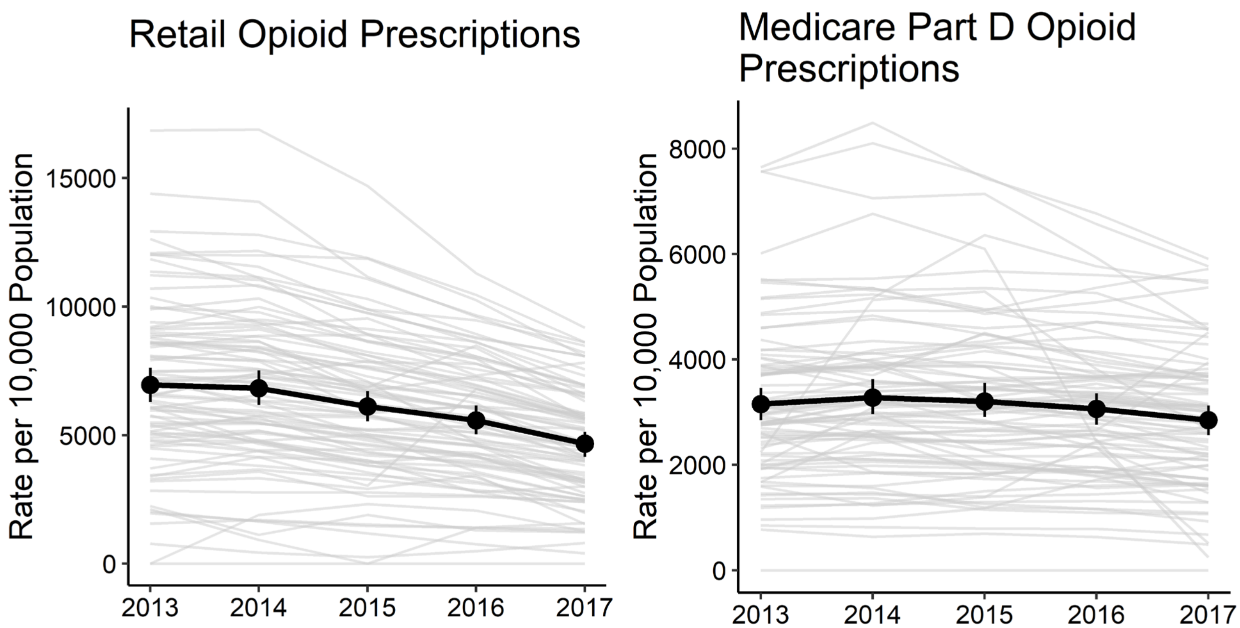
Opioid Prescription Trends

The next set of figures consider county-level trends in opioid prescriptions. As noted in the methodology, we differentiate between retail (non-Medicare) prescriptions submitted to be filled at pharmacies from those that were submitted pursuant to Medicare Part D, which would more likely reflect prescriptions to individuals over age 65, in poverty, and living in rural communities (Kimmel et al. 2016). The estimated prescription rates are presented in Figure 9. Several patterns are noteworthy.

The rate of opioid prescriptions in Michigan is high. A nationwide survey in 2012 found that Michigan had the 10th highest rate of opioid prescriptions (Paulozzi, Mack, & Hockenberry, 2014). In these data, there 7130 retail prescriptions per 10,000 population and 3190 Medicare prescriptions per 10,000 in 2013, which adds up to a rate of more than one prescription per person in that year. However, the rate of retail prescriptions decreased on average between 2013 and 2017, decreasing 34% over that time period. Medicare Part D prescriptions remained relatively stable, increasing slightly between 2013 and 2015, and then decreasing in 2016 and 2017.

The individual county trends in Figure 9 also make it apparent that the rate of prescribing varies considerably across counties. For retail prescriptions, Roscommon county had the highest prescription rate – more than 16,000 per 10,000 population. For Medicare Part D prescriptions, Ogemaw county had the highest rate, with more than 8,000 per 10,000 population. It is also worth noting that comparing the prescription trend data with the opioid-related death trends suggests that opioid related deaths were increasing sharply during a time when legal prescriptions were decreasing or staying stable. This comparison highlights the need to incorporate data on illegal opioid activity as a correlate of opioid-related death rates.

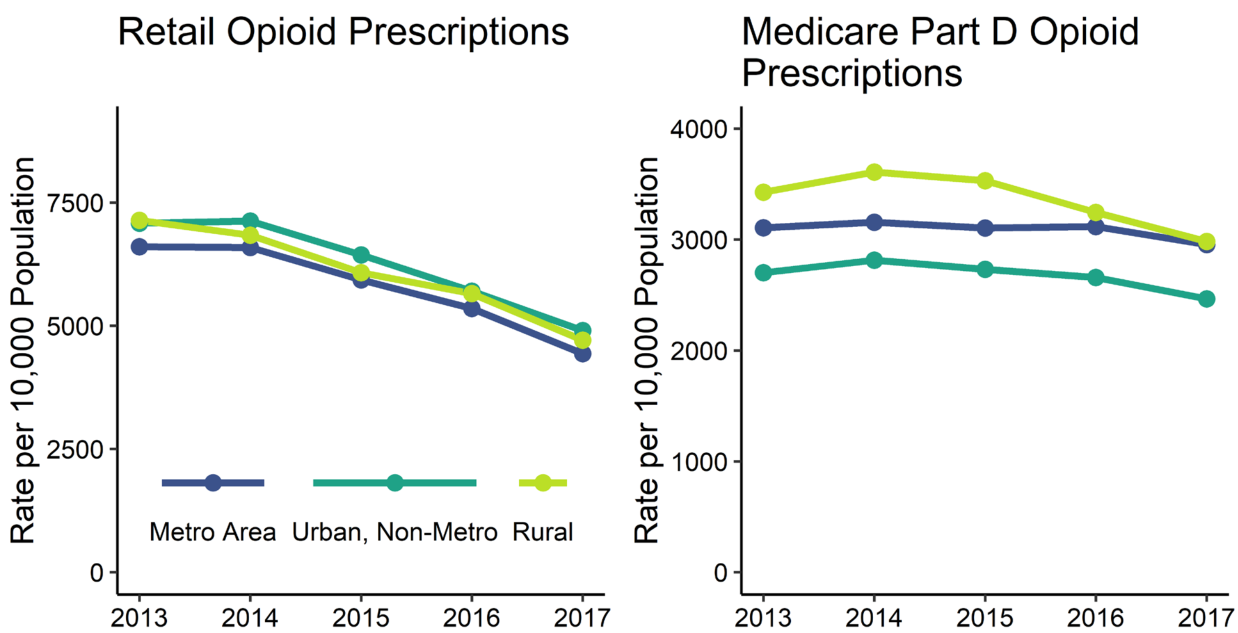
Figure 9. Trends in Opioid Prescriptions in Michigan Counties, 2013-2017



Note: Black lines and points represent averages. Vertical black lines represent bootstrapped confidence intervals. Gray lines are individual trends for each county.

Figure 10 disaggregates prescription trends by the rural-urban continuum for each county. The panels of this figure suggest that the downward trend in retail prescriptions occurred across all counties, regardless of population density. Indeed, the average prescription rate in metro, urban, and rural counties was approximately equal in each year. A different picture emerges when considering Medicare Part D prescriptions. For this measure, prescription rates were highest in rural counties, and decreased over time, while prescription rates in metro and urban counties were relatively stable. By 2017, Part D prescriptions in rural (3,066 per 10,000) and metro counties (2,954 per 10,000) were approximately equal.

Figure 10. Trends in Opioid Prescriptions in Michigan Counties by Rural Category, 2013-2017

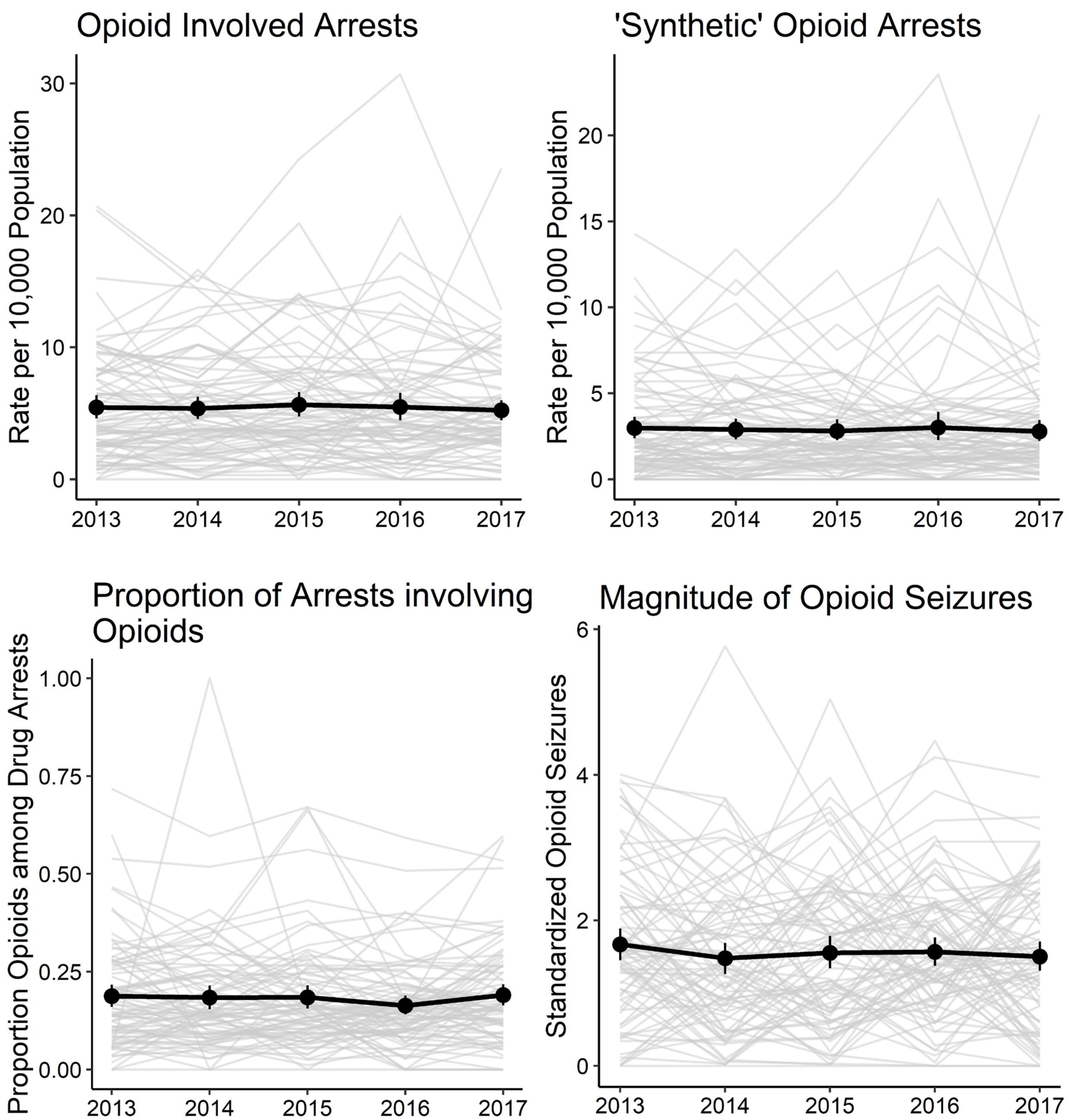


Law Enforcement Trends – Opioid-related Arrests and Seizures

The next set of figures utilize data from MICR to describe county-level trends in law enforcement activity related to opioids. Specifically, Figure 11 displays trends in arrests per 10,000 population for opioids, "synthetic" opioids, and opioid seizures. Concerning arrests, although there was variation between counties in terms of the opioid-related arrest rate, on average opioid arrests were relatively stable, ranging from 5.43 per 10,000 in 2013 to 5.22 in 2017. The rate of arrests for synthetic opioids demonstrated similar consistency. Similarly, Figure 11 displays the share of arrests that involve opioids to consider whether, despite stable arrest rates, opioids made up a varying proportion of all drug arrests. These results suggest that between 2013 and 2017 opioids made up a relatively consistent share of all drug arrests, approximately 19 percent.

