Mathematical and statistical views on the opioid epidemic

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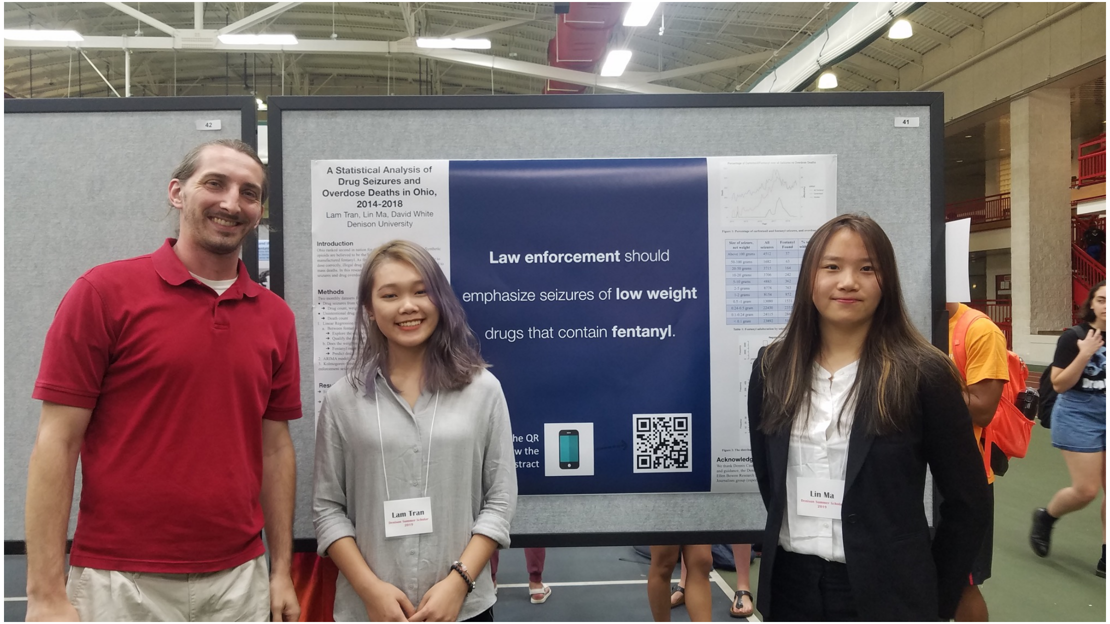
Joint with Lin Ma ('20) and Lam Tran ('21)

Inspired by work of Dennis Cauchon (Harm Reduction Ohio)



Our research team

Plan for today:

- Overdose Deaths in Ohio and USA
  - History = Triple Wave Epidemic: Pills, Heroin, Fentanyl.
  - Iron Law of Prohibition. Efforts of Harm Reduction Ohio.
- Police Seizures of Drugs (BCI)
  - 130,000 drug seizures in 2014-2018: types of drugs seized, weight, county, date, name of the law enforcement department.
- Ohio SUDORS Data: Unintentional Overdose
  - 9,300 individuals who died of drug overdose, 750 attributes for each: demographics, mental health/substance abuse history, personal problems, bystanders, Naloxone, polysubstance abuse, etc.
  - This study includes data provided by the Ohio Department of Health, which should not be considered an endorsement of this study or its conclusions.

- Key Take-Aways
  - There are tons of freely available datasets about the opioid epidemic: CDC, SUDORS, BCI, NSDUH, epicenter (hospitals), prescriptions (OARRS), marijuana laws, NFLIS (DEA), FBI, OMAS Medicaid survey, mental health.
  - There is a huge need to educate people about what actually works to combat the opioid epidemic. This is a heavy topic, but the data tell us very important information.
  - Many data sets have never been analyzed – lots of low-hanging fruit, and nowhere near enough math/stats people working on this.
  - Even simplistic analyses are valuable to harm reduction professionals, can save lives, and can get published. Great for students.
  - I’m happy to help you get involved, sharing datasets, analyses, and papers, and connecting you to experts. Current team includes faculty and students from Denison, Kent State, Ohio State, Kenyon, University of Dayton, plus Harm Reduction Ohio.

- Overdose Deaths in USA
    - The yearly number of drug overdose deaths surged in the US from 16,849 cases in 1999 to 107,941 cases in 2022.
    - In 2022, more than 295 people died every day in the US after overdosing on opioids.
    - The number of fentanyl encounters has been increasing exponentially, from 5,343 in 2014 to 117,045 in 2020. It has continued to increase.
    - As of now, an American is more likely to die from an unintentional drug overdose than in a car accident.
    - Ohio has average drug use patterns, but in 2017 was second in the country for unintentional drug overdose deaths, and now seventh highest. Why?
    - Iron Law of Prohibition: if you crack down on one type of drugs, dealers will select more potent drugs to traffic in.

Figure 1. National Drug-Involved Overdose Deaths*, Number Among All Ages, by Gender, 1999-2021

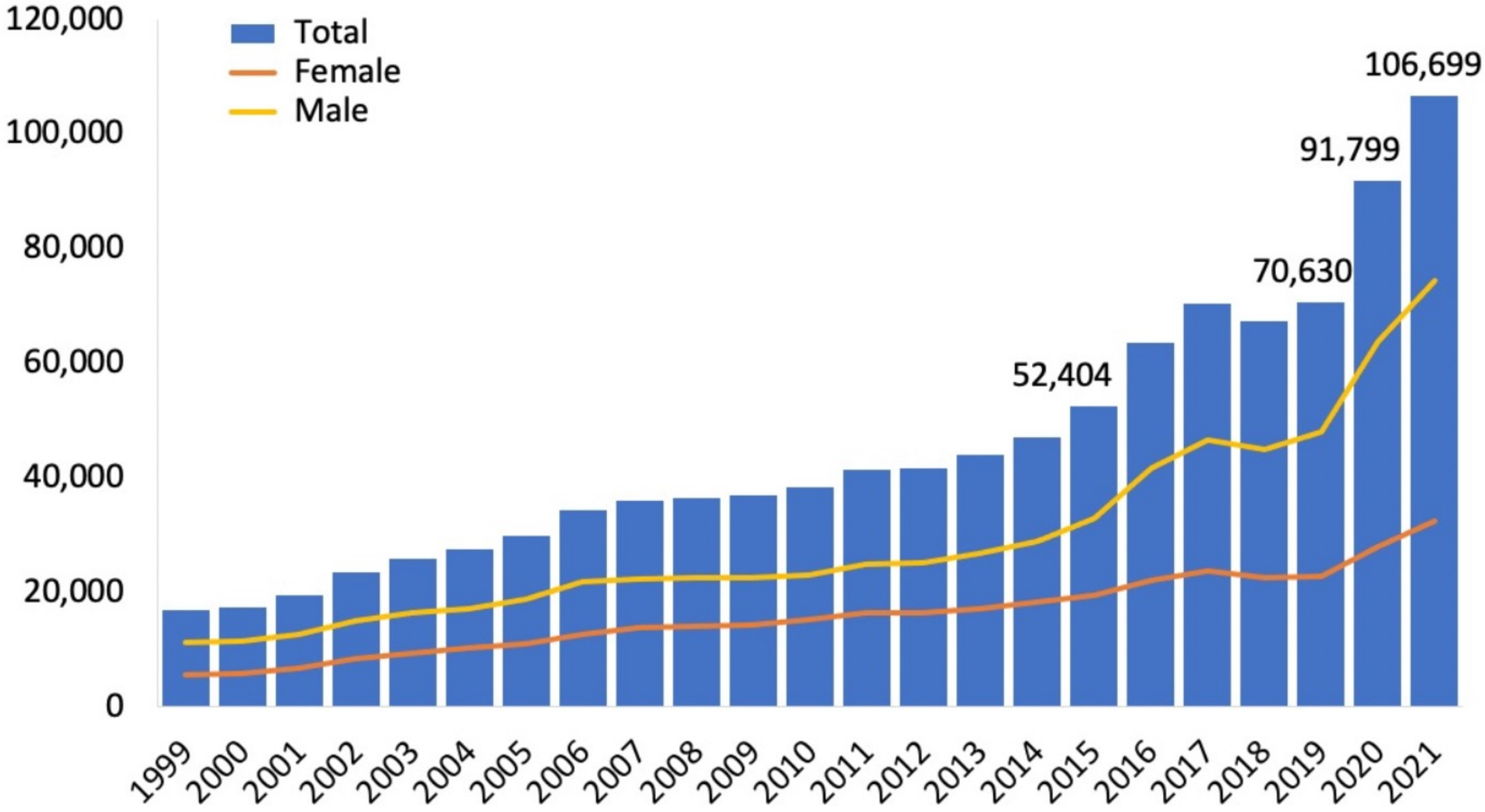


Figure 3. National Overdose Deaths Involving Any Opioid*, Number Among All Ages, by Gender, 1999-2021

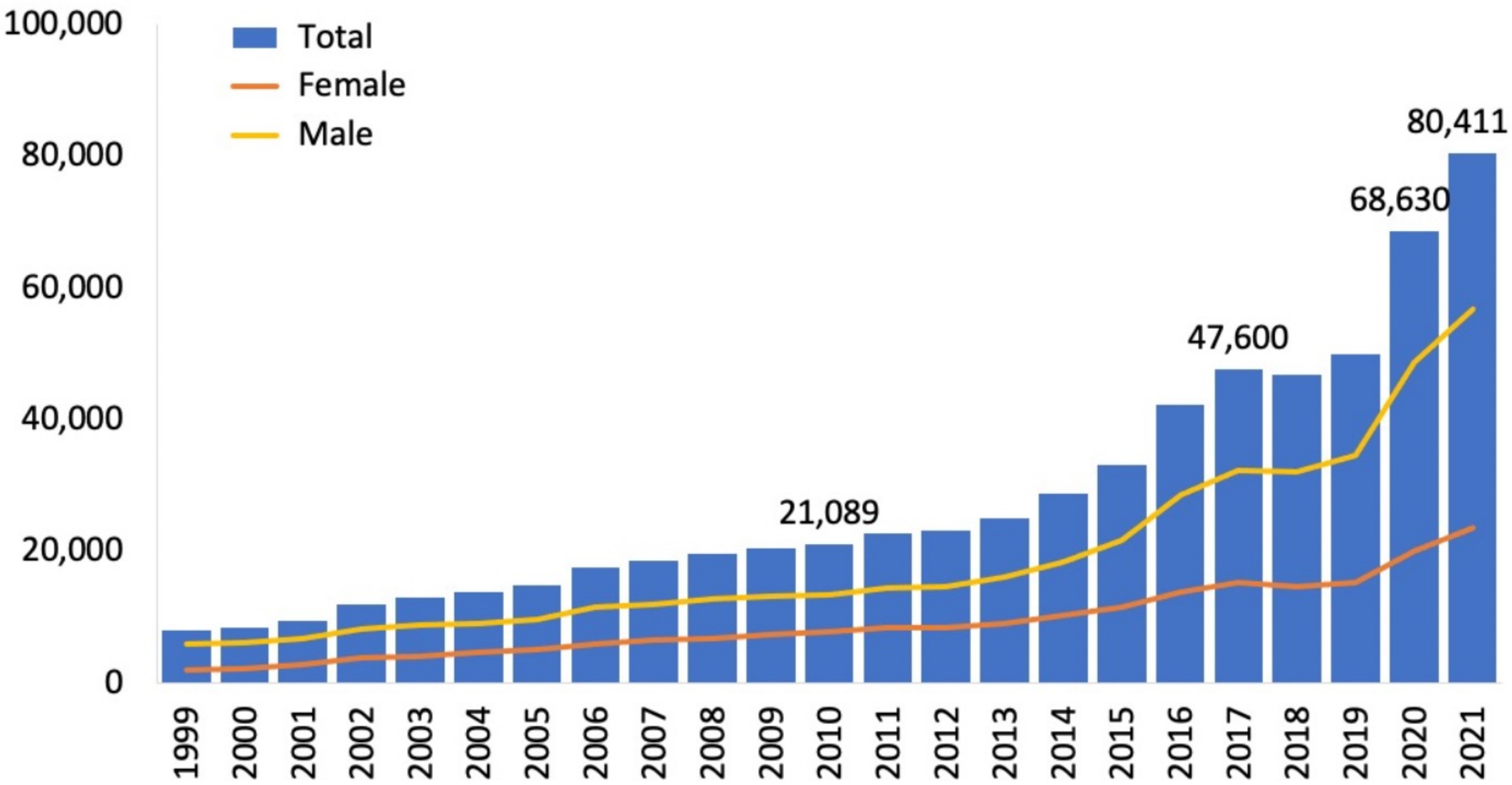


Figure 6. National Overdose Deaths Involving Stimulants (Cocaine and Psychostimulants*), by Opioid Involvement, Number Among All Ages, 1999-2021

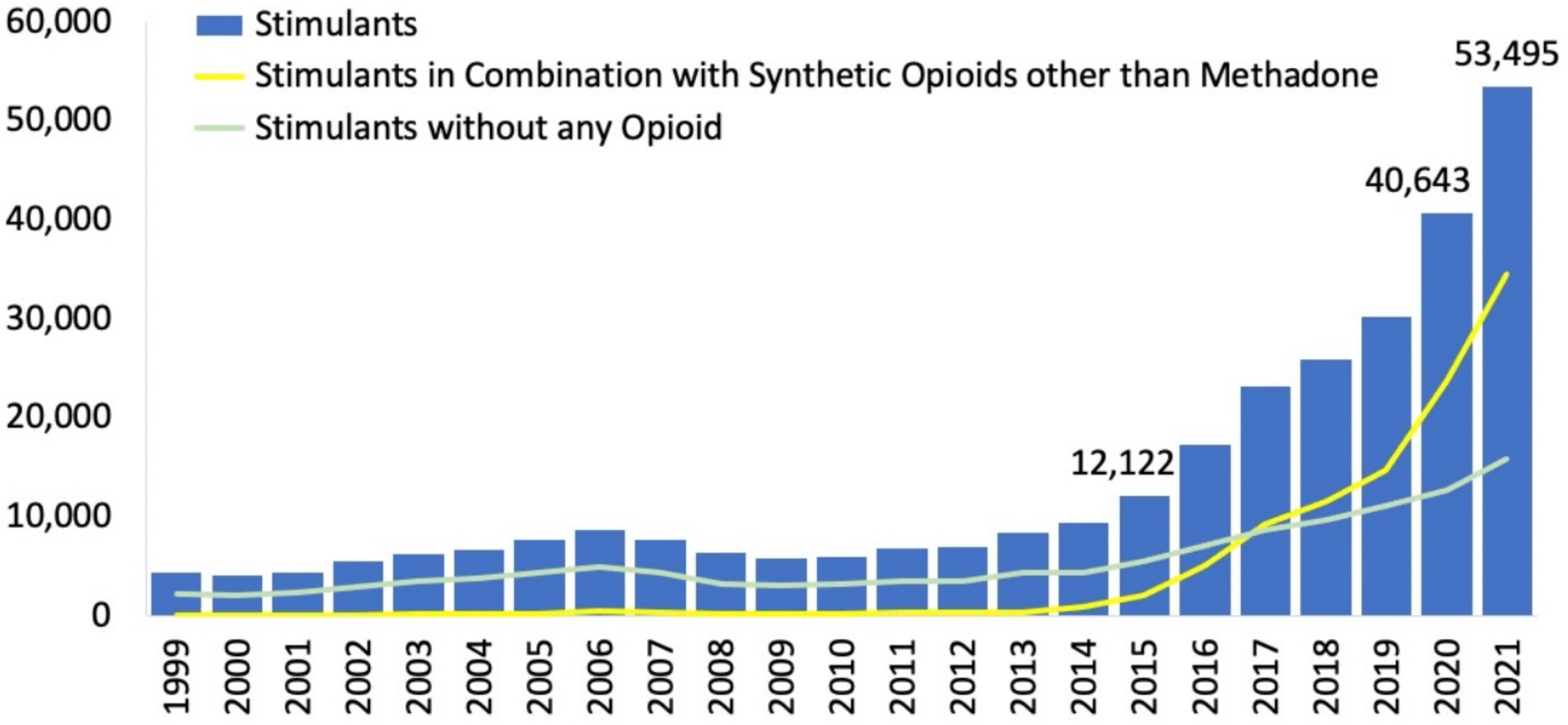


Figure 7. National Overdose Deaths Involving Psychostimulants with Abuse Potential (Primarily Methamphetamine)*, by Opioid Involvement, Number Among All Ages, 1999-2021

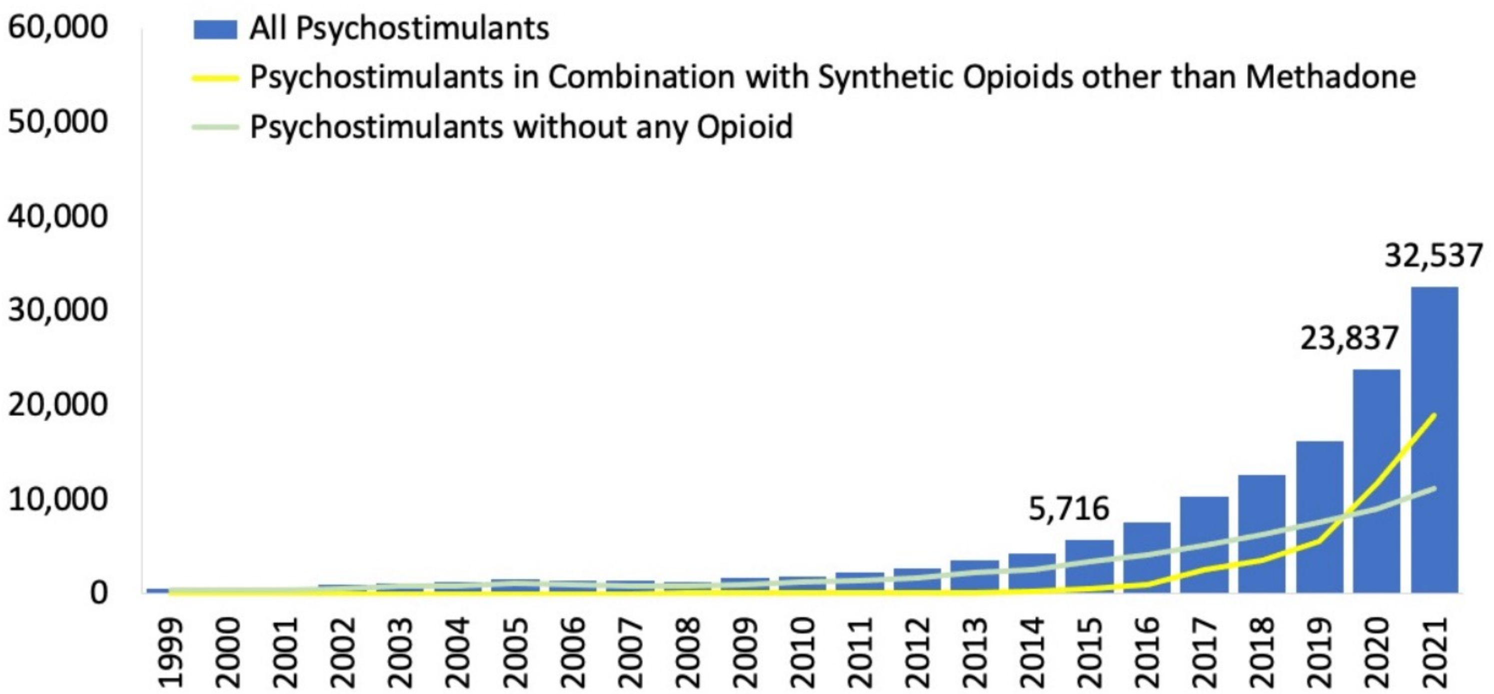


Figure 8. National Drug Overdose Deaths Involving Cocaine*, by Opioid Involvement, Number Among All Ages, 1999-2021

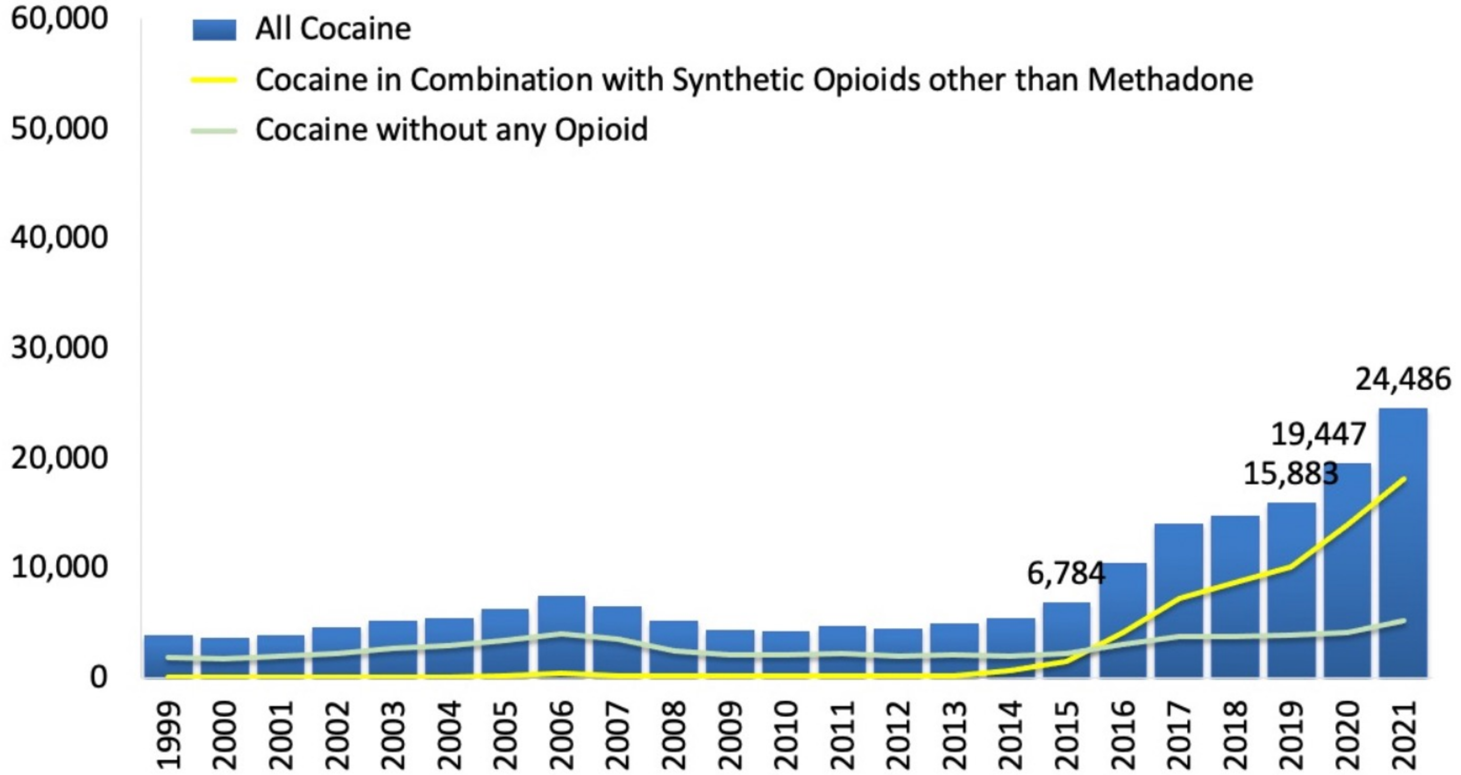
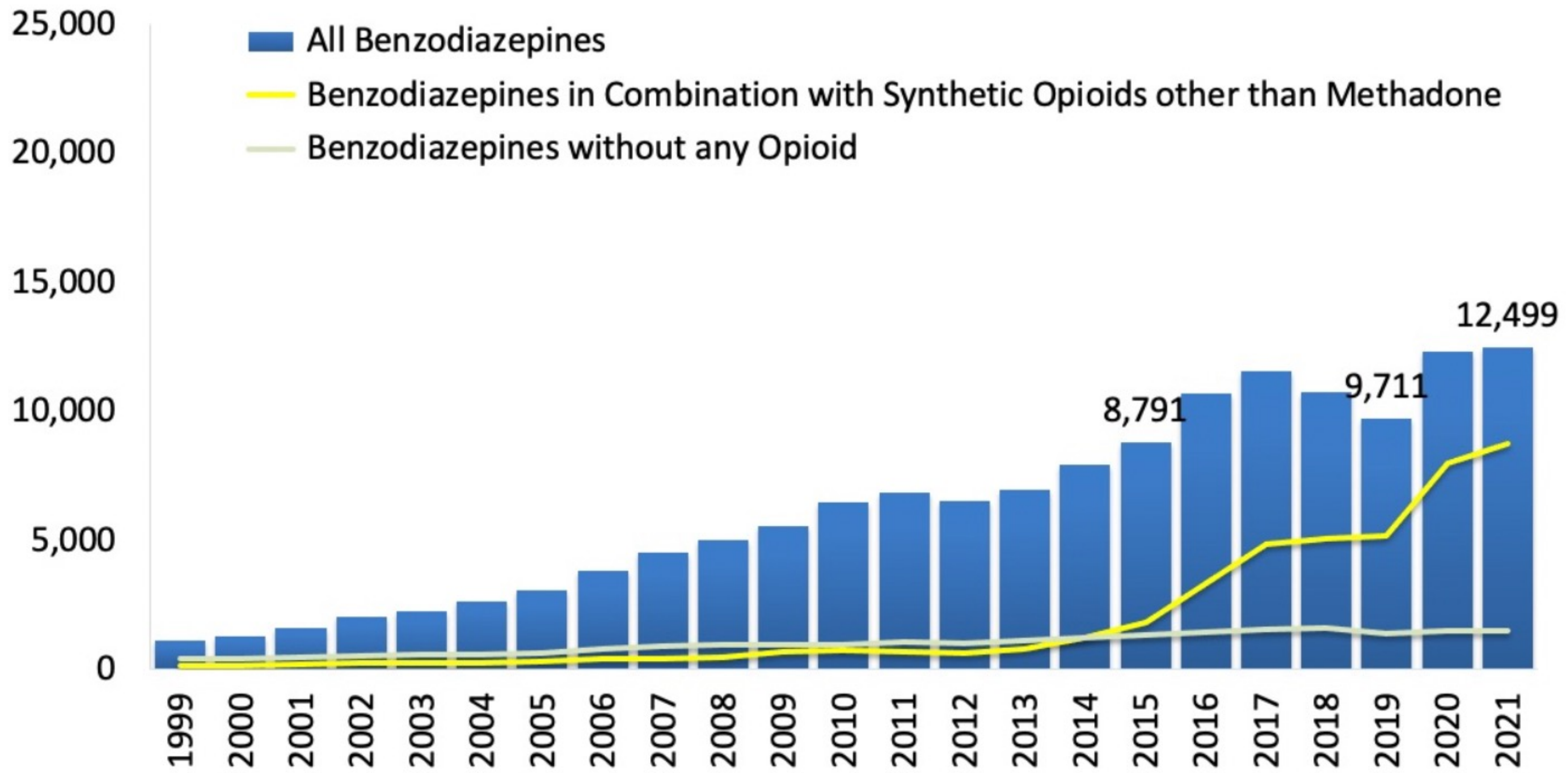


Figure 9. National Drug Overdose Deaths Involving Benzodiazepines*, by Opioid Involvement, Number Among All Ages, 1999-2021



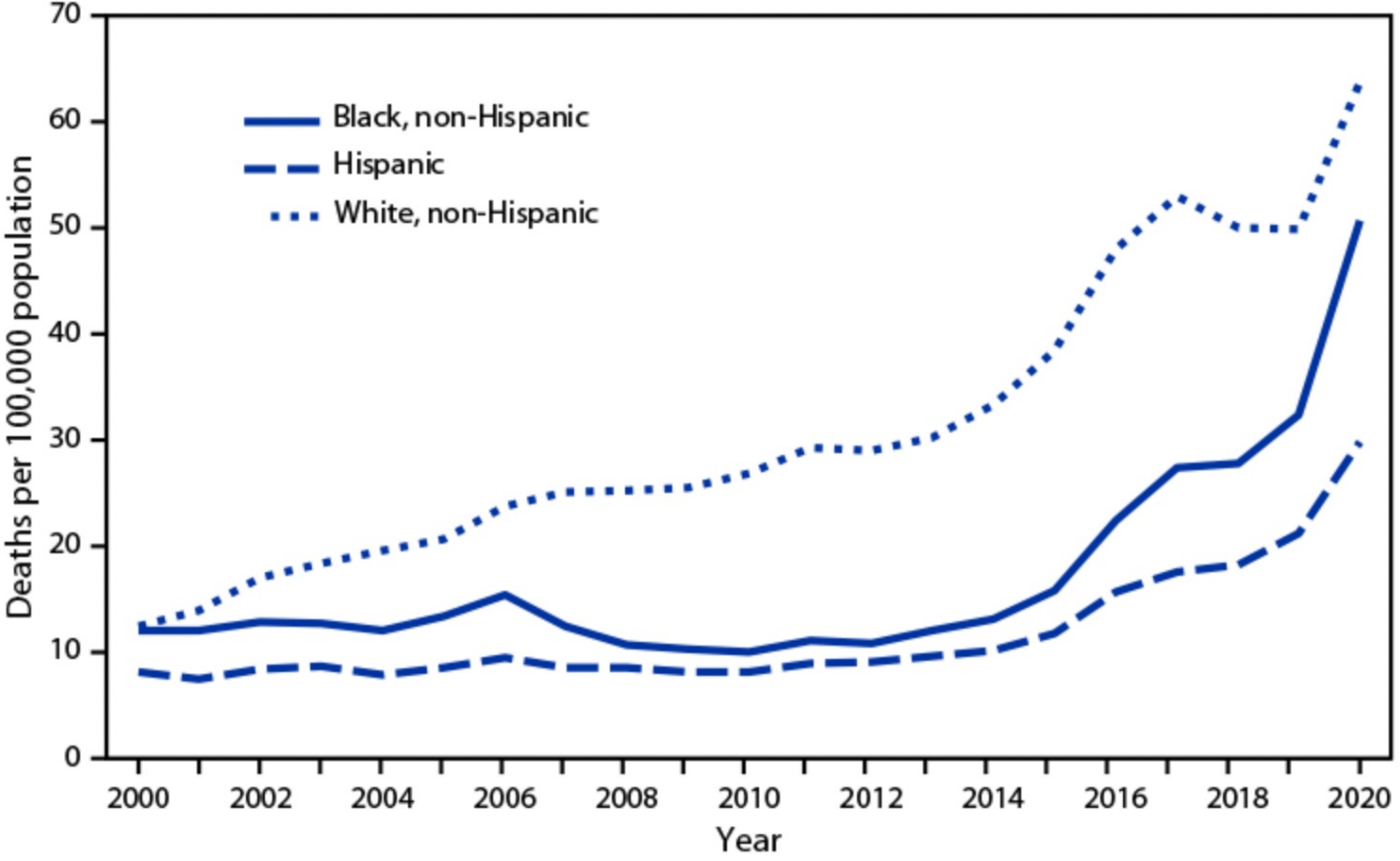
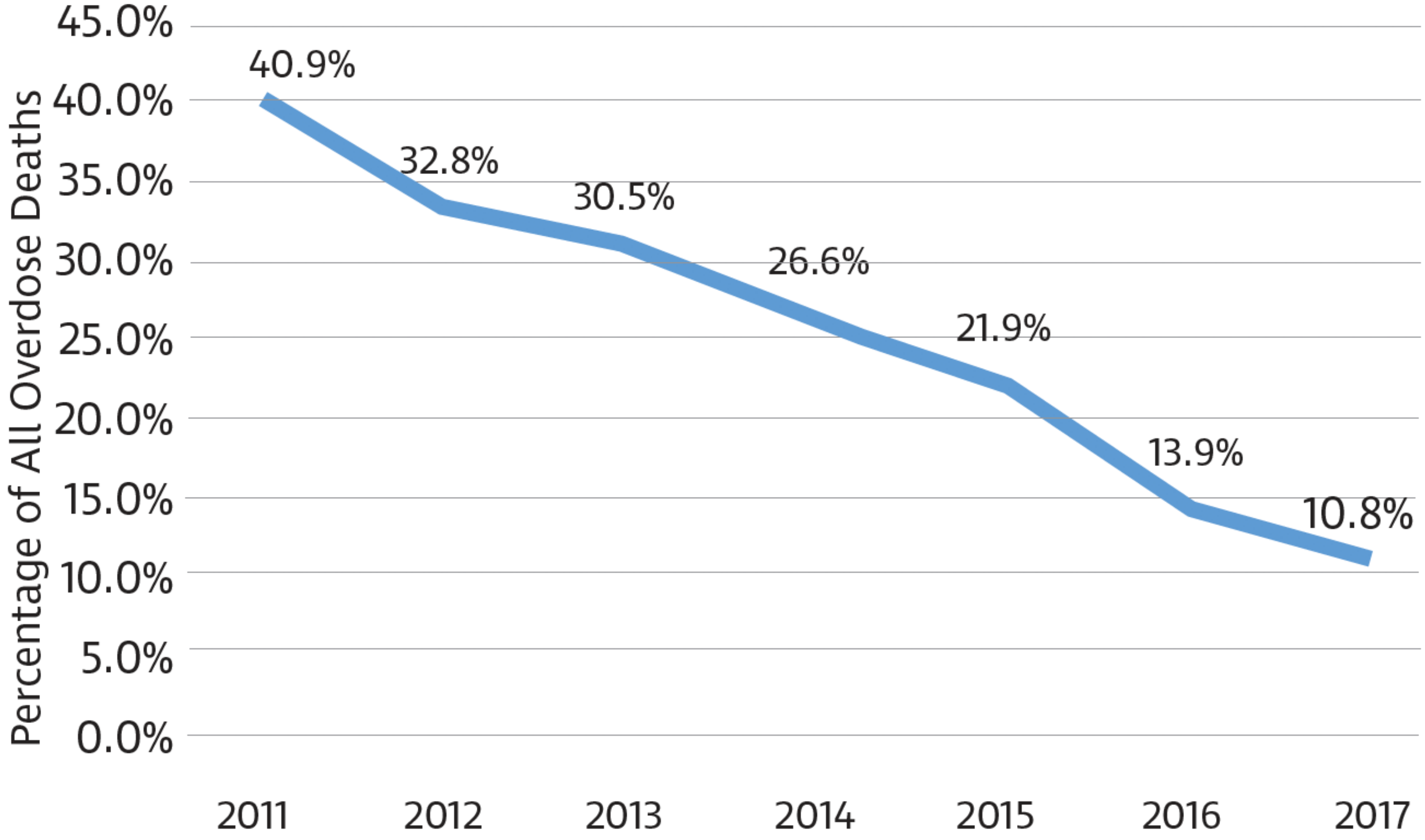
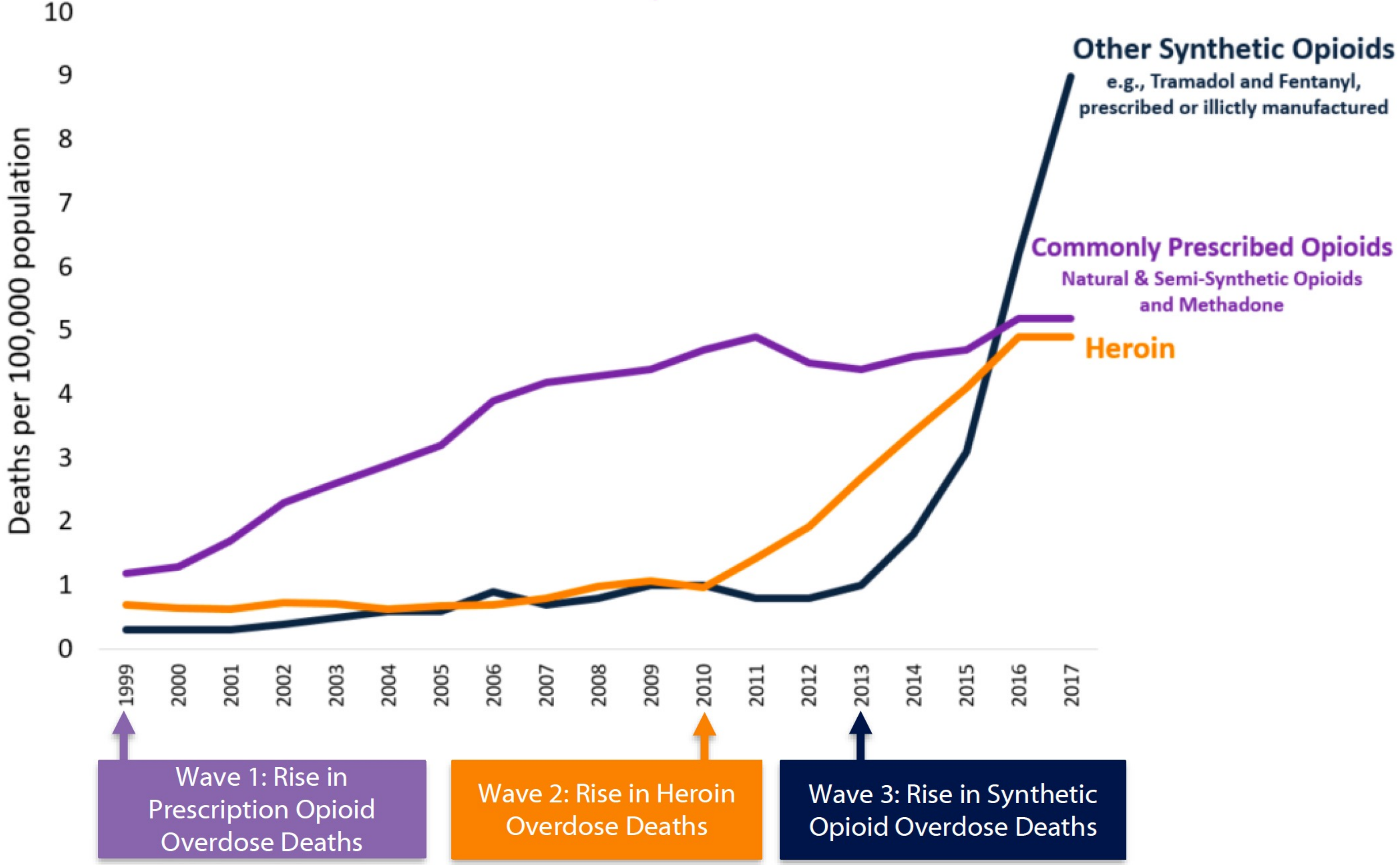

