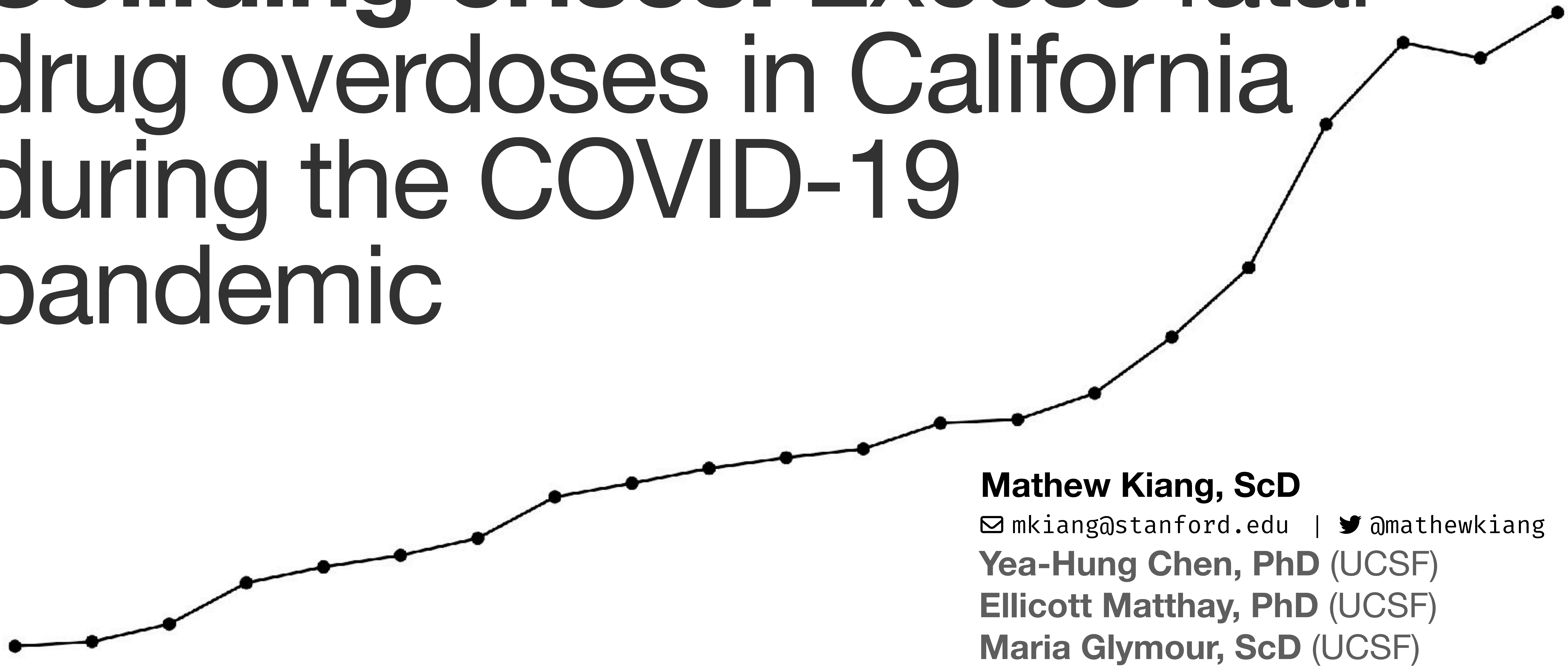
Colliding crises: Excess fatal drug overdoses in California during the COVID-19 pandemic



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Over 51,000 opioid-related deaths in 2019

Prescription opioids: 1990's - 2010

Heroin: 2010 - 2016

Synthetic opioids: 2013 - current

A “Triple Wave” Epidemic

Cumulative opioid deaths

Cumulative opioid and COVID-19 deaths

What happened in 2020?

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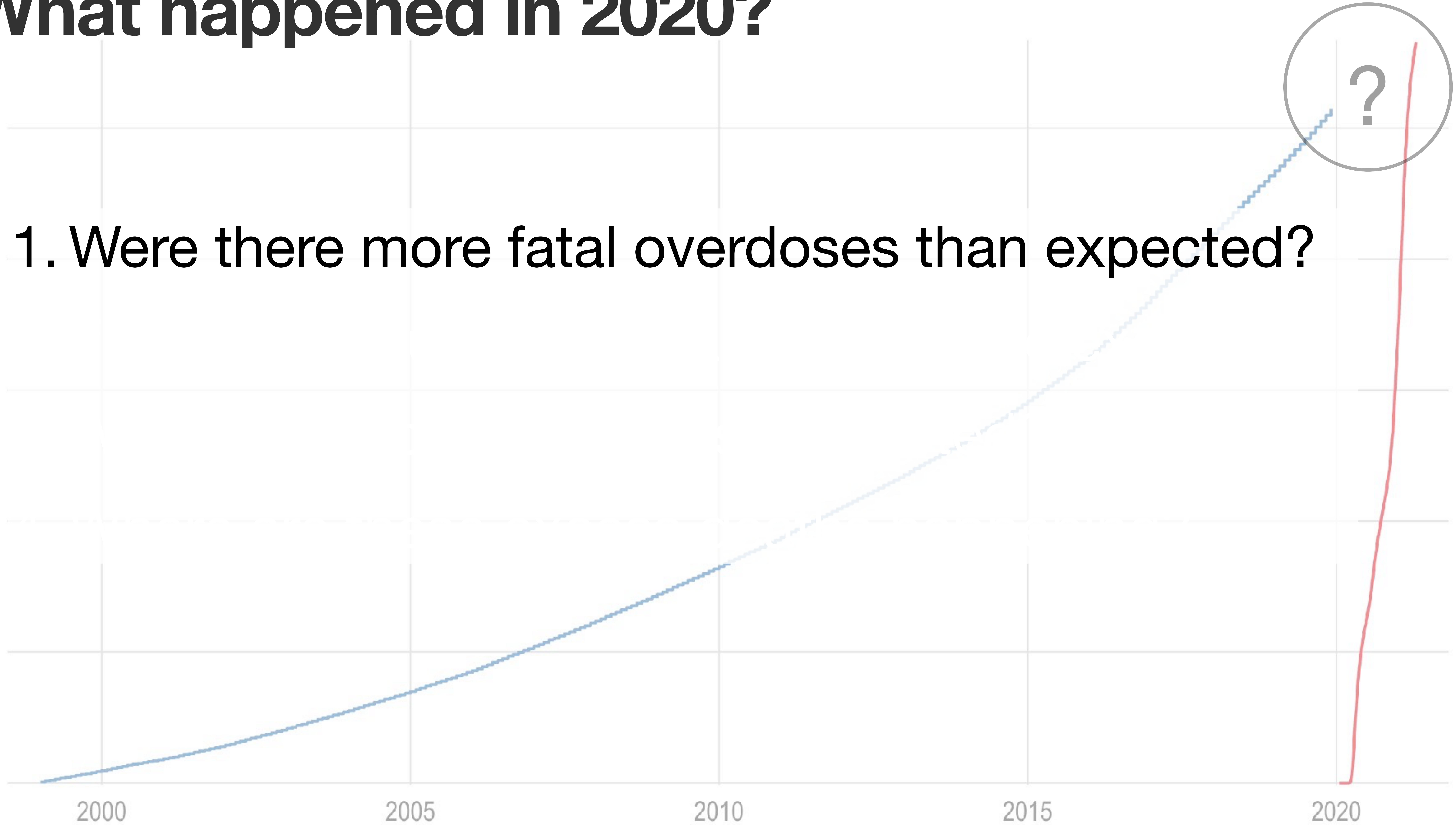