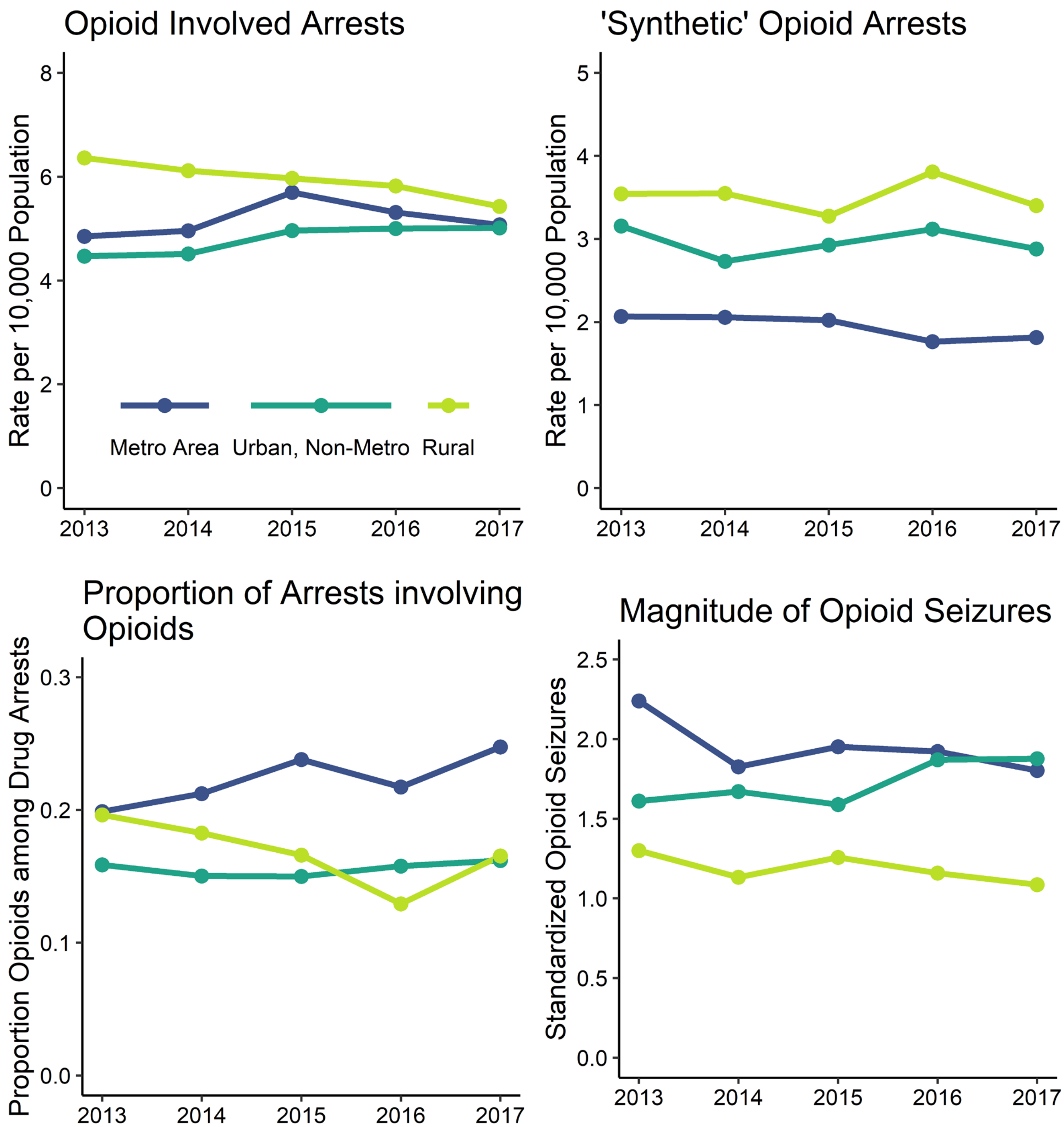
Examining changes in seizures over time is complicated by the fact that seizures are measured in a variety of forms on different scales (e.g., kgs, liters, units). In order to examine changes in the overall magnitude of seizures over time, all seizure amounts were standardized by dividing each amount by two times the standard deviation for each unit type. This procedure turned each seizure amount into a numeric score starting at 0, and higher scores represented a larger magnitude of opioids seized. The seizure panel in Figure 11 highlights a similar story as the others – the magnitude of seizures varies across counties, but on average is relatively stable over time.

Figure 11. Trends in Opioid Arrests and Seizures in Michigan Counties, 2013-2017



Note: Black lines and points represent averages. Vertical black lines represent bootstrapped confidence intervals. Gray lines are individual trends for each county. Opiate seizures standardized in order to scale the various measurement units (i.e., kg, liters, units). Higher values indicate relatively higher seizures.

Figure 12. Trends in Opioid Arrests and Seizures in Michigan Counties, 2013-2017



Note: Black lines and points represent averages. Vertical black lines represent bootstrapped confidence intervals. Gray lines are individual trends for each county. Opiate seizures standardized in order to scale the various measurement units (i.e., kg, liters, units). Higher values indicate relatively higher seizures.

Figure 12 disaggregates these trends by county rural category, and reveals several noteworthy patterns. First, there are varying trends in opioid-related arrest rates in rural counties, as opposed to metro and urban counties. Between 2013 and 2017, the rate of arrests for opioid-related offenses in rural counties decreased, from 6.4 per 10,000 in 2013 to 5.4 in 2017. During the same period, rates of arrest in urban counties increased slightly, from 4.5 in 2013 to 5.0 in 2017. By 2017, rates of arrest for opioids were consistent across metro, urban, and rural counties. “Synthetic” opioids demonstrated a different pattern. Rates of arrest for these drugs was relatively stable over time, but varied in level, with the highest rate of arrests in rural counties, followed by urban, and the lowest rate of arrests was observed in metro counties.

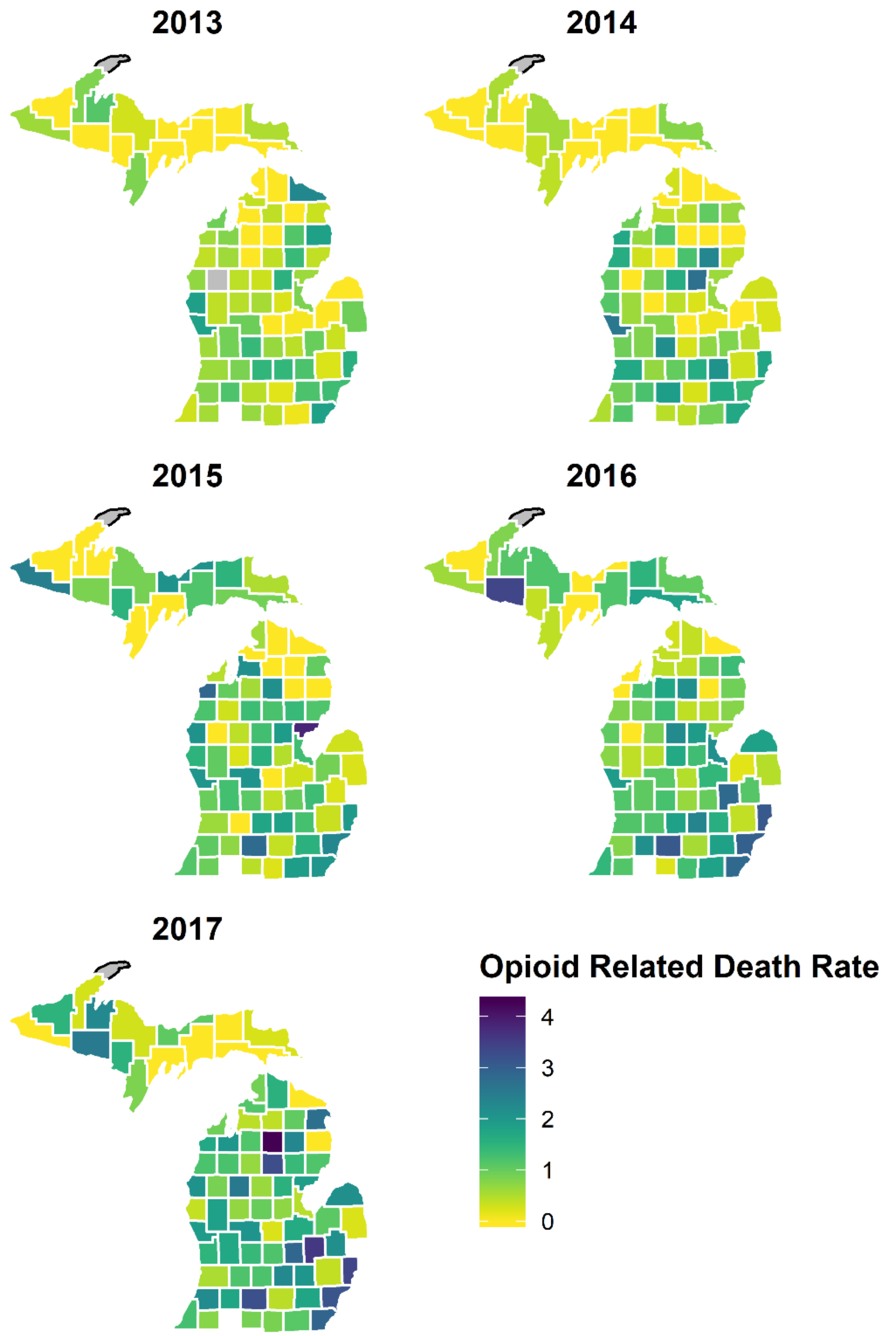
Considering whether opioids made up a smaller or larger proportion of total drug arrests across counties, metro and rural counties demonstrated divergent patterns. In 2013, in both metro and urban counties opioids made up approximately 20% of all drug arrests. From that point on, opioids made up an increasing share of drug arrests in metro counties, and a decreasing share of such arrests in rural counties. By 2017, opioids made up 24.7% of drug arrests in metro counties, and 16.5% of drug arrests in rural counties. During the time period, opioids consistently comprised 16% of drug arrests in urban counties.

For opioid seizures, there was a greater magnitude of seizures in metro counties, and a lower magnitude in rural counties, and over time magnitudes in both types of counties decreased. That is, between 2013 and 2017 the amount of opioids that police seized in both metro and rural counties fell. However, in urban counties the magnitude of seizures increased over time, where there were similar amounts of opioids seized in urban counties as in metro counties in 2017. This patterning of trends highlights the importance of disaggregation by rural-urban continuum, as the overall trend (Figure 11) appears flat, failing to identify this source of variation.