Black, non-Hispanic
Hispanic
White, non-Hispanic
Deaths per 100,000 population
70
60
50
40
30
20
10
0
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020
Year

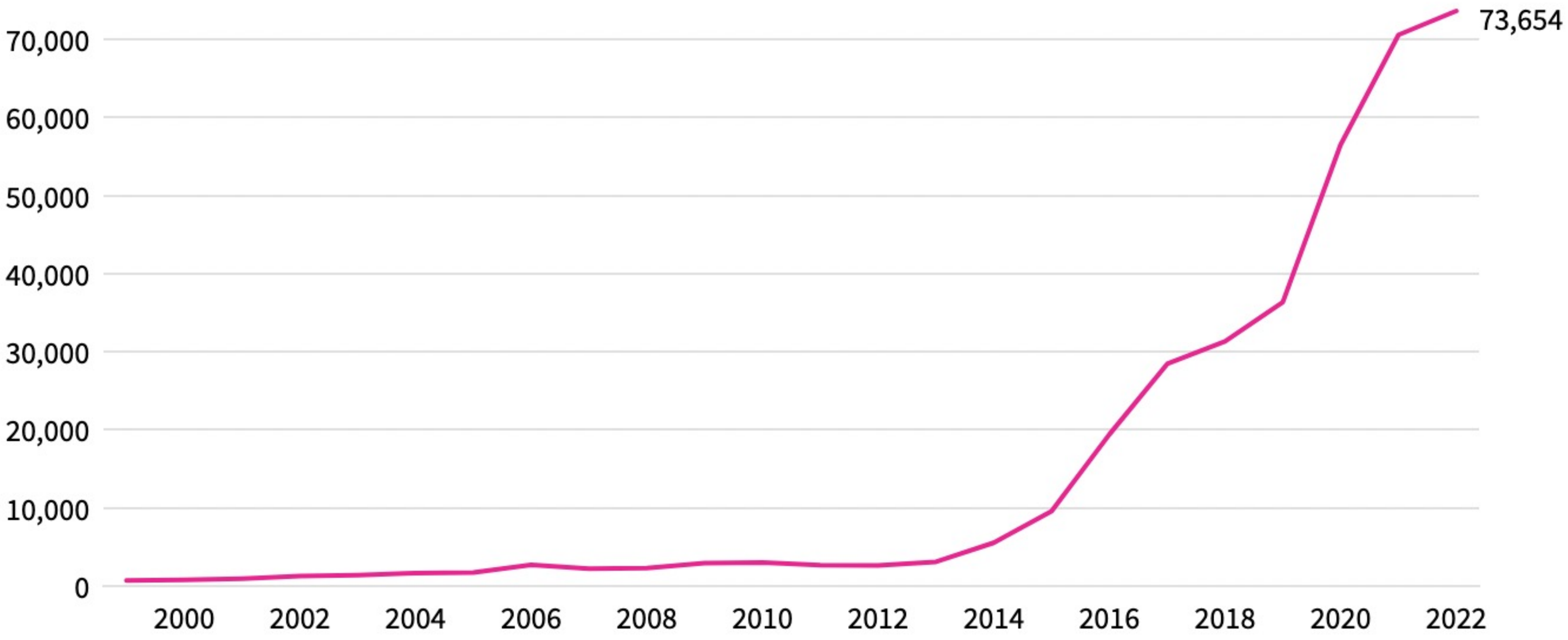
Figure 2. Percentage of Unintentional Drug Overdose Deaths Involving Prescription Opioids, 2011-2017



3 Waves of the Rise in Opioid Overdose Deaths



Synthetic opioid overdose deaths (mostly fentanyl), 1999–2022



Fentanyl is a synthetic opioid

- Cheap to manufacture.
- Very powerful.
- Easy to mix with other drugs.
- Many variants of unknown strength.
- Strongest known variant is Carfentanil.

Overdose Deaths per 100,000 Residents

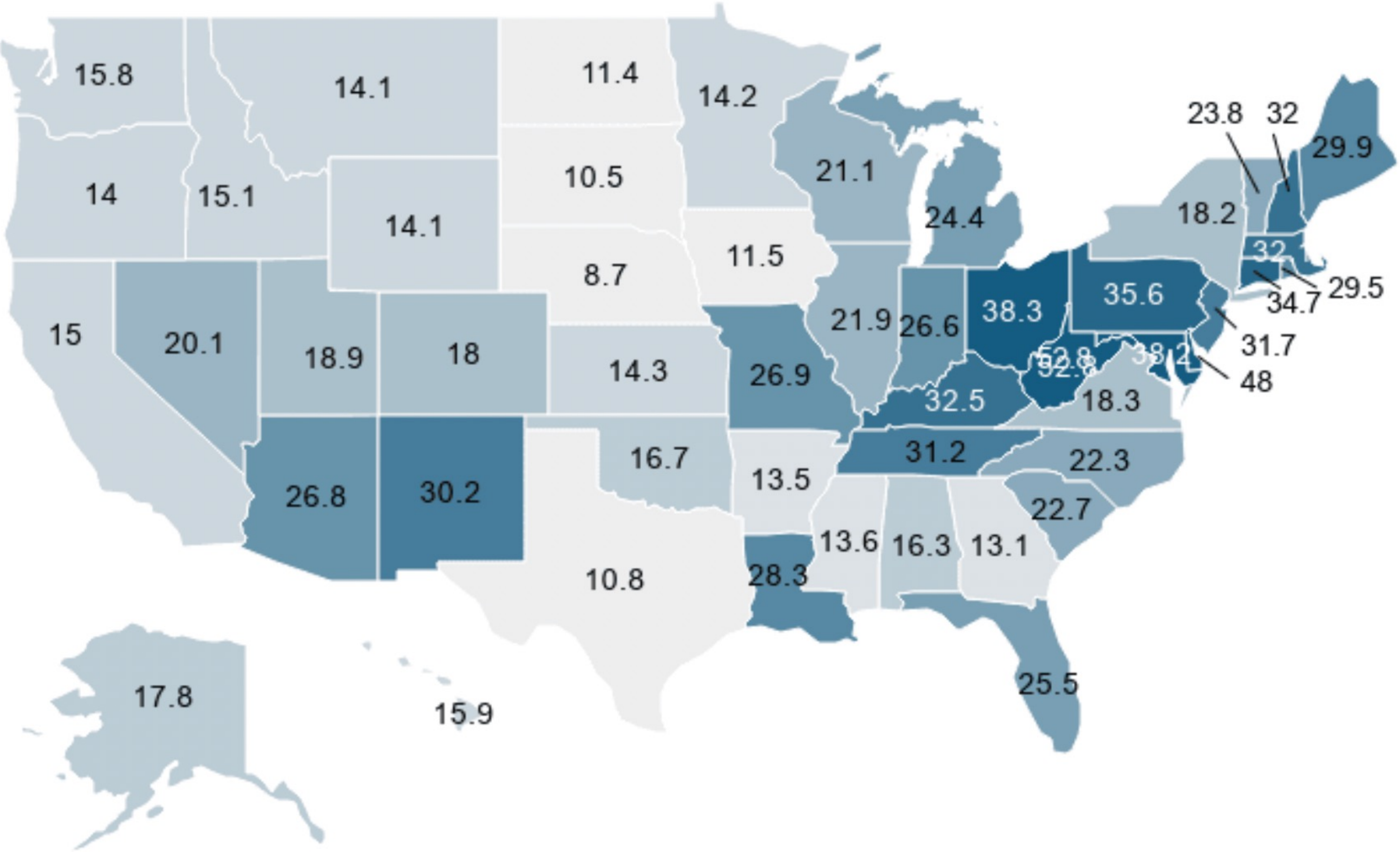
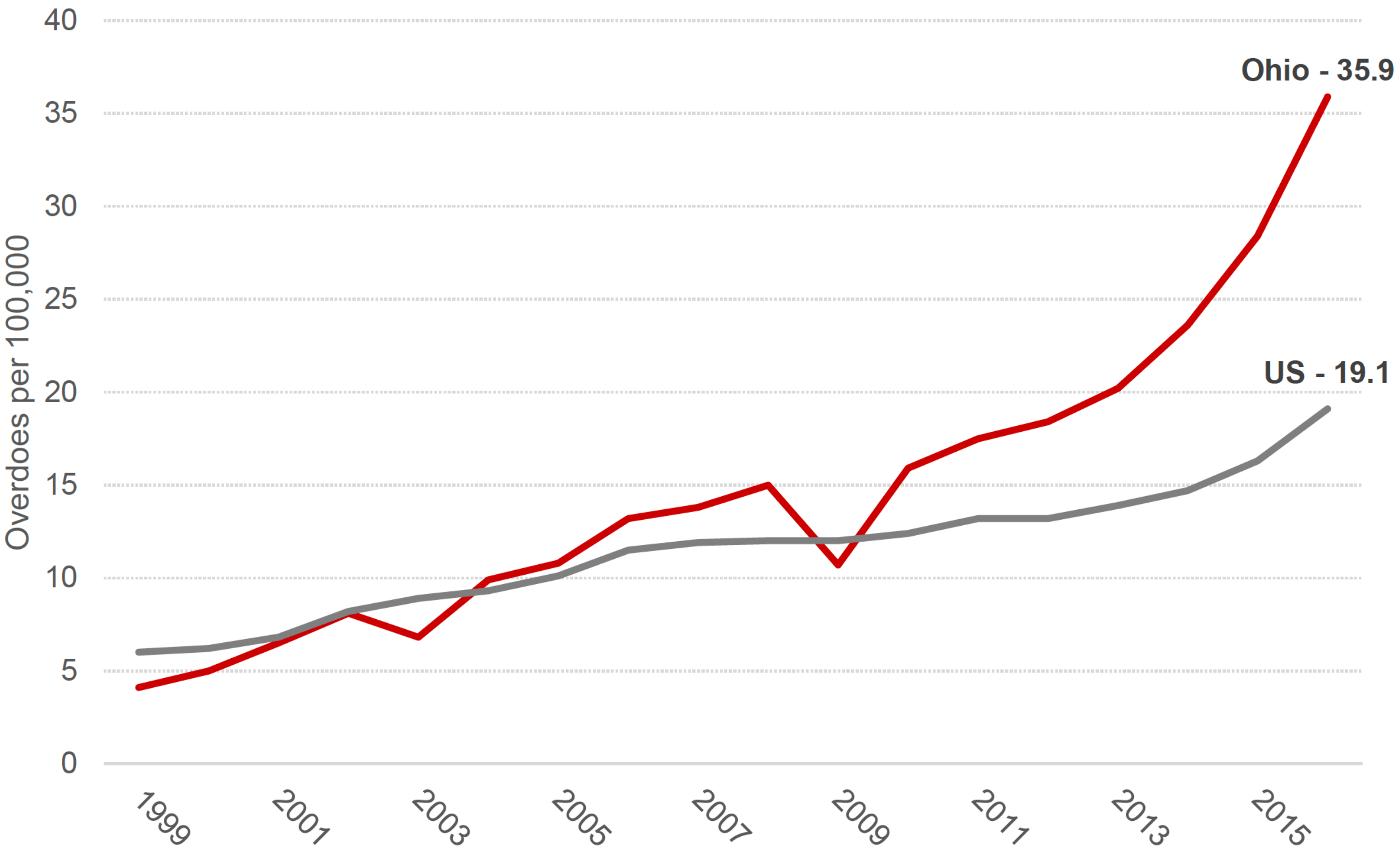
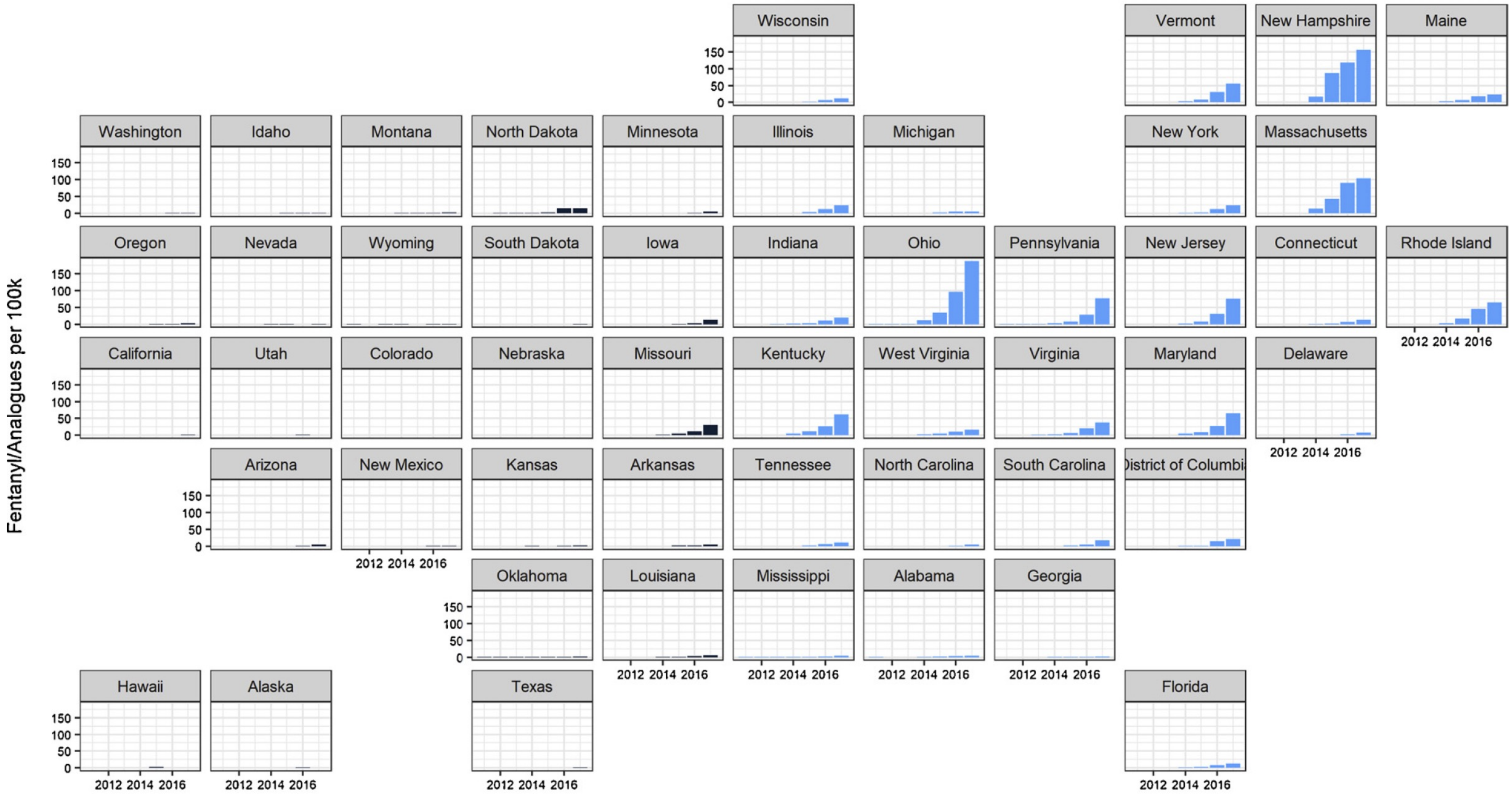


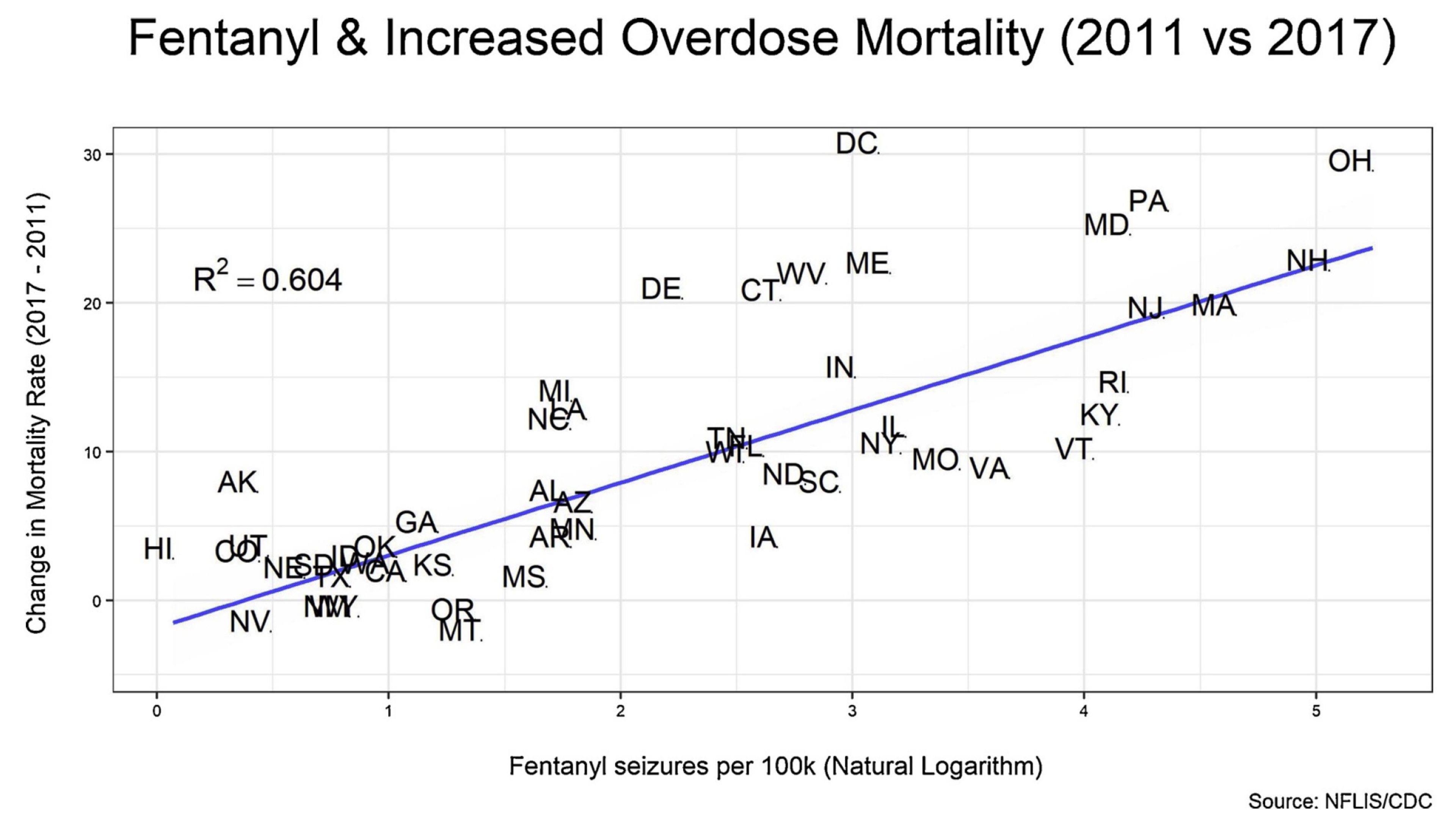
FIGURE 1: Drug Overdose Rates 1999-2016



Drug Seizures with Fentanyl (2011-2017)



Source: National Forensic Laboratory Information System (NFLIS)



Fentanyl & Increased Overdose Mortality (2011 vs 2017)
$R^2 = 0.604$
Change in Mortality Rate (2017 - 2011)
Fentanyl seizures per 100k (Natural Logarithm)
Source: NFLIS/CDC
30
20
10
0
0
1
2
3
4
5
DC
OH
PA
MD
NH
ME
WV
DE
CT
NJ
MA
IN
RI
MI
LA
NC
KY
IL
TN
NY
FL
WI
VT
MO
VA
ND
SC
AK
AL
AZ
GA
MN
AR
IA
HI
UT
CO
OK
ID
NE
SD
WA
KS
CA
TX
MS
NM
WY
OR
NV
MT

Figure 8. Percentage of Unintentional Drug Overdose Deaths Involving Selected Drugs, by Year, Ohio, 2010-2017

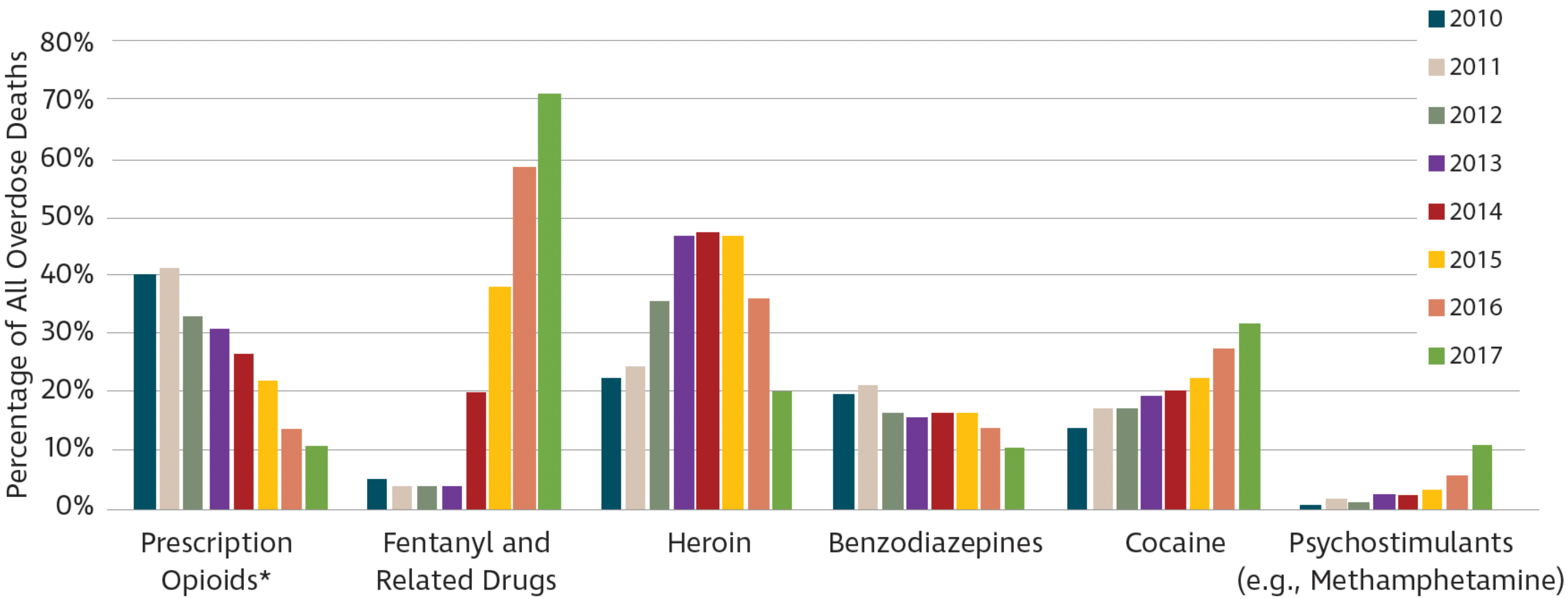
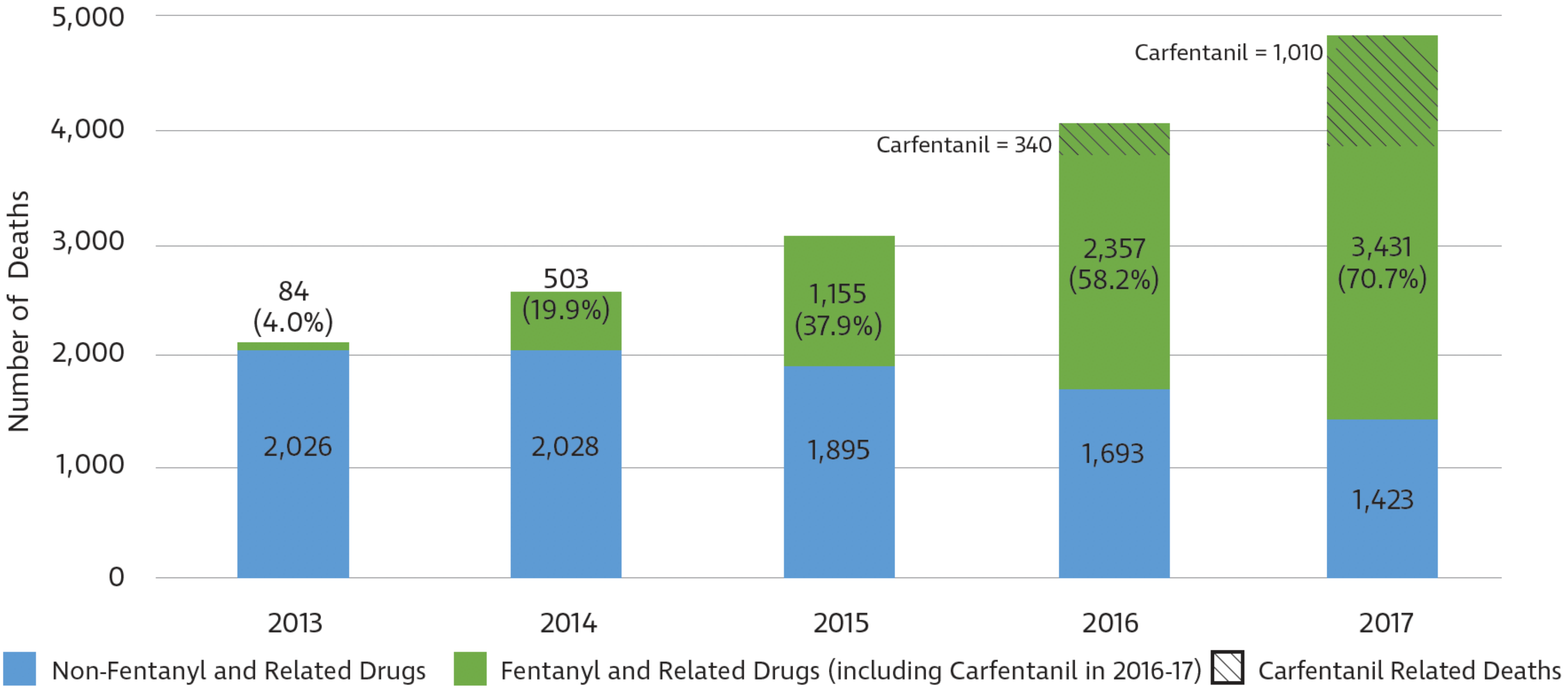
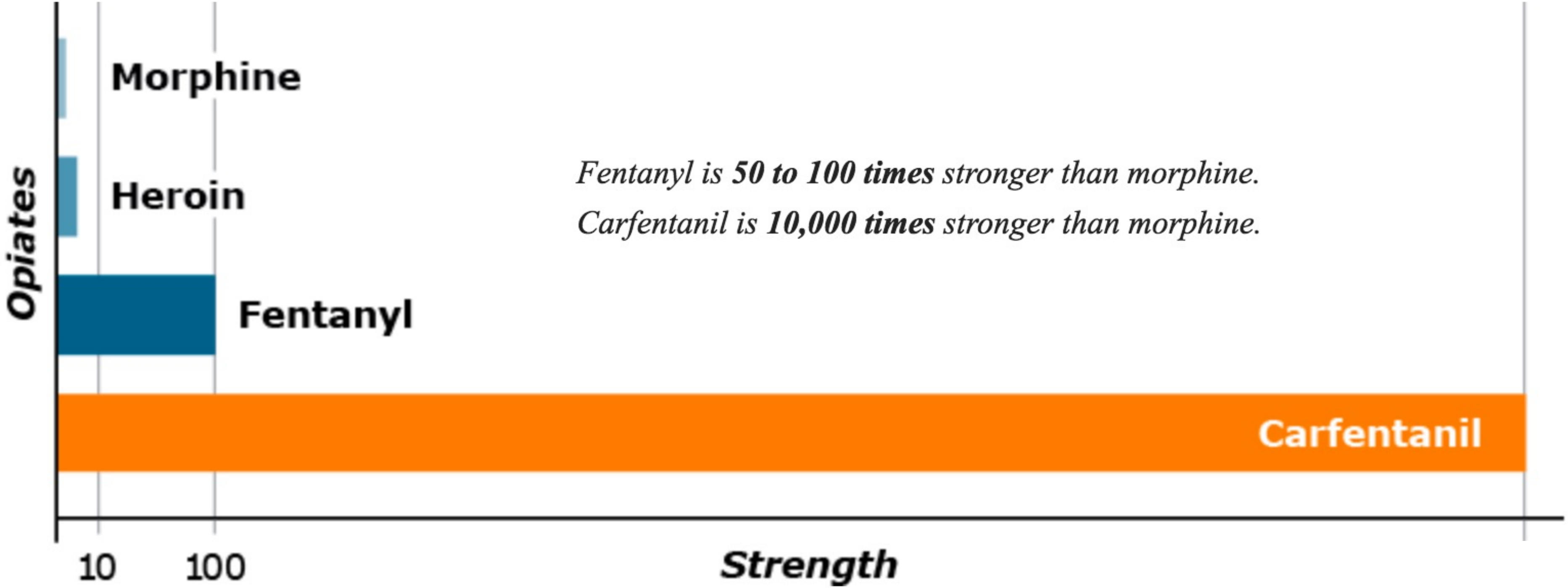


Figure 7. Number of Fentanyl and Related Drug Deaths and Percentage of Unintentional Drug Overdose Deaths, by Year, Ohio, 2013-2017



Relative Strength Compared to Morphine



*Fentanyl is **50 to 100 times** stronger than morphine.*

*Carfentanil is **10,000 times** stronger than morphine.*

- Overdose Deaths in Ohio
    - Ohio drug use patterns are statistically average, but there was a rapid increase in fentanyl related deaths in recent years. The huge spike in Ohio overdose deaths in 2017 is due to fentanyl analogs, especially carfentanil.
    - One problem: death data is often delayed by a year or more. Coroners are sometimes wrong, and the CDC has to correct coroner data.
- Ohio Bureau of Criminal Investigations (BCI) Drug Lab Data
    - Shows large increase in synthetic opioids mixed into the Ohio drug supply.
    - Police data is immediate and can be an “early warning system”
- BCI Test Data is Strongly Correlated with Deaths
    - One additional positive test of carfentanil predicts 0.45 more deaths.
    - One additional positive test of fentanyl/fentanyl analog predicts 0.2 more deaths.

Discussion of data that we had:

- Number of overdose deaths per (month, county) pair.
- BCI data set with one row per drug seizure by police, with date, county, list of drugs taken, and weight.