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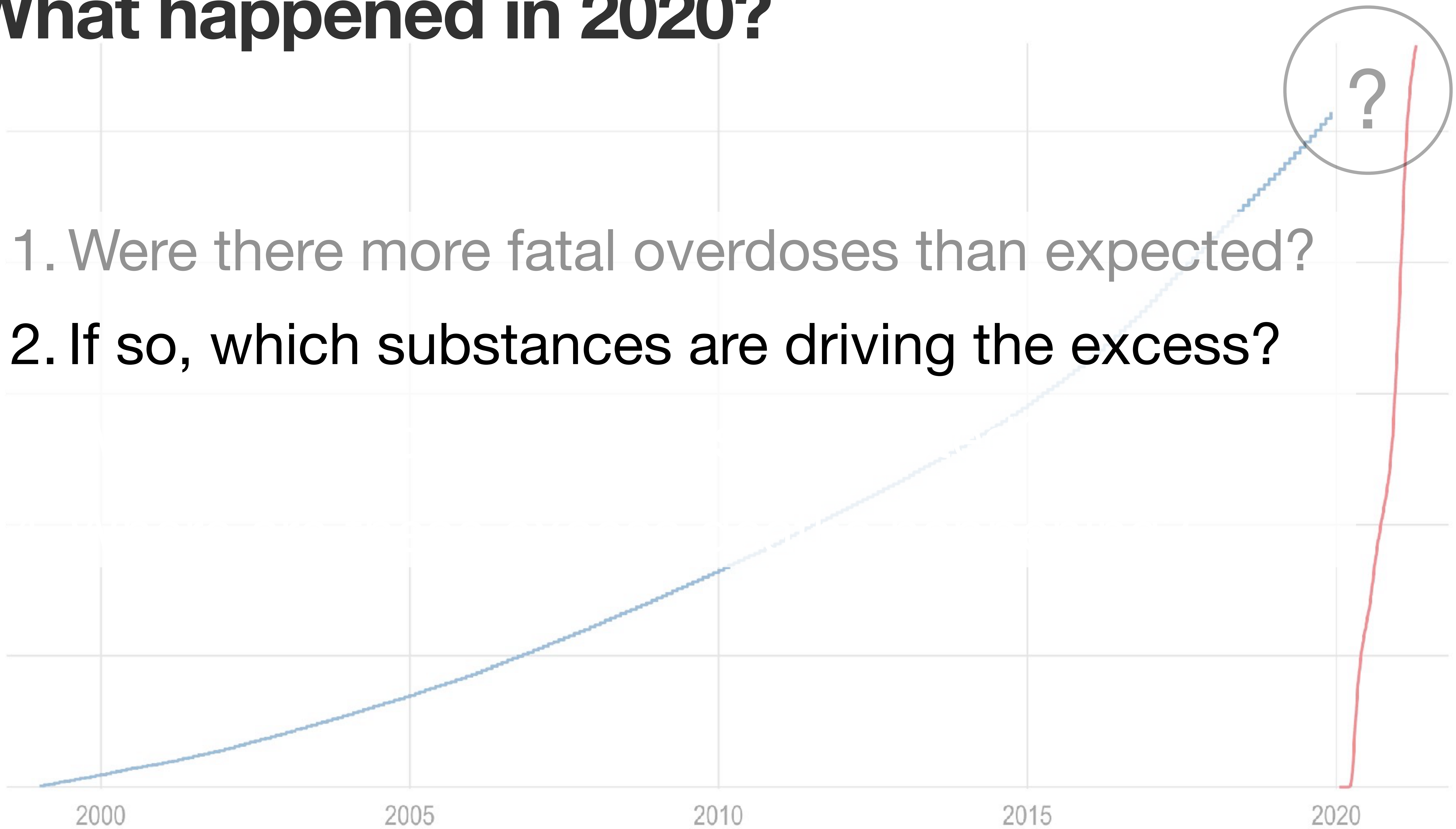
2. If so, which substances are driving the excess?