County-level Geographic Variation

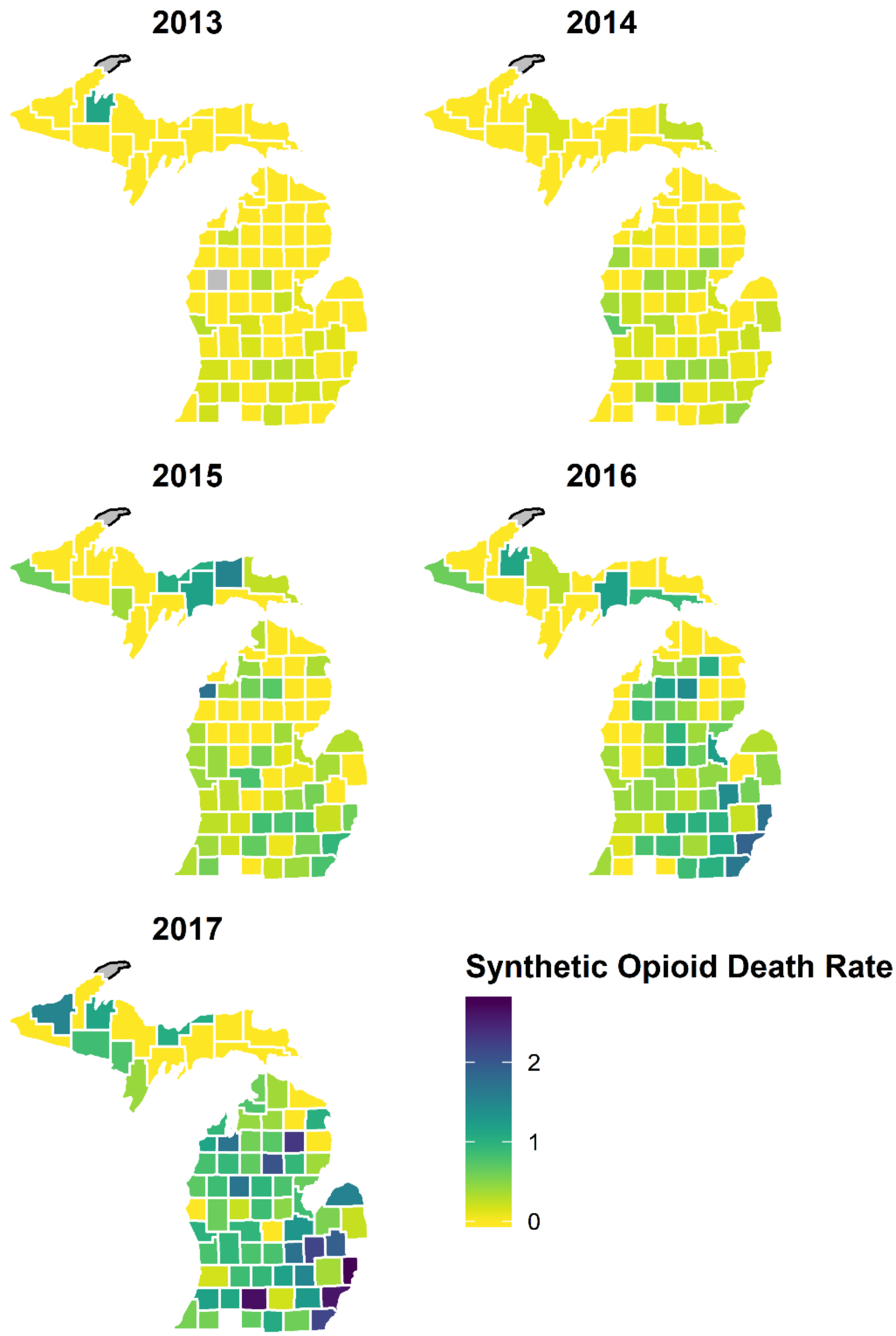
Figures 13 through 19 present 2013 to 2017 trends for the same variables as those displayed above, but geographically across counties. The most striking is Figure 14, which displays synthetic opioid-related death rates across counties. From 2013 to 2017, this figure contextualizes the 1242 percent increase in the synthetic opioid-related death rate by showing how it spread across counties over that period. Indeed, in 2013 the death rate was relatively low across all counties, and year after year denser concentrations of synthetic opioid deaths appeared, with the strongest concentrations in 2017 in metro counties surrounding Detroit.

Figure 13. Opioid-Related Death Rate across Michigan Counties, 2013-2017



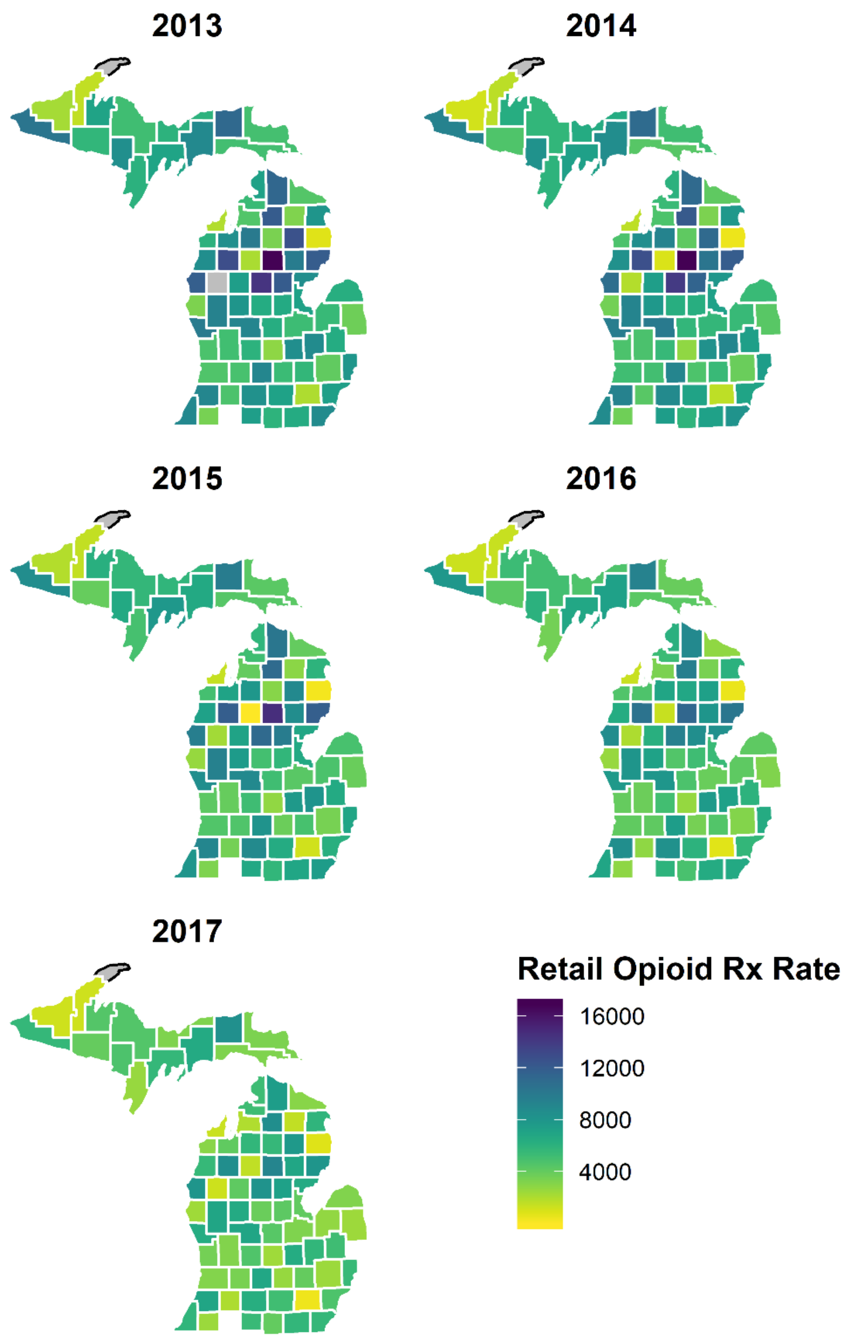
Note: Blank (white) counties had missing data for that particular variable and year.

Figure 14. Synthetic Opioid Death Rate across Michigan Counties, 2013-2017



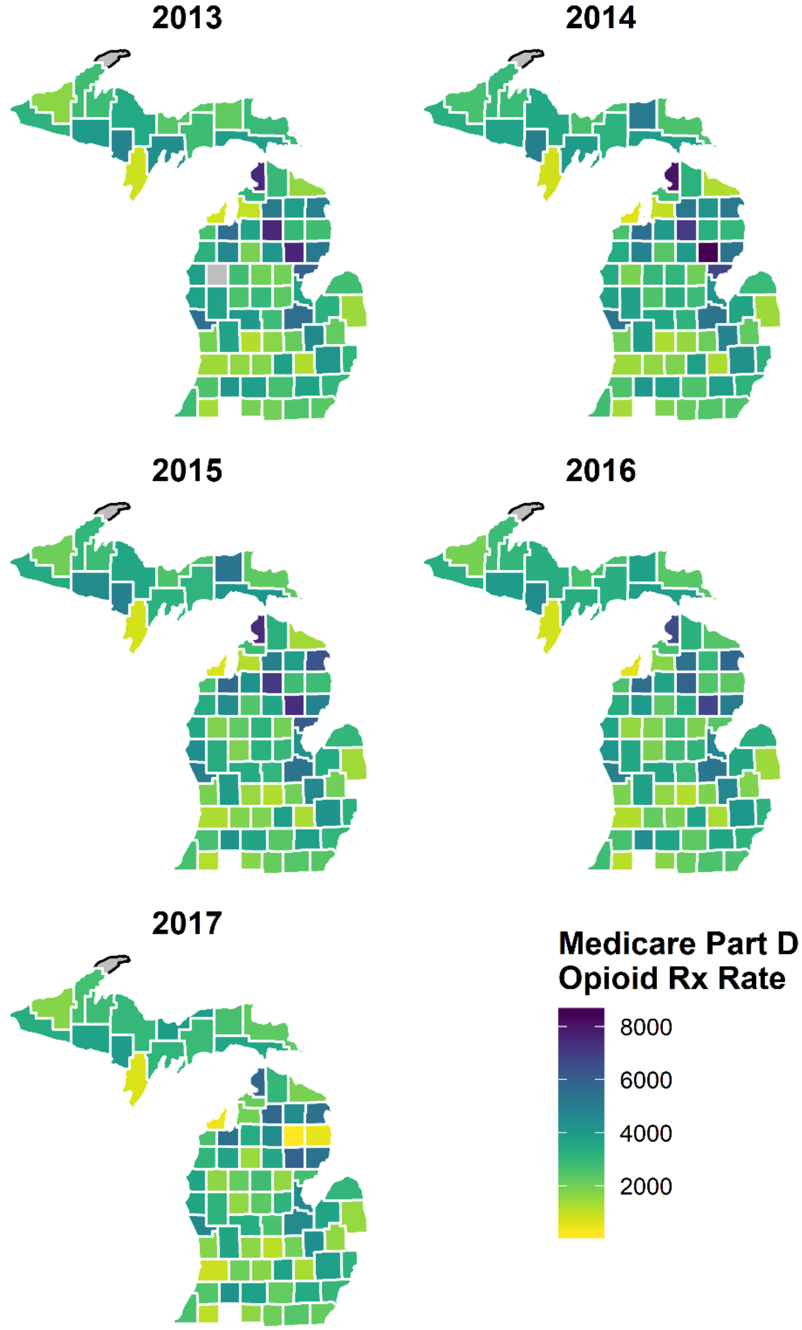
Note: Blank (white) counties had missing data for that particular variable and year.