Data wrangling:

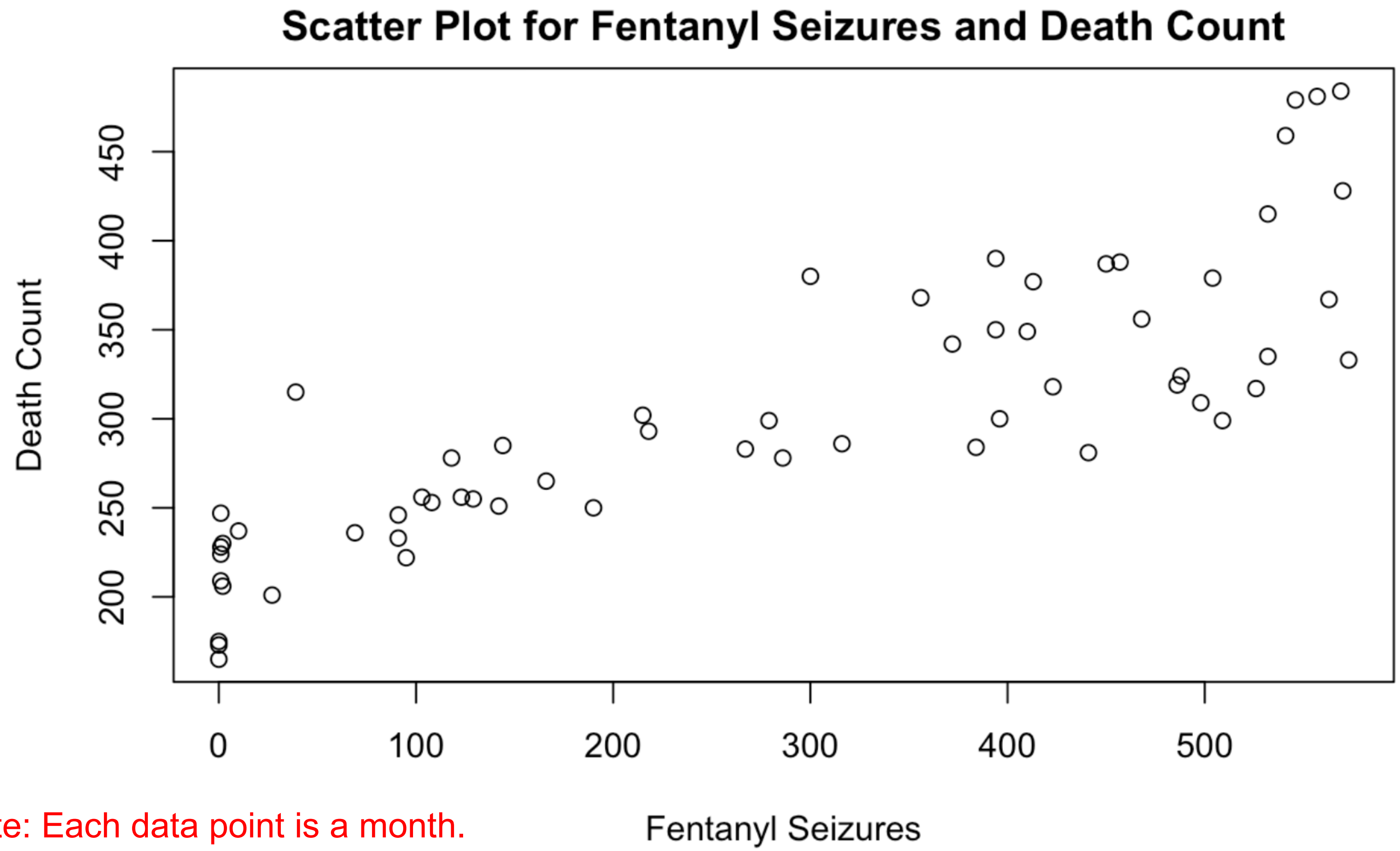
- Aggregate the BCI data to the monthly level.
- In the BCI data, use text-matching algorithms to identify the seizures that contained fentanyl and other fentanyl variants.
- Merge the data sets together so we can regress deaths on seizures.

Two analyses:

1. Aggregate all counties together, to study Ohio as a whole, one row per month.
2. Do a county-by-county analysis, with a general linear mixed model.

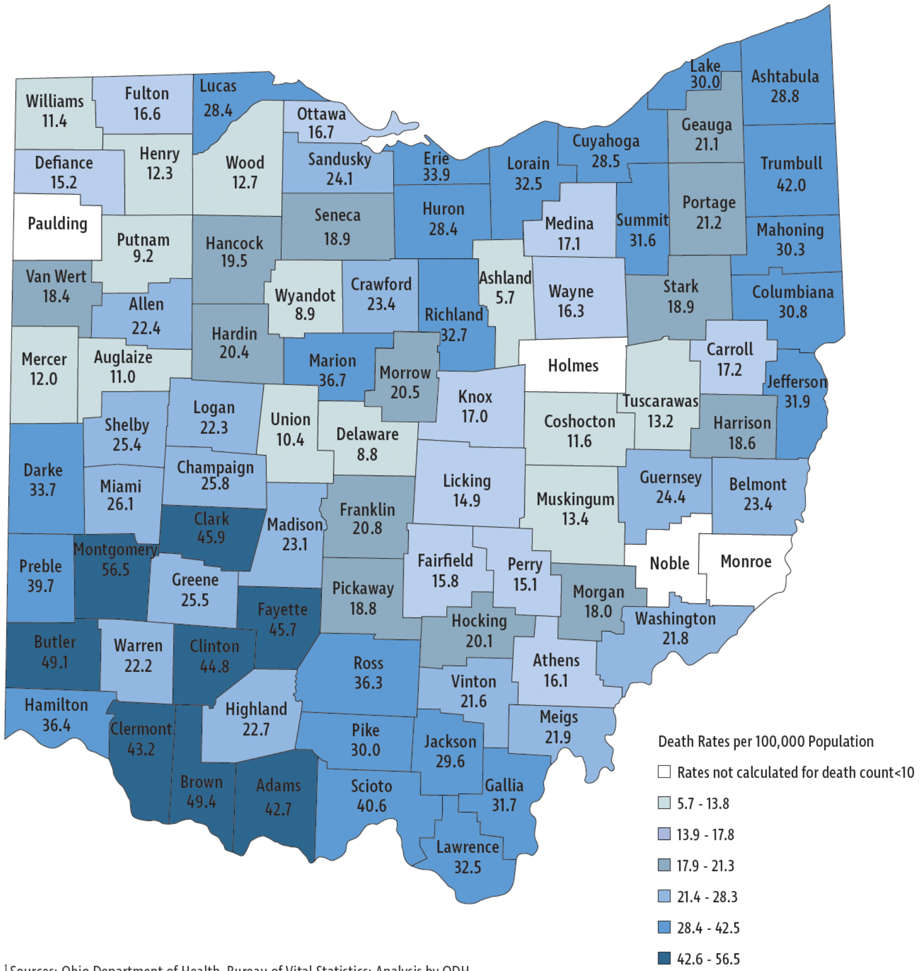
Analyzing BCI dataset alongside Ohio Dept of Health (ODH) Mortality data. Plan:

1. Exploratory: Fentanyl seizures and deaths track together over time.
2. Quantify the amount of variability in deaths that it explained by drug seizures and by fentanyl seizures. Seizures is a powerful predictor for deaths.
3. Use time-series analysis to quantify lag between seizures and deaths.
4. Low weight drug seizures are more likely to contain fentanyl than higher weight seizures. The weight variable adds predictive power.
5. Fit an ARIMA model for deaths and seizures, then a general linear mixed model.
6. Compare the efficacy of different types of law enforcement, including national law enforcement (FBI/DEA), drug task forces, and local police and sheriff’s departments



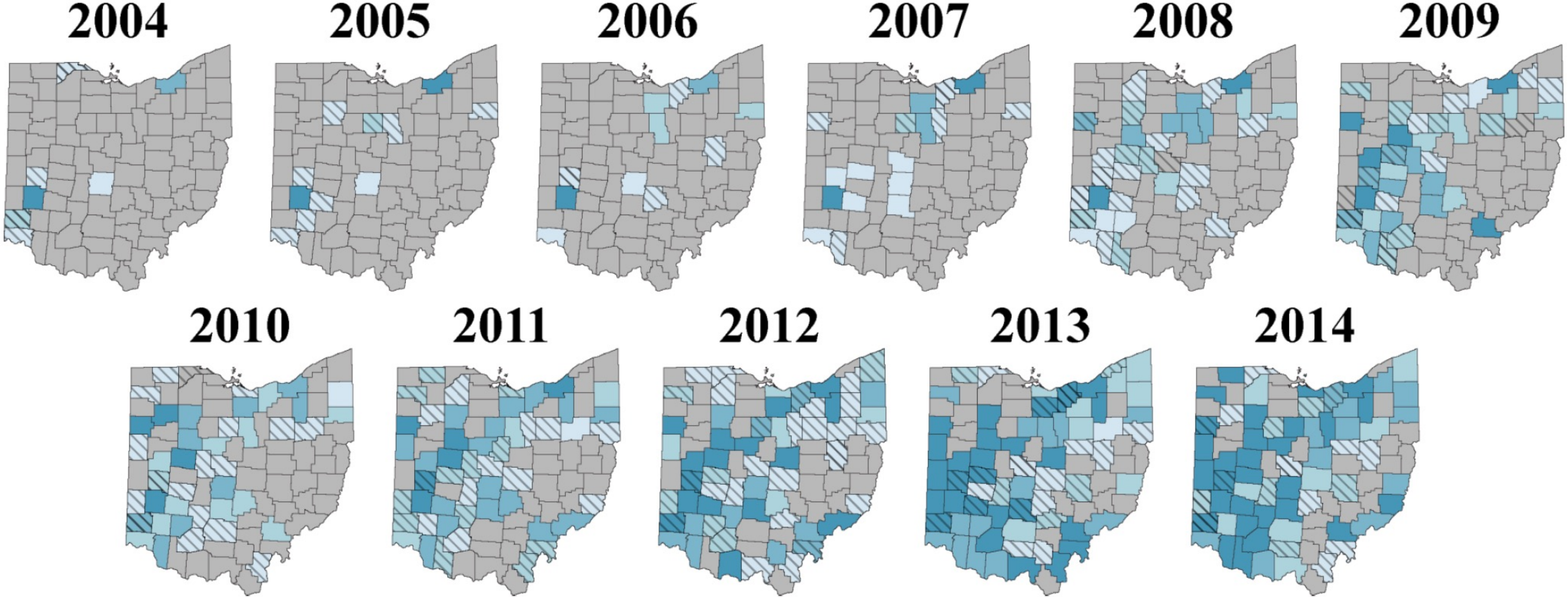
Note: Each data point is a month.

Figure 13. Average Age-Adjusted Unintentional Drug Overdose Death Rate Per 100,000 Population, by County, 2012-2017 [1,2]



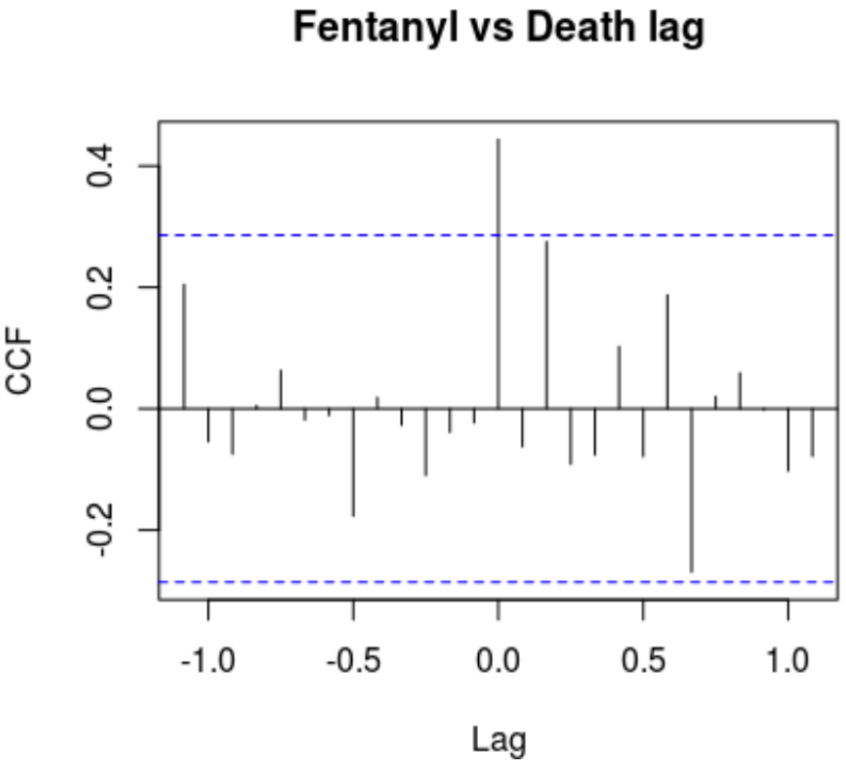
[1] Sources: Ohio Department of Health, Bureau of Vital Statistics; Analysis by ODH Injury Prevention Program; U.S. Census Bureau (Vintage 2016 population estimates).

Figure 21: Heroin-Related Crime in Ohio, 2004-2014



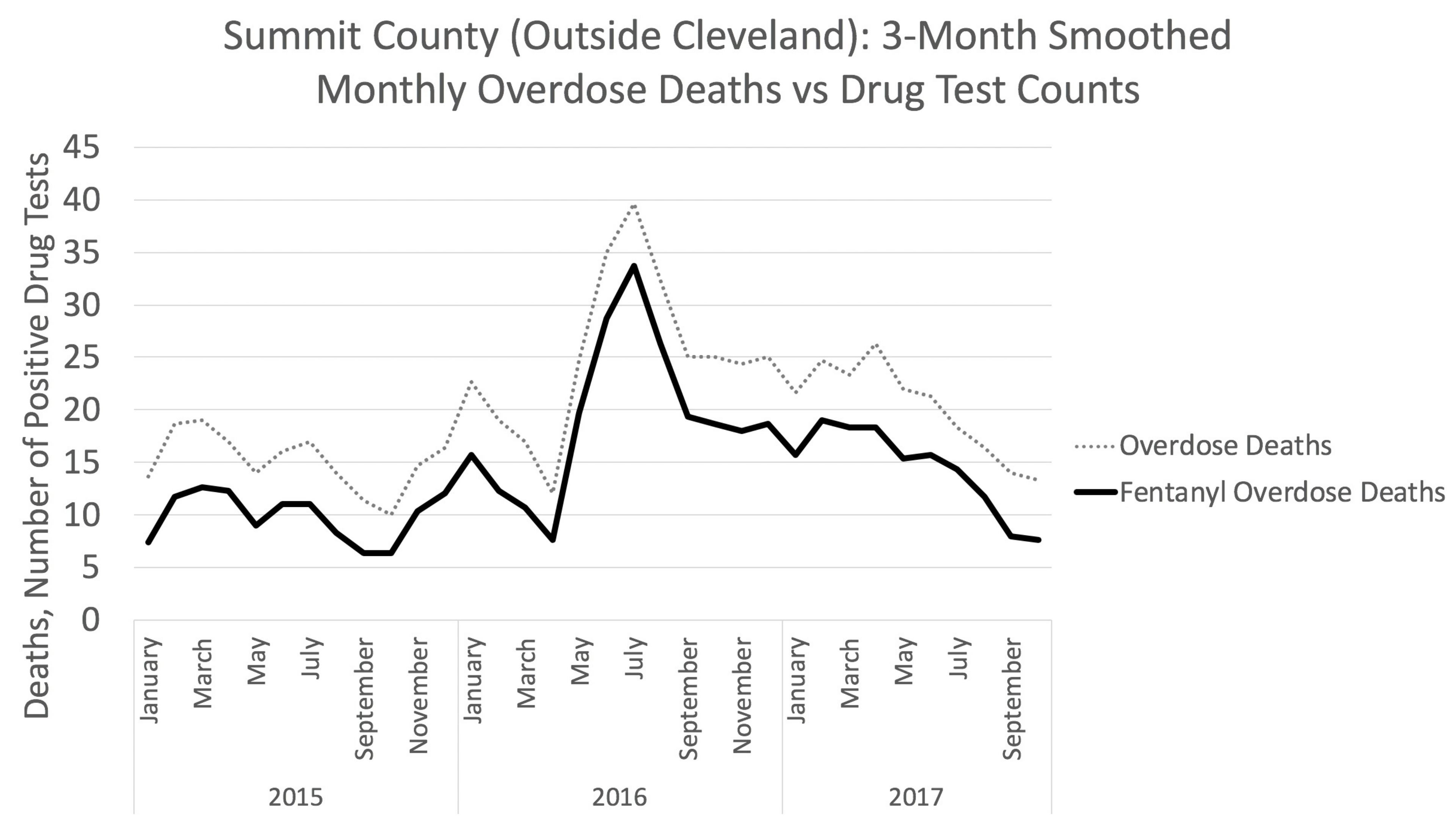
Seizure data tracks with death data.

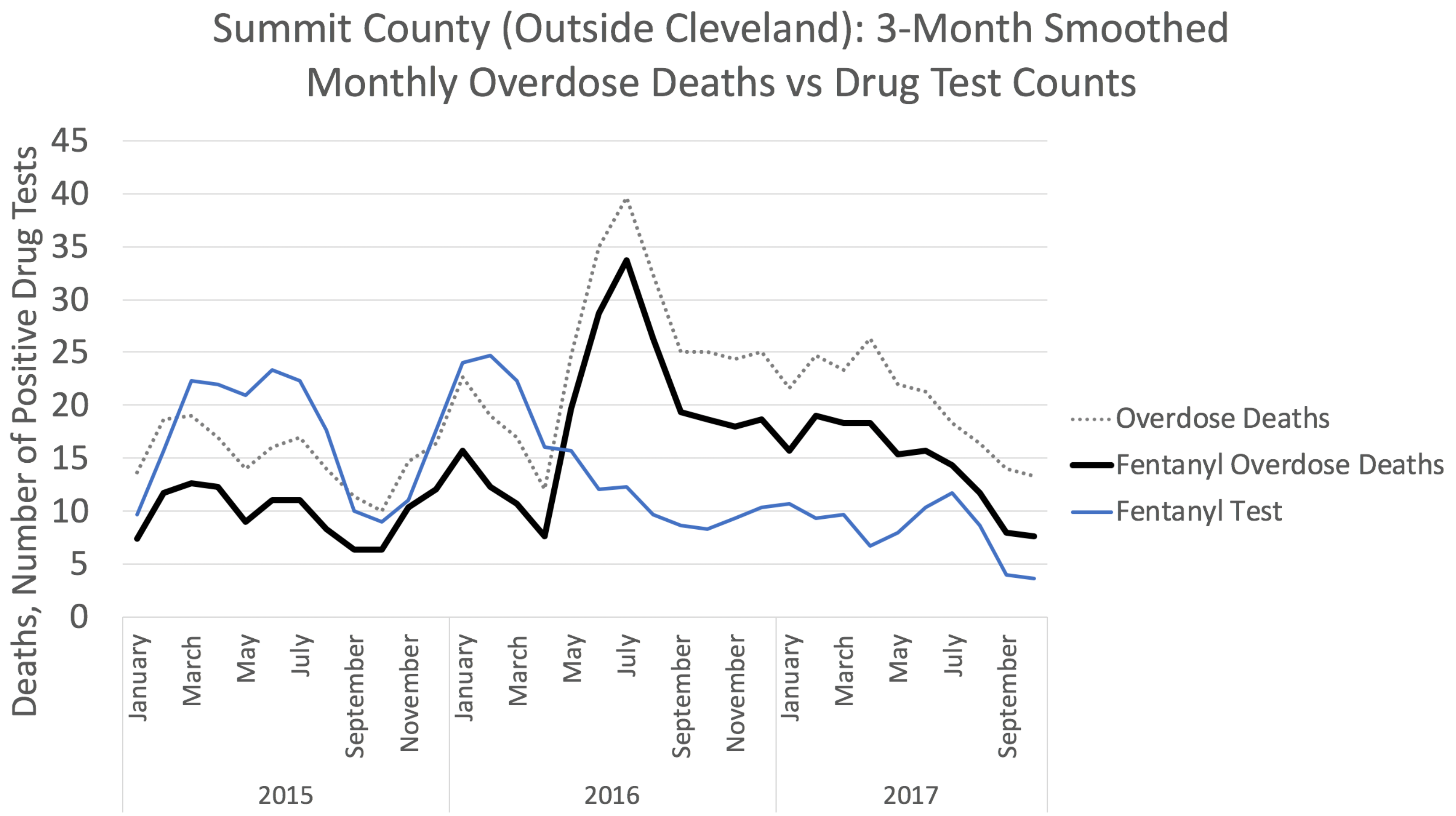
A natural question: are police seizures lagging behind deaths?
Cross-correlation function (CCF) shows highest correlation is at lag 0.



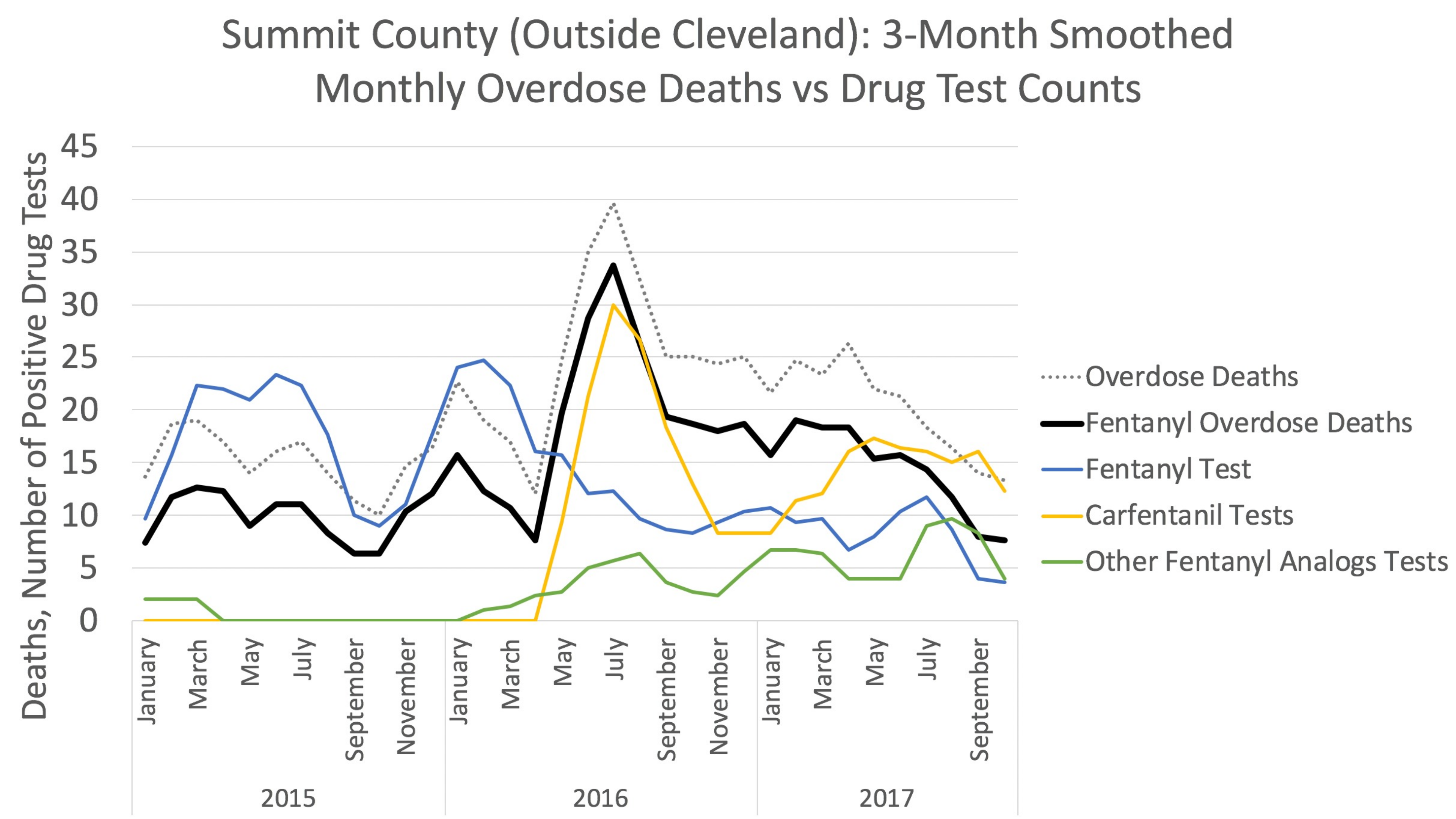
For every integer, h, the CCF at h is the correlation between:
x_t = fentanyl seizures at time t, and the shifted time series
y_{t-h} = deaths h months ago,
after both are pre-whitened.

Here, the only statistically significant cross-correlation is h = 0. There is no lag between seizures and deaths.

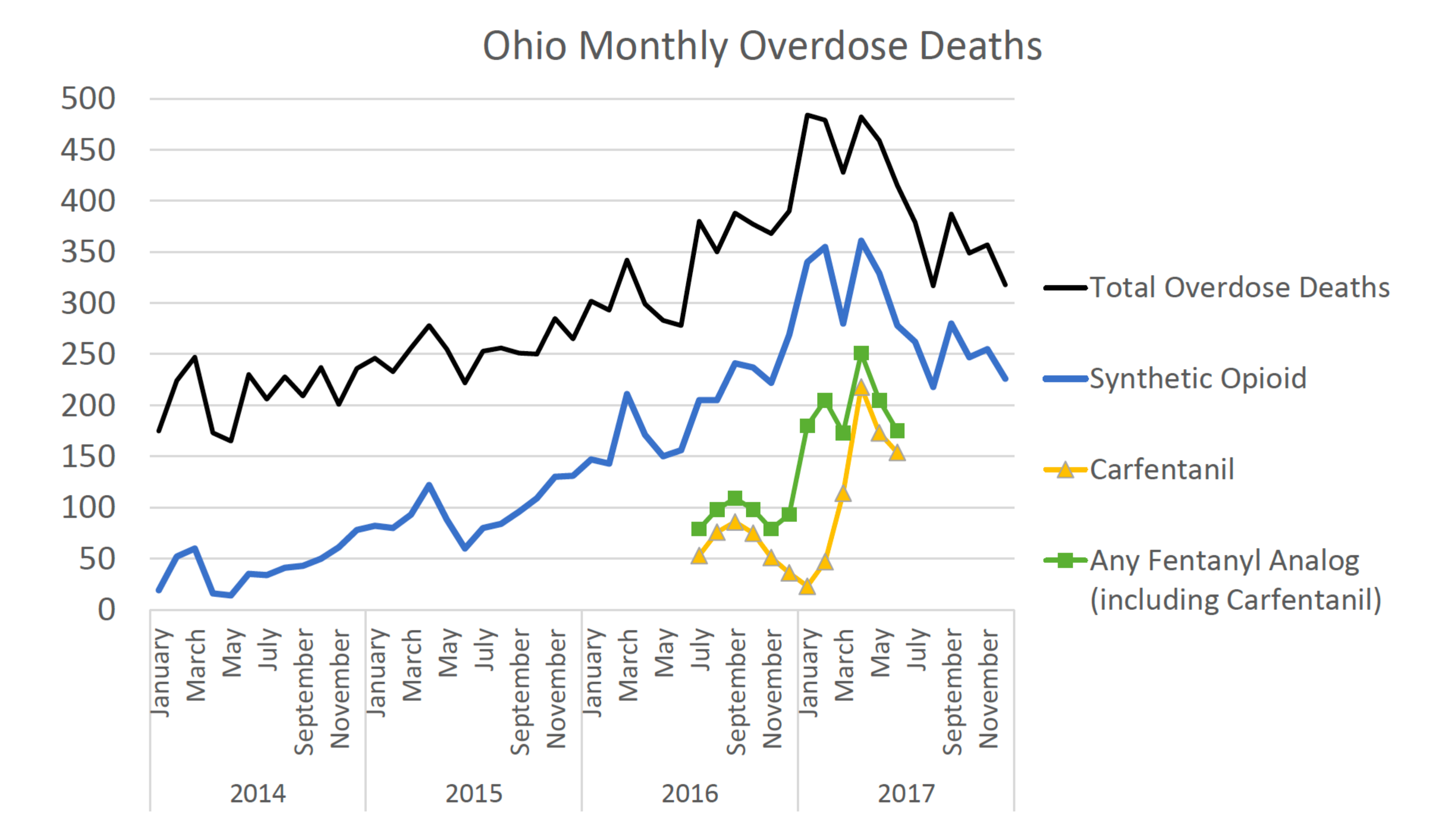

Summit County (Outside Cleveland): 3-Month Smoothed Monthly Overdose Deaths vs Drug Test Counts
Deaths, Number of Positive Drug Tests
45
40
35
30
25
20
15
10
5
0
January
March
May
July
September
November
January
March
May
July
September
November
January
March
May
July
September
2015
2016
2017
Overdose Deaths
Fentanyl Overdose Deaths



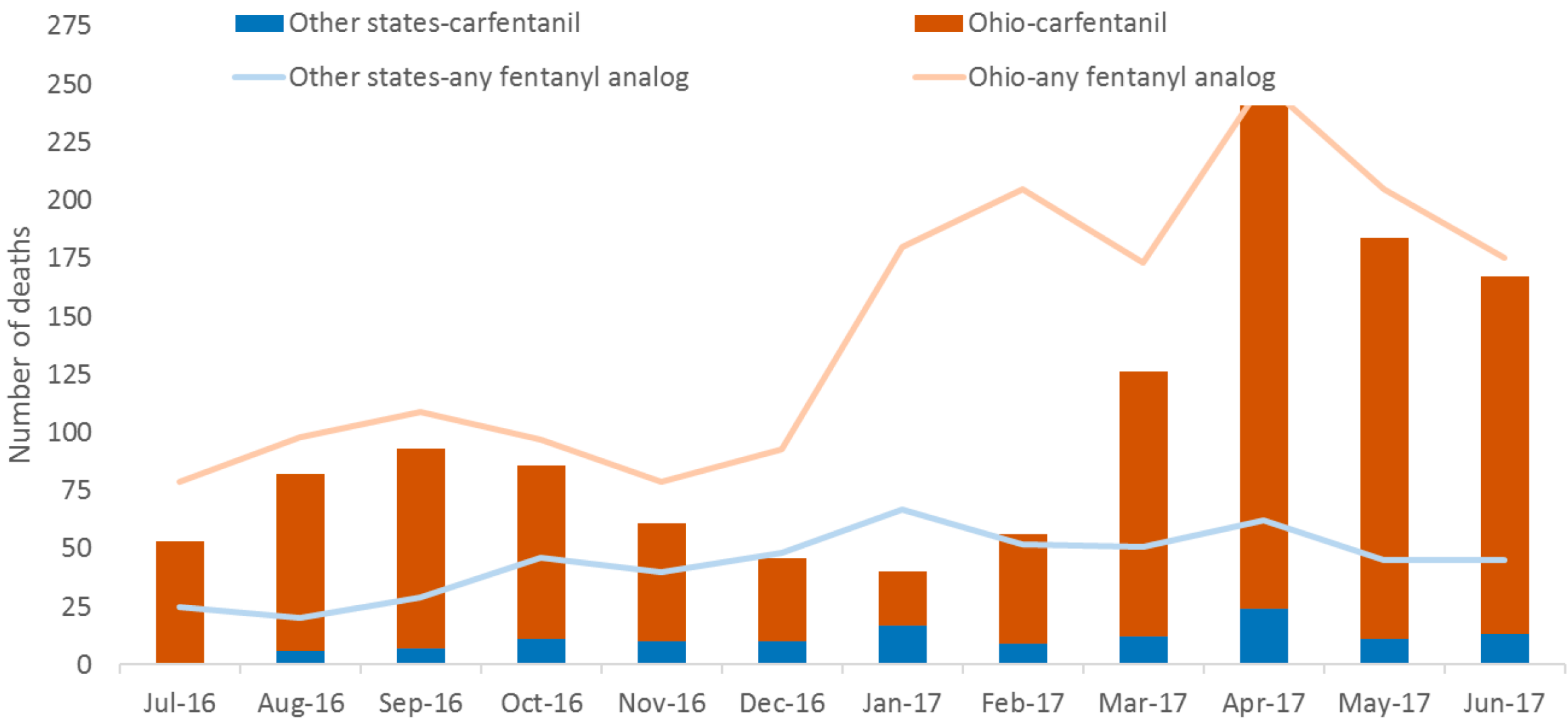
Summit County (Outside Cleveland): 3-Month Smoothed Monthly Overdose Deaths vs Drug Test Counts
Deaths, Number of Positive Drug Tests
45
40
35
30
25
20
15
10
5
0
January
March
May
July
September
November
2015
2016
2017
Overdose Deaths
Fentanyl Overdose Deaths
Fentanyl Test



Summit County (Outside Cleveland): 3-Month Smoothed Monthly Overdose Deaths vs Drug Test Counts
Deaths, Number of Positive Drug Tests
45
40
35
30
25
20
15
10
5
0
January
March
May
July
September
November
2015
2016
2017
Overdose Deaths
Fentanyl Overdose Deaths
Fentanyl Test
Carfentanil Tests
Other Fentanyl Analogs Tests



Ohio Monthly Overdose Deaths
500
450
400
350
300
250
200
150
100
50
0
January
March
May
July
September
November
2014
2015
2016
2017
Total Overdose Deaths
Synthetic Opioid
Carfentanil
Any Fentanyl Analog (including Carfentanil)



Other states-carfentanil
Ohio-carfentanil
Other states-any fentanyl analog
Ohio-any fentanyl analog
Number of deaths
0
25
50
75
100
125
150
175
200
225
250
275
Jul-16
Aug-16
Sep-16
Oct-16
Nov-16
Dec-16
Jan-17
Feb-17
Mar-17
Apr-17
May-17
Jun-17

Analyzing BCI dataset alongside Ohio Dept of Health (ODH) Mortality data. Plan:

1. Exploratory: Fentanyl seizures and deaths track together over time.
2. Quantify the amount of variability in deaths that it explained by drug seizures and by fentanyl seizures. Seizures is a powerful predictor for deaths.
3. Use time-series analysis to quantify lag between seizures and deaths.
4. Low weight drug seizures are more likely to contain fentanyl than higher weight seizures. The weight variable adds predictive power.
5. Fit an ARIMA model for deaths and seizures, then a general linear mixed model.
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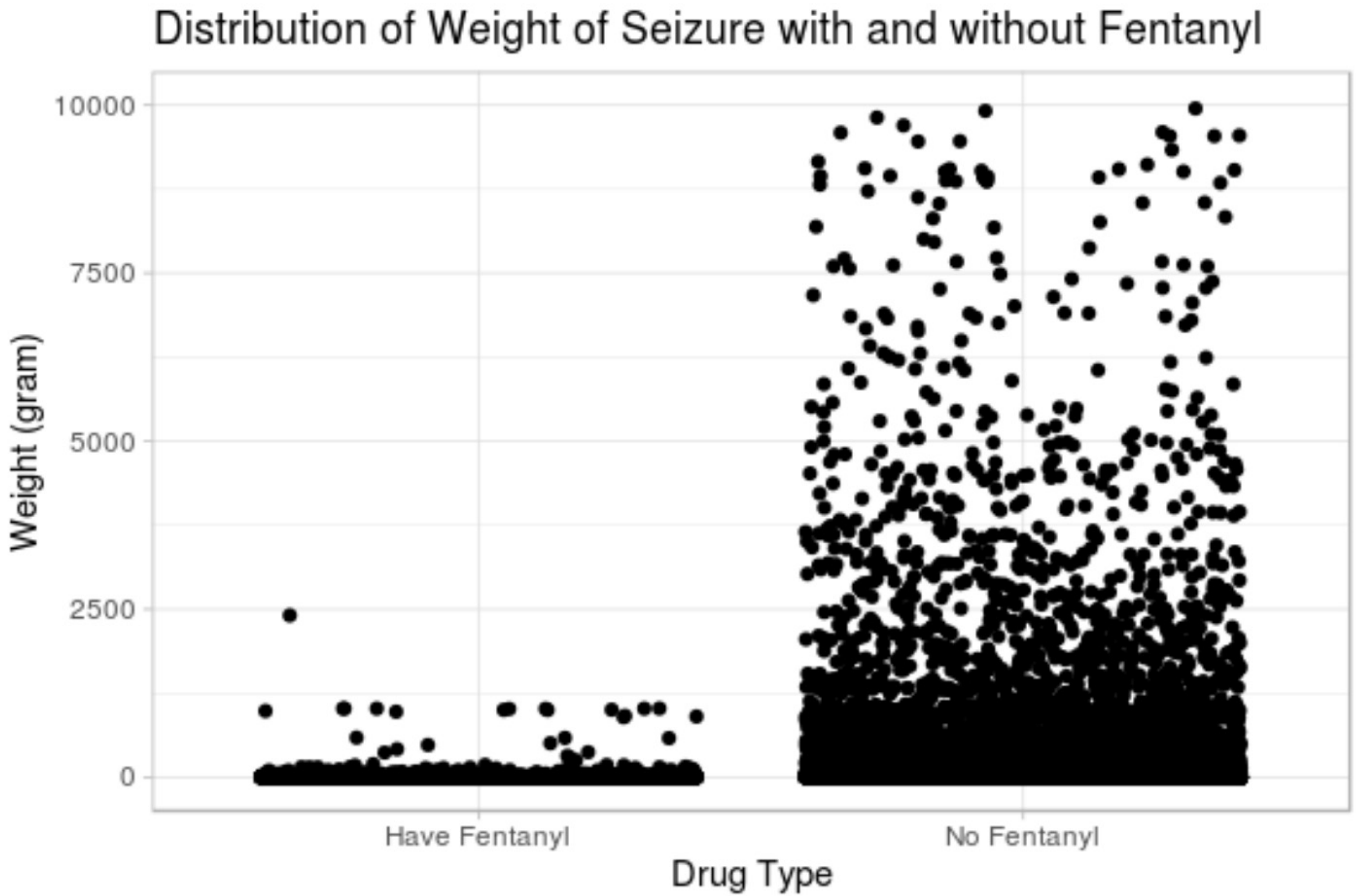

Distribution of Weight of Seizure with and without Fentanyl
10000
7500
5000
2500
0
Weight (gram)
Have Fentanyl
No Fentanyl
Drug Type

Size of seizure, net weight	All seizures	Fentanyl Found	% seizures with fentanyl	R^2
Above 100 grams	4512	57	1.26%	0.2213
50-100 grams	1682	63	3.74%	0.2164
20-50 grams	3715	164	4.41%	0.2210
10-20 grams	3706	242	6.53%	0.2810
5-10 grams	4883	362	7.41%	0.2541
2-5 grams	8778	763	8.69%	0.2606
1-2 grams	8154	852	10.45%	0.2670
0.5 -1 gram	13080	1531	11.70%	0.3436
0.24-0.5 gram	22430	2337	10.42%	0.4136
0.1-0.24 gram	24115	2869	11.90%	0.3963
< 0.1 gram	23892	5143	21.53%	0.4776

- Drug seizure composition and weight have strong predictive value for drug overdose deaths
- Low weight seizures are more likely to contain fentanyl, have a larger R^2 for predicting drug overdose deaths.
- Recall our scatterplot relating deaths and seizures. But, linear regression inference assumes data points are independent. Our data points represent months. Number of deaths in January is probably related to number of deaths in February! So, not independent!
- The solution: time series analysis.
- We build a statistically significant model with $R^2 = .7799$.