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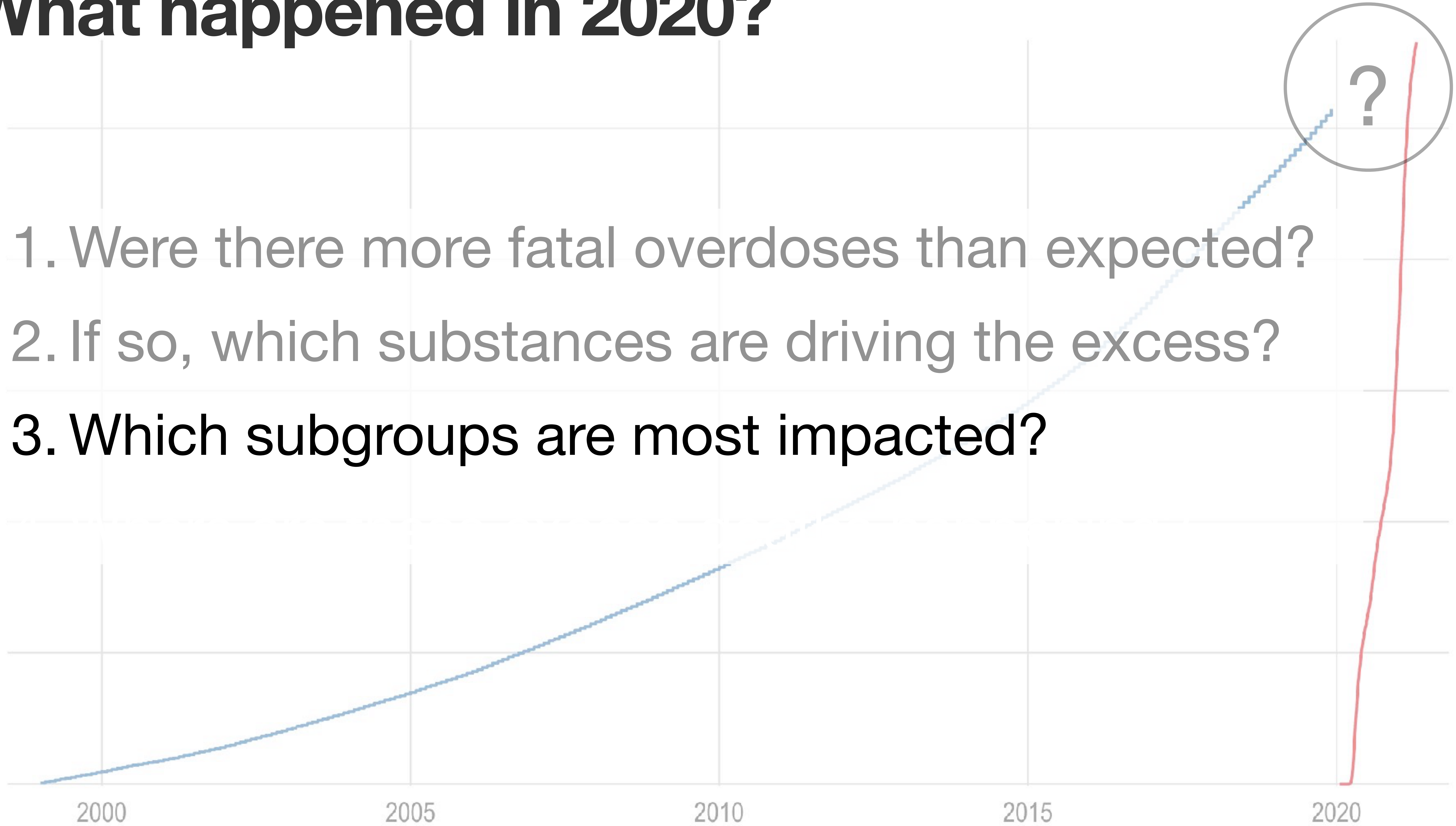
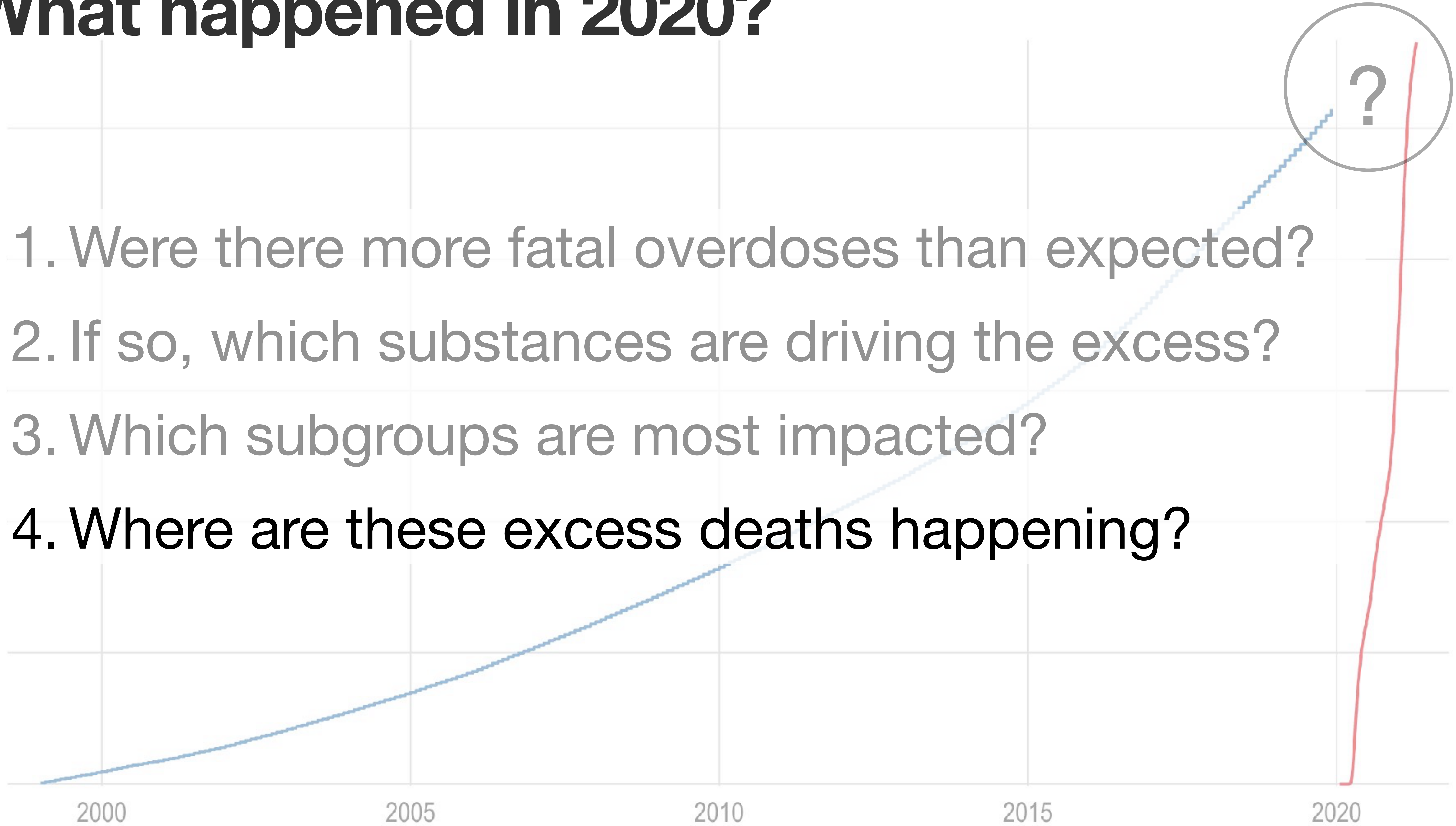