Figure 15. Retail Opioid Prescription Rate across Michigan Counties, 2013-2017



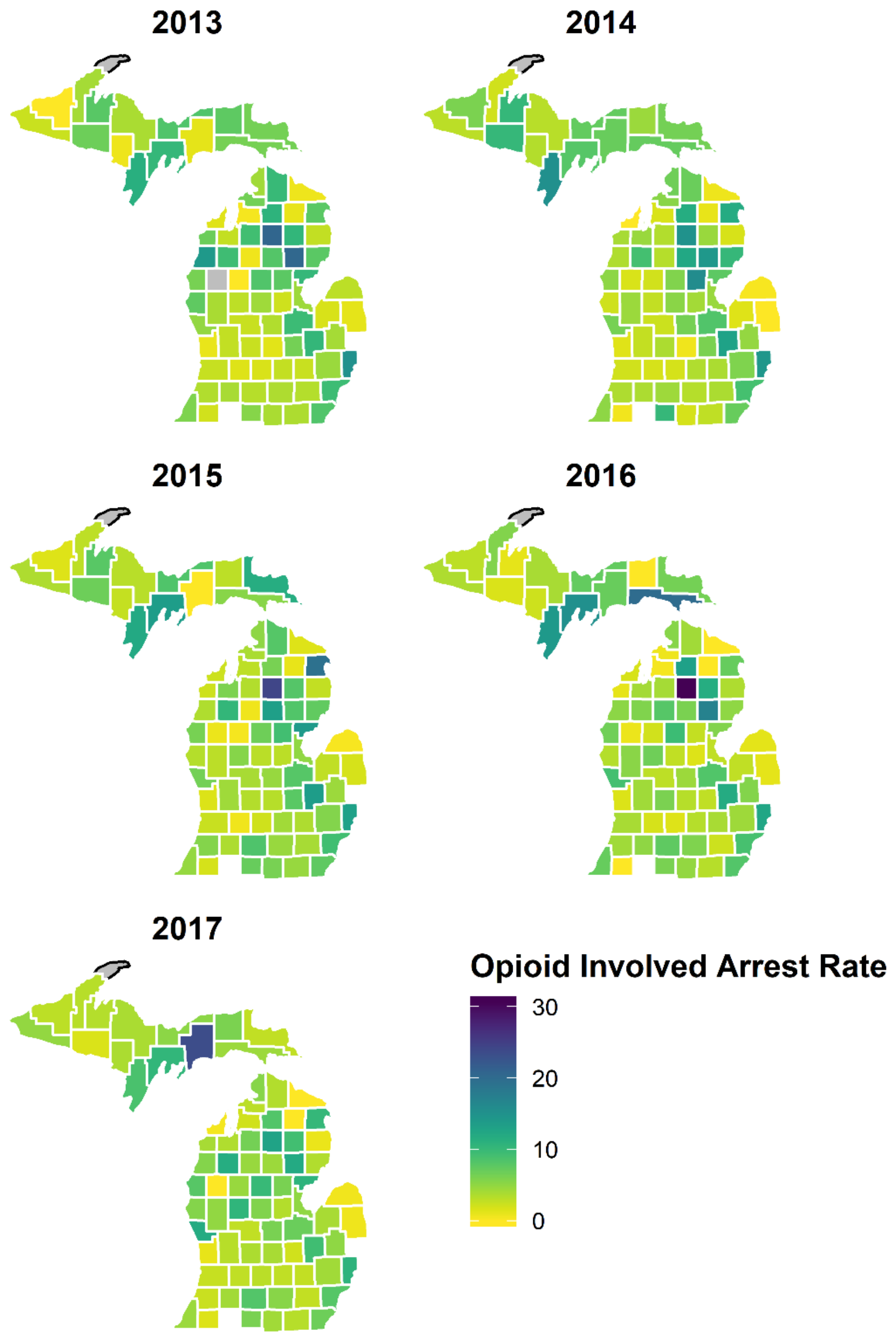
Note: Blank (white) counties had missing data for that particular variable and year

Figure 16. Medicare Part D Opioid Prescription Rate across Michigan Counties, 2013-2017



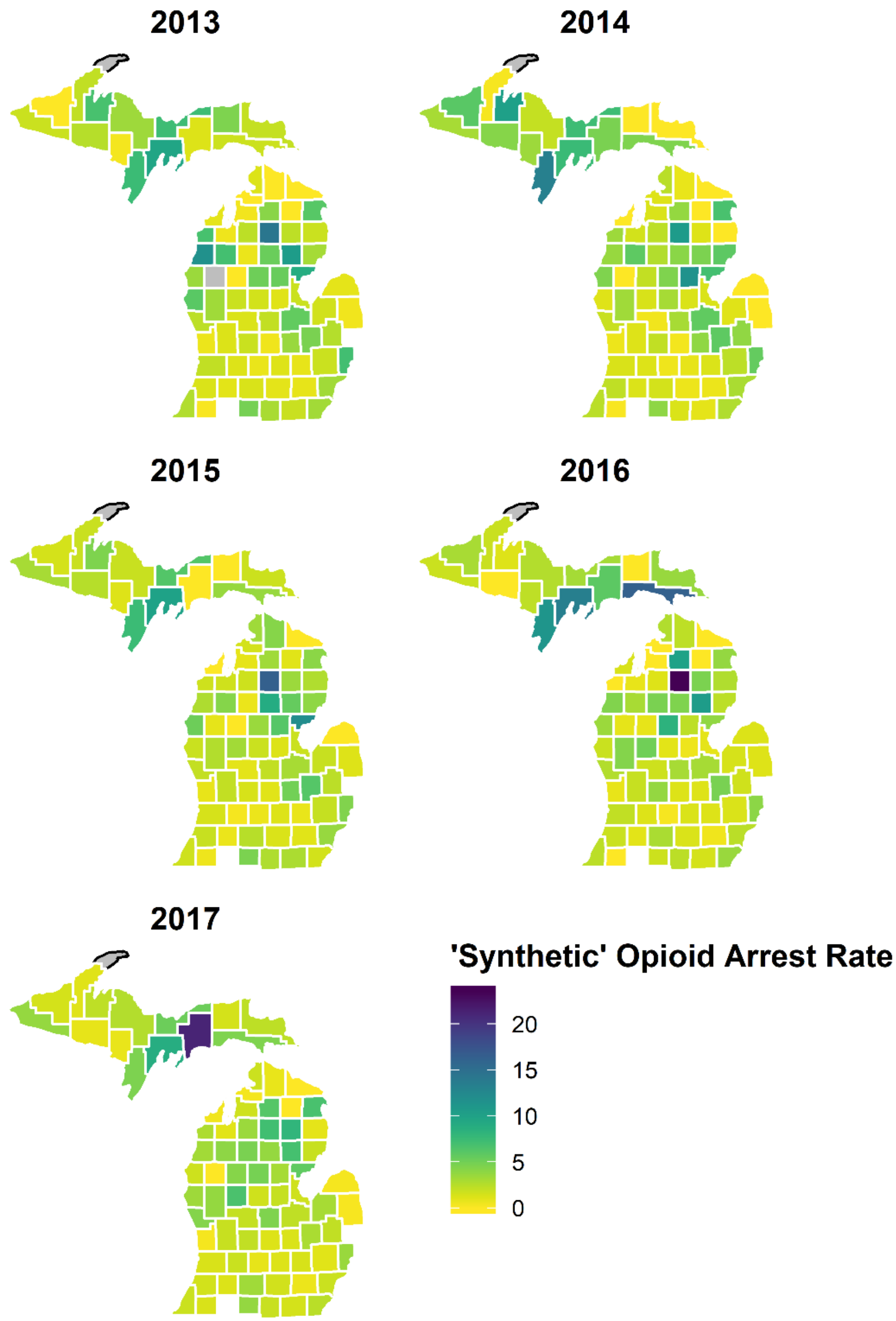
Note: Blank (white) counties had missing data for that particular variable and year

Figure 17. Opioid Related Arrest Rate across Michigan Counties, 2013-2017



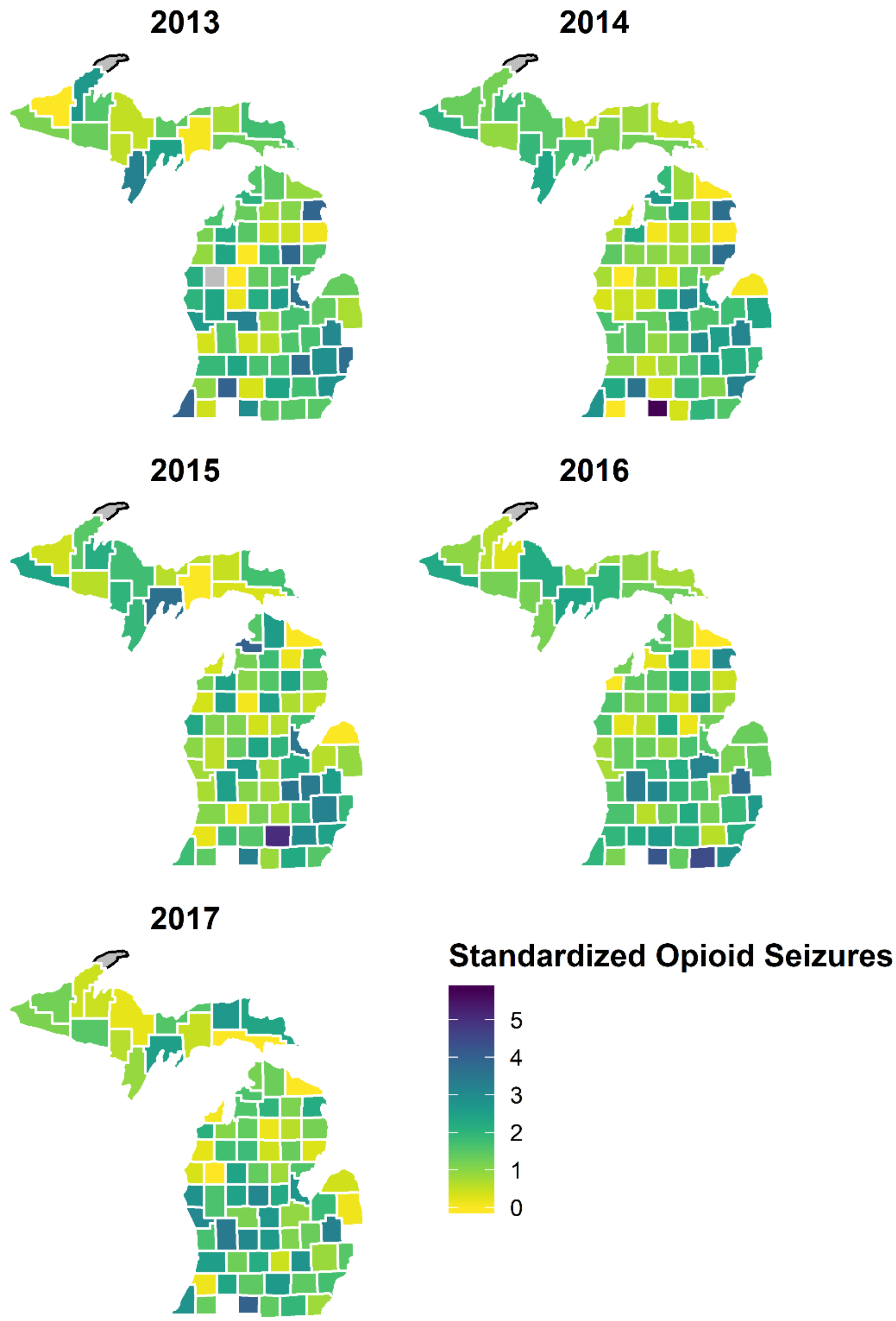
Note: Blank (white) counties had missing data for that particular variable and year

Figure 18. "Synthetic" Opioid Arrest Rate across Michigan Counties, 2013-2017



Note: Blank (white) counties had missing data for that particular variable and year

Figure 19. Opioid Seizures across Michigan Counties, 2013-2017



Note: Blank (white) counties had missing data for that particular variable and year. Opiate seizures standardized in order to scale the various measurement units (i.e., kg, liters, units). Higher values indicate relatively higher seizures.