Time Series Analysis

How much do deaths at time t depend on deaths in previous months?

Goal: fit an ARIMA(p,d,q) model ("autoregressive integrated moving average")

AR(p) is Deaths_t depends on Deaths_{t-1}, Deaths_{t-2}, …, Deaths_{t-p}

I(d) if you have to do "differencing" d-times to make the time series stationary.

MA(q) if Deaths_t depends on ε_{t-1}, ε_{t-2}, …, ε_{t-q}

Find optimal (p,d,q) using

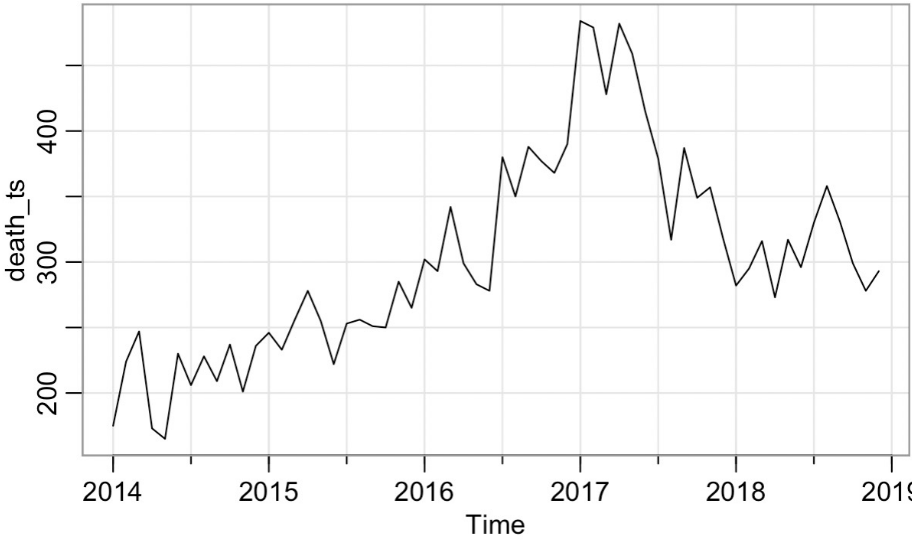
1. Autocorrelation function (ACF) = $\text{corr}(\text{Deaths}_t, \text{Deaths}_{t-x})$ for all x.
2. Partial autocorrelation function (PACF) = autocorrelation that remains after removing "carried over" autocorrelation; useful for error terms ε_{t-x}

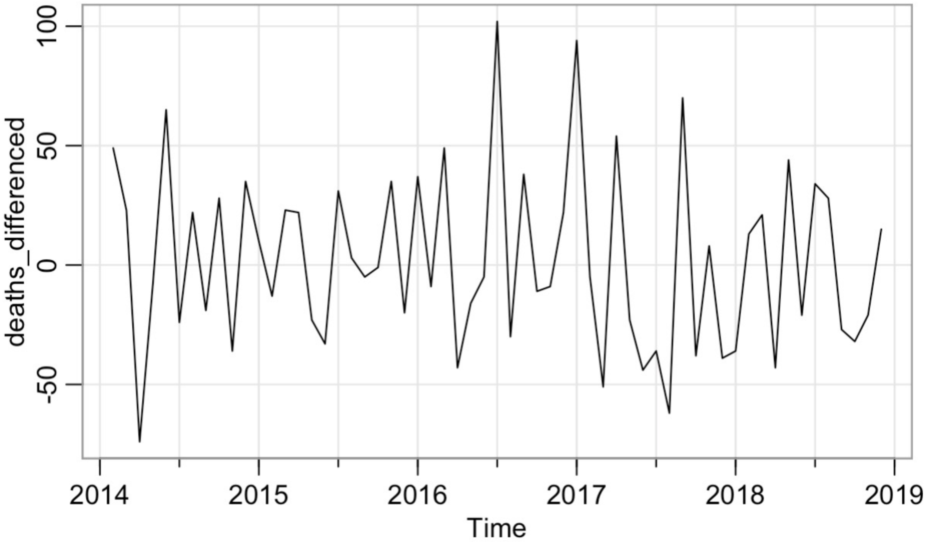
Next, use Seizures_t to predict Deaths_t

Recall: no lag between police seizures and overdose deaths.

Death time series is not stationarity, so difference it

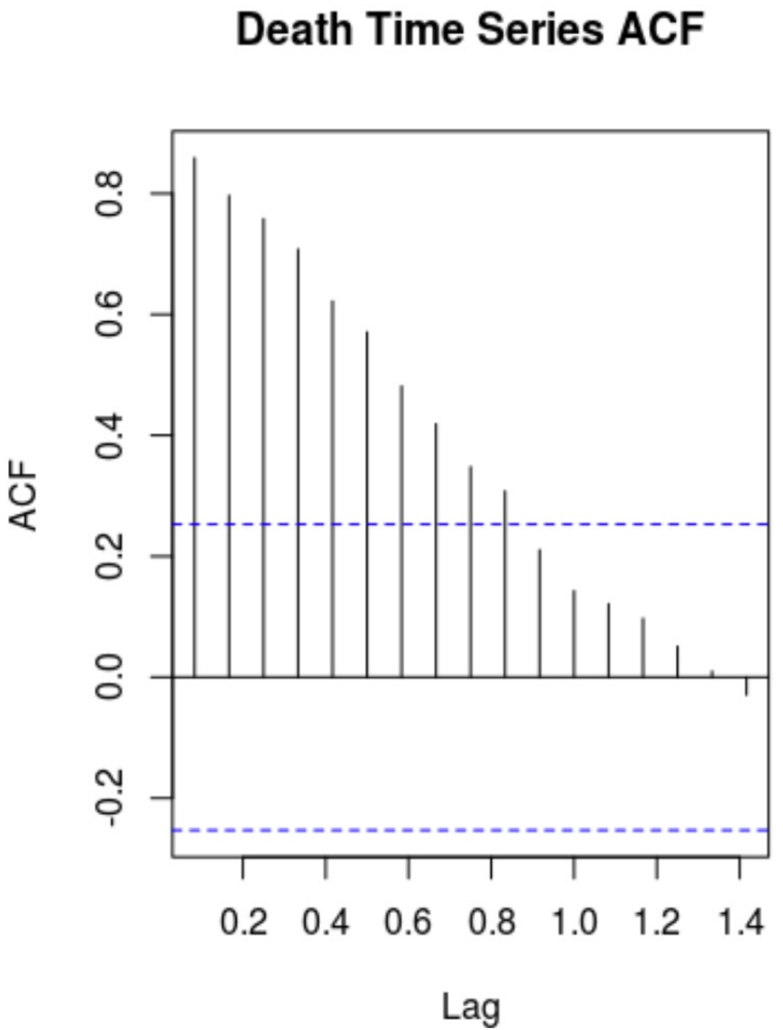
Δ Deaths$_t$ = Deaths$_t$ - Deaths$_{t-1}$

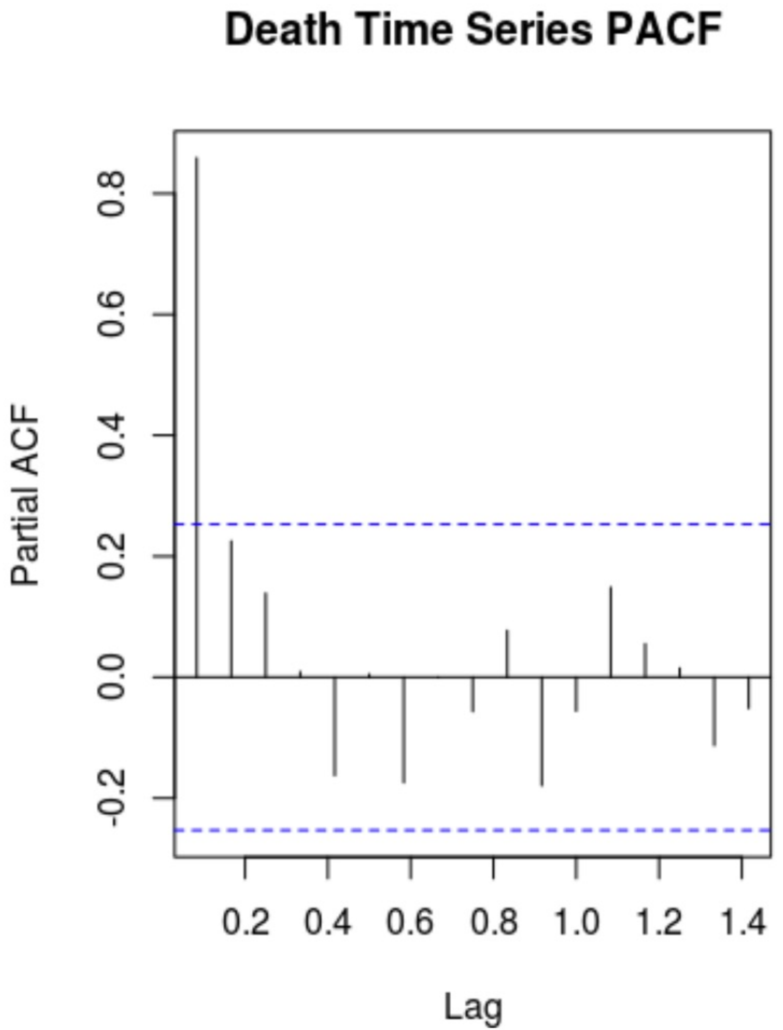




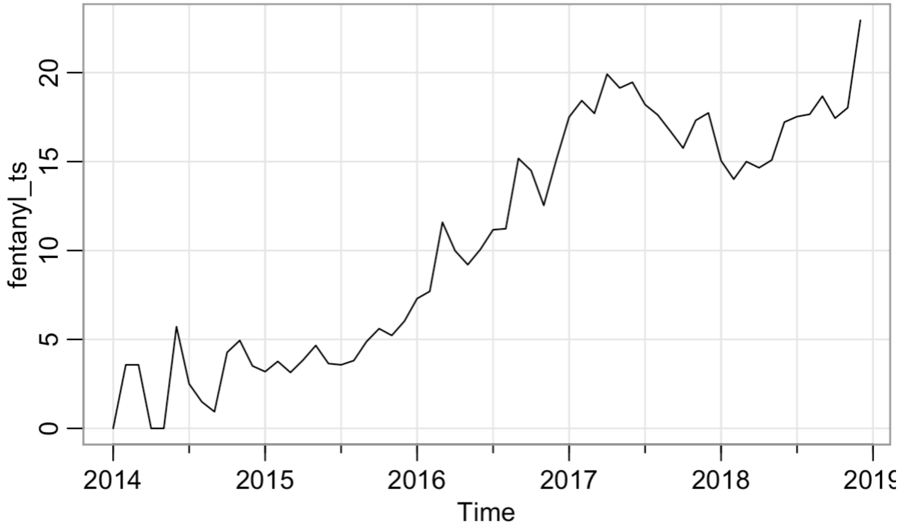
Δ Deaths$_t$ is stationary and passes the Augmented Dickey-Fuller test.

Next question: does Δ Deaths$_t$ depend on its own history? If so, how much?
We want random and independent residuals at the end of the day.

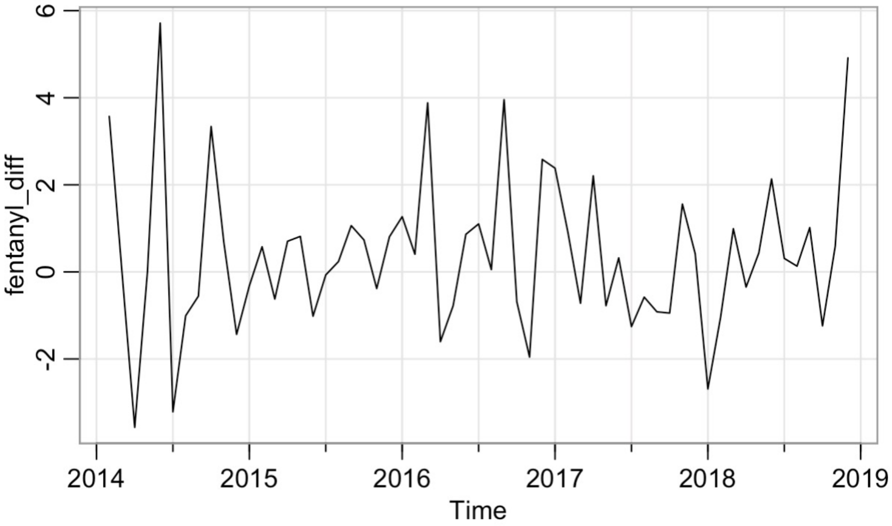

Death Time Series ACF
ACF
Lag
0.8
0.6
0.4
0.2
0.0
-0.2
0.2
0.4
0.6
0.8
1.0
1.2
1.4


Death Time Series PACF
Partial ACF
Lag
0.8
0.6
0.4
0.2
0.0
-0.2
0.2
0.4
0.6
0.8
1.0
1.2
1.4

Fentanyl time series is not stationarity, so difference it



$\Delta\ Fent_t = Fent_t - Fent_{t-1}$



$\Delta\ Fent_t$ is stationary and passes the Augmented Dickey-Fuller test.

In our final model, we do not need any lags of $\Delta\ Fent_t$; impact of the past is in the death ARIMA(1,1,0) model. No seasonal lags either.

Introducing more complex models (ARIMA and GLMM)

- The best ARIMA model for drug overdose deaths alone is an ARIMA(1,1,0) model.
- Best time series model ($R^2 = .7799$) for Deaths based on BCI:

$$\text{Deaths}_t \sim \text{ARIMA}(1,1,0) + \beta_1 {*}\text{Seizures}_t + \beta_2 {*}\text{Weight}_t^{0to0.1} + \beta_3 {*}\text{Weight}_t^{0.1to0.24} + \varepsilon$$

- Here $\text{Weight}_t^{0to0.1}$ is the number of seizures in month t of weight 0 – 0.1 grams (smallest weight), and $\text{Weight}_t^{0.1to0.24}$ similar.
- Note: this model treats all of Ohio as one. But we also have county-level data on seizures, deaths, unemployment, etc.
- Linear mixed model includes both fixed effects and random effects. Powerful application of linear algebra to statistics!
- Fixed effects are constant across individuals, and random effects vary.

Best General Linear Mixed Model:

$$Deaths_{it} = \beta_{\mathbf{it}} * \mathbf{Tests_{it}} + \delta_{\mathbf{it}} * \mathbf{X_{it}} + \alpha_i + \gamma_t + \alpha_i * T + e_{it} \quad (1)$$

where $Deaths_{it}$ are the number of overdose deaths in county i and month t. $Tests_{it}$ is a vector of positive drug tests from the BCI crime labs. X_{it} is a vector of time-varying county-level controls: annual poverty rates and median income,[16] quarterly amounts of distributed oxycodone,[17] and monthly unemployment rates.[18] α_i and γ_t are county and month fixed effects respectively and $\alpha_i * T$ are county-specific linear time trends. e_{it} is the error term

Month fixed effect controls for time trends in deaths that are the same across Ohio.
County fixed effect controls for county differences that do not vary over time. The county-year linear time trends control for any county-specific linear time trends in deaths.
Next: determine significance of random effects (seizures and X), compute R^2.

Table 2: OLS: Relationship Between Monthly BCI Crime Lab Tests and Monthly Overdose Deaths, 2015-2017

	(1)	(2)	(3)	(4)	(5)	(6)
Fentanyl	0.4026**	0.1829*	0.1645*	0.1470*	0.1484*	0.1510*
	(0.1612)	(0.0929)	(0.0832)	(0.0818)	(0.0810)	(0.0840)
Carfentanil	0.5014**	0.3301**	0.3214**	0.3115**	0.3090**	0.2683**
	(0.1938)	(0.1359)	(0.1413)	(0.1400)	(0.1386)	(0.1208)
Other Fentanyl Analogs	0.2838	0.2551**	0.2526**	0.2516**	0.2508**	0.2586**
	(0.2195)	(0.1239)	(0.1194)	(0.1209)	(0.1188)	(0.1126)
Heroin	0.1905**	-0.1062*	-0.0970**	-0.0866**	-0.0870**	-0.0735**
	(0.0731)	(0.0583)	(0.0480)	(0.0434)	(0.0429)	(0.0349)
Cocaine			-0.0031	0.0019	0.0037	0.0389**
			(0.0256)	(0.0236)	(0.0238)	(0.0164)
Cannabis			-0.0459**	-0.0312	-0.0314	0.0044
			(0.0216)	(0.0203)	(0.0202)	(0.0225)
Synthetic Stimulants			0.0717	0.0883	0.0914	0.1616**
			(0.0619)	(0.0638)	(0.0623)	(0.0682)
Oxycodone Distributed (gms)				-0.0004***	-0.0004***	-0.0000
				(0.0001)	(0.0001)	(0.0002)
Unemployment Rate(%*100)					-0.0436	-0.1262
					(0.1350)	(0.0951)
Poverty Rate(%*100)					-0.0725	-0.1596
					(0.0983)	(0.1027)
Median Income (1000s)					-0.0918*	-0.0822*
					(0.0511)	(0.0427)
Other Drug Tests	no	no	yes	yes	yes	yes
County and Month FE	no	yes	yes	yes	yes	yes
County-Month Linear Trends	no	no	no	no	no	yes
R-Squared	0.35	0.86	0.86	0.86	0.86	0.88
Observations	3132	3132	3132	3132	3132	3132

(* p<0.1, ** p<0.05, *** p<0.01)

Notes: Robust standard errors, clustered at county level (87 counties), are reported in parentheses. Other drug tests control for the number of monthly positive tests of benzodiazepenes, synthetic cannabis, methamphetamine/amphetamines, MDMA, psychedelics, and other designer drugs (each as a separate variable). None of these have a statistically significant relationship with overdose deaths. Each observation is at the county-month level. Oxycodone distribution is only available quarterly and the poverty rate and median income are only available annually.

GLMM Results:

Seizures are statistically significant (except cannabis).

With covariates (column 6) we achieve an R^2 of 0.88.

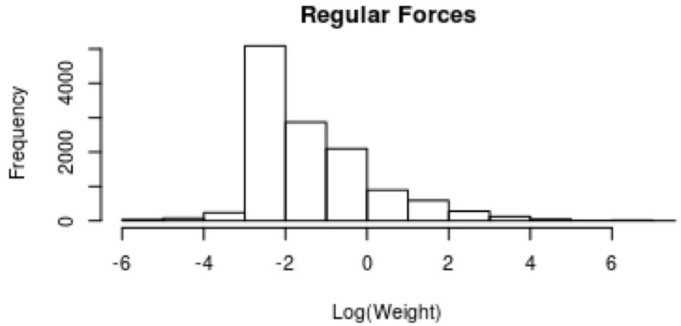
20 more seizures of fentanyl predict for 3 more deaths.

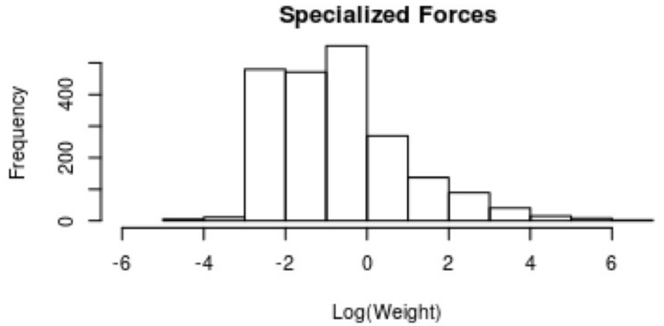
20 more seizures of carfentanil (or other analog) predicts for 5 more deaths.

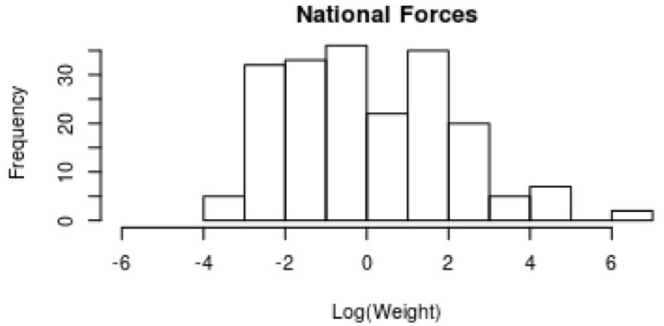
How do different types of law enforcement do in terms of seizing drugs? Seizing fentanyl?

	All drug seizures	Seizures involved fentanyl
National level forces	1426	197
Specialized forces	18496	2082
Regular forces	99075	12372
Unrelated forces	2375	181

Note: we spend a lot of money on specialized drug task forces. Are they saving lives?





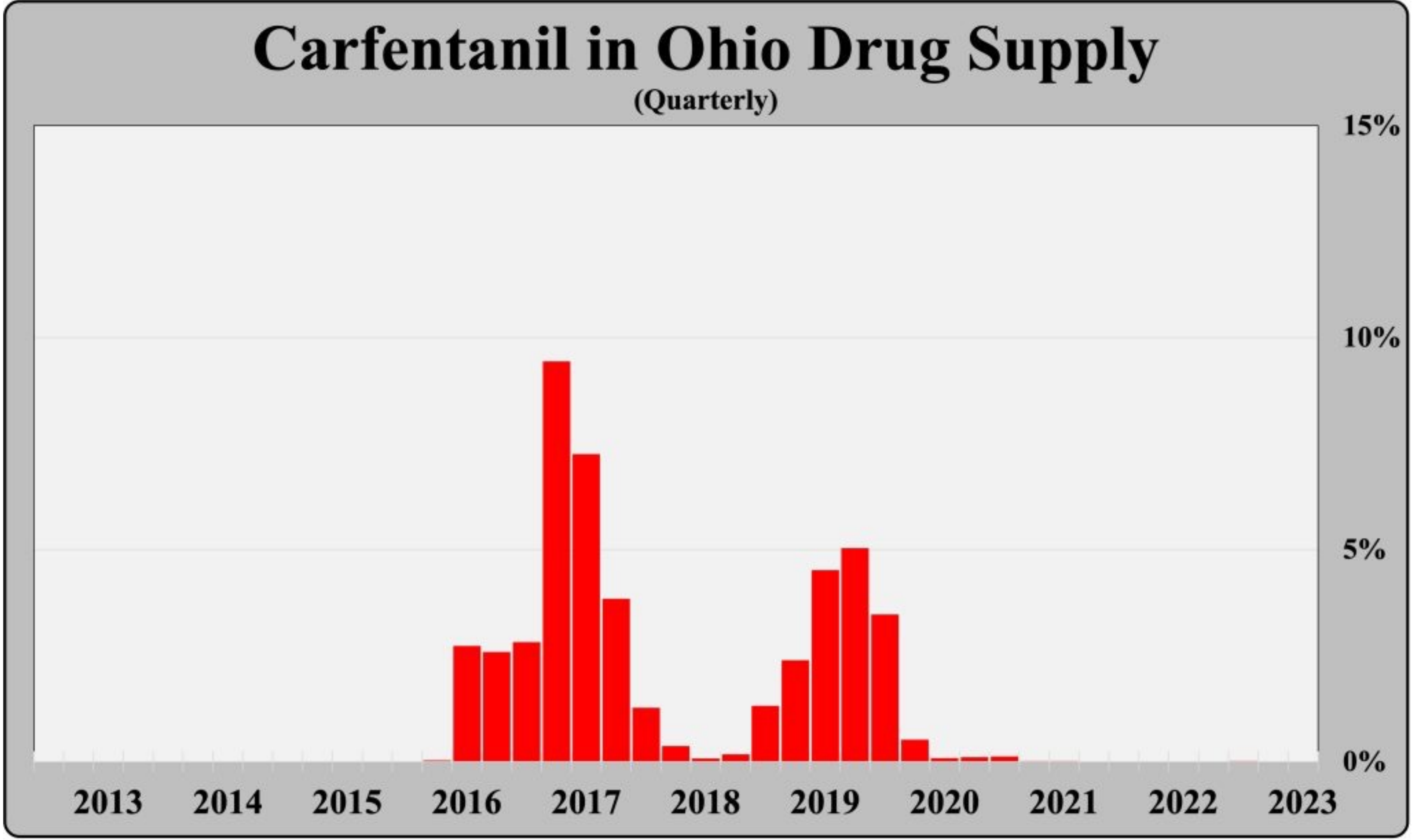


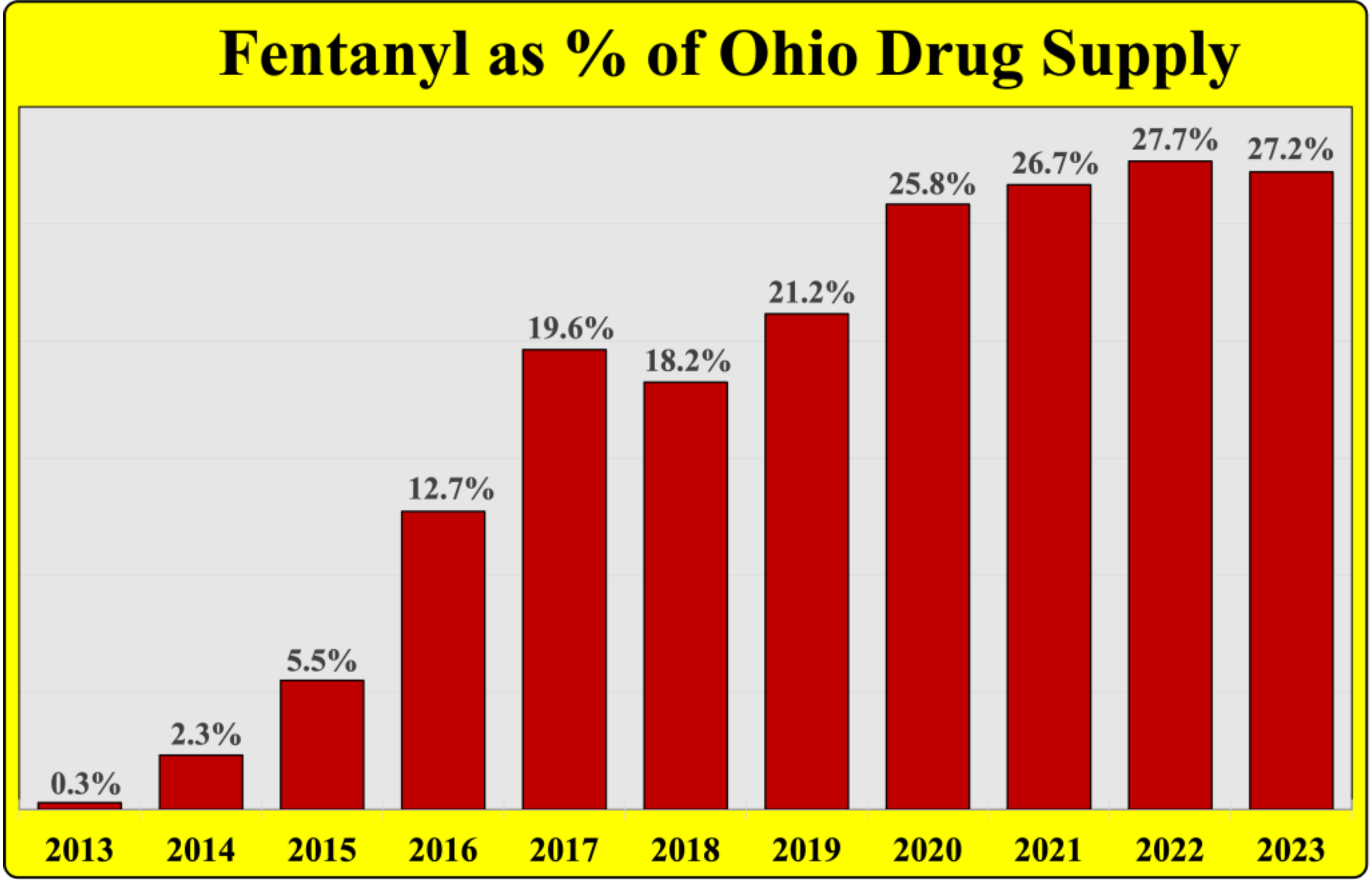
Regular forces include local police, sheriffs.
Specialized forces include drug task forces.
National forces include DEA and FBI.

Notice the y-axis labels!
Regular forces make most seizures (there are more of them).

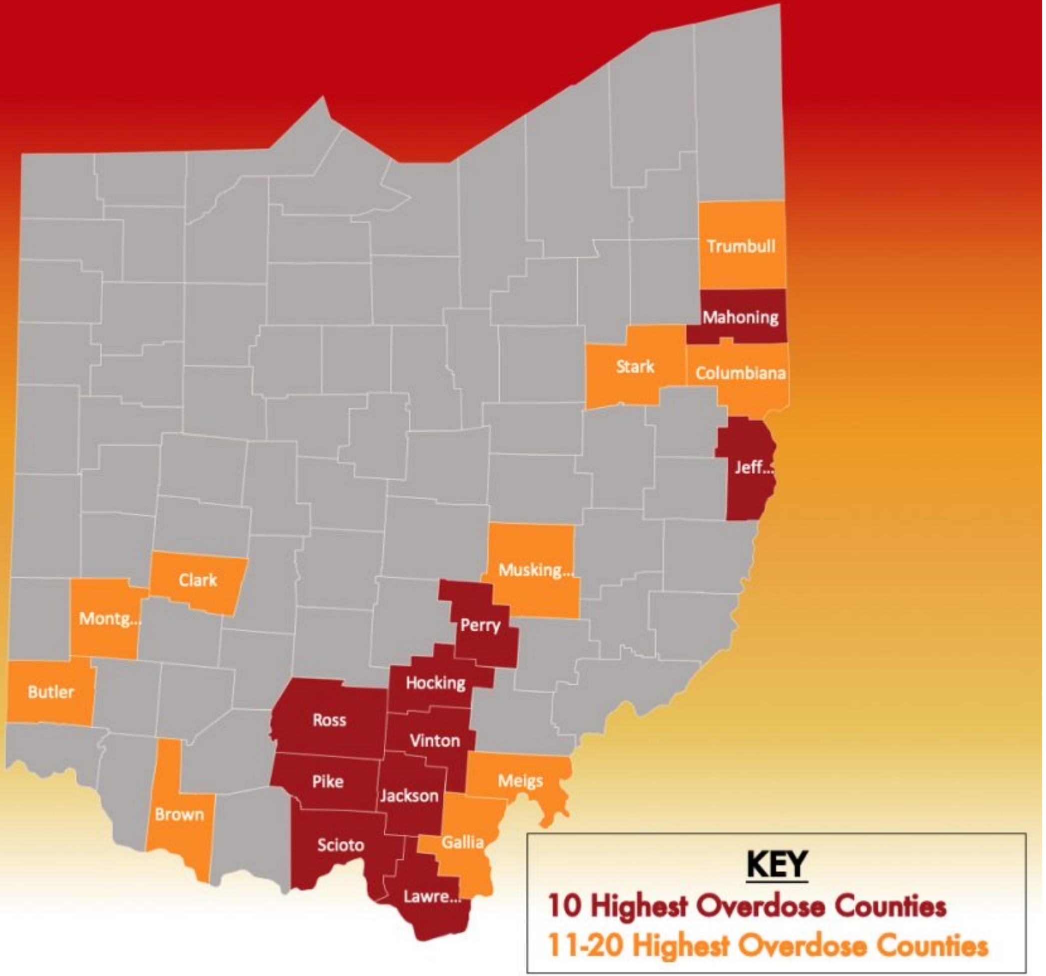
Regular forces seize lots of low weight.
Specialized forces seize a mixture.
National forces seize mostly mid-weight and high-weight.