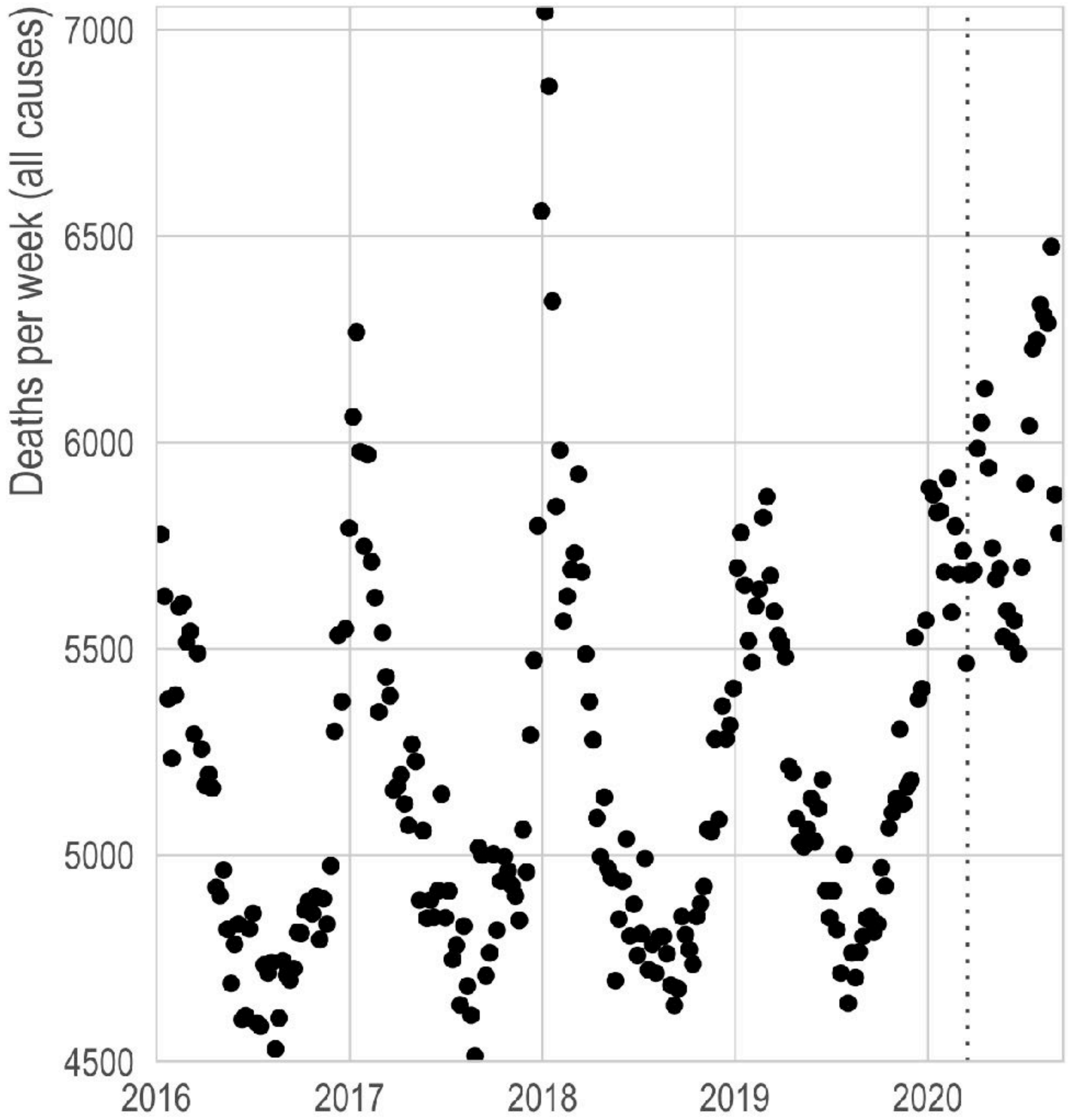
What happened in 2020?



1. Were there more fatal overdoses than expected?
2. If so, which substances are driving the excess?
3. Which subgroups are most impacted?
4. Where are these excess deaths happening?