Correlates of Opioid-Related Deaths and Arrests

The final set of analyses consider which variables are associated with opioid-related deaths and arrests across Michigan counties over time. These analyses address questions such as whether within-county variation in opioid prescriptions over time is associated with changes in the opioid-related death rate, after controlling for factors such as law enforcement activitiy, economic characteristics, and demographics. Specifically, we primarily sought to determine whether the number of opioid-related deaths, synthetic opioid-related deaths, and opioid-related arrests were associated with the following factors:

- **Retail and Medicare Part D Prescriptions:** As described previously, these measures were obtained from the Centers for Disease Control (CDC) the Centers for Medicare & Medicaid Services (CMS). These reflect the number of prescriptions written to be filled for every 10,000 residents.
- **Police Density:** The rate of law enforcement officers per 10,000 population, obtained from the LEOKA component of the Uniform Crime Reports. This variable is meant to act as a representation of law enforcement resources.
- **Opioid-Related Arrests:** We assess whether the rate of opioid-related arrests are associated with variation in the number of opioid-related deaths. This variable is based on the MICR data analyzed here, and is meant to reflect opioid-related law enforcement activities. This is only used as a predictor for deaths.
- **Opioid Seizures:** A standardized measure of the magnitude of opioid-seizures, as calculated through MICR. This measure is meant to reflect the productivity of opioid-related law enforcement activities. This is only used as a predictor for deaths.

For each of these variables, we leverage the longitudinal nature of the data (i.e., 5 years of data for each county) to assess the impact of two types of variation using a hybrid model (Allison, 2009). This type of longitudinal data analysis draws on strengths from both random and fixed effects regression models to allow a more nuanced understanding of a variables' impact on an outcome.

- **Between-County Differences:** We assess whether between-county variation in any of the above factors is associated with deaths and arrests. This is like asking "when we compare a county with a given overall rate of opioid prescriptions to a county that has a higher rate of prescriptions, what is the impact on opioid-related deaths?" These are obtained by estimating county-specific means for any of the above variables across all years of data. These are equivalent to random effects estimates from a multi-level model applied to longitudinal data.
- **Within-County Change:** We also assess the impact of year-to-year variation in these variables on the outcomes. This is like asking, "for any given county, when the rate of opioid prescriptions increases in that county, what is the impact on opioid-related deaths?" These are equivalent to fixed-effects estimates of a variable's impact, meaning that they are not influenced by the inclusion or exclusion of any additional time-stable variables in the regression model. These were calculated by subtracting the value of that variable in any given year from the county-specific mean described above. This turned each value into a mean deviation score.

In addition to the primary measures of interest above, we also control for the influence of a number of socio-ecological variables, similar to those used in other analyses of county-level variation in drug overdose deaths (Monnat, 2018). These measures include:

- **Economic Distress:** A weighted factor score based on unemployment, households with supplemental security income, educational defecits, poverty, household income, and teen birth rates. Higher values indicate greater levels of economic distress within the county. Loadings and reliability for this measure are included in the Appendix. These data were obtained from the American Community Survey and the Robert Wood Johnson Foundation county health rankings.
- **Housing Distress:** A weighted factor score based on vacant housing units that are available for rent, and the ratio of the median contract rent to the fair market rent for a one-bedroom apartment. Higher values reflect housing market tension. These data were obtained from the American Community Survey and the Department of Housing and Urban Development.
- **Family Distress:** A weighted factor score based on single parent households with children and divorce rates. Higher scores reflect greater levels of family disruption. These data were obtained from the American Community Survey.
- **Primary Care Providers per Capita:** A measure reflecting the number of physicians per 100,000 residents in the county. Higher values reflect a stronger health environment. These data were obtained from the Robert Wood Johnson Foundation county health rankings.
- **Uninsured Population:** The percentage of the population (children and adults) without health insurance. Higher values reflect a weaker health environment. These data were obtained from the Robert Wood Johnson Foundation county health rankings.

Based on the distribution of the counts of opioid-related deaths and arrests, the regression models were estimated using a negative binomial family. County population as an exposure term, ensuring that the coefficients represent the impact of a unit increase in the predictor on the population rate of opioid-related deaths and arrests. Coefficients were estimated via Bayesian inference with weakly informative, regularizing priors through the brms package in R (Bürkner, 2017).

Multivariate Analysis Results

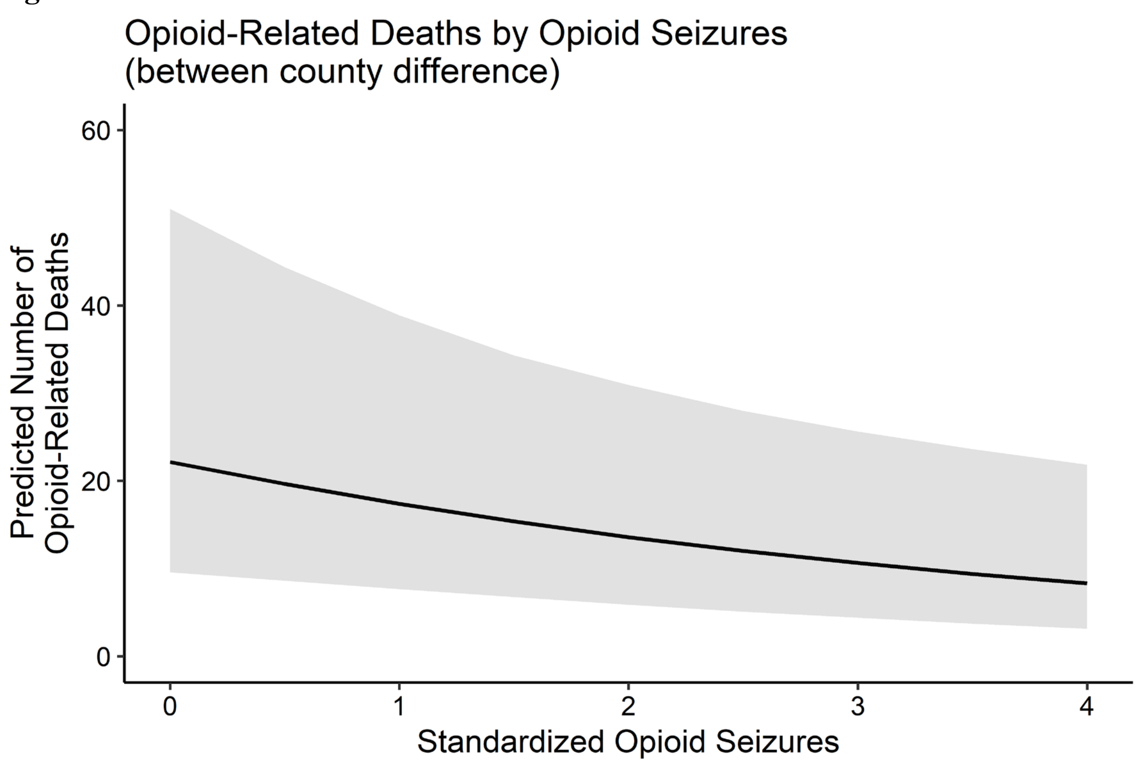
The following summarizes the general conclusions from the regression analysis, but full results are available in the Appendix. The following reflects factors that were statistically significantly associated with the outcome measures:

Opioid-Related Deaths

Several factors were found to be associated with variation in the rate of opioid-related deaths – between county opioid seizures, within county police density, and rural category.

- **Opioid Seizures (between-county differences):** There was a negative association between standardized opioid seizures and opioid-related deaths, where a two standard deviation difference in opioid seizures between counties was predicted to reduce the opioid-related death rate by 22%.[8] This was a between-county effect, meaning that counties with a higher magnitude of seizures have a lower death rate, but there was no evidence that the death rate changes within any given county when they increase the magnitude of their seizures. This effect is displayed graphically in Figure 20.

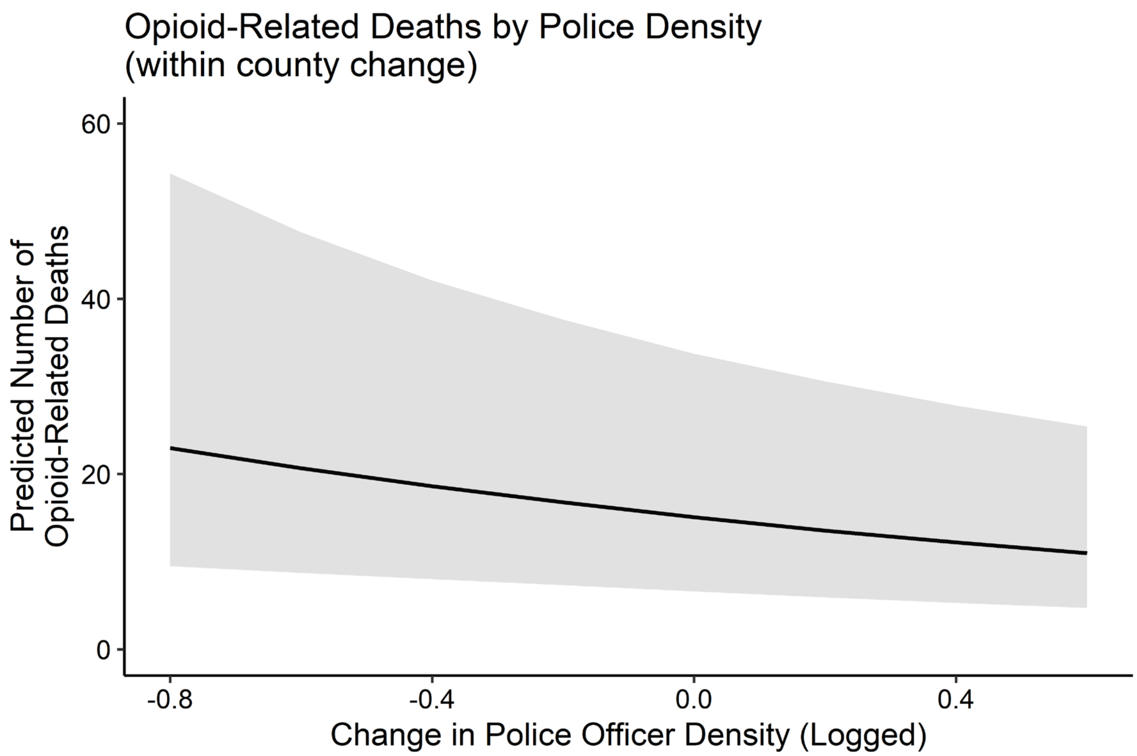
Figure 20



[8] Based on estimating an incident rate ratio from the log rate coefficients in Table A3 in the appendix.