All are important, but it's essential to remember the Law of Prohibition: when you crack down, people turn to more potent drugs.


Carfentanil in Ohio Drug Supply
(Quarterly)
15%
10%
5%
0%
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023


Fentanyl as % of Ohio Drug Supply
0.3%
2.3%
5.5%
12.7%
19.6%
18.2%
21.2%
25.8%
26.7%
27.7%
27.2%
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023

Highest Overdose Death Rates 2021



Since 2019, deaths due to carfentanil are down, fentanyl-contaminated meth overdoses are up.

Normal drug-use pattern but more contaminated drug supply in Ohio.

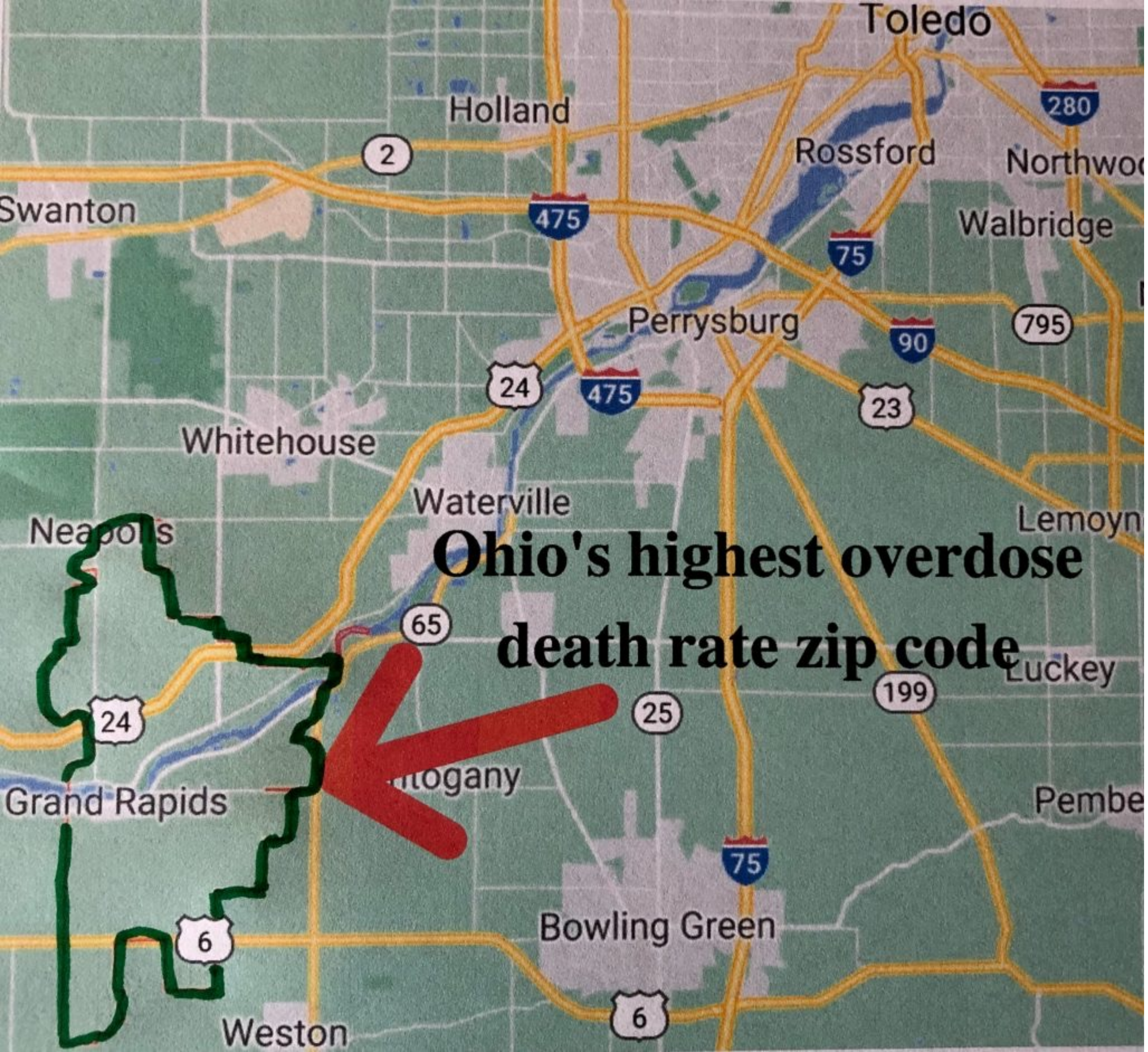
The crisis has shifted from the southwest to the south and east.

Now black people make up 22% of overdose deaths but 14% of the population.

Ohio Overdose Deaths

Yellow = most deaths that month					Red = most deaths ever				
	2015	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023***
January	246	302	**484**	284	306	336	451	404	*406*
February	233	293	**479**	302	282	342	380	376	*392*
March	256	342	428	319	354	365	**478**	437	*385*
April	278	299	**482**	281	321	391	480	378	*406*
May	255	283	459	325	329	**574**	451	380	*337*
June	222	278	415	302	335	**503**	394	397	*229*
July	253	380	379	336	365	**474**	470	435	*103*
August	256	350	317	367	329	374	**435**	413	*3*
September	251	388	387	334	329	411	**417**	392	
October	250	377	349	310	349	418	420	**448**	
November	285	368	357	287	391	**393**	393	**413**	
December	265	390	318	317	338	**436**	405	**441**	
Total deaths	**3,050**	**4,050**	**4,854**	**3,764**	**4,028**	**5,017**	**5,174**	**4,914**	***N/A***

Source: Harm Reduction Ohio analysis of Ohio Department of Health mortality data. Data as of 8/30/23.
* 2023 Data is preliminary and can't be compared to be previous years.



In the spring of 2021, we were able to get data at the level of zip codes instead of county.

Ohio has about 1,300 zip codes.

Data in raw numbers skews attention towards population centers. Data in terms of proportions is more susceptible to outliers.

This is from Jan 2018 - Dec 2020.
Zip code 43522 was worst.
894 per 100,000 died, i.e., 31 people out of 3,466 population.

Narcan can help!

Harm Reduction talking points

- Naloxone – convincing people to carry and use it
- Fentanyl test strips – determine if drugs have fentanyl
- Good Samaritan laws
- Needle exchanges + educating those who come
- Medication-Assisted Treatment for addiction
- Drug Courts, and treating drug users like human beings
- Counseling for those with mental health disorders
- Alternative treatments for pain
- Marijuana legalization – does it help?
- Study fentanyl analogues: there are many; unknown strength.
- Punchline: Harm Reduction saves lives and is much more cost effective (and ethical) than letting people suffer/die.

Ohio SUDORS Data (2016-2018)

- 9,300 individuals who died of drug overdose,
  750 attributes for each: demographics, mental health/substance abuse history, personal problems, bystanders, Naloxone, polysubstance abuse, etc.
- Data curated by the Ohio Department of Health
- Includes data from law enforcement, coroners, hospitals, prisons, mental health treatment centers, etc.
- Never previously analyzed in Ohio. Our analysis is based on a 2018 paper on the Rhode Island SUDORS dataset.
- There is much left to be done!

Characteristic	n	%
Age group		
18-24	725	7.79
25-44	5029	54.00
45-65	3366	36.14
Other	193	2.07
Sex		
Male	6348	68.16
Female	2965	31.84
Race/ethnicity		
Black, non-Hispanic	1069	11.48
White, non-Hispanic	8003	85.93
Hispanic	186	2
Other	55	0.59
Education level		
Less than high school	2071	22.61
High school Graduate/ GED completed	5111	54.88
Some college/ technical school or more	1974	21.55

Marital Status		
Never married / single	4902	53.01
Divorced/ separated	2480	26.8
Widowed	330	3.57
Married/ partnered	1535	16.69
Occupation		
Employed/ self-employed	7526	80.81
Unemployed	322	3.46
Unknown	1465	15.73
City/ town of residence		
Urbanized	5279	64.43
Urban clusters	478	5.83
Rural	2461	30.03
Out of state		
Injury location		
House or apartment	7551	81.08
Other	1336	14.35
Injured at victim home		
Yes	5696	35.5
No	3135	64.5

Precipitating Circumstance	n	%
Life stressor		
Physical health problem	565	6.55
Recent criminal legal problem	70	0.81
History of child abuse/ neglect	17	0.2
Job problem	54	0.63
Interpersonal		
Intimate partner problem	210	2.43
Family relationship problem	55	0.64
Suicide event		
History of suicide attempt	207	2.4
Precipitating circumstance known	8529	98.89

Mental health/Substance abuse		
Other substance abuse problem (excludes alcohol)	7363	86.55
Alcohol problem	1144	13.45
Current diagnosed mental health problem	3497	41.11
Depression/ dysthymia	174	-
Anxiety disorder	270	-
Bipolar disorder	83	-
Post-traumatic stress disorder	64	-
ADD or ADHD	61	-
Other mental problem	102	-
Current mental health treatment	2775	32.17
History of ever being treated for a mental health problem	4190	48.58

Toxicology test positive	**n**	**%**
Substance class and drug cause of death		
Opioid	8230	88.37
Fentanyl	7446	81.01
Heroine and/or Morphine	2662	28.96
Oxycodon	970	10.55
Methadone	262	2.85
Buprenorphine	216	2.35
Hydrocodone	446	4.85
Cocaine	3387	36.37
Alcohol	1901	20.41
BAC >= 0.08	42	2.68
BAC < 0.08	1525	97.32
Benzodiazepine	2433	26.12
Alprazolam	1204	13.10
Clonazepam	562	6.11
Marijuana	2156	23.15
Antidepressant	1331	14.29
Amphetamine	1178	12.65
Anticonvulsant	1015	10.90
Antipsychotic	274	2.94
Number of substance causing death		
1	781	8.53
2	945	10.32
3	1072	11.71
4	1022	11.16
5 or more	5337	58.28

Substance abuse	n	%
Previous drug overdose		
No previous overdose reported	7839	86.8
Previous OD within the past month	335	3.71
Previous OD between a month and 1 year prior	341	3.78
Previous OD that occurred more than 1 year prior	149	1.65
Previous OD, timing unknown	367	4.06
Recent opioid use relapse		
No evidence	8334	92.4
Relapse mentioned, timing unclear	290	3.22
Relapse occurred < 2 weeks of fatal overdose	363	4.02
Relapse occurred > 2 weeks < 3 months of fatal overdose	32	0.35
Treatment for substance abuse		
No treatment	7280	80.61
No current treatment, but treated in the past	1076	11.91
Current treatment	675	7.47

History of opioid abuse		
None	3045	33.72
Substance unknown	2259	25.01
Current or past abuse of heroin	3024	33.48
Prescription opioids	362	4.01
Both prescription opioids & heroin	341	3.78
Scene indications of drug use		
Any evidence of drug use	5884	65.05
Evidence of rapid overdose	797	8.81
Needle close to the body	681	7.53
Route of drug administration		
Evidence of injection	3033	33.53
Needle/syringe	2042	22.57
Track marks on victim	1712	18.93
Cooker	1097	12.13
Filter report	292	3.23
Touniquet report	337	3.73
Witness report	90	0.99
Evidence of ingestion	1745	19.29
Evidence of snorting	1139	12.59
Evidence of smoking	709	7.84

Drug type and response to drug overdose	**n**	**%**
Illicit drug	3413	37.73
Evidence of illicit drug: powder	1127	12.46
Evidence of illicit drug: crystal	108	1.19
Evidence of illicit drug: witness report	591	6.53
Prescription drug	2153	23.8
Prescribed to the victim	1445	15.97
Unknown who prescribed	782	8.64
Not prescribed to the victim	264	2.92
Form of prescription drug		
Pills/tablets	644	7.12
Bottle	1596	17.64
Patch	47	0.52
Response to drug overdose		
Bystander present at time of overdose		
No bystander present	173	1.92
One bystander present	1623	17.97
Multiple bystander present	690	7.64
Bystanders present, unknown num	1003	11.11

No person witnessed drug overdose	626	6.93
1+ person withnessed drug overdose	564	6.25
Naloxone administered		
Yes	1174	12.98
No	1802	19.92
Unknown	355	3.92
Who administered naloxone?		
By EMS/firefighter	642	7.1
By law enforcement	111	1.23
By hospital (ED/Inpatient)	117	1.29
By family member	32	0.35
By intimate partner	24	0.27
Medical history		
Yes, treated for pain	1954	21.63
No/Unknown	7080	78.37
Prescription information		
Prescribed buprenorphine/methadone	309	3.42

Much more research that can be done

- Any question featuring time series analysis, e.g. interrupted time series, changepoint detection, spectral/Fourier.
- Any question using the spatial (geolocation) component of the data. Topological data analysis approaches.
- Polysubstance abuse
- Interaction terms, e.g., polysubstance and race.
- Danger for recent releases from prison to overdose
- Overdoses and local laws
- How many drug users are there? We only see deaths.
- How many lives would it save to open one more needle exchange? Where to open it? Is it cost effective?

- Key Take-Aways
    - There are tons of freely available datasets about the opioid epidemic: CDC, SUDORS, BCI, NSDUH, hospitals, prescriptions (OARRS), marijuana laws, NFLIS (DEA), FBI, OMAS Medicaid survey, mental health, etc.
    - Many have never been analyzed – lots of low-hanging fruit, and nowhere near enough math/stats people working on this.
    - Even simplistic analyses are valuable to harm reduction professionals, can save lives, and can get published. Great for students.
    - Huge need to educate people about what actually works to combat the opioid epidemic.
    - I’m happy to help you get involved, sharing datasets, analyses, and papers, and connecting you to experts. Email: david.white@denison.edu

References

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2. Lin Ma, Lam Tran, David White, “A Statistical Analysis of Drug Seizures and Opioid Overdose Deaths in Ohio from 2014 to 2018,” Journal of Student Research, 10(1), 2021.

3. Lin Ma, Lam Tran, David White, State Unintentional Drug Overdose Reporting Surveillance: Opioid Overdose Deaths and Characteristics in Ohio.

4. Rosenblum, et al., “The Rapidly Changing US Illicit Opioid Market and the Potential for an Improved Early Warning System: Evidence from Ohio Drug Crime Labs, 2015-2017.” 2020.

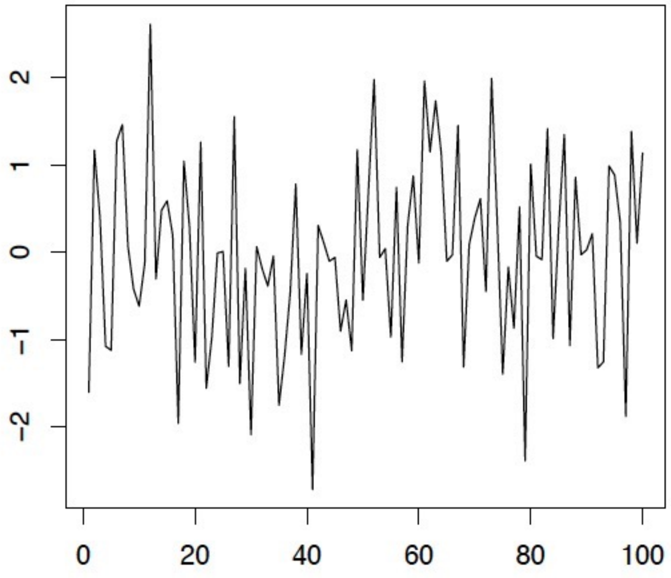
5. Zibbell, et al., “Association of Law Enforcement Seizures of Heroin, Fentanyl, and Carfentanil with Opioid Overdose Deaths in Ohio, 2014-2017.

6. Hall, et. al. “Street-drug lethality index: a novel methodology for predicting unintentional drug overdose fatalities in population research.”

7. Bonifonte, et. al. “Morphine Equivalent Total Dosage as Predictor of Adverse Outcomes in Opioid Prescribing.”

THANK YOU

Fourier models



Fit a model like:

$$\sum_{j=1}^{m} \left[A_j \cos(2\pi\omega_j t) + B_j \sin(2\pi\omega_j t)\right]$$

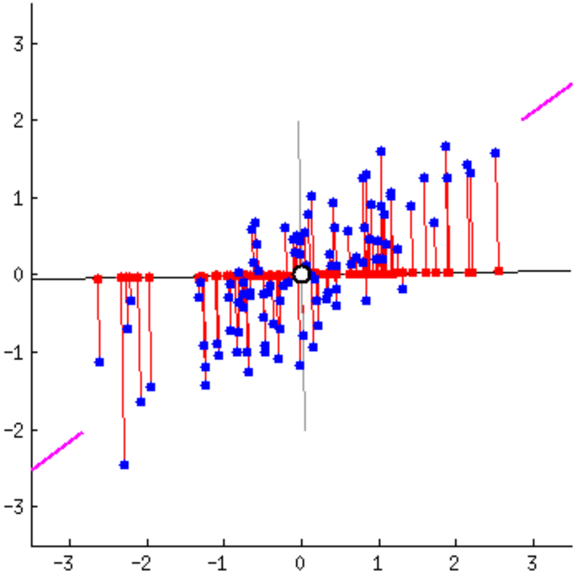
Problem: what's m? What are the periods?

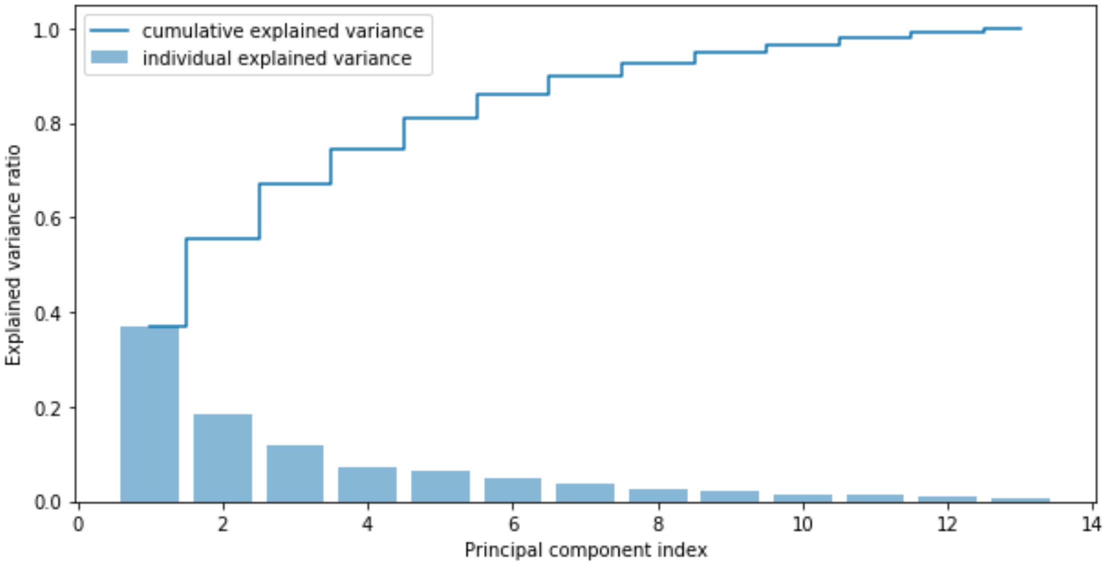
Solution: take the Fourier transform!

Idea: change to a basis where basis vectors correspond to periods, ordered by how much variability they explain. Then just keep the first few.

Same math as Shazam or Sound Hound!

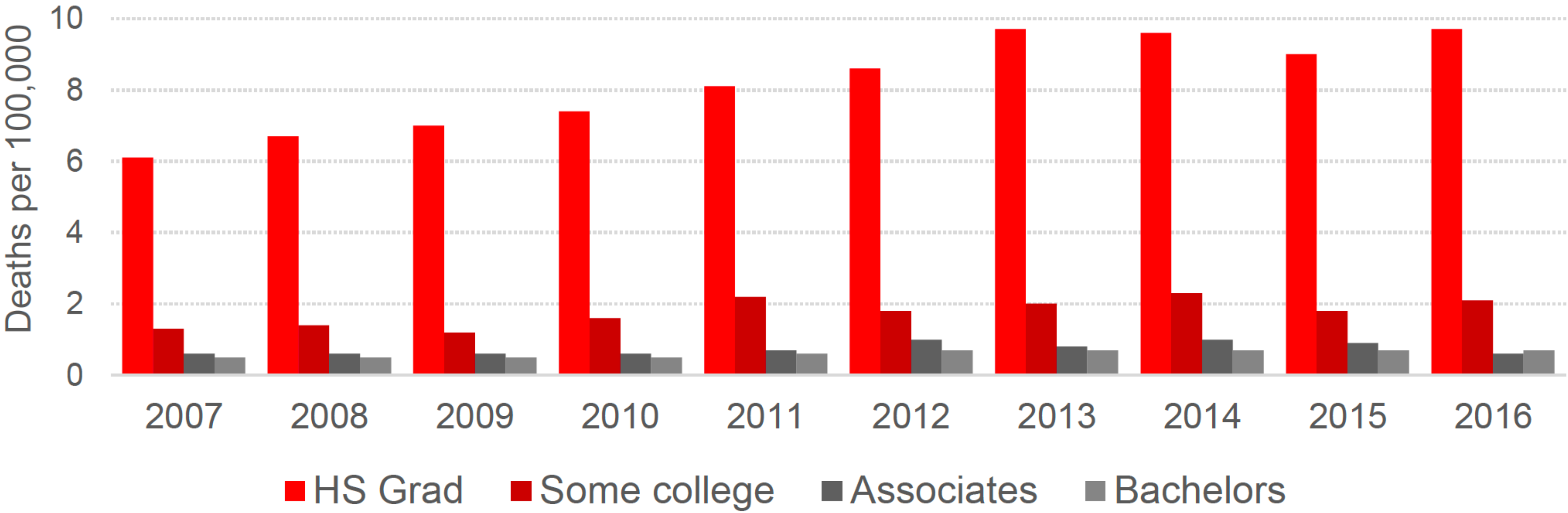
Principal Component Analysis (PCA)



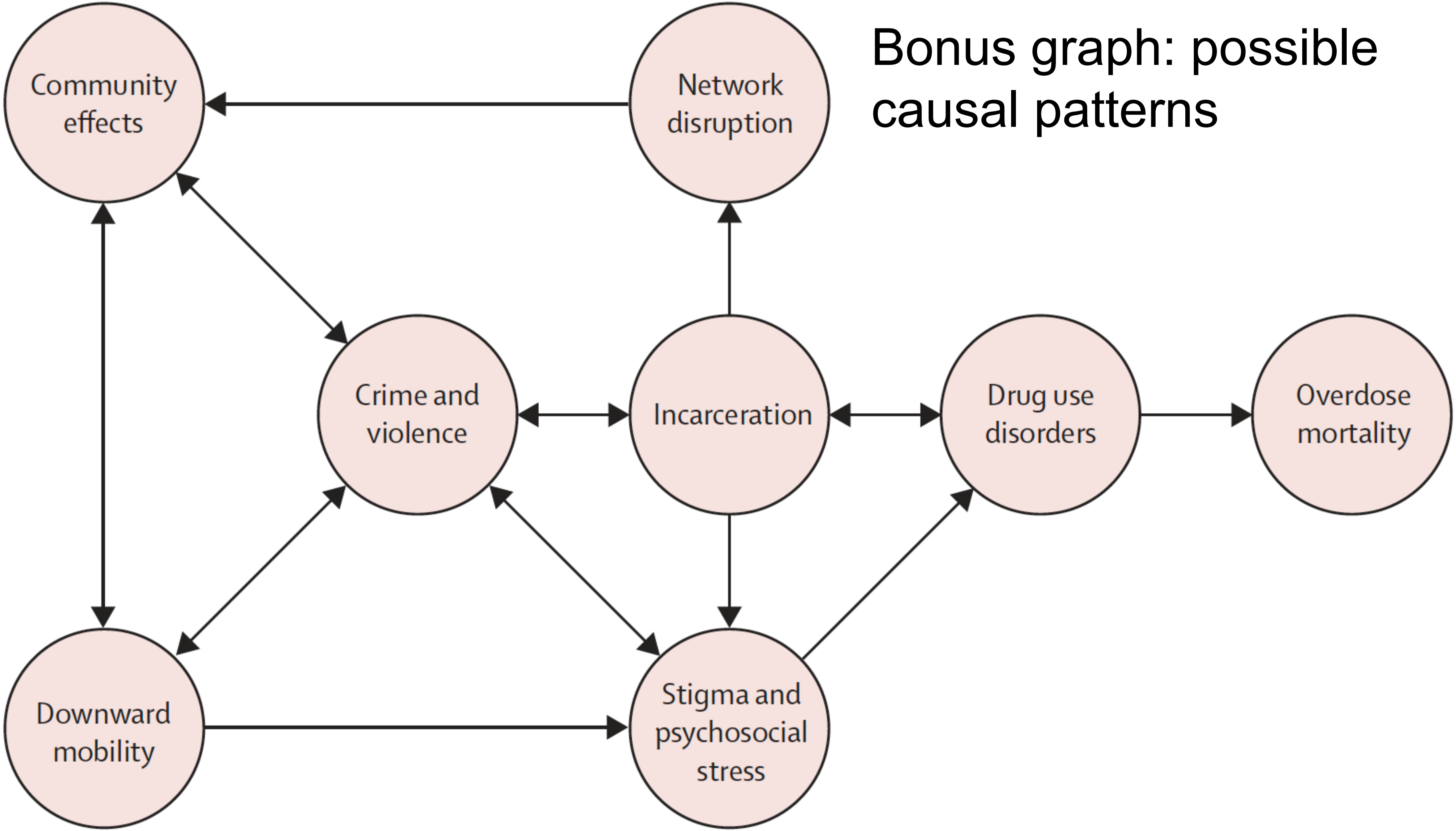


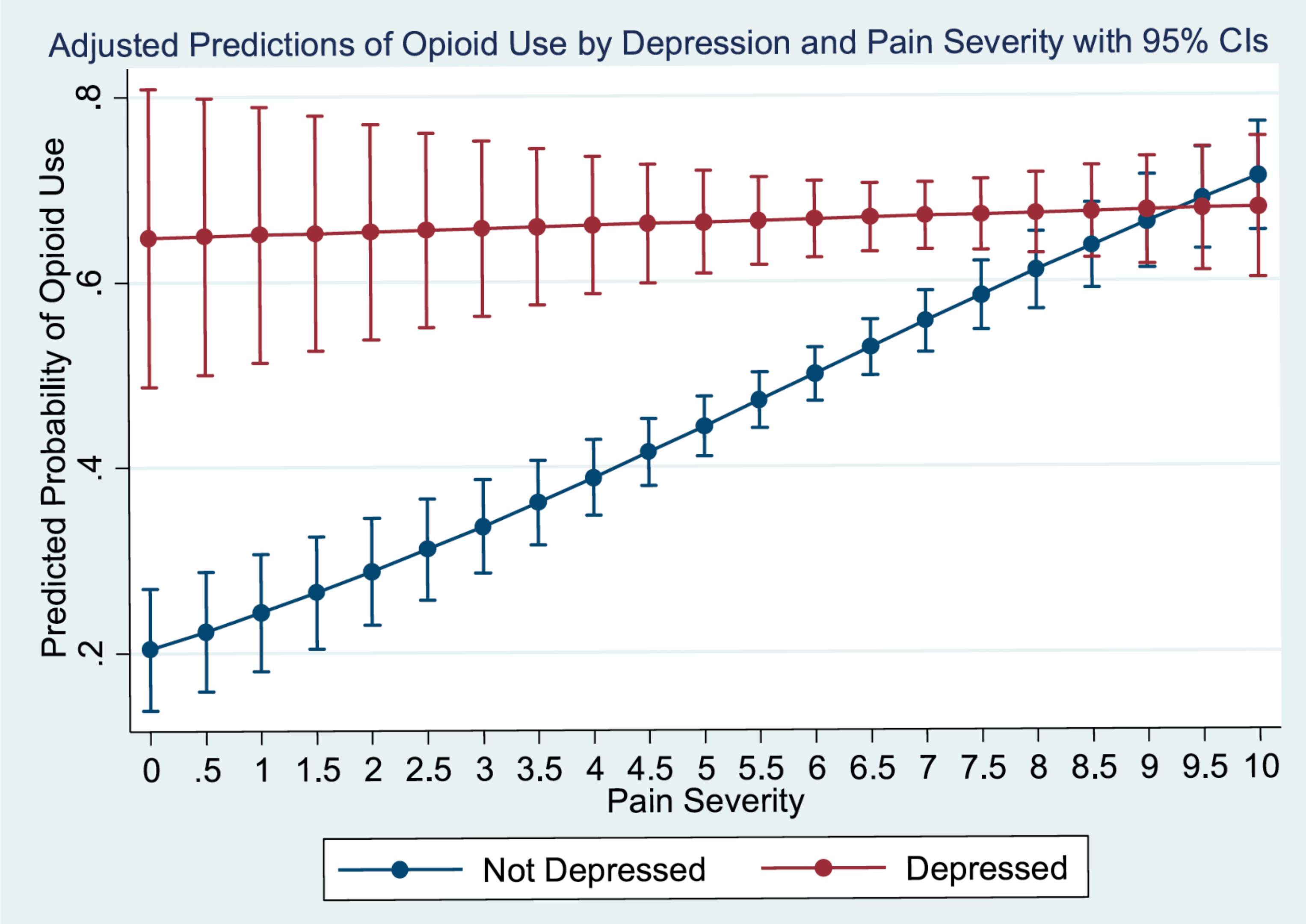
Exact same concept as PCA. Accomplish via Singular Value Decomp.