Data – Description

- All death certificates in California from Jan 1, 2016 to Dec 31, 2020 (N ~ 1.3 million)
- Population estimates from US Census Bureau public use microdata



Methods – Creating a counterfactual model

$$Y_t|\epsilon_t \sim \text{Poisson}(\mu_t[1 + f(t)]\epsilon_t)$$
$$\mu_t = N_t \exp[\alpha(t) + s(t) + w(t)]$$

Details at: Acosta RJ, Irizarry RA, Monitoring Health Systems by Estimating Excess Mortality, Preprint on medRxiv, doi: 2020.06.06.20120857

Methods – Creating a counterfactual model

- Assume deaths per week are Poisson distributed

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Methods – Creating a counterfactual model

- Assume deaths per week are Poisson distributed
- The expected number of deaths at week *t* is a function of:

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Methods – Creating a counterfactual model

- Assume deaths per week are Poisson distributed
- The expected number of deaths at week *t* is a function of:
  - Population at risk at week *t*
  - Long-term trend

$$\boxed{Y_t} | \epsilon_t \sim \text{Poisson}(\boxed{\mu_t}[1 + f(t)]\epsilon_t)$$
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Methods – Creating a counterfactual model

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  - Long-term trend
  - Seasonal trend

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Methods – Creating a counterfactual model

- Assume deaths per week are Poisson distributed
- The expected number of deaths at week *t* is a function of:
  - Population at risk at week *t*
  - Long-term trend
  - Seasonal trend
  - Weekday effect (ignored)

$$\boxed{Y_t}|\epsilon_t \sim \text{Poisson}(\boxed{\mu_t}[1+f(t)]\epsilon_t)$$

$$\boxed{\mu_t} = \boxed{N_t}\exp[\boxed{\alpha(t)} + \boxed{s(t)} + \boxed{w(t)}]$$

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Methods – Creating a counterfactual model

- Assume deaths per week are Poisson distributed
- The expected number of deaths at week *t* is a function of:
  - Population at risk at week *t*
  - Long-term trend
  - Seasonal trend
  - Weekday effect
- An "event effect"

$$\boxed{Y_t} | \epsilon_t \sim \text{Poisson}\left(\boxed{\mu_t}\left[1 + \boxed{f(t)}\right]\epsilon_t\right)$$

$$\boxed{\mu_t} = \boxed{N_t} \exp\left[\boxed{\alpha(t)} + \boxed{s(t)} + \boxed{w(t)}\right]$$

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Constraining the model space

- Long-term trend:
  - Linear
  - Natural cubic spline with 1 to 2 (intraboundary) knots

$$Y_t|\epsilon_t \sim \text{Poisson}(\mu_t[1 + f(t)]\epsilon_t)$$
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Constraining the model space

- Long-term trend:
  - Linear
  - Natural cubic spline with 1 to 2 (intraboundary) knots
- Seasonal trend
  - 1 to 4 harmonics

$$Y_t|\epsilon_t \sim \text{Poisson}(\mu_t[1 + f(t)]\epsilon_t)$$
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Constraining the model space

- Long-term trend:
  - Linear
  - Natural cubic spline with 1 to 2 (intraboundary) knots
- Seasonal trend
  - 1 to 4 harmonics
- Use time-series cross validation to select the "best" model
- Repeat for every outcome and subpopulation

$$Y_t|\epsilon_t \sim \text{Poisson}(\mu_t[1 + f(t)]\epsilon_t)$$
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Model walk-through

All drug poisonings in California (2016-2019)

All drug poisonings in California (2016-2019)

All drug poisonings in California (2016-2019)