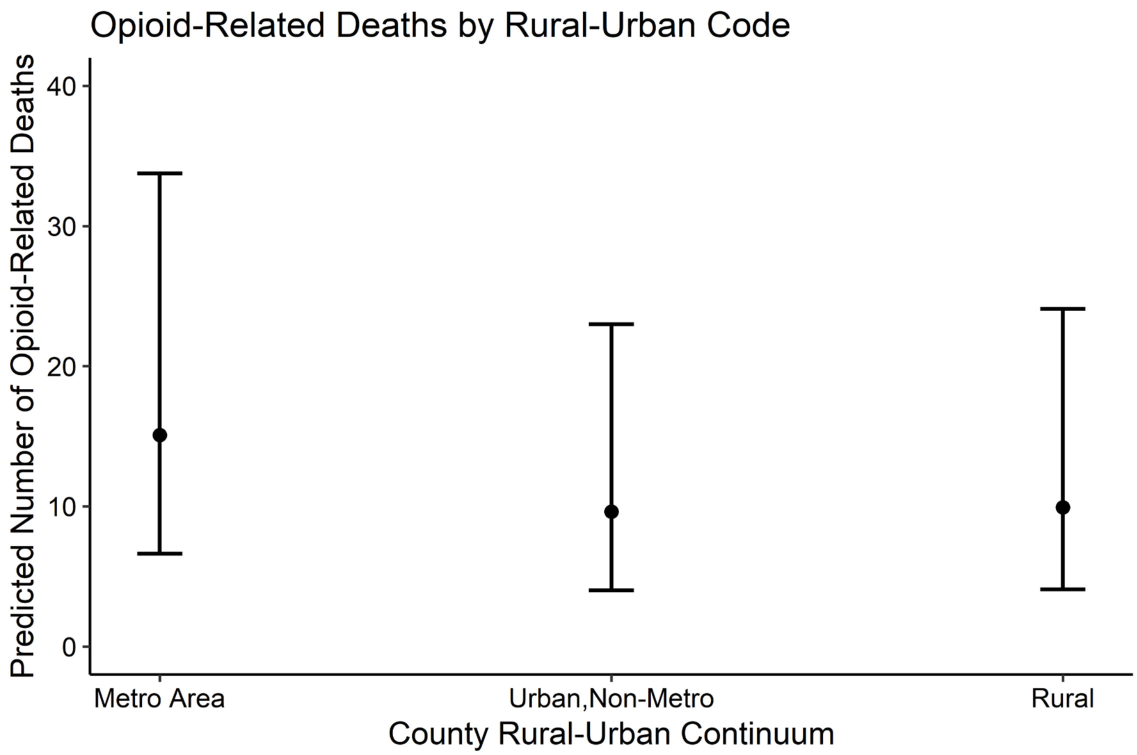
- **Police Density (within-county change):** There was a negative association between police density and opioid-related deaths, where a 1% increase in police density was predicted to reduce the opioid-related death rate by half a percent. This was a within-county change effect, meaning that it reflects the predicted change in opioid-related deaths when any given county experiences changes in the size of their police force. This effect is displayed graphically in Figure 21.

Figure 21



- **Rural Category:** The regression results suggested that, after controlling for other variables, metro area counties experience higher death rates than urban or rural counties. Specifically, urban counties experienced opioid-related death rates 36% lower than metro-area counties. This association is represented in Figure 22 below.

Figure 22

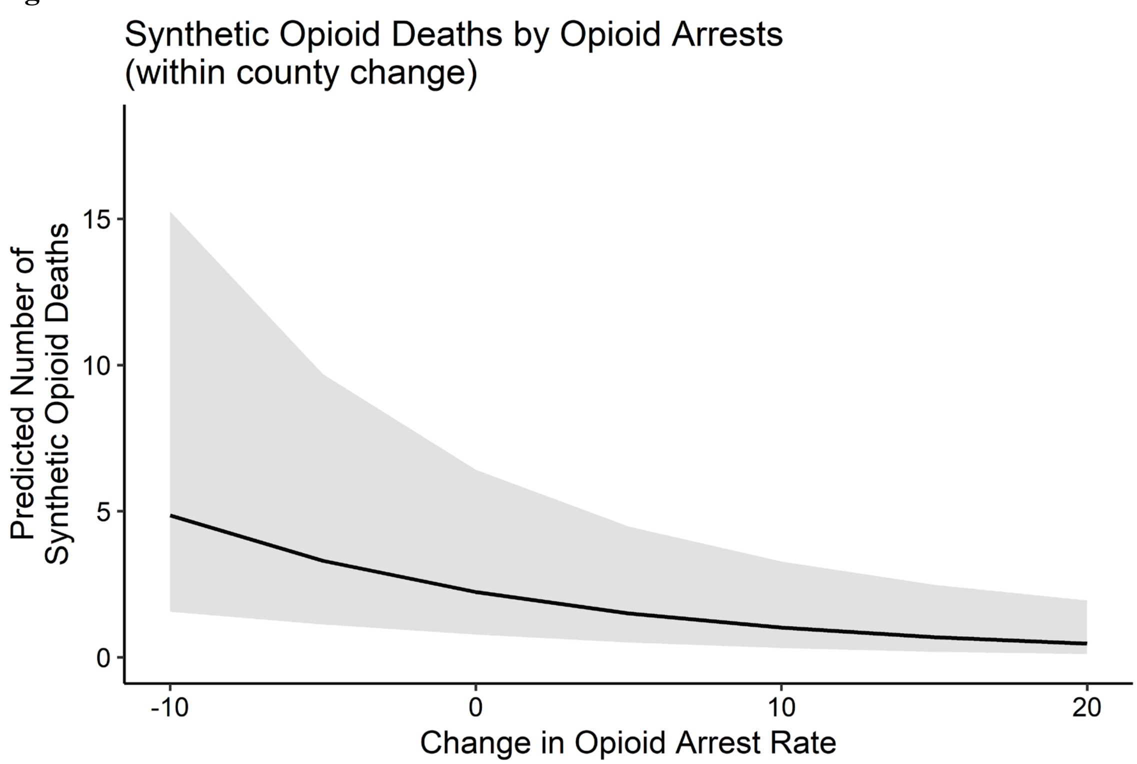


Synthetic Opioid-Related Deaths

Several variables were found to be associated with deaths attributable to synthetic opioids in particular – within-county opioid-related arrests, population over 65 years old, and rural category.

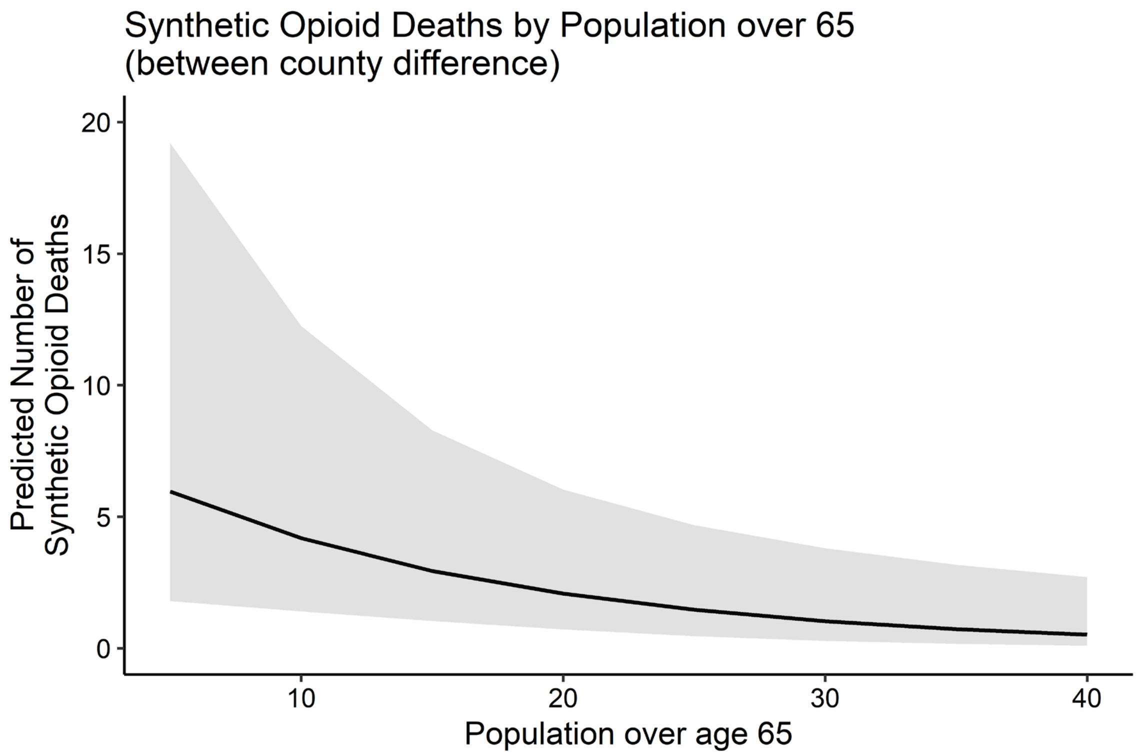
- **Opioid-Related Arrests (within-county change):** There was a negative association between within-county change in the opioid-related arrest rate and the rate of synthetic opioid-related deaths. Specifically, when a county experienced an increase in arrests of 1 per 10,000 residents, there was a predicted 7.7% decrease in the synthetic opioid-related death rate. This association is presented graphically in Figure 23.