Bonus graph: deaths by education level

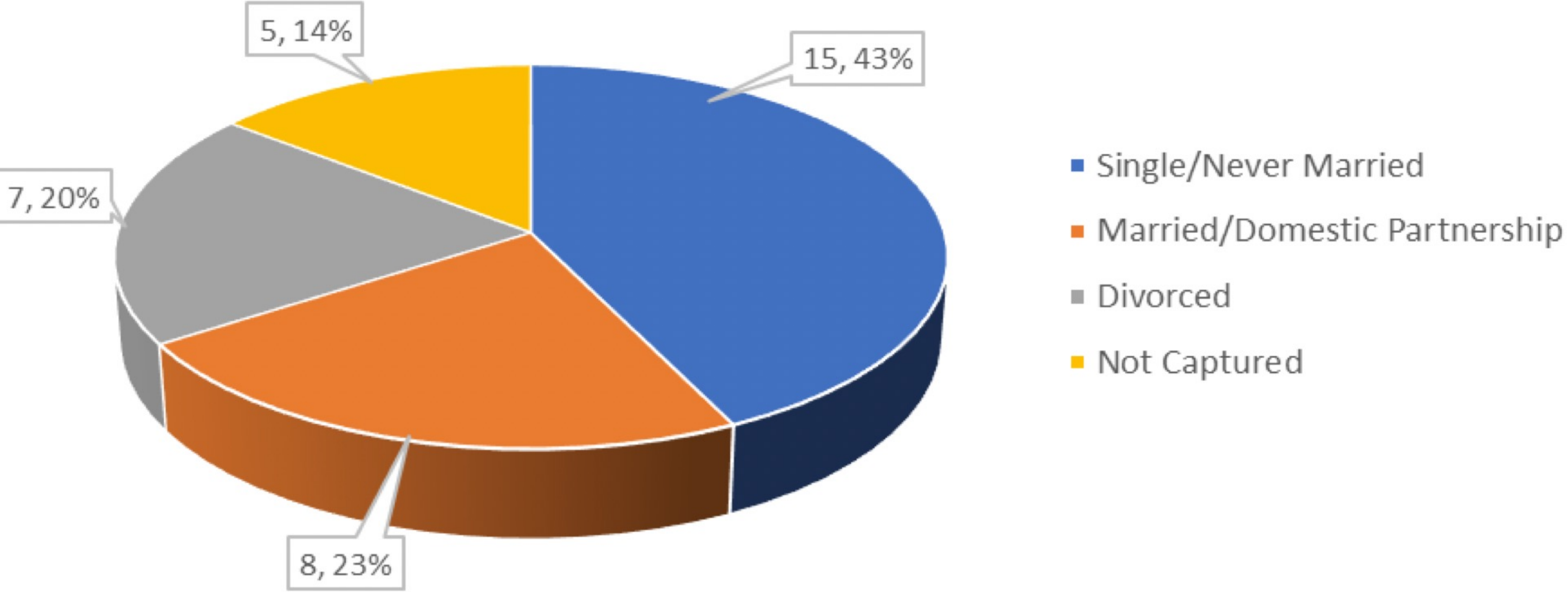


Bonus graph: possible causal patterns




Adjusted Predictions of Opioid Use by Depression and Pain Severity with 95% CIs
Predicted Probability of Opioid Use
.2
.4
.6
.8
0
.5
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5
6
6.5
7
7.5
8
8.5
9
9.5
10
Pain Severity
Not Depressed
Depressed

Bonus graph: deaths by marriage status



Bonus graph: deaths by age group

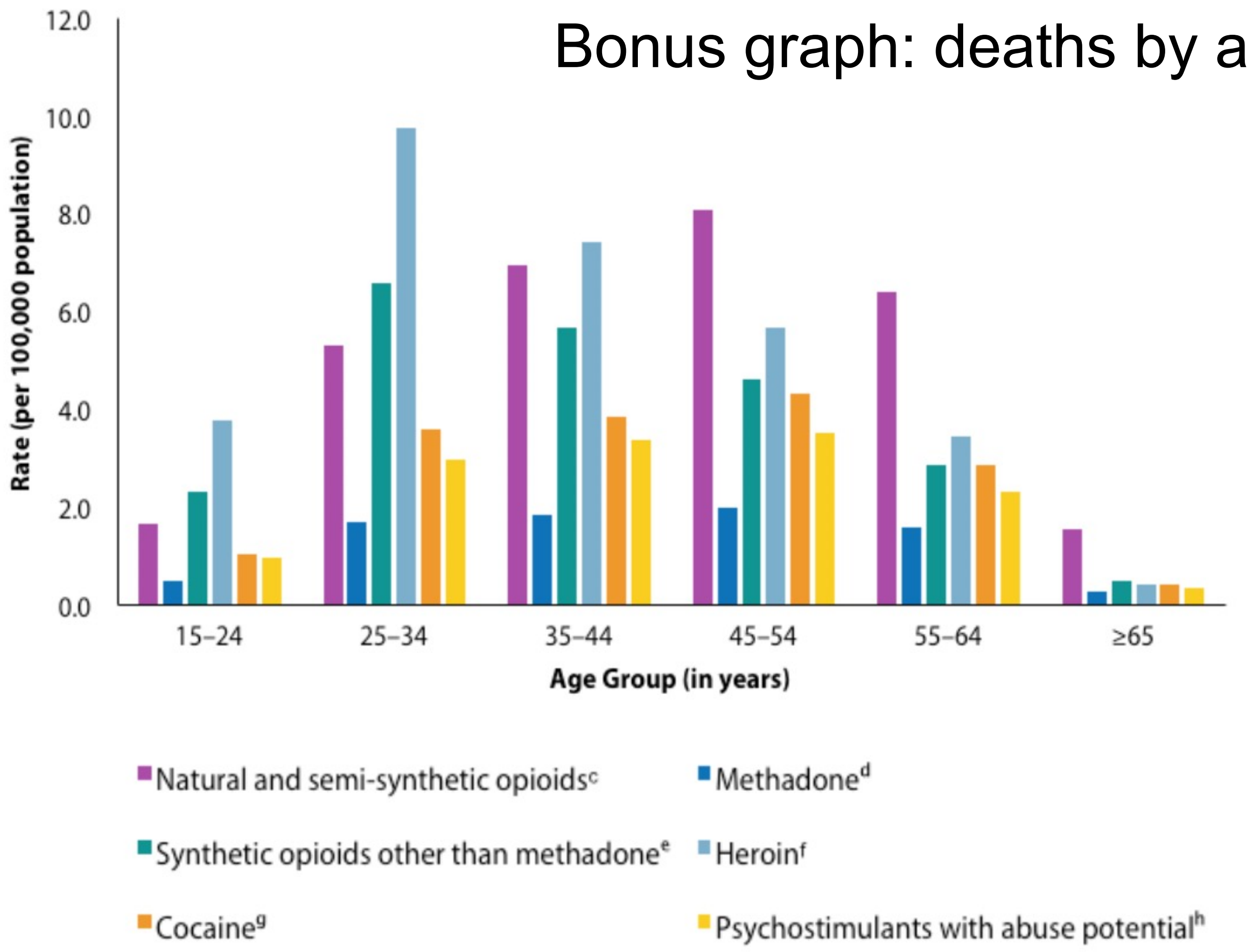
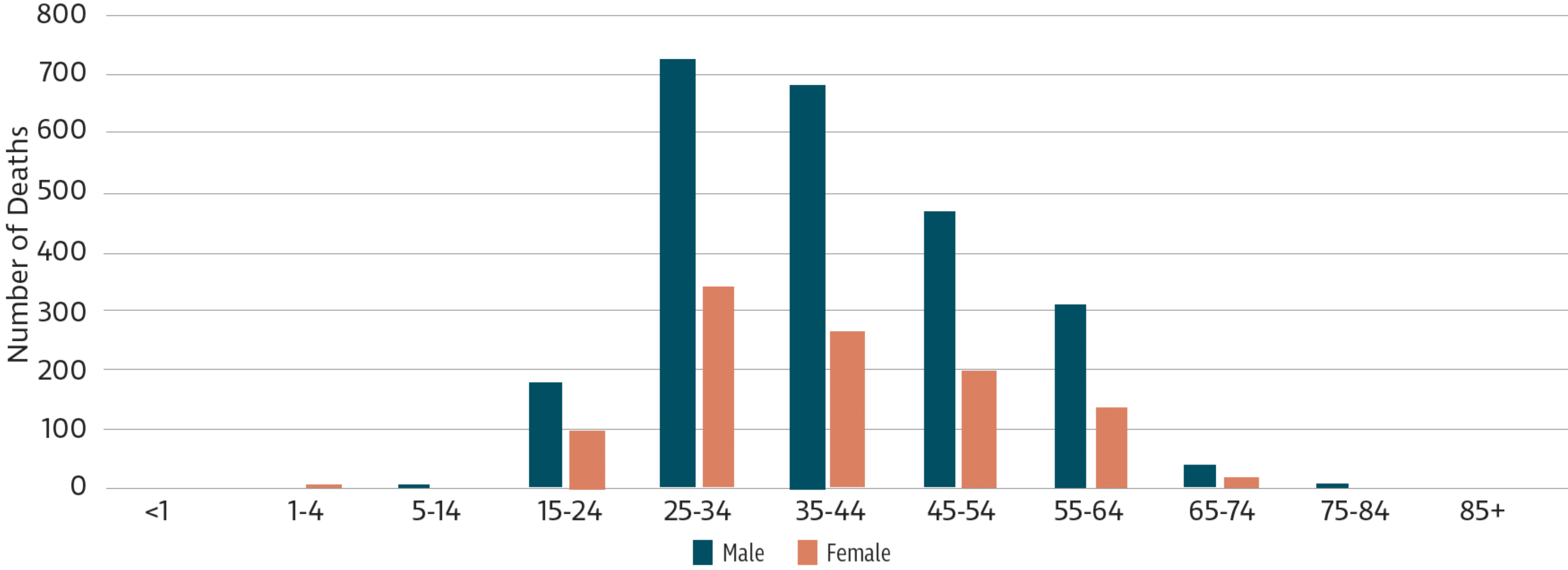


Figure 9. Fentanyl and Related Drugs Unintentional Overdose Deaths, by Age and Sex, Ohio, 2017



Bonus graph: deaths by census block

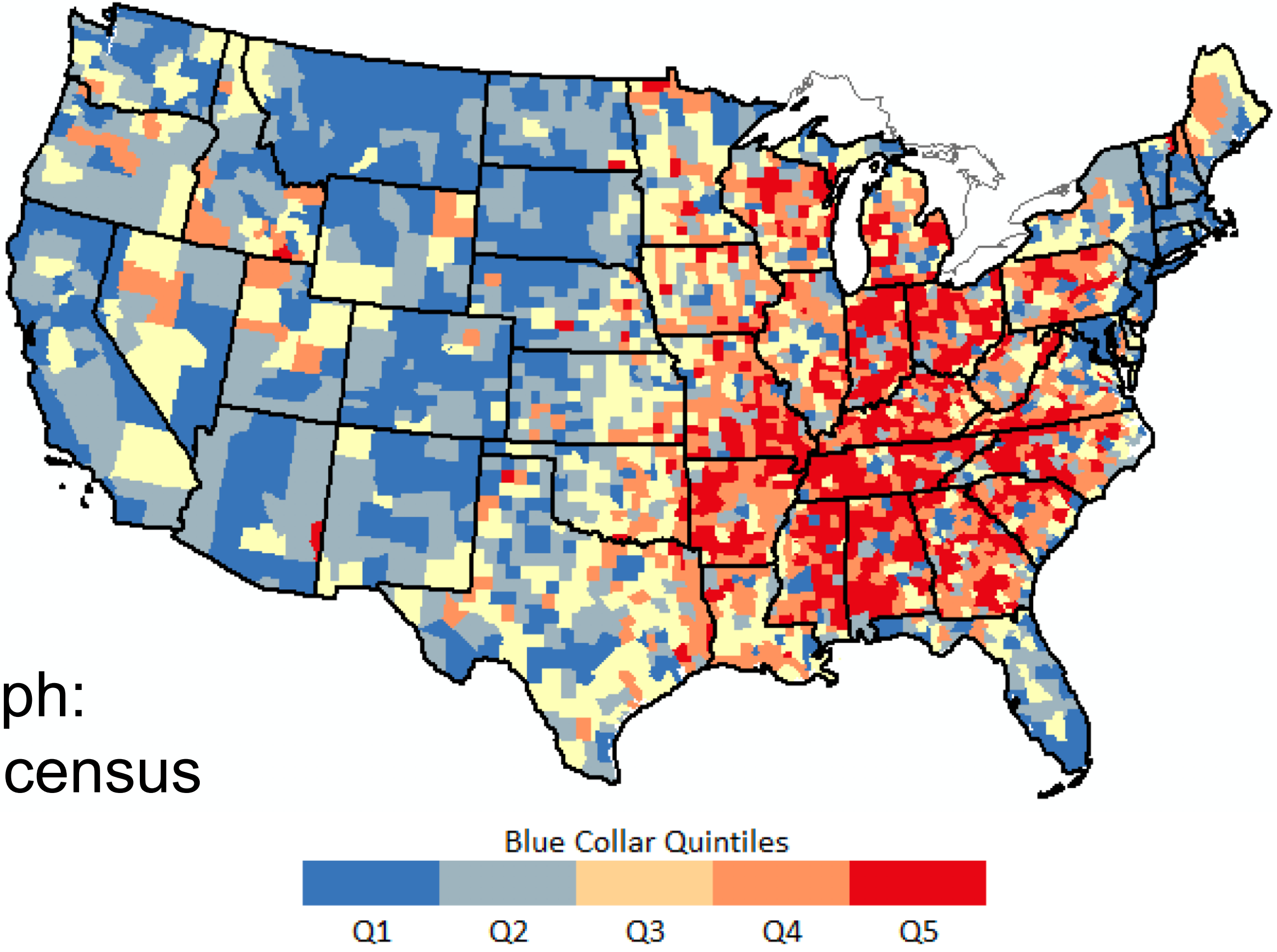
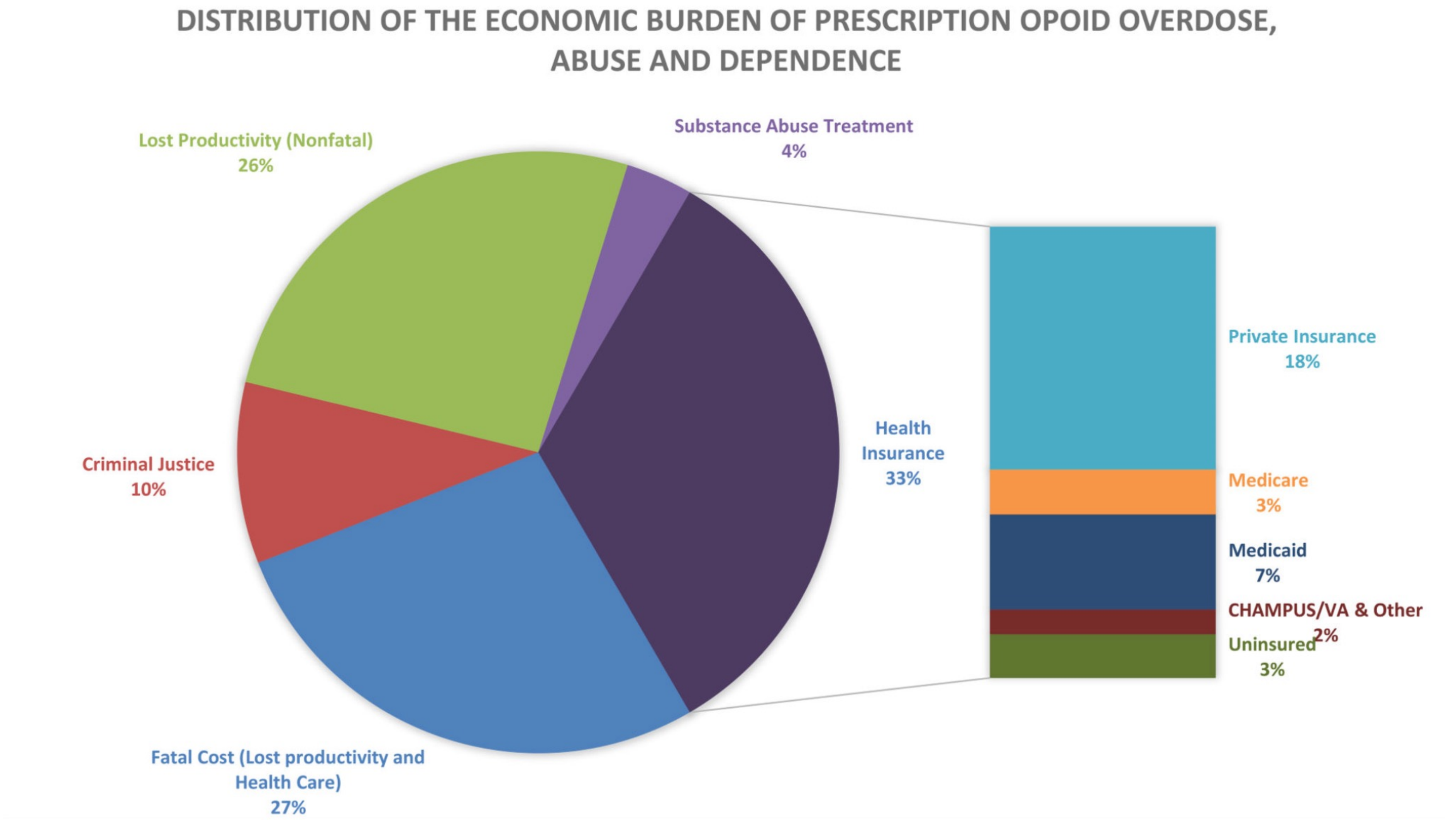
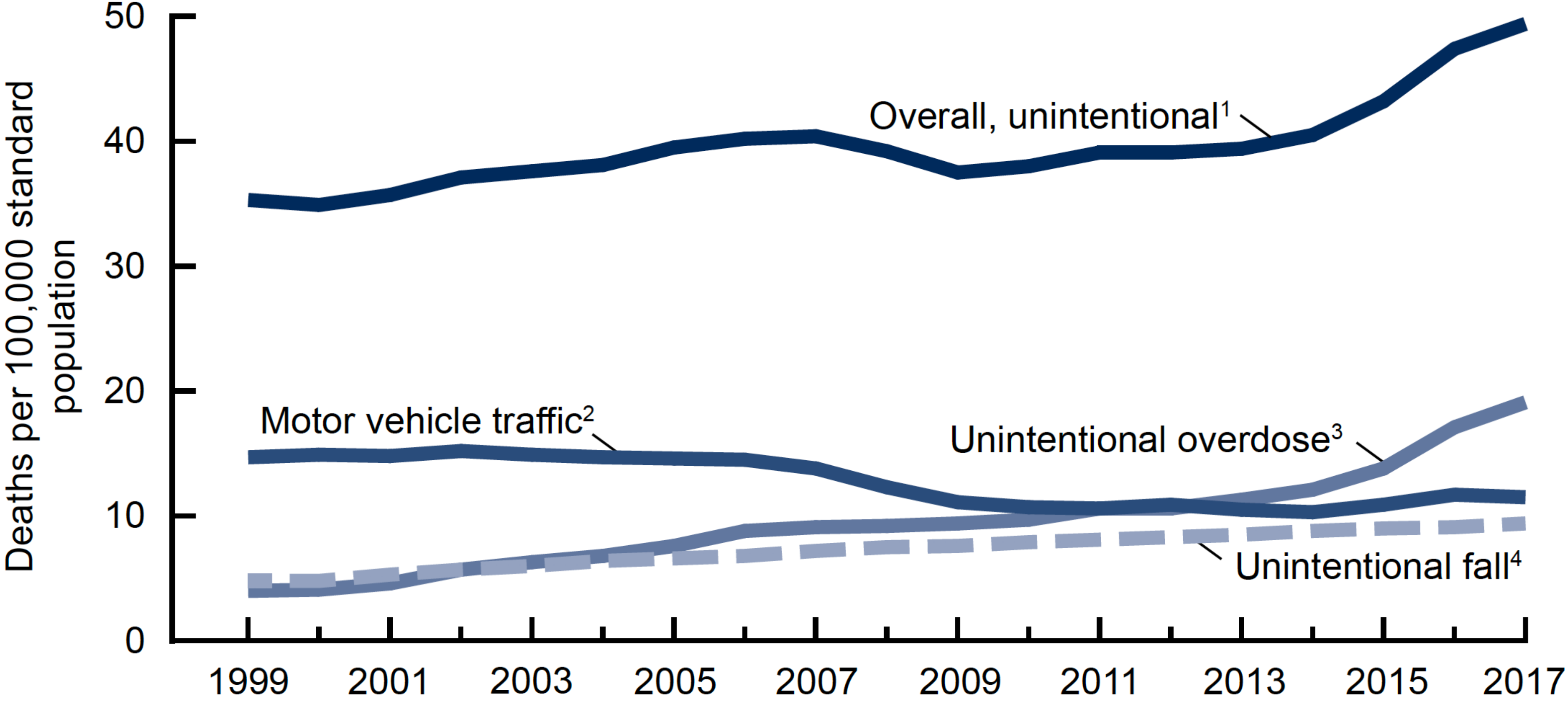


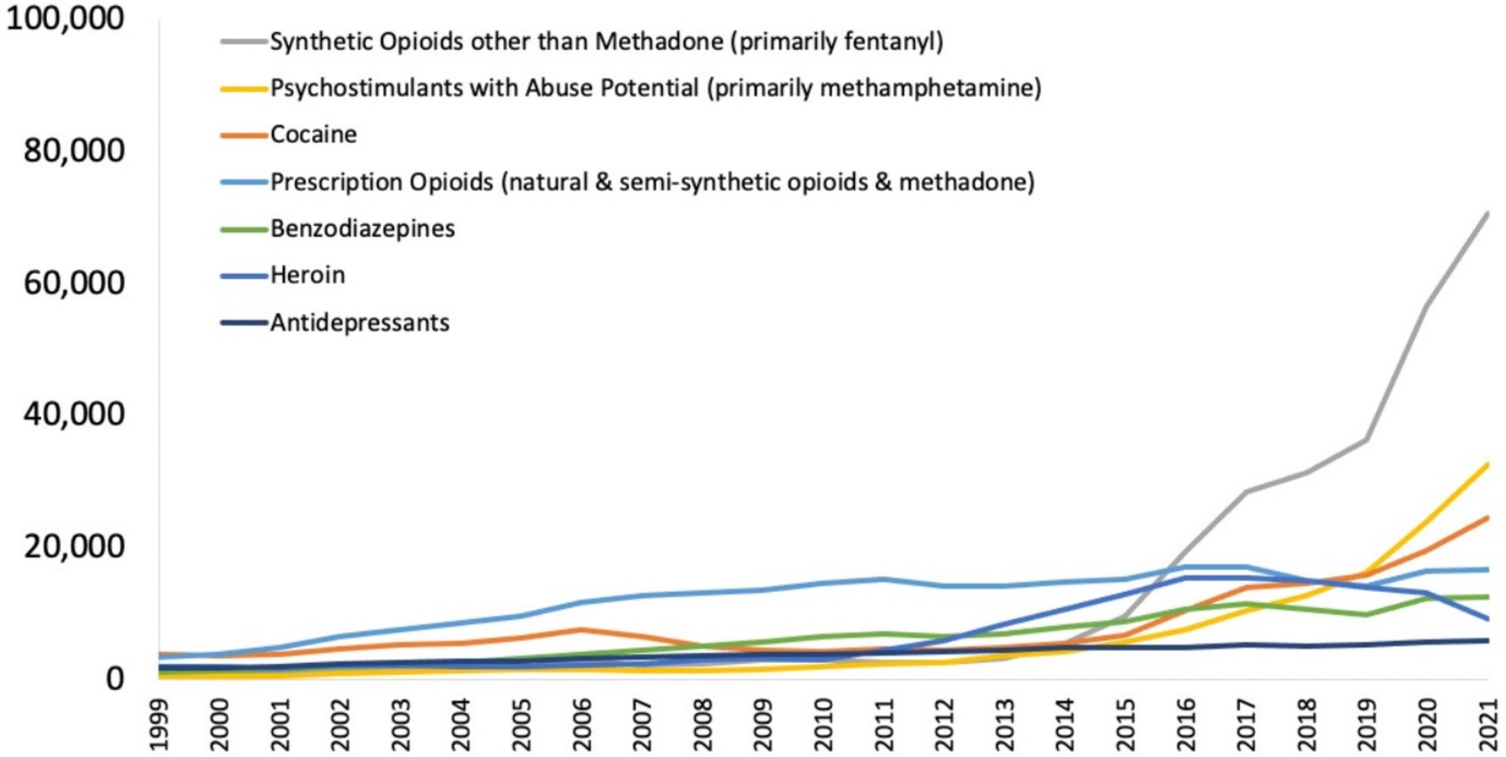
Figure D2. Blue Collar Index Quintiles, 2000

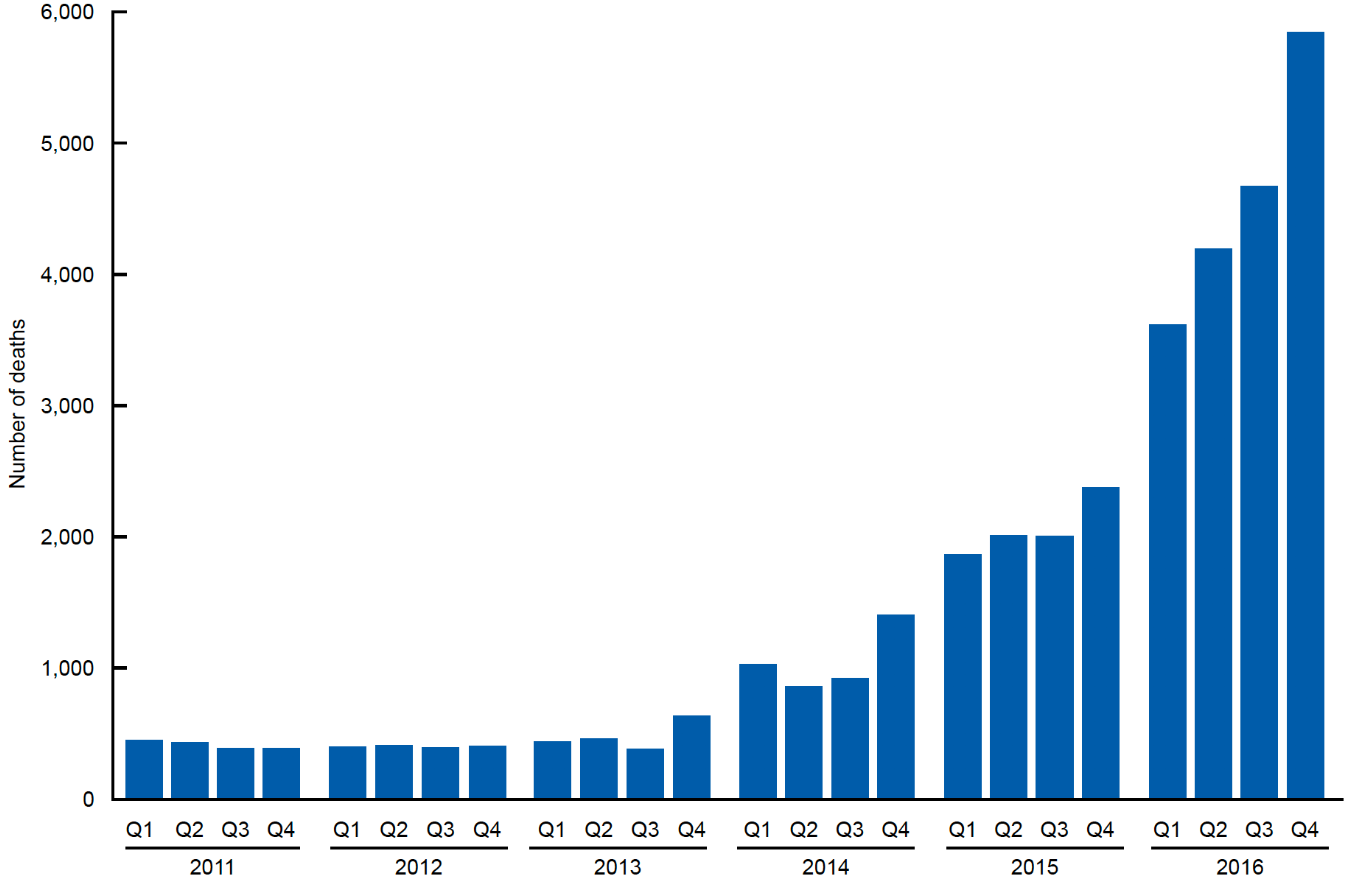

DISTRIBUTION OF THE ECONOMIC BURDEN OF PRESCRIPTION OPOID OVERDOSE, ABUSE AND DEPENDENCE
Lost Productivity (Nonfatal) 26%
Substance Abuse Treatment 4%
Criminal Justice 10%
Health Insurance 33%
Fatal Cost (Lost productivity and Health Care) 27%
Private Insurance 18%
Medicare 3%
Medicaid 7%
CHAMPUS/VA & Other 2%
Uninsured 3%



Deaths per 100,000 standard population
50
40
30
20
10
0
1999
2001
2003
2005
2007
2009
2011
2013
2015
2017
Overall, unintentional1
Motor vehicle traffic2
Unintentional overdose3
Unintentional fall4

Figure 2. National Drug-Involved Overdose Deaths*, Number Among All Ages, 1999-2021

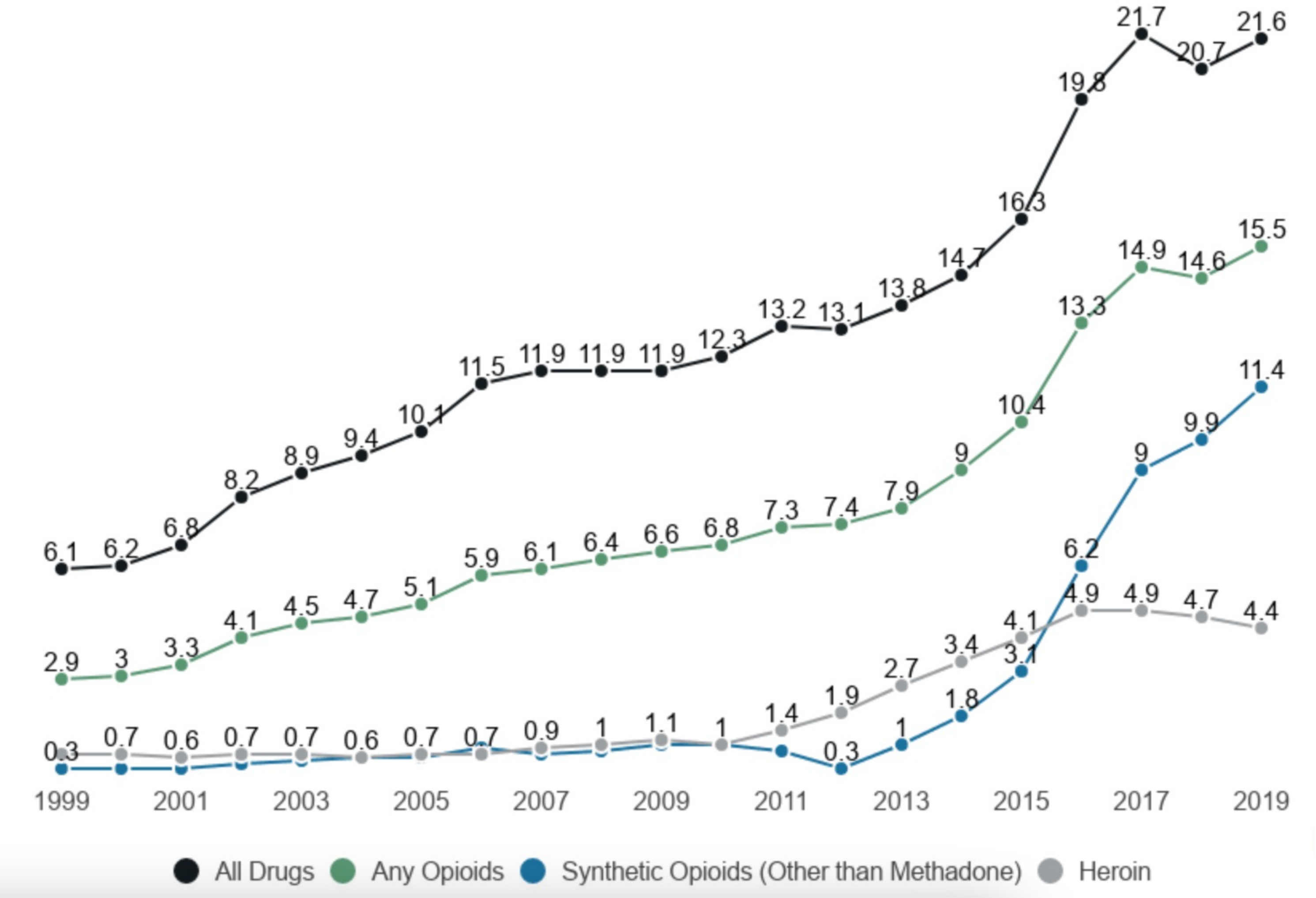




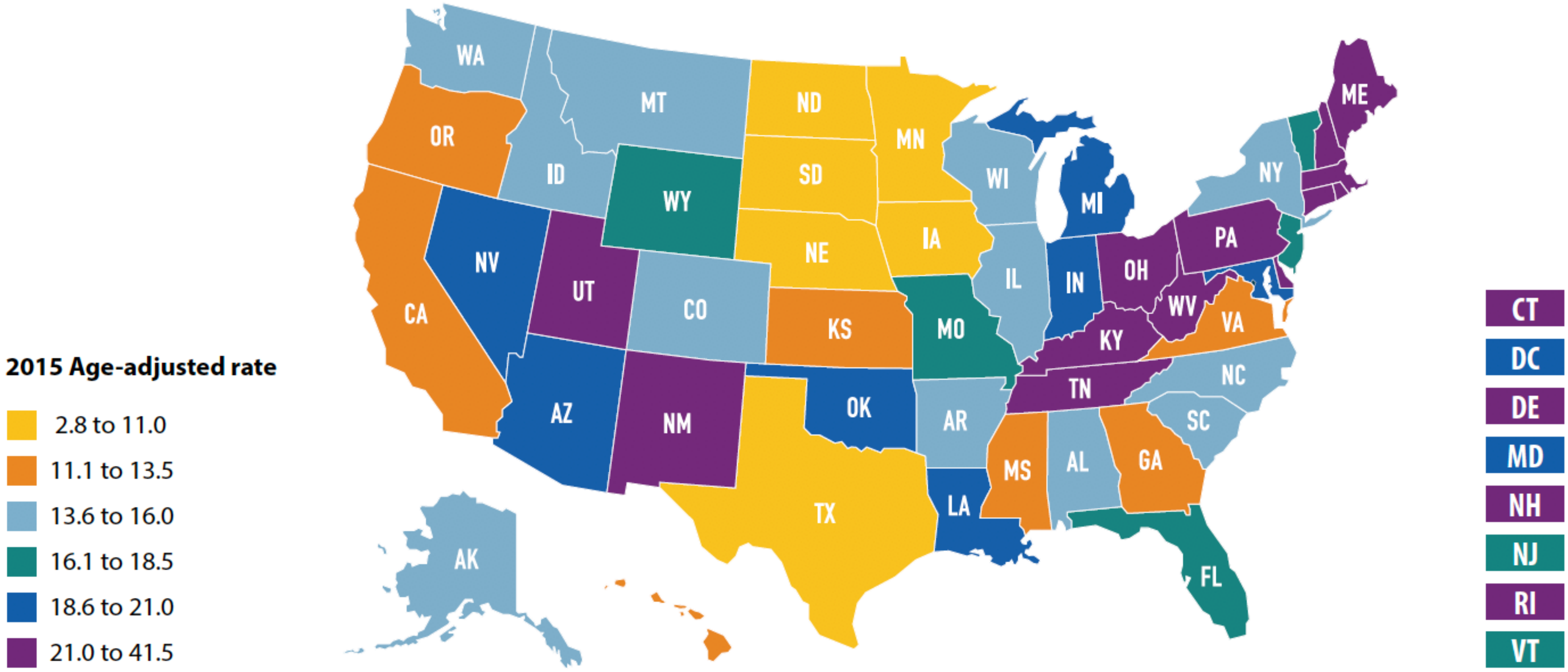
NOTES: Drug overdose deaths are identified using *International Classification of Diseases, 10th Revision* underlying cause-of-death codes X40–X44, X60–X64, X85, and Y10–Y14. Deaths may involve other drugs in addition to fentanyl. Caution should be used when comparing numbers across years. The reporting of at least one specific drug or drug class in the literal text, as identified by multiple cause-of-death codes T36–T50.8, improved from 75.0% of drug overdose deaths in 2011 to 85.4% in 2016.
SOURCE: NCHS, National Vital Statistics System, Mortality files linked with death certificate literal text.