Select baseline model using TS-CV

Our baseline model

Long term trend

Seasonal trend

Predicted fatal drug overdoses in 2020

Observed fatal drug overdoses in 2020

Observed fatal drug overdoses in 2020

Focusing on 2020

Excess fatal drug overdoses per week

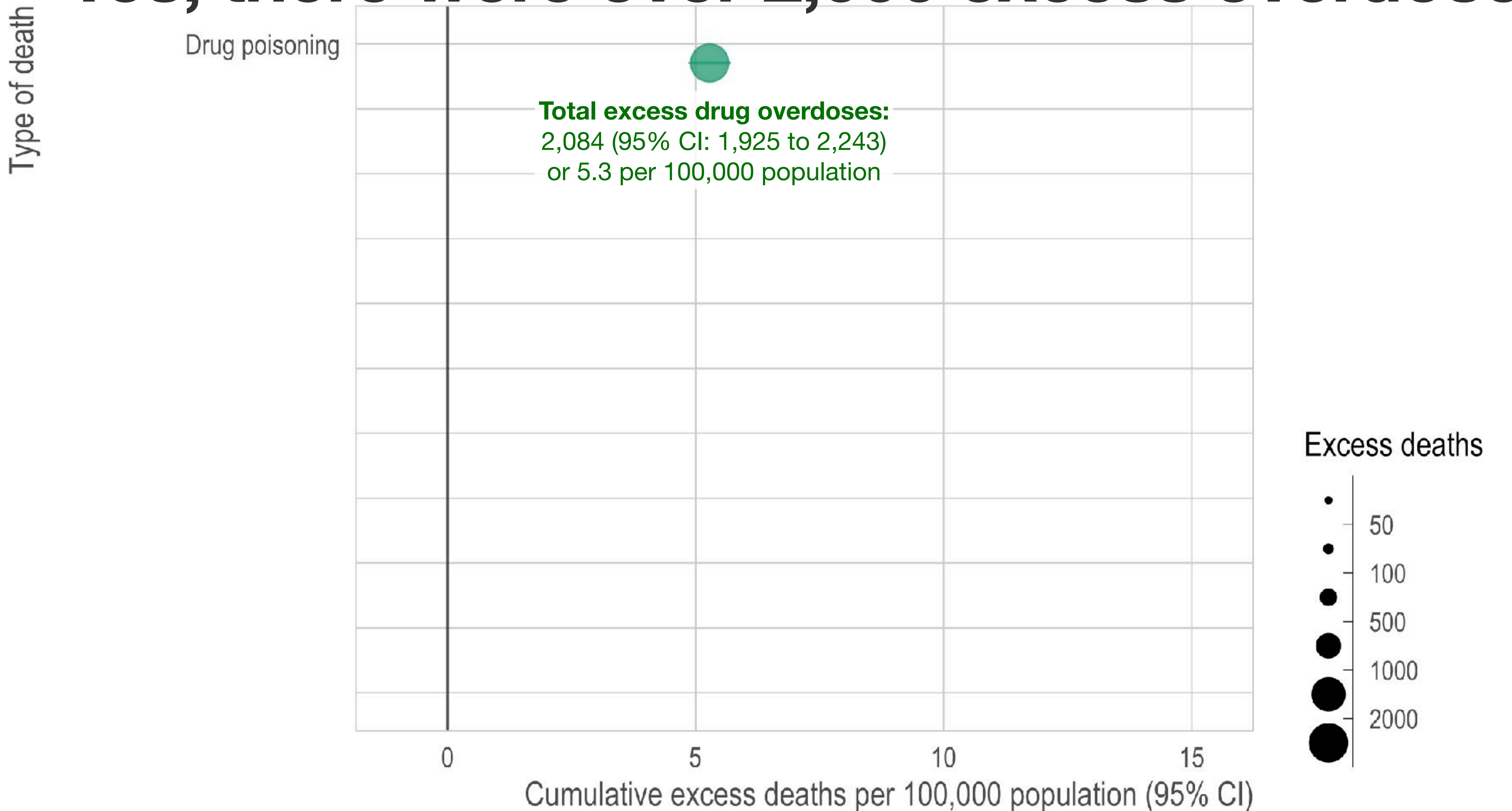
Cumulative excess fatal drug overdoses

Cumulative excess fatal drug overdoses

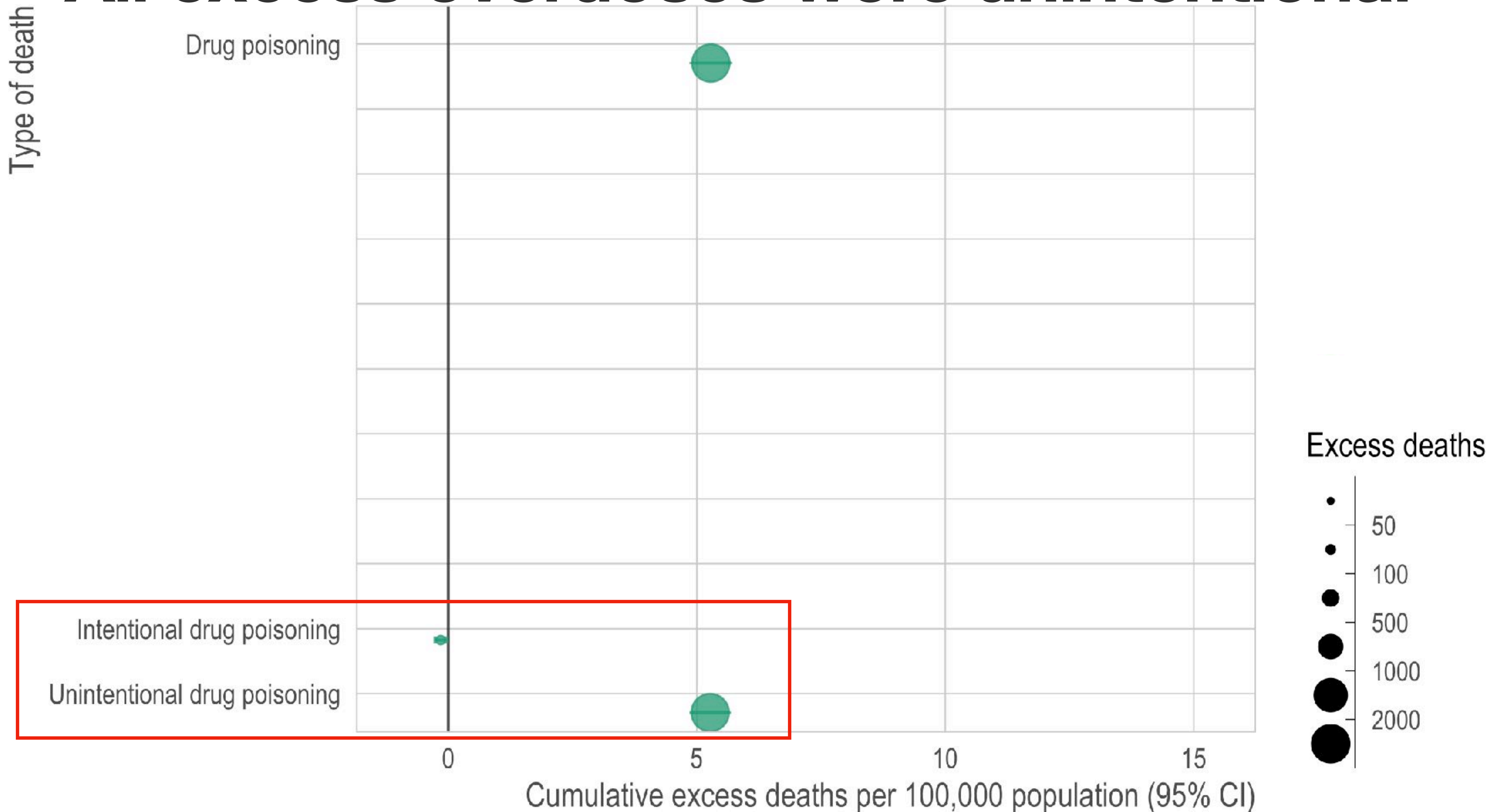
Results

1. Were there excess fatal overdoses?

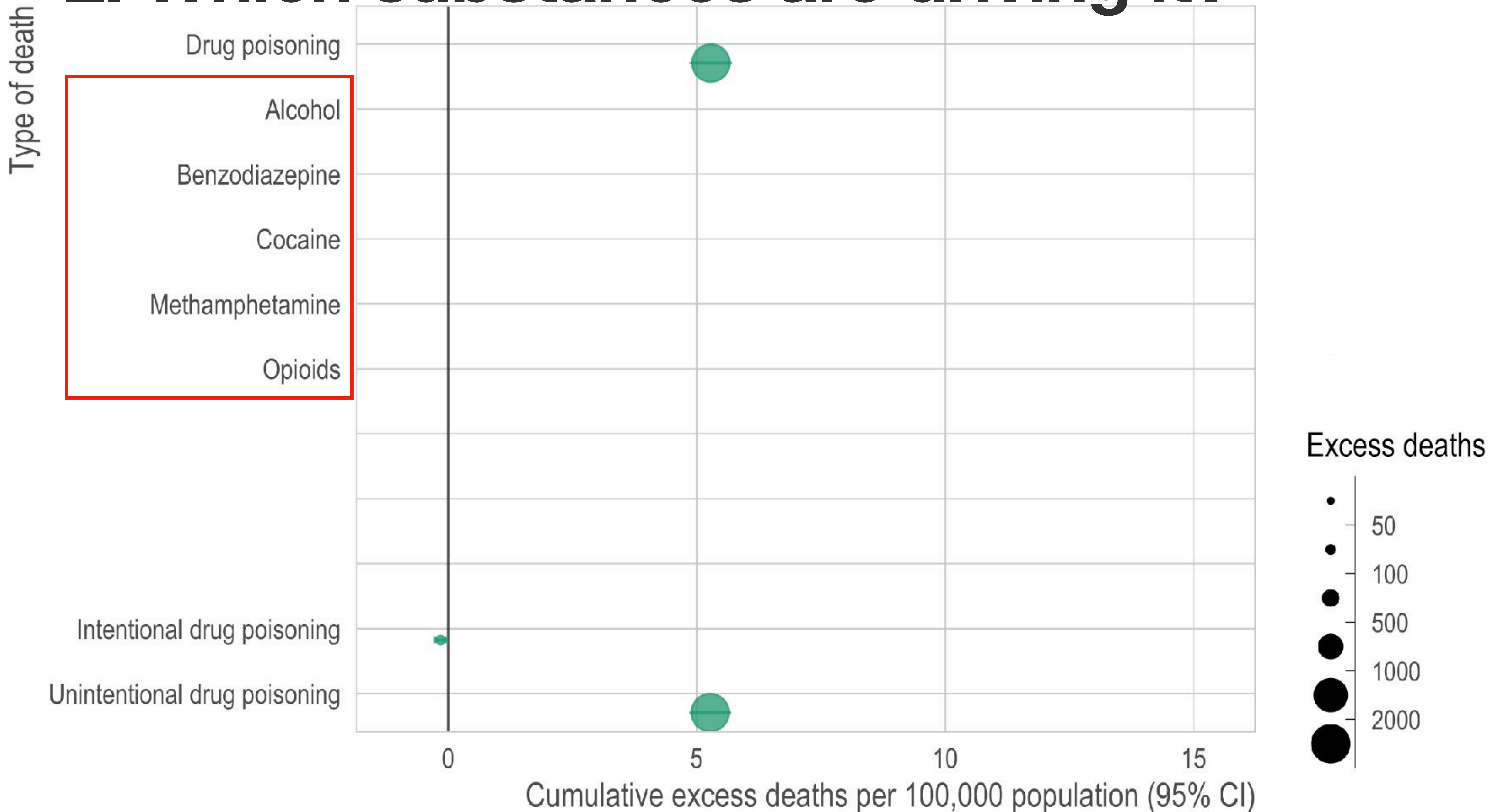
Yes, there were over 2,000 excess overdoses