Figure 23



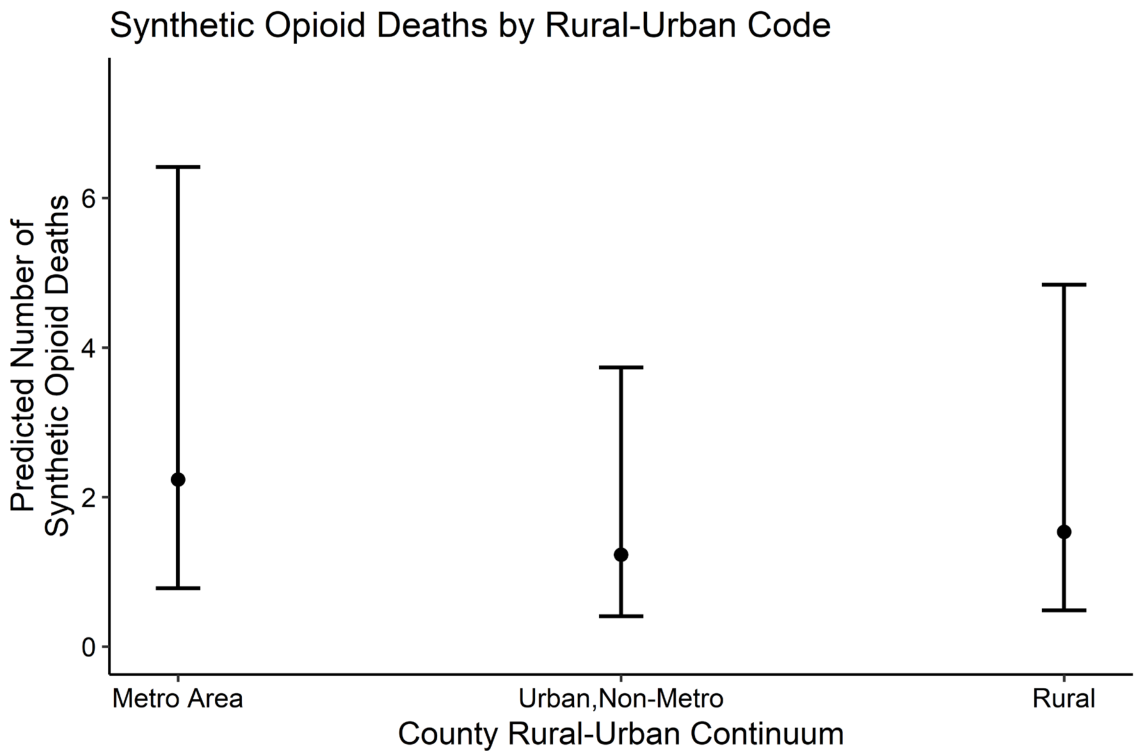
- **Population over 65:** The regression analysis suggested that, after controlling for other factors, counties with larger populations over the age of 65 experienced lower rates of synthetic opioid-related deaths. Specifically, a one percentage point difference in population over 65 translated to a 6.8% lower rate of synthetic opioid-related deaths. This association is presented graphically in Figure 24.

Figure 24



- **Rural Category:** The regression results suggested that, after controlling for other variables, metro area counties experience higher synthetic opioid death rates than urban or rural counties. Specifically, urban counties experienced synthetic opioid-related death rates 45% lower than metro-area counties. This association is represented in Figure 25 below.

Figure 25

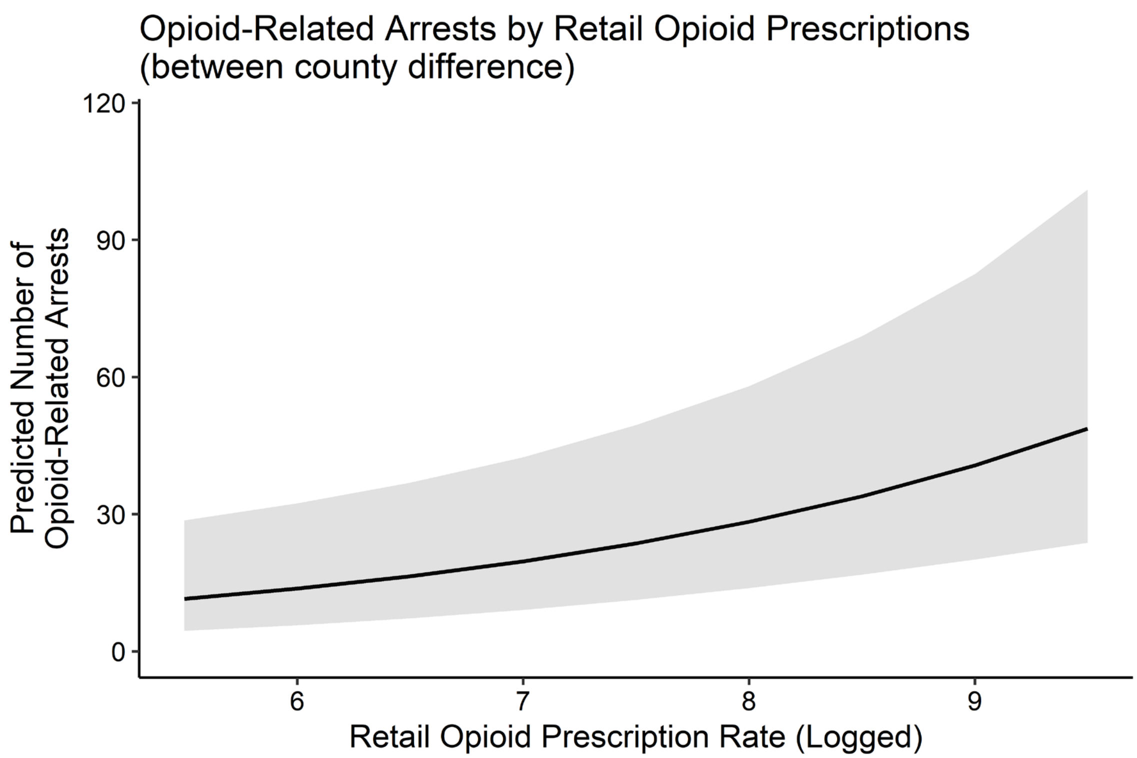


Opioid-Related Arrests

The final set of analyses pertained to predictors of variation in opioid-related arrests. Several factors were found to be associated with arrests at the county level – between- and within-county variation in retail prescriptions, and between-county differences in Medicare Part D prescriptions.

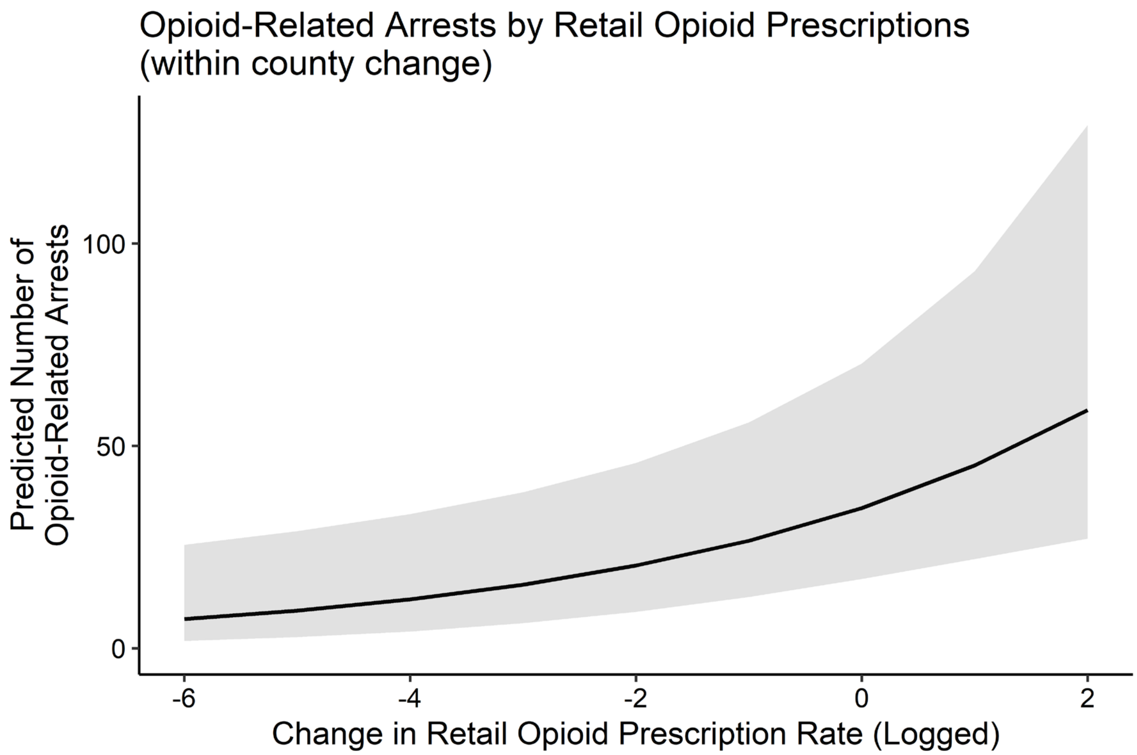
- **Retail Opioid Prescriptions (between-county differences):** There was a direct association linking the retail opioid prescription rate to the rate of opioid-related arrests. Specifically, a 1% difference in retail prescriptions between counties translated to a half a percent (0.04) increase in the rate of opioid-related arrests. This association is presented graphically in Figure 26.

Figure 26



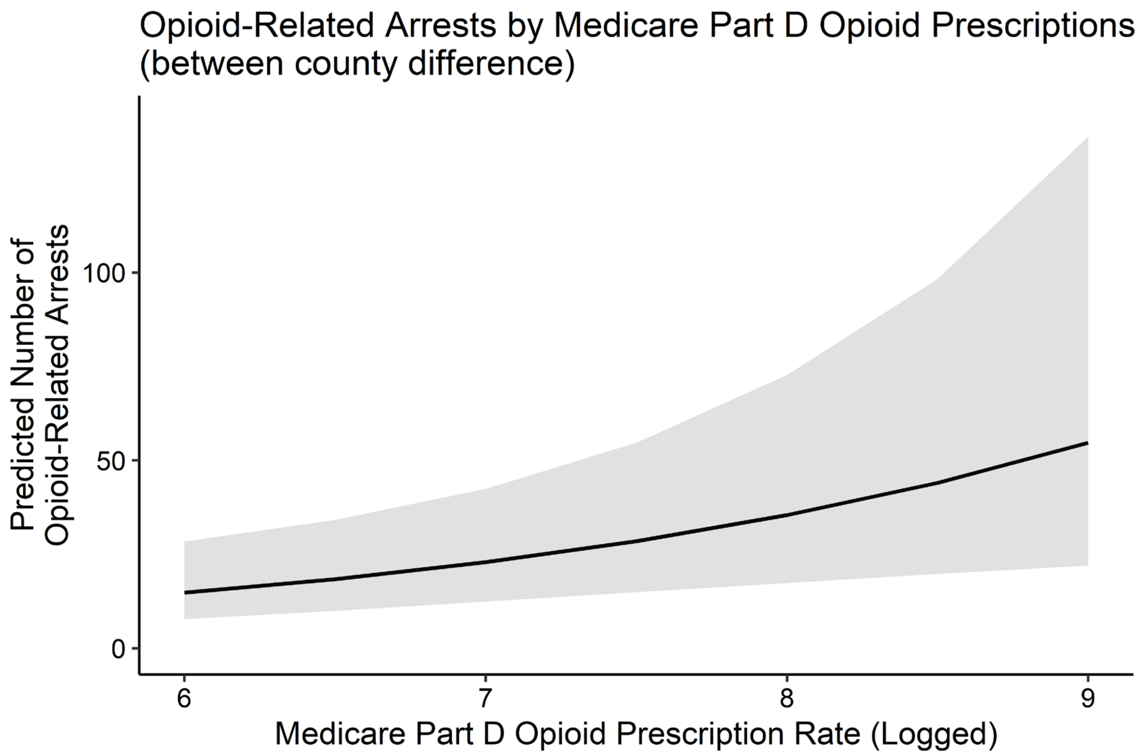
- **Retail Opioid Prescriptions (within-county change):** Similarly, there was a direct association between within-county change in retail opioid prescriptions and the opioid-related arrest rate. Specifically, when the rate of retain prescriptions in a county increased by 1%, there was a 0.3% increase in the rate of opioid-related arrests. This association is presented graphically in Figure 27.