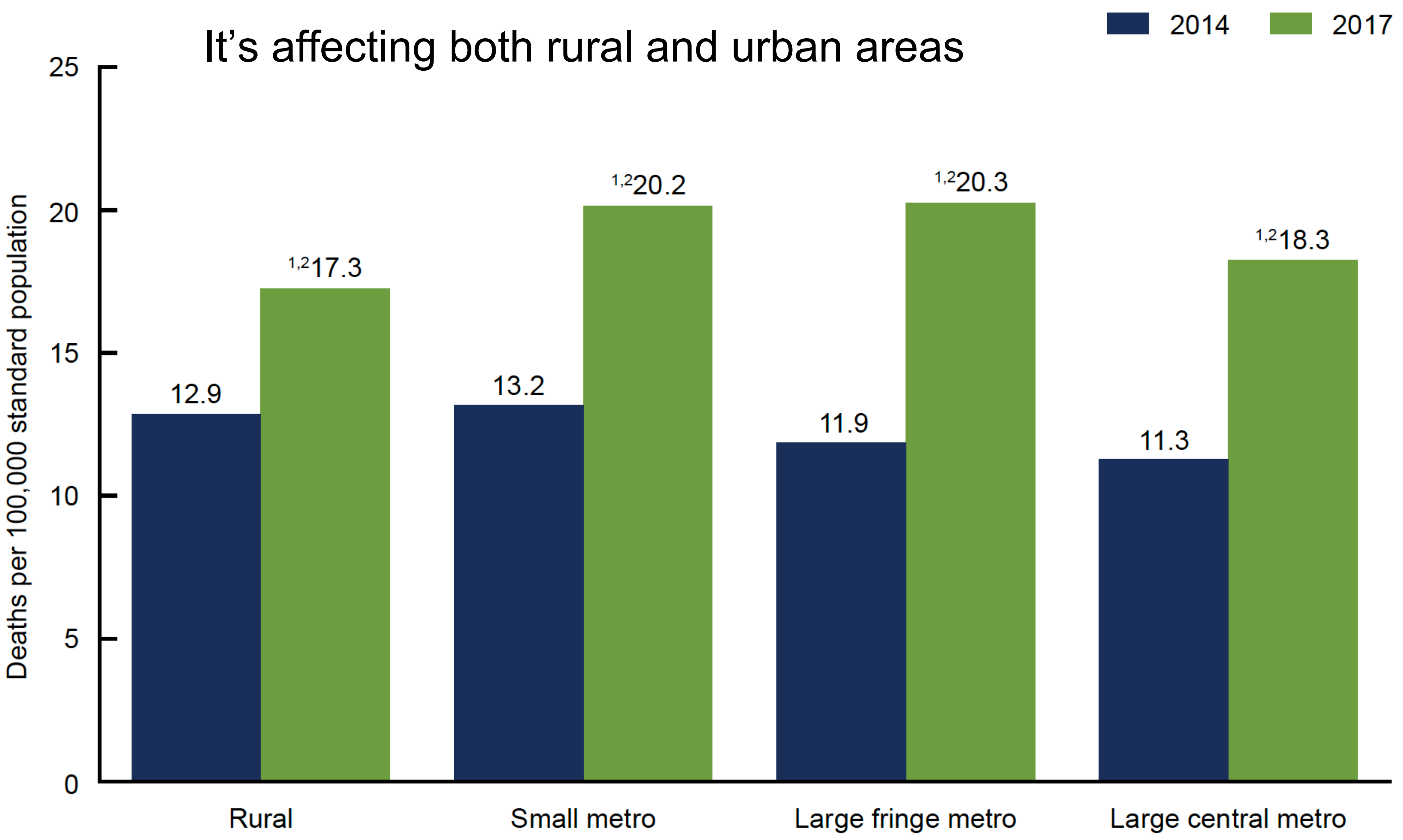
Figure 1. Number of drug overdose deaths involving fentanyl, by quarter: United States, 2011–2016

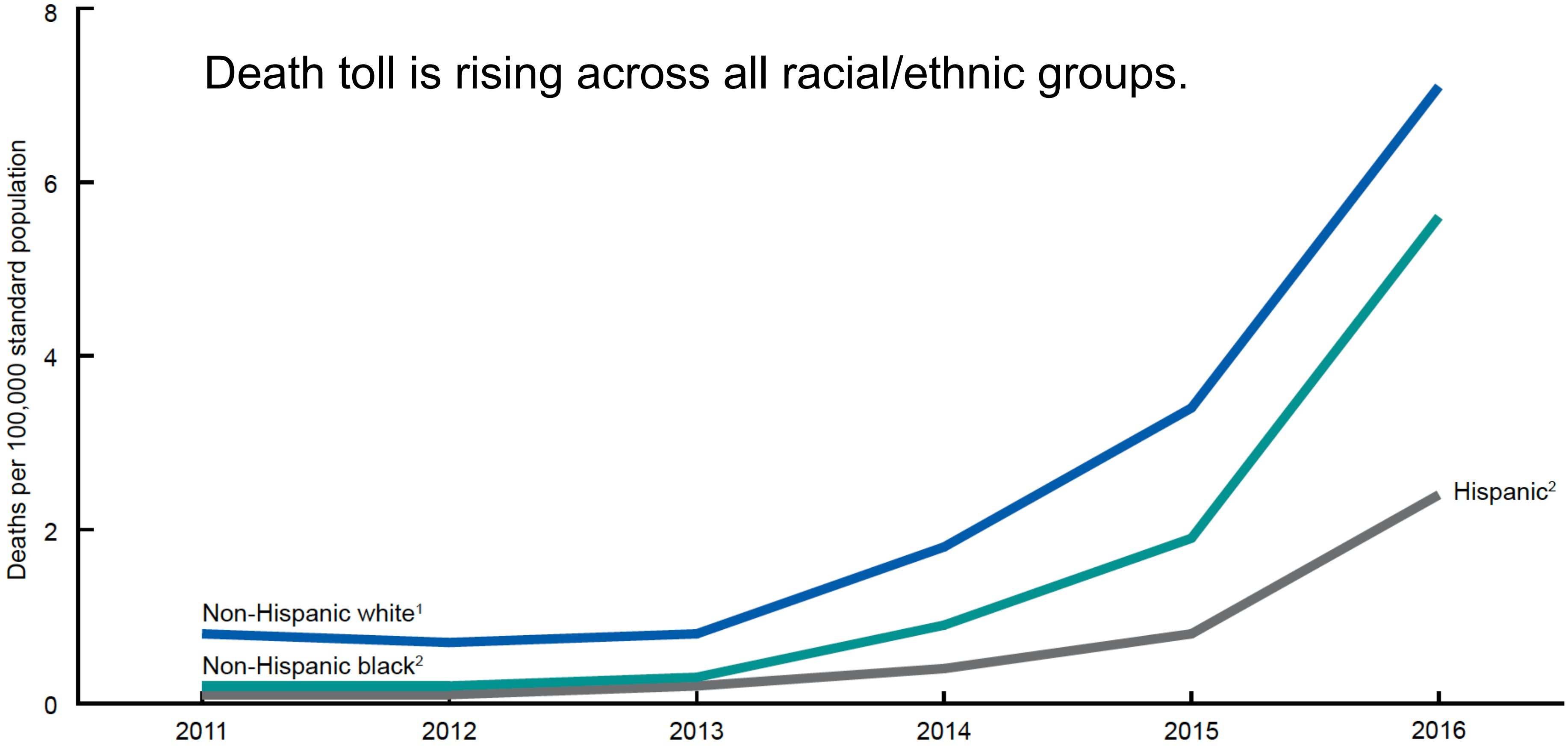
Historical Trends in Opioid Overdose Deaths per 100,000 Residents



Which states have been most affected?

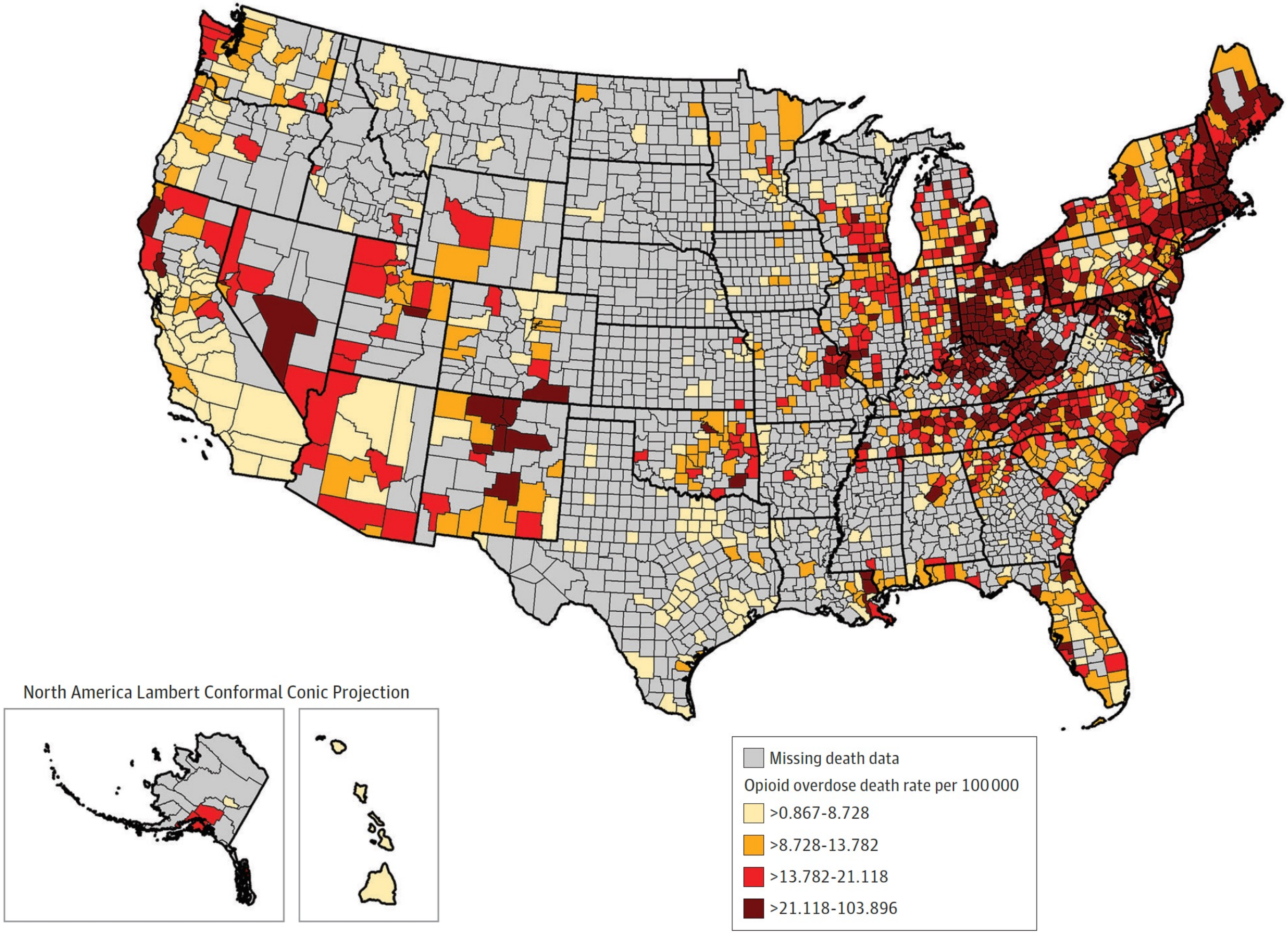



It's affecting both rural and urban areas
2014
2017
Deaths per 100,000 standard population
25
20
15
10
5
0
12.9
1,2 17.3
13.2
1,2 20.2
11.9
1,2 20.3
11.3
1,2 18.3
Rural
Small metro
Large fringe metro
Large central metro

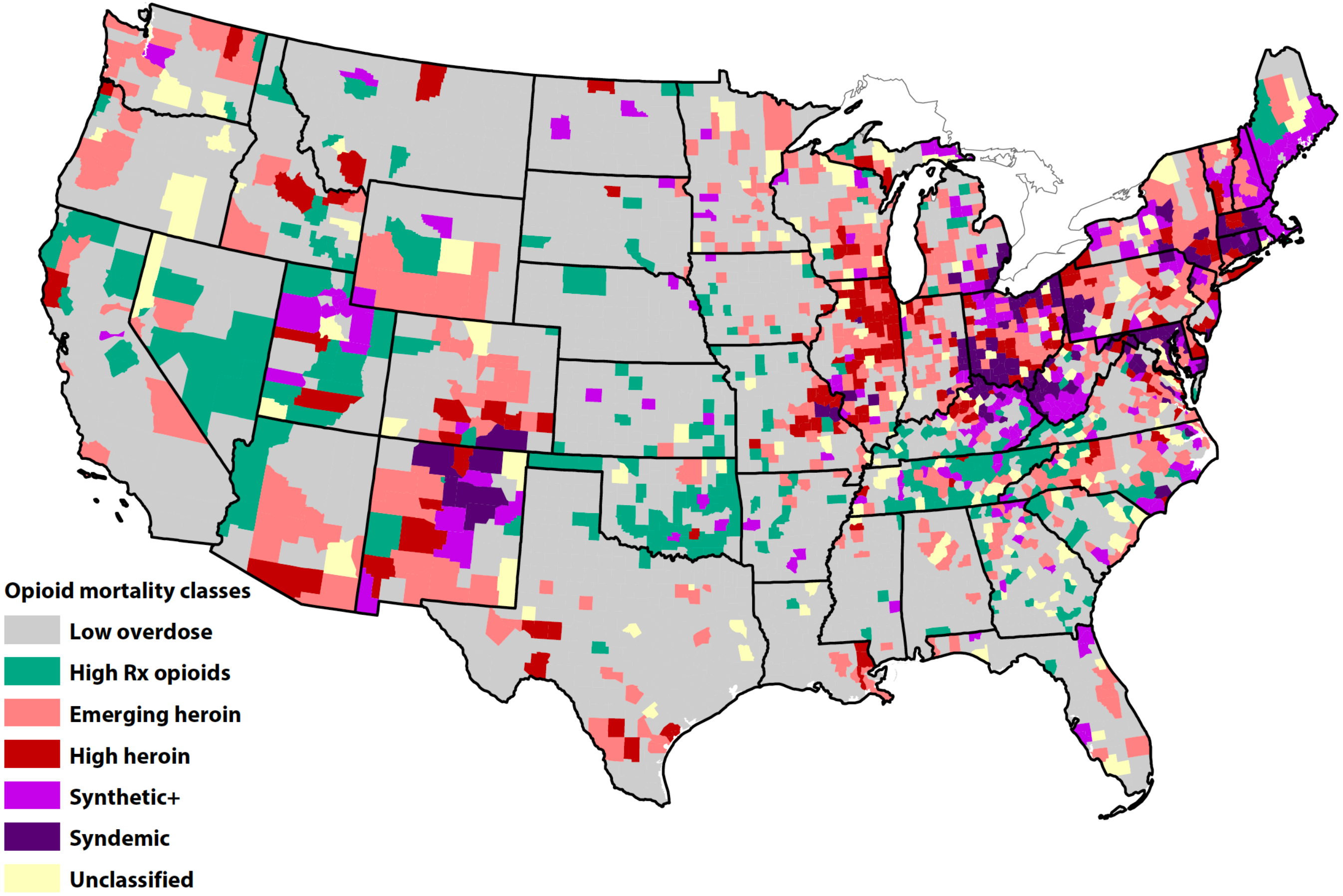


[1]Increasing trend for 2013–2016 is statistically significant ($p < 0.05$).
[2]Increasing trend for 2011–2016 is statistically significant ($p < 0.05$).
NOTES: Drug overdose deaths are identified using *International Classification of Diseases, 10th Revision* underlying cause-of-death codes X40–X44, X60–X64, X85, and Y10–Y14. Deaths may involve other drugs in addition to fentanyl. Death rates are age adjusted. Caution should be used when comparing numbers across years. The reporting of at least one specific drug or drug class in the literal text, as identified by multiple cause-of-death codes T36–T50.8, improved from 75.0% of drug overdose deaths in 2011 to 85.4% in 2016.
SOURCE: NCHS National Vital Statistics System, Mortality files linked with death certificate literal text.

Figure 1. Opioid Overdose Death Rate per 100 000 People by US County, 2015-2017



Different states face different issues



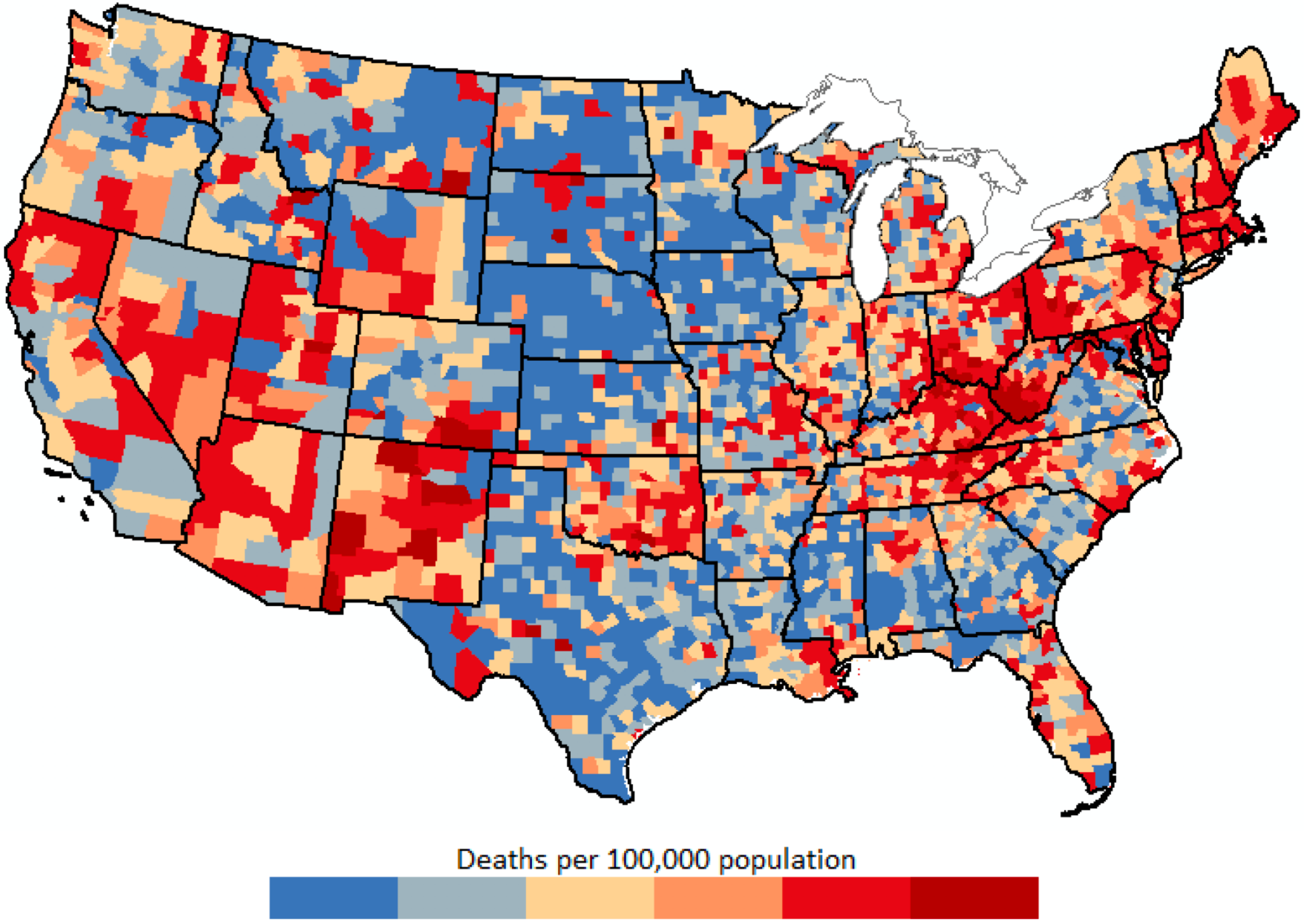
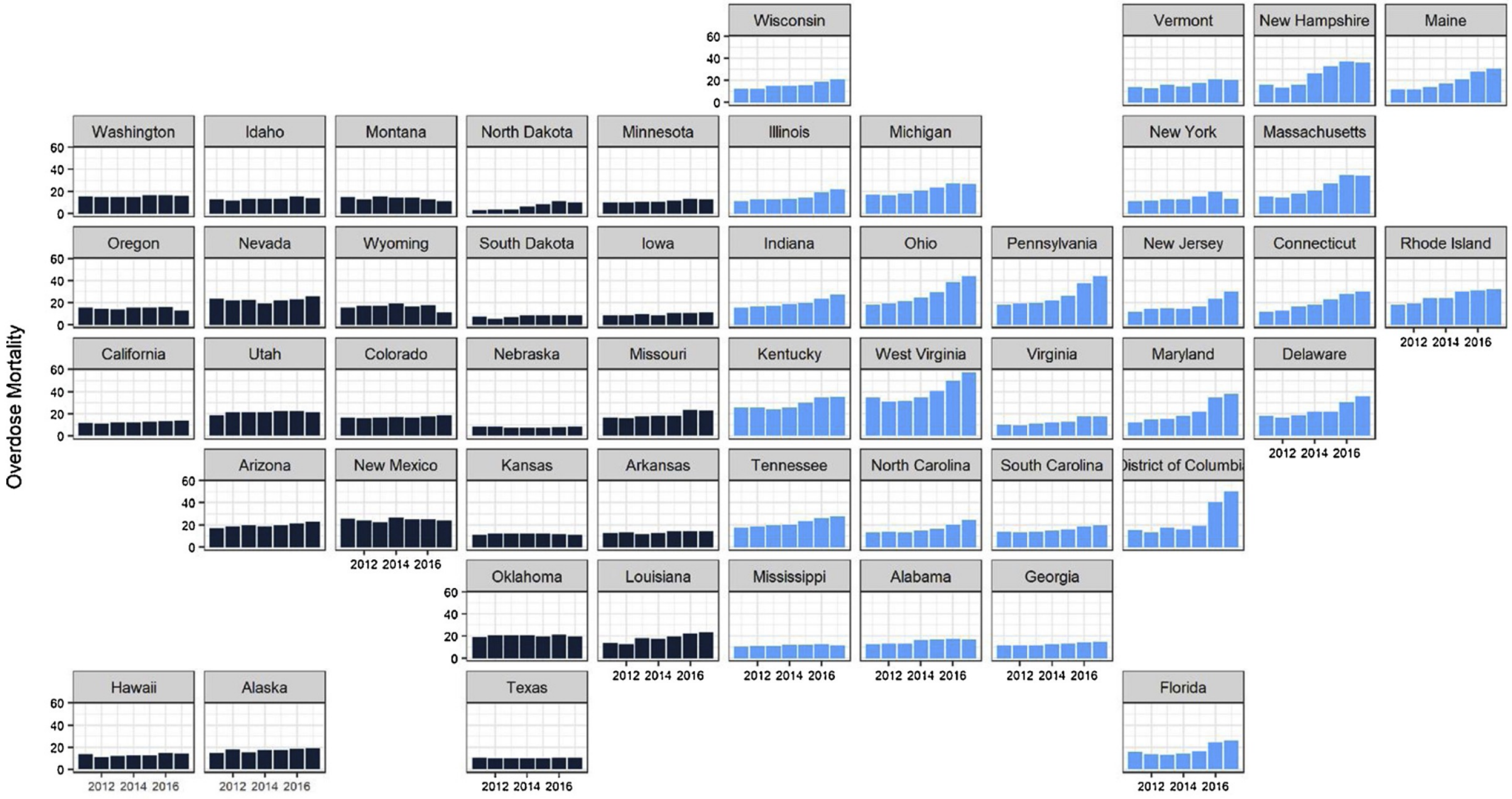
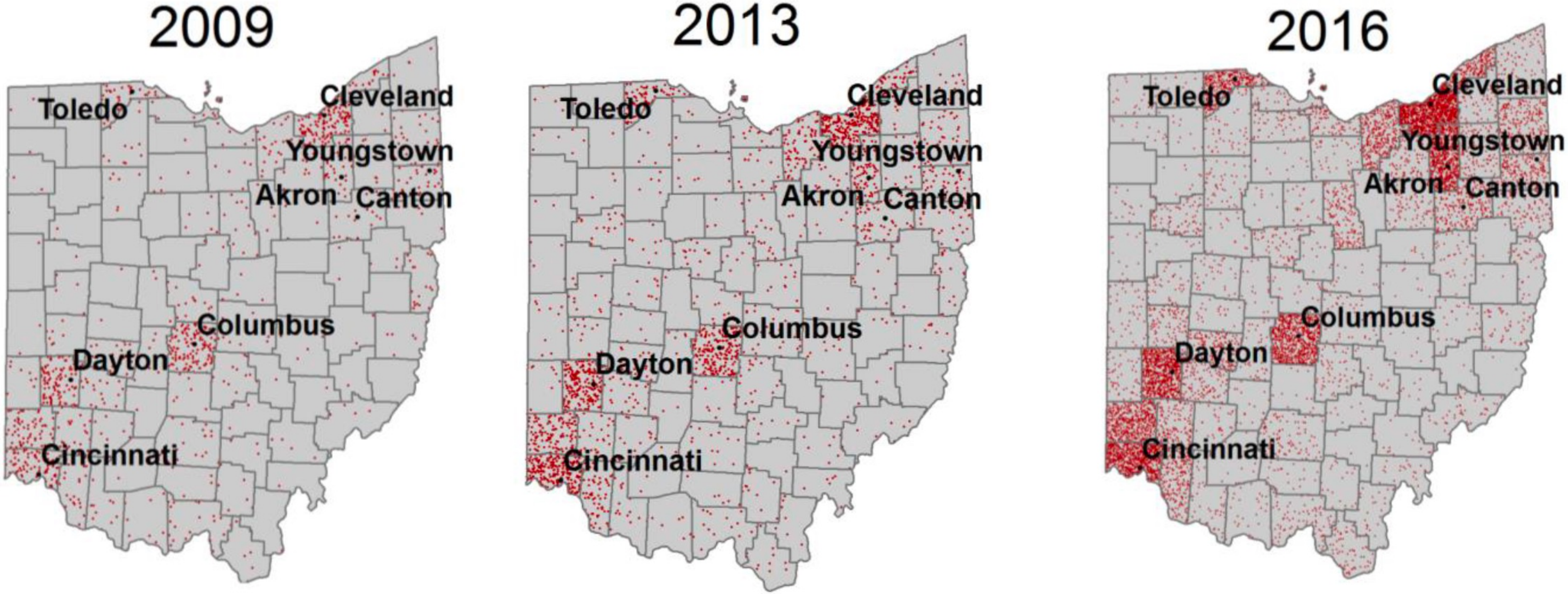


Figure C1. Age-Adjusted County-Level Drug Mortality Rates, 2014-16

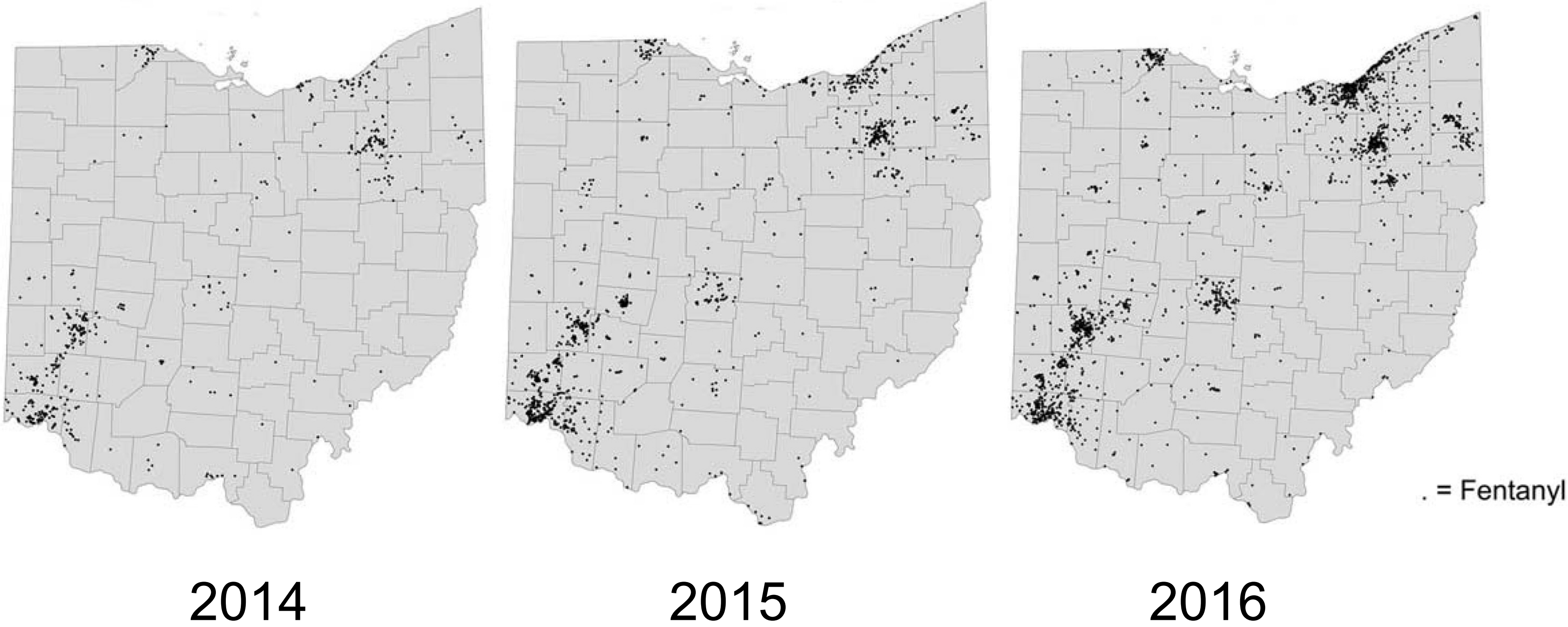
Trend in Overdose Mortality (2011-2017)



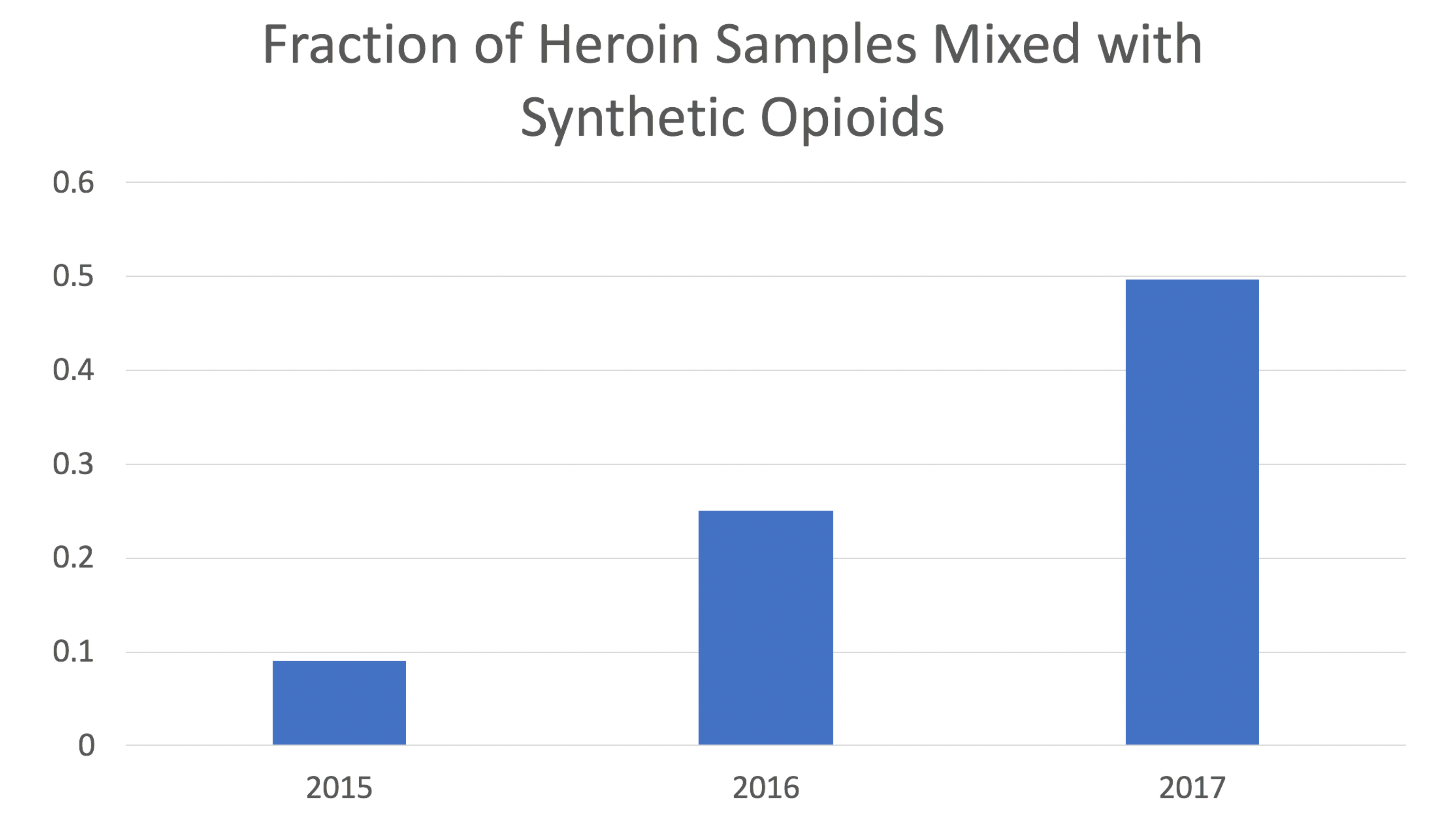
Source: CDC WONDER



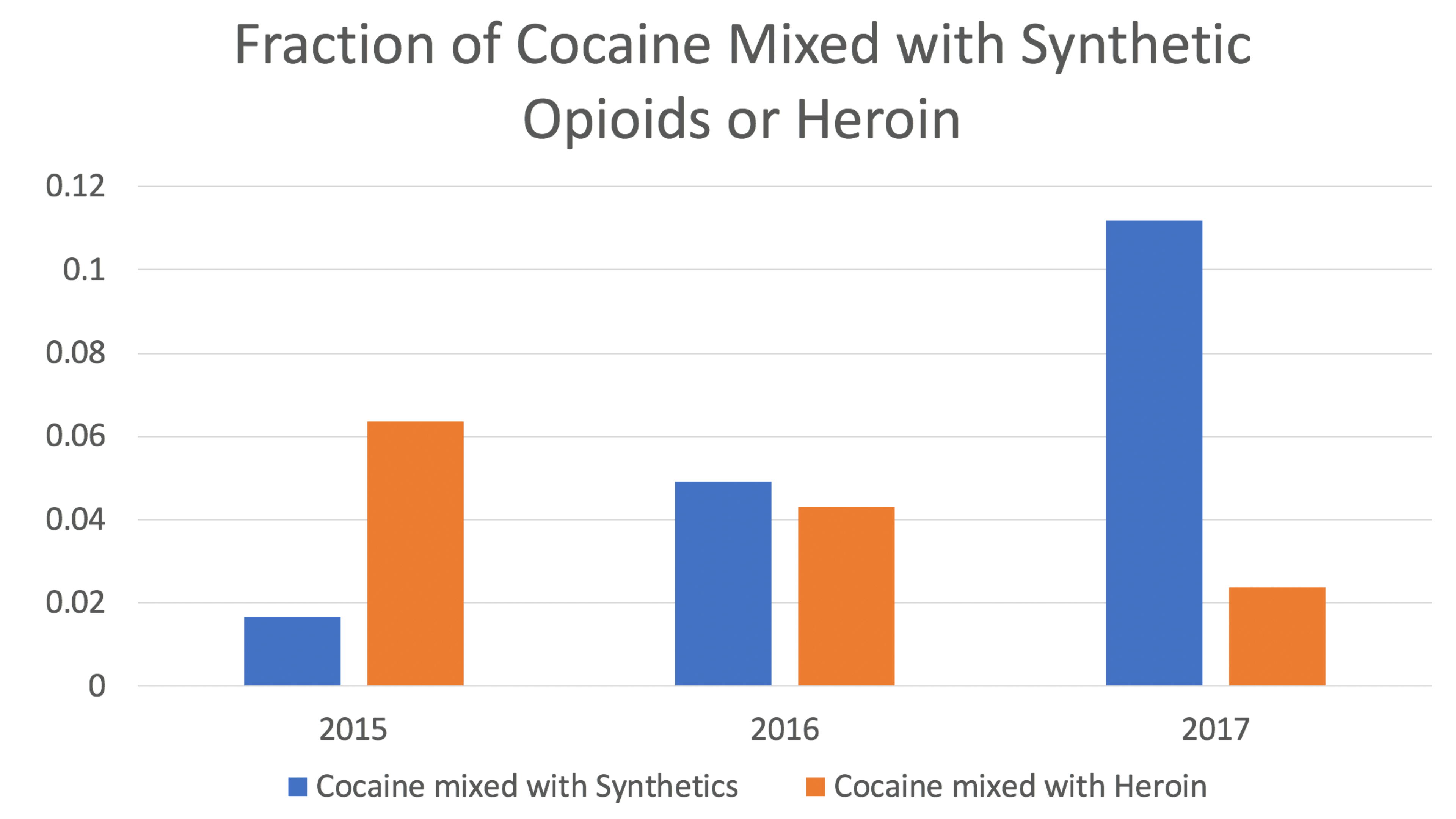
- One problem: death data is often delayed by a year or more.
- Coroners are sometimes wrong, and the CDC has to correct coroner data.
- Police data is immediate and can be an “early warning system”