Figure 27



- **Medicare Part D Prescriptions (between-county difference):** There was a direct association between the rate of Medicare Part D opioid prescriptions between counties, and the rate of opioid-related arrests. Specifically, a 1% difference in Medicare prescription rates between counties translated to a half a percent increase (0.06) in the opioid-related arrest rate. This association is presented graphically in Figure 28.

Figure 28



Discussion and Implications

If the goal of law enforcement activity is to alleviate the effects of the opioid crisis (including overdose deaths, opioid-involved injury and disease, and associated offending and victimization), then we must (1) integrate data systems to allow for tracking and analysis of law enforcement and public health data together, and (2) adopt law enforcement practices that are demonstrated to be effective at reaching these goals. The current analyses cannot speak directly to ongoing law enforcement activities in Michigan and their impacts, but it is important to emphasize that *we will not arrest our way out of the opioid crisis*. Law enforcement certainly has a role in seizing illicit drugs and reducing the available supply of opioids, but thus far the effectiveness of supply-side law enforcement interventions has not been evaluated in terms of improved health outcomes. For example, prescription drug monitoring programs (PDMPs) were intended to reduce the supply of opioids in our communities, but evaluation results have been mixed (Delcher et al., 2015). Where such interventions are used primarily for law enforcement rather than for public health purposes (e.g., reducing overdose deaths), public health outcomes may not be fully realized. Furthermore, PDMPs are unlikely to have much impact in areas experiencing high rates of opioid overdose deaths involving heroin and illicitly manufactured synthetic opioids like fentanyl.

Fortunately, in Michigan there is already recognition of these issues and steps being taken in response. The Michigan State Police strategic plan includes multijurisdictional drug task forces prioritizing enforcement of substances based on harm, and these teams have been responsive to these priorities (Nguyen & McGarrell, 2016). As responses are implemented, it is important to recognize that some law enforcement responses may contribute to increased risk of overdose. It is well-established that people leaving jails and prisons are at extremely increased risk of death by overdose in the weeks and months following their release. For example, in North Carolina, the risk of opioid overdose death for former inmates was 40 times higher in the two weeks post-release than for general NC residents. Specifically, the risk of heroin overdose death was 74 times higher for this population than for general NC residents (Ranapurawala et al., 2014). Thus, the widespread arrest and incarceration of opioid-using people, absent efforts to provide treatment both inside correctional institutions and through the transition back to the community, is likely to be associated with *increased* opioid overdose deaths. Medication-assisted treatment with buprenorphine, methadone, or extended-release naltrexone during incarceration and through the immediate post-release period is associated with reduced rates of overdose death, reduced relapse rates, reduced recidivism, and more likely engagement with treatment post-release (NIDA, 2017). Providing methadone or buprenorphine has also been demonstrated to results in considerable cost savings to the criminal justice system (Krebs et al., 2017).

As Michigan continues to develop comprehensive strategies to combat the opioid crisis, and as it continues to develop treatment and reentry services for substance involved individuals, it may be helpful to consider promising practices from other states on the "front lines." Indeed, although Michigan is already engaging in a number of promising approaches, it may be helpful for law enforcement agencies to look to innovations from other areas of the country, especially those hardest-hit by the crisis. For example, Vermont is taking steps toward decriminalizing the possession of non-prescribed buprenorphine (Landen, 2019). Buprenorphine (e.g. Suboxone) is a medication available by prescription for treatment of opioid use disorder. People struggling with opioid use sometimes illegally purchase diverted buprenorphine to manage withdrawal symptoms or to try and reduce their use of heroin and other opioids. People surveyed in Rhode

Island (Carroll, Rich, & Green, 2018) and Baltimore, MD (Genberg et al., 2013) reported using street-obtained buprenorphine to manage withdrawal symptoms and to self-treat their opioid use disorder, and only very rarely to get high. Many people who reported using diverted medication were also seeking formal substance use treatment (Carroll et al., 2018). However, it is important to recognize that the purpose of decriminalizing buprenorphine possession is not to treat opioid dependence, but rather to mitigate withdrawal symptoms which would otherwise lead to more problematic behavioral outcomes (e.g., criminal offending associated with acquiring street drugs, exposure to contaminated drug supply). Ideally, treatment with methadone and buprenorphine would be coupled with a comprehensive suite of other substance use disorder services in order to maximize opportunities for recovery

Another promising innovation for law enforcement is having police officers trained in and equipped with the overdose-reversing drug naloxone (e.g. Narcan, Evzio). Training and equipping officers to use naloxone has faced resistance in some areas. For example, a sheriff in one Ohio county told a reporter "This Narcan, all it does is save peoples' lives for another day. … You enable these people when you give them this Narcan" (*Wing, 2017*). However, saving someone's life so that they can begin their recovery another day is exactly the purpose of these medications. Fortunately, other departments have instituted naloxone programs and have been deemed safe from liability (Davis, Carr, Southwell, & Beletsky, 2015). Naloxone administration by police is associated with decreased opioid overdose deaths (Rando, Broering, Olson, Marco, & Evans, 2015). Furthermore, officers can be trained to provide referral to treatment post-naloxone administration (Dahlem et al., 2017).

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Appendix

Table A1. Offender and Arrestee Characteristics in Opioid and Non-Opioid Involved Incidents, 2013-2017

	Opioid Involved		**All Other Drugs**	
Characteristic	Offenders (%)	Arrestees (%)	Offenders (%)	Arrestees (%)
Age				
Under 18	997	563	25,222	14,584
	(2.1)	(1.8)	(9.5)	(7.7)
18-24	11,851	8,201	98,056	72,795
	(24.8)	(25.5)	(36.8)	(38.4)
25-34	19,410	12,965	75,820	55,173
	(40.6)	(40.4)	(28.5)	(29.1)
35-44	8,792	5,856	36,613	25,811
	(18.4)	(18.2)	(13.7)	(13.6)
45-54	4,470	3,020	20,956	14,745
	(9.3)	(9.4)	(7.9)	(7.8)
55-64	2,013	1,317	8,343	5,588
	(4.2)	(4.1)	(3.1)	(2.9)
65-74	312	173	1,192	699
	(0.7)	(0.5)	(0.4)	(0.4)
75-84	15	7	72	36
	(0.0)	(0.0)	(0.0)	(0.0)
85+	5	2	21	3
	(0.0)	(0.0)	(0.0)	(0.0)
Sex				
Female	13,440	8,745	59,788	40,161
	(27.9)	(27.2)	(22.4)	(21.2)
Male	34,649	23,364	207,049	149,310
	(72.1)	(72.8)	(77.6)	(78.8)
Race				
White	31,849	21,576	166,695	116,708
	(66.1)	(67.2)	(62.3)	(61.6)
African American	14,824	9,789	89,814	66,406
	(30.8)	(30.5)	(33.6)	(35.0)
American Indian	308	150	893	599
	(0.6)	(0.5)	(0.3)	(0.3)
Asian / Pacific Island	98	65	802	565
	(0.2)	(0.2)	(0.3)	(0.3)
Unknown	1,078	534	9,280	5,231
	(2.3)	(1.7)	(3.5)	(2.8)
Arrestee Residence				
Same Community		8,331		49,018
		(40.9)		(41.0)
Same County		6,588		39,894
		(32.4)		(33.3)
Different MI County		4,769		25,588
		(23.4)		(21.4)
Out of State		318		2,135
		(1.7)		(2.5)
Total	48,280	32,114	268,084	189,509

Table A2. Factor Loadings and Reliabilities for Items used in Construction of County-level Distress Scores

Construct / Item	Factor Loading	α if item removed
Economic Distress (α = 0.89)		
% Labor force that is unemployed	0.52	0.90
% Households receiving supplemental security income	0.76	0.87
% Population over 25 with no high school diploma	0.84	0.86
% Population under 18 living below poverty level	0.95	0.84
Median household income (inverse)	0.81	0.86
Teen birth rate	0.68	0.88
Housing Distress (α = 0.68)		
% Vacant housing units that are for rent	0.72	0.51
Median contract rent divided by fair market rent (1 bedroom)	0.72	0.51
Family Distress (α = 0.72)		
% Households headed by single parent with children	0.75	0.57
% population divorced or separated	0.75	0.57

Table A3. Bayesian Hybrid Mixed-Effect Negative Binomial Regression Model Results

Outcome → Predictor ↓	Opioid-Related Deaths		Synthetic Opioid Deaths		Opioid-Related Arrests	
	Est. (SE)		Est. (SE)		Est. (SE)	
Between-County Differences						
Retail Rx (ln)	0.13 (0.13)		0.26 (0.18)		0.36 (0.12)	*
Medicare Part D Rx (ln)	0.15 (0.20)		0.33 (0.26)		0.44 (0.19)	*
Police Density (ln)	-0.09 (0.18)		-0.05 (0.21)		-0.02 (0.20)	
Opioid Arrests	0.04 (0.02)	#	0.02 (0.03)			
Opioid Seizures	-0.25 (0.11)	*	-0.24 (0.13)	#		
Within-County Change						
Retail Rx (ln)	0.10 (0.15)		0.46 (0.29)		0.27 (0.11)	*
Medicare Part D Rx (ln)	0.13 (0.27)		-0.11 (0.41)		-0.02 (0.15)	
Police Density (ln)	-0.53 (0.24)	*	-0.59 (0.43)		-0.08 (0.14)	
Opioid Arrests	-0.02 (0.02)		-0.08 (0.03)	*		
Opioid Seizures	0.00 (0.04)		-0.01 (0.06)			
Control Variables						
Economic Distress	-0.07 (0.11)		-0.15 (0.15)		-0.04 (0.09)	
Housing Distress	0.08 (0.10)		0.09 (0.14)		-0.11 (0.08)	
Family Distress	0.14 (0.11)		0.17 (0.15)		0.12 (0.08)	
PCP per Capita (ln)	-0.23 (0.19)		-0.46 (0.25)		0.11 (0.16)	
% Uninsured	0.01 (0.04)		0.00 (0.05)		0.01 (0.03)	
% White	-0.00 (0.01)		-0.01 (0.01)		-0.01 (0.01)	
% Over 65	-0.03 (0.03)		-0.07 (0.03)	*	-0.02 (0.02)	
Metro County	(reference)		(reference)		(reference)	
Urban (non-metro)	-0.45 (0.20)	*	-0.59 (0.23)	*	0.07 (0.21)	
Rural	-0.42 (0.25)	#	-0.37 (0.30)		0.13 (0.24)	
2013	(reference)		(reference)		(reference)	
2014	0.23 (0.09)	*	0.83 (0.18)	*	0.01 (0.07)	
2015	0.46 (0.10)	*	1.17 (0.18)	*	0.14 (0.08)	#
2016	0.73 (0.12)	*	2.34 (0.21)	*	0.10 (0.10)	
2017	0.92 (0.21)	*	2.94 (0.32)	*	0.14 (0.17)	
Intercept	-10.11 (1.81)		-12.88 (2.30)		-14.01 (1.76)	
Random Effects Std. Dev.						
Intercept	0.46 (0.06)		0.46 (0.07)		0.55 (0.06)	

Notes: N = 83 counties, T = 5 years, N × T = 415
ln = natural logarithm
All models include the county population as an exposure term
* = Statistically distinguishable from zero based on 95% highest density interval
# = Statistically distinguishable from zero based on 90% highest density interval