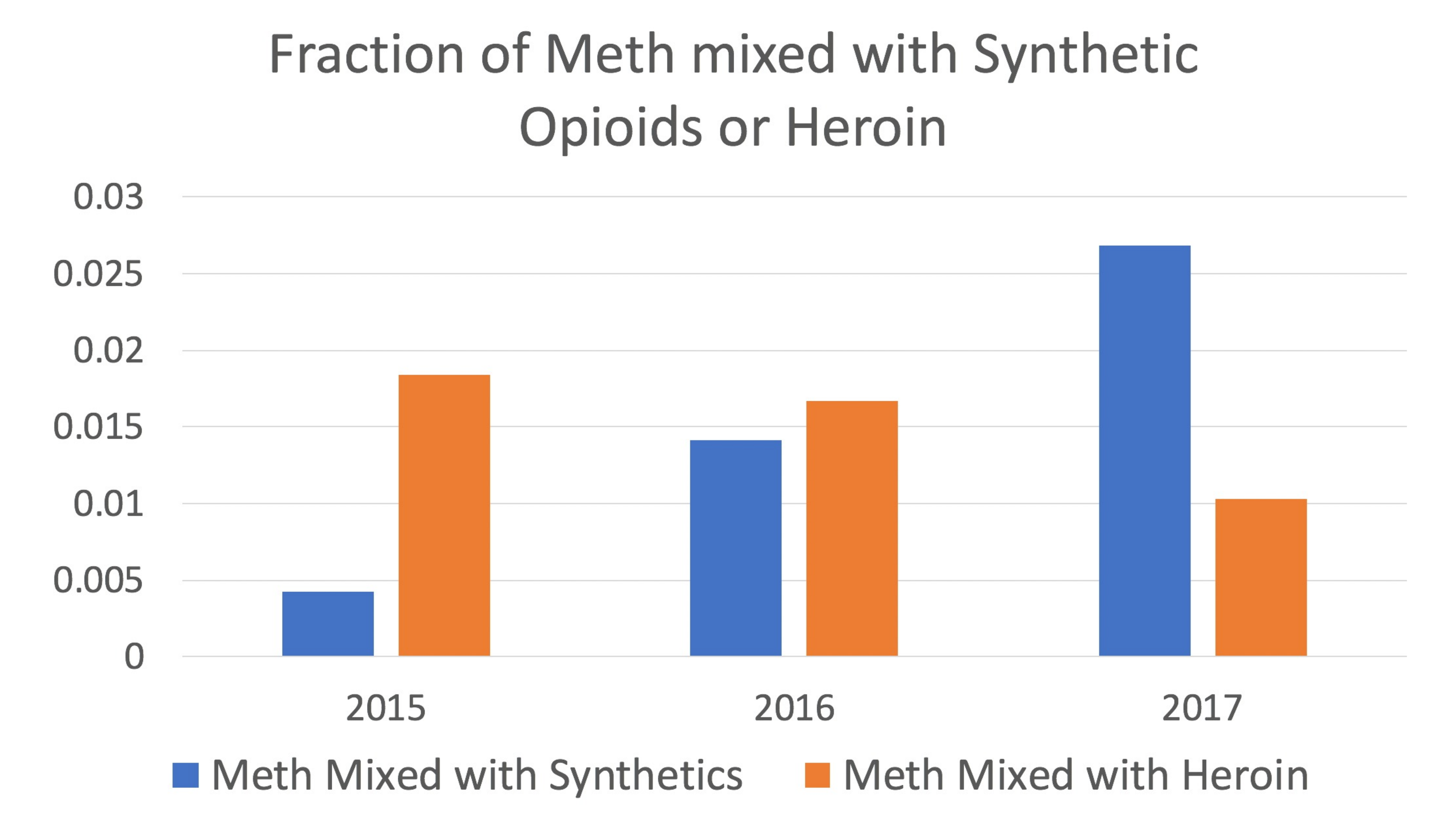


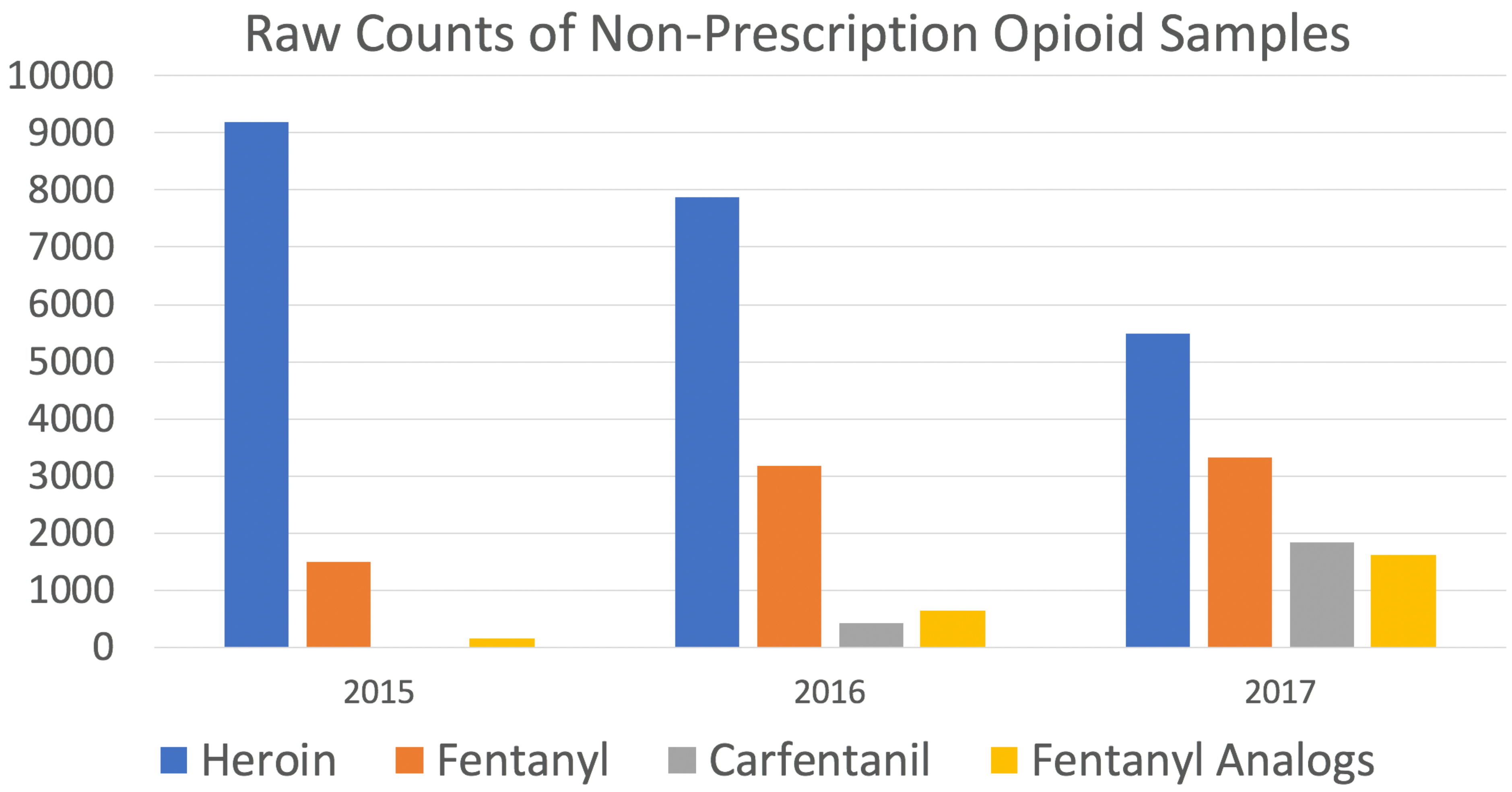
Deaths due to fentanyl are driving the increase in deaths.

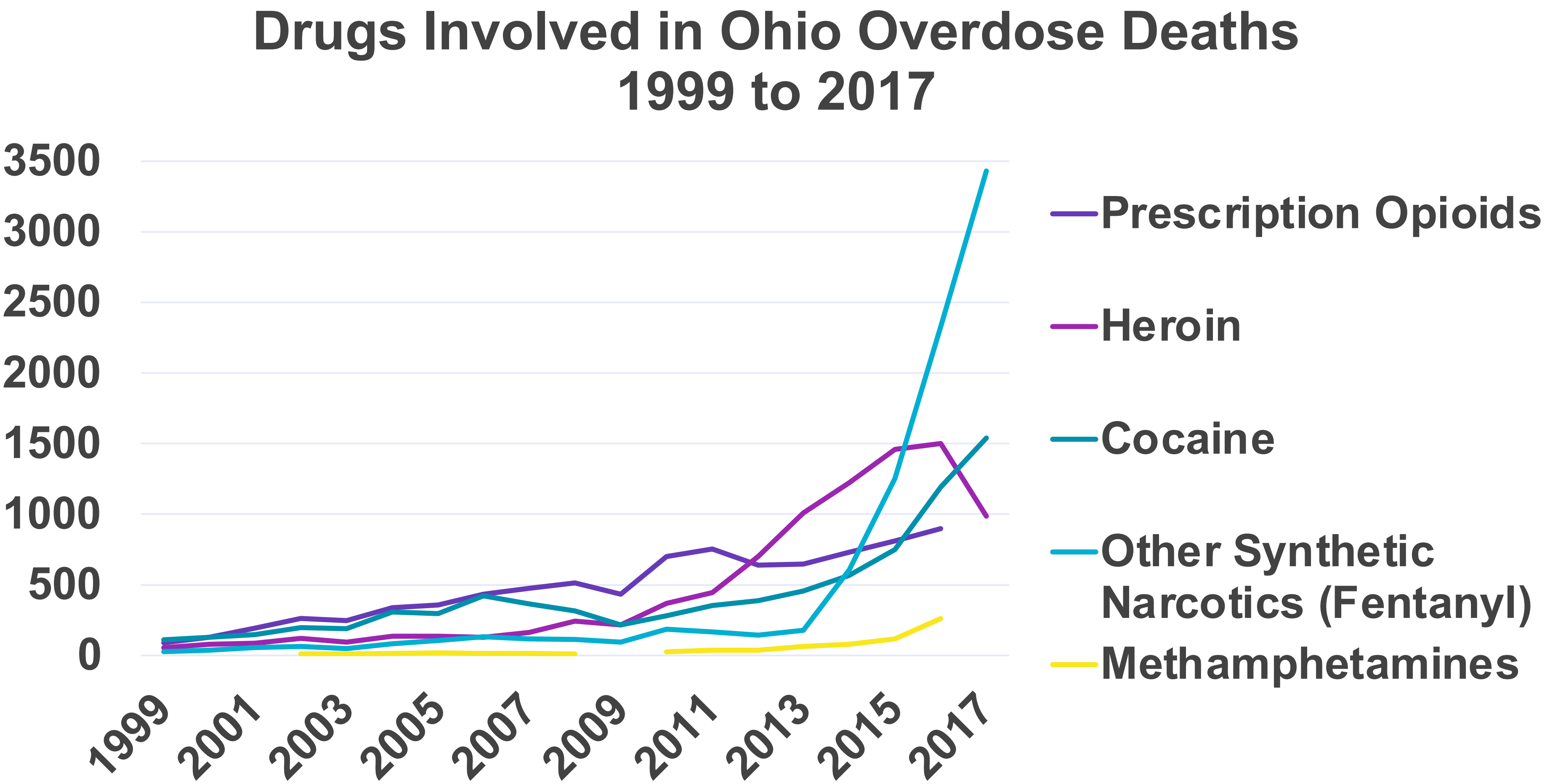


Fraction of Heroin Samples Mixed with Synthetic Opioids
0.6
0.5
0.4
0.3
0.2
0.1
0
2015
2016
2017

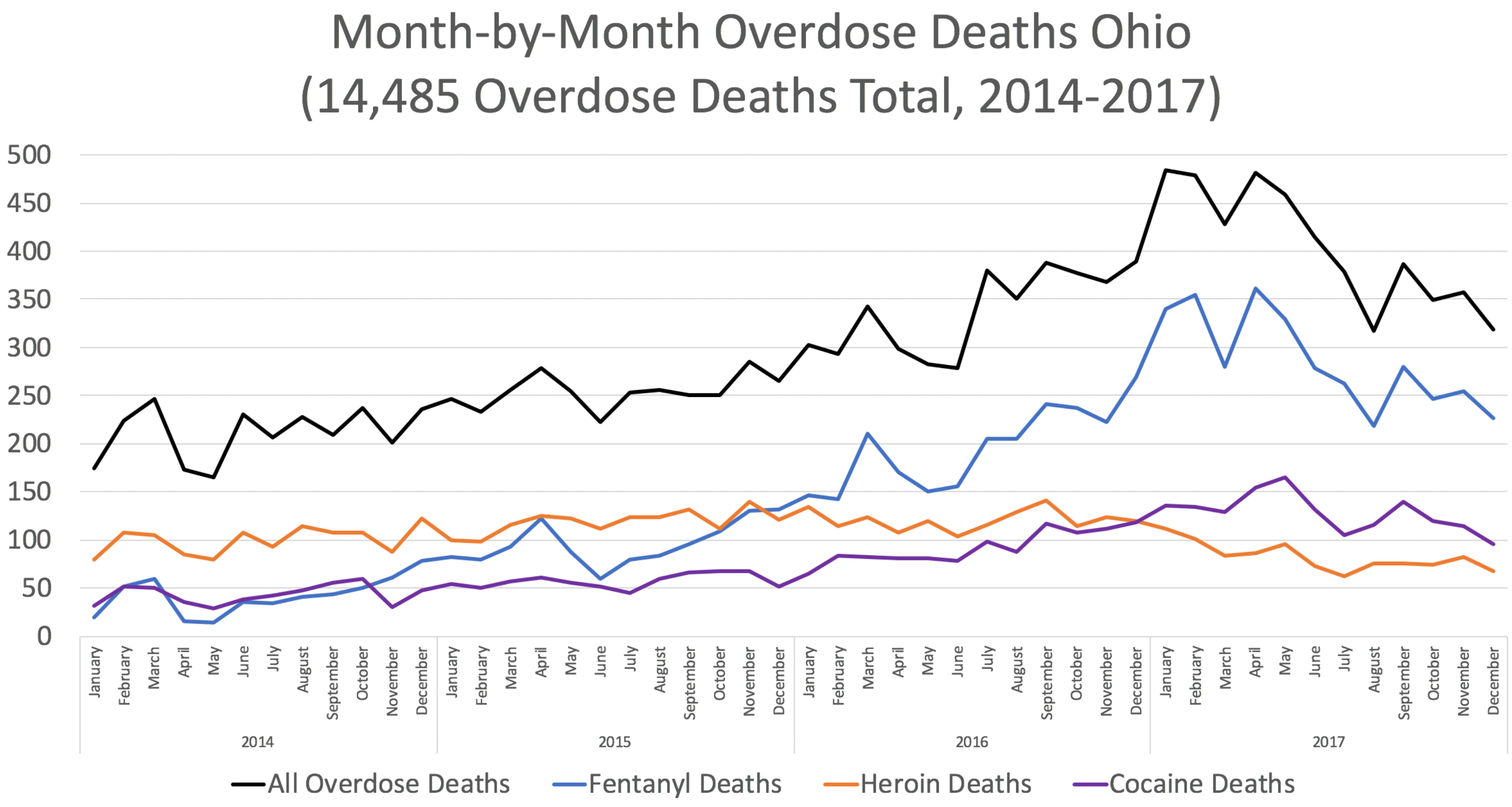

Fraction of Cocaine Mixed with Synthetic Opioids or Heroin
0.12
0.1
0.08
0.06
0.04
0.02
0
2015
2016
2017
Cocaine mixed with Synthetics
Cocaine mixed with Heroin

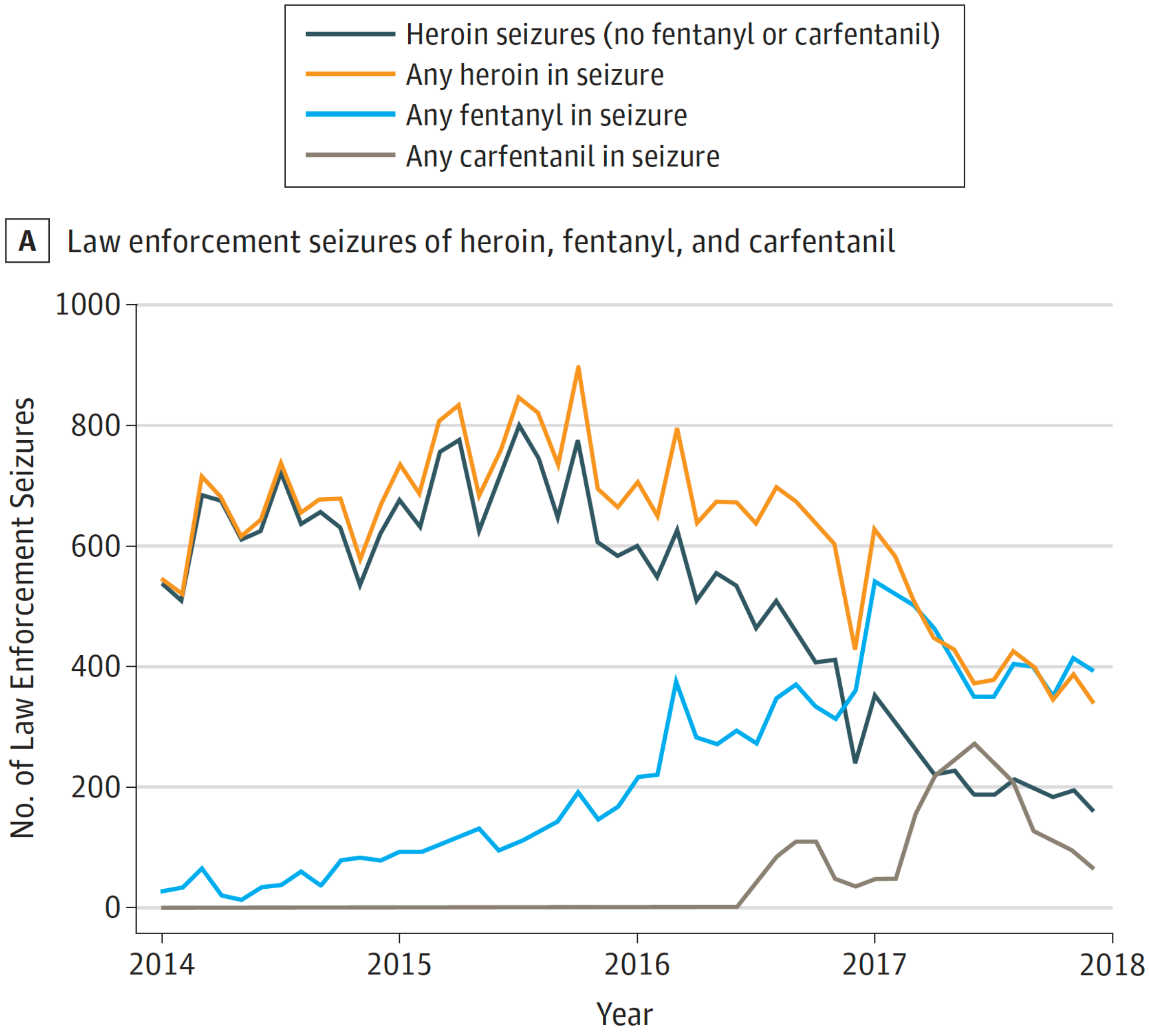

Fraction of Meth mixed with Synthetic Opioids or Heroin
0.03
0.025
0.02
0.015
0.01
0.005
0
2015
2016
2017
Meth Mixed with Synthetics
Meth Mixed with Heroin


Raw Counts of Non-Prescription Opioid Samples
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
2015
2016
2017
Heroin
Fentanyl
Carfentanil
Fentanyl Analogs



Drugs Involved in Ohio Overdose Deaths
1999 to 2017
3500
3000
2500
2000
1500
1000
500
0
1999
2001
2003
2005
2007
2009
2011
2013
2015
2017
Prescription Opioids
Heroin
Cocaine
Other Synthetic Narcotics (Fentanyl)
Methamphetamines


Month-by-Month Overdose Deaths Ohio
(14,485 Overdose Deaths Total, 2014-2017)
500
450
400
350
300
250
200
150
100
50
0
January
February
March
April
May
June
July
August
September
October
November
December
2014
2015
2016
2017
All Overdose Deaths
Fentanyl Deaths
Heroin Deaths
Cocaine Deaths


Heroin seizures (no fentanyl or carfentanil)
Any heroin in seizure
Any fentanyl in seizure
Any carfentanil in seizure
A
Law enforcement seizures of heroin, fentanyl, and carfentanil
1000
800
600
400
200
0
No. of Law Enforcement Seizures
2014
2015
2016
2017
2018
Year

Fentanyl adulteration of cocaine, by seizure size, Ohio, 2018

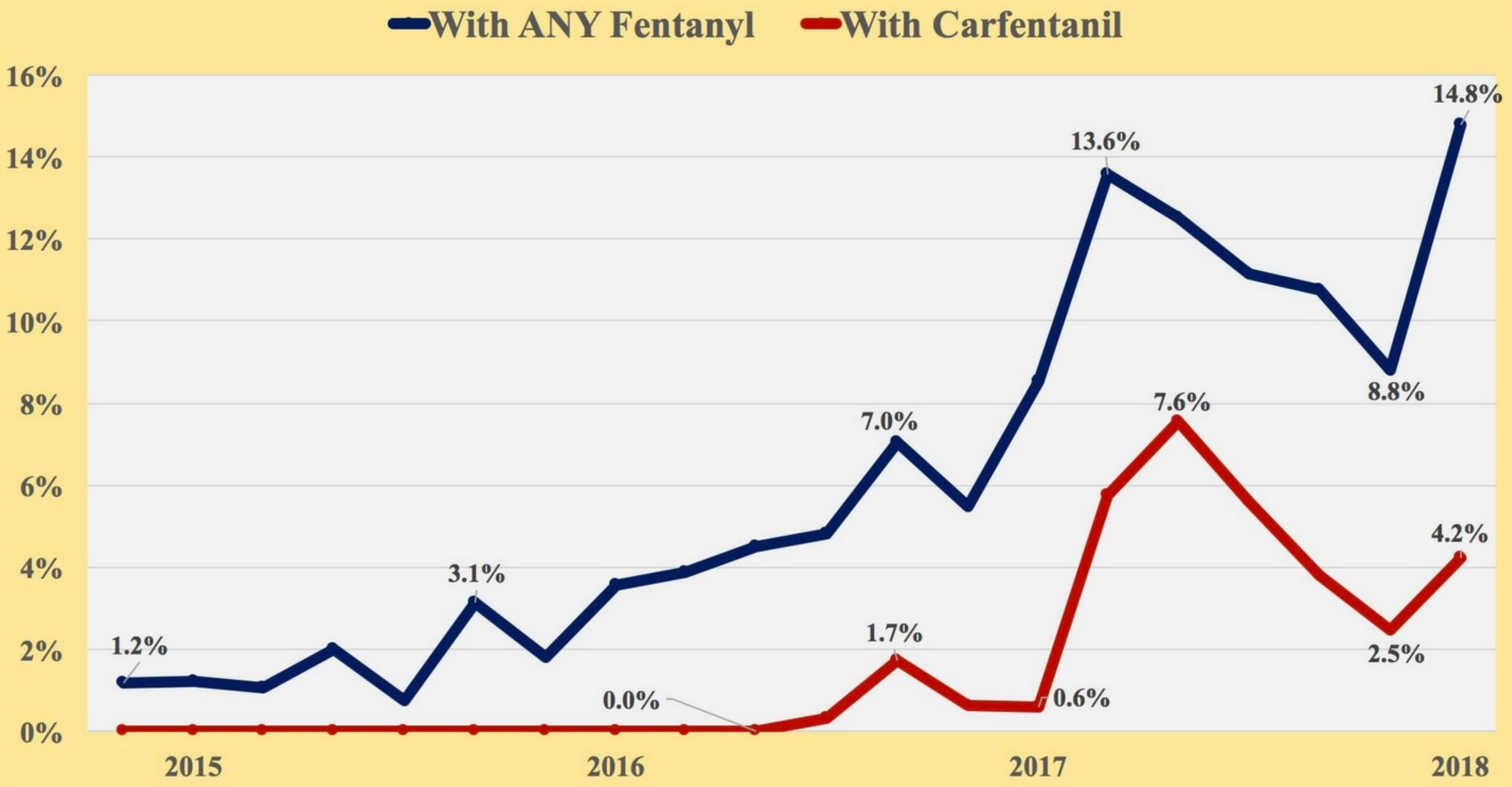
Size of seizure, net weight	Cocaine seizures	Fentanyl found	% cocaine with fentanyl
Above 100 grams	68	0	0.0%
50-100 grams	44	2	4.5%
20-50 grams	139	5	3.6%
10-20 grams	172	5	2.9%
5-10 grams	240	6	2.5%
2-5 grams	475	21	4.4%
1-2 grams	456	22	4.8%
.5-1 gram	693	52	7.5%
0.25-.49	848	58	6.8%
0.1-0.24	838	85	10.1%
< 0.1 gram	790	111	14.1%

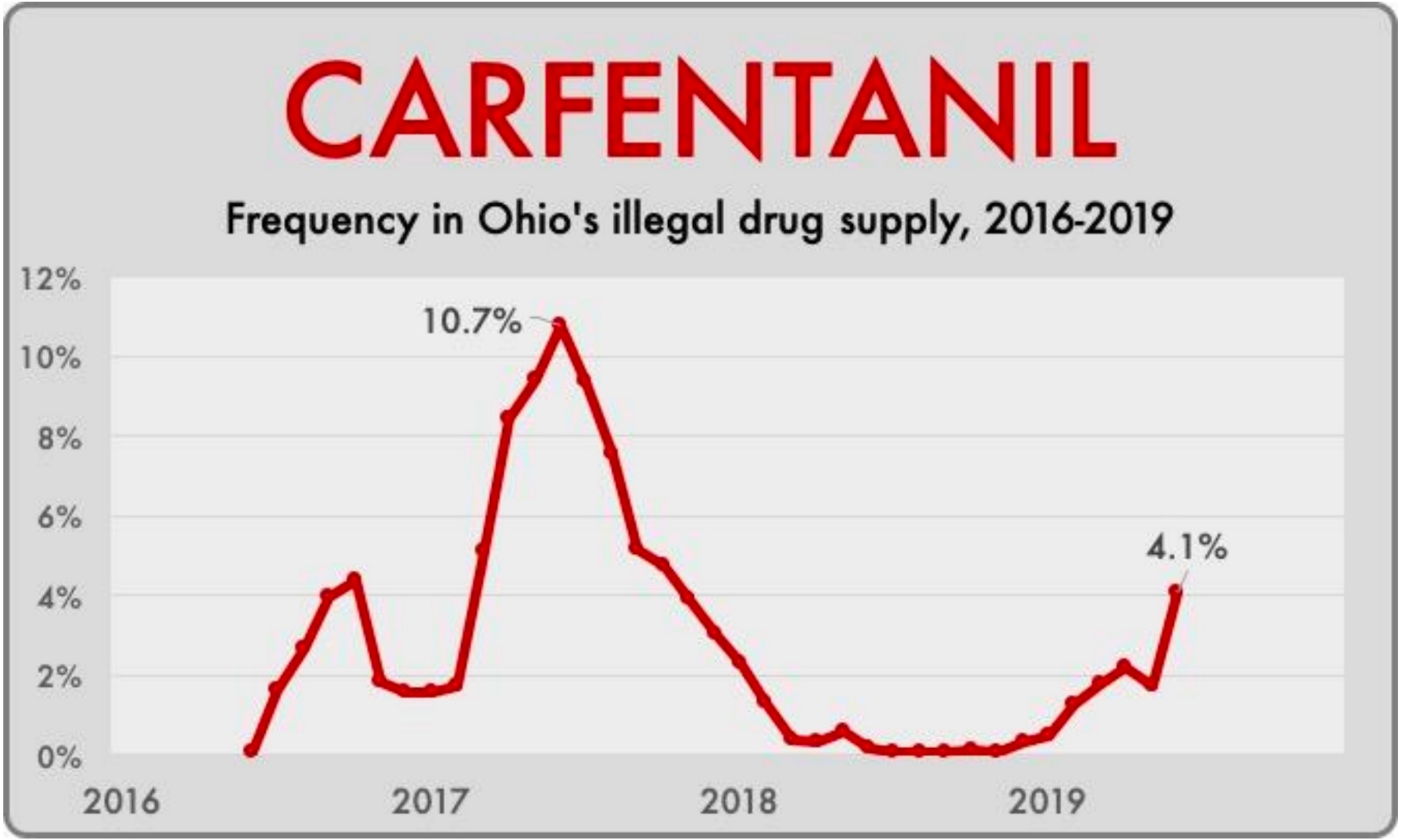
Note: Fentanyl includes fentanyl analogs.

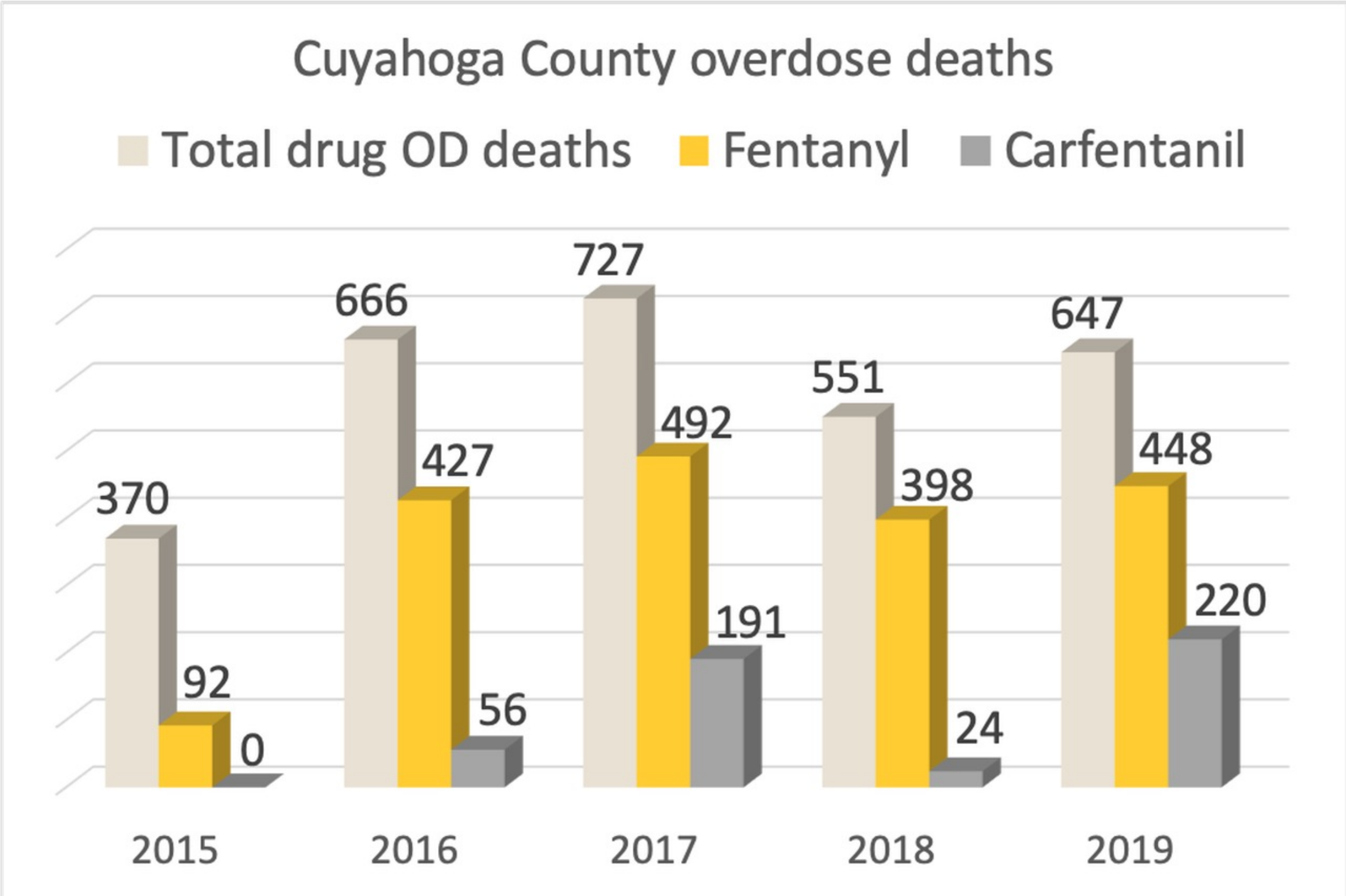
Fentanyl-laced cocaine in Ohio, by year

	Cocaine-fentanyl	Cocaine-carfentanil
2014	0.7%	0.0%
2015	1.7%	0.0%
2016	4.9%	0.5%
2017	11.3%	4.4%
2018	8.5%	0.5%

Carfentanil-laced cocaine




CARFENTANIL
Frequency in Ohio's illegal drug supply, 2016-2019
12%
10%
8%
6%
4%
2%
0%
10.7%
4.1%
2016
2017
2018
2019


Cuyahoga County overdose deaths
Total drug OD deaths
Fentanyl
Carfentanil
370
92
0
666
427
56
727
492
191
551
398
24
647
448
220
2015
2016
2017
2018
2019