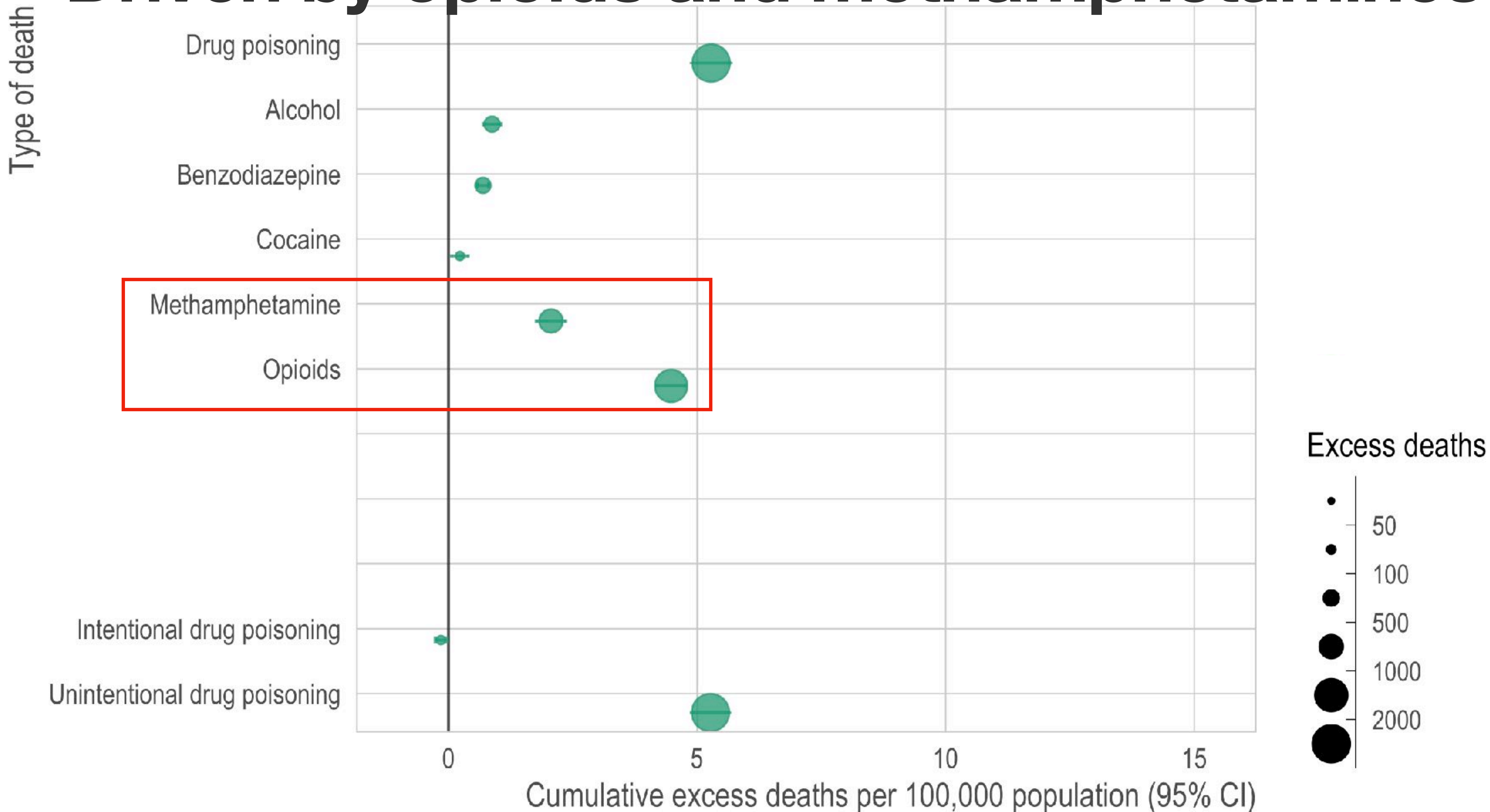
All excess overdoses were unintentional



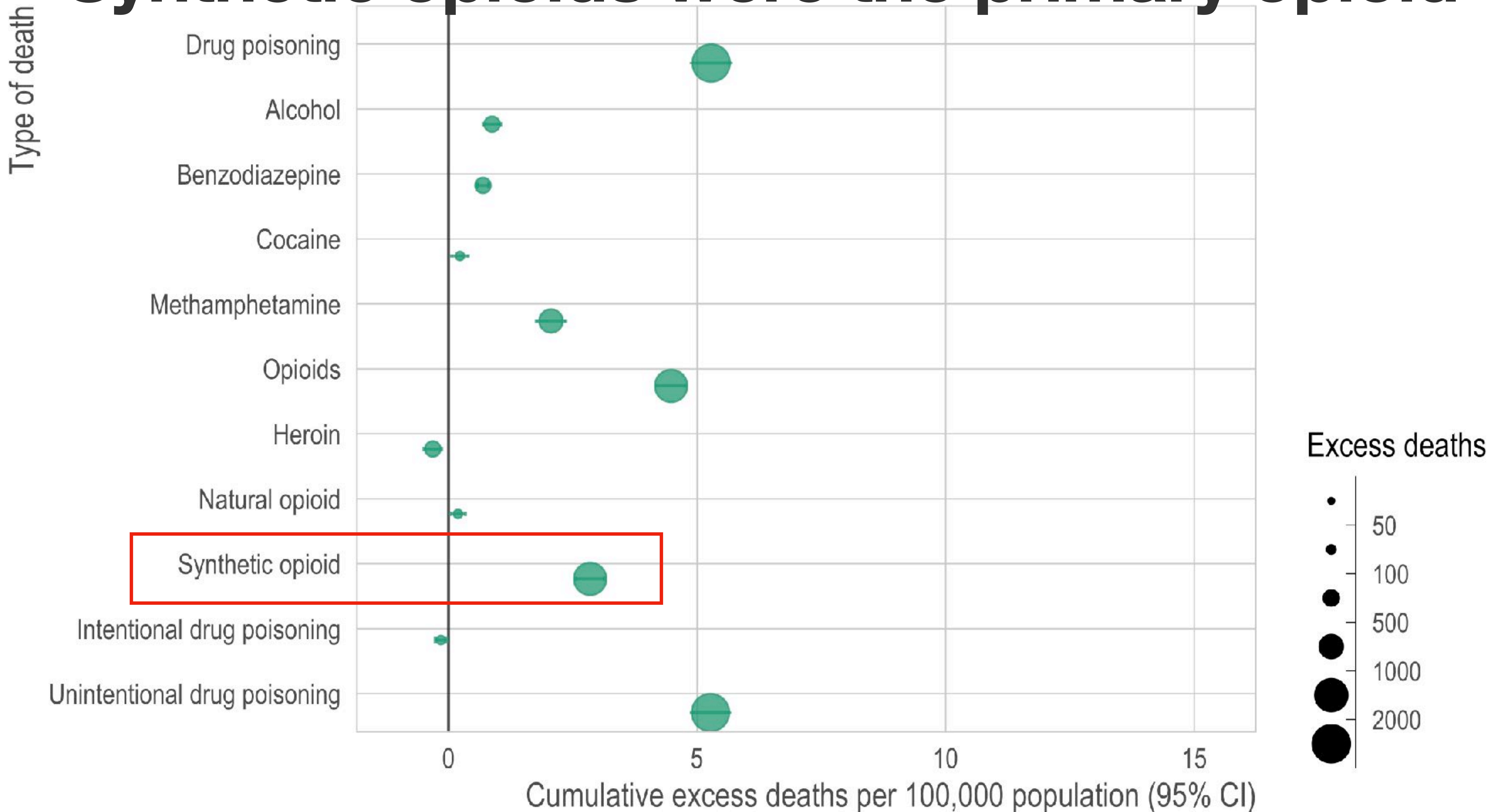
2. Which substances are driving it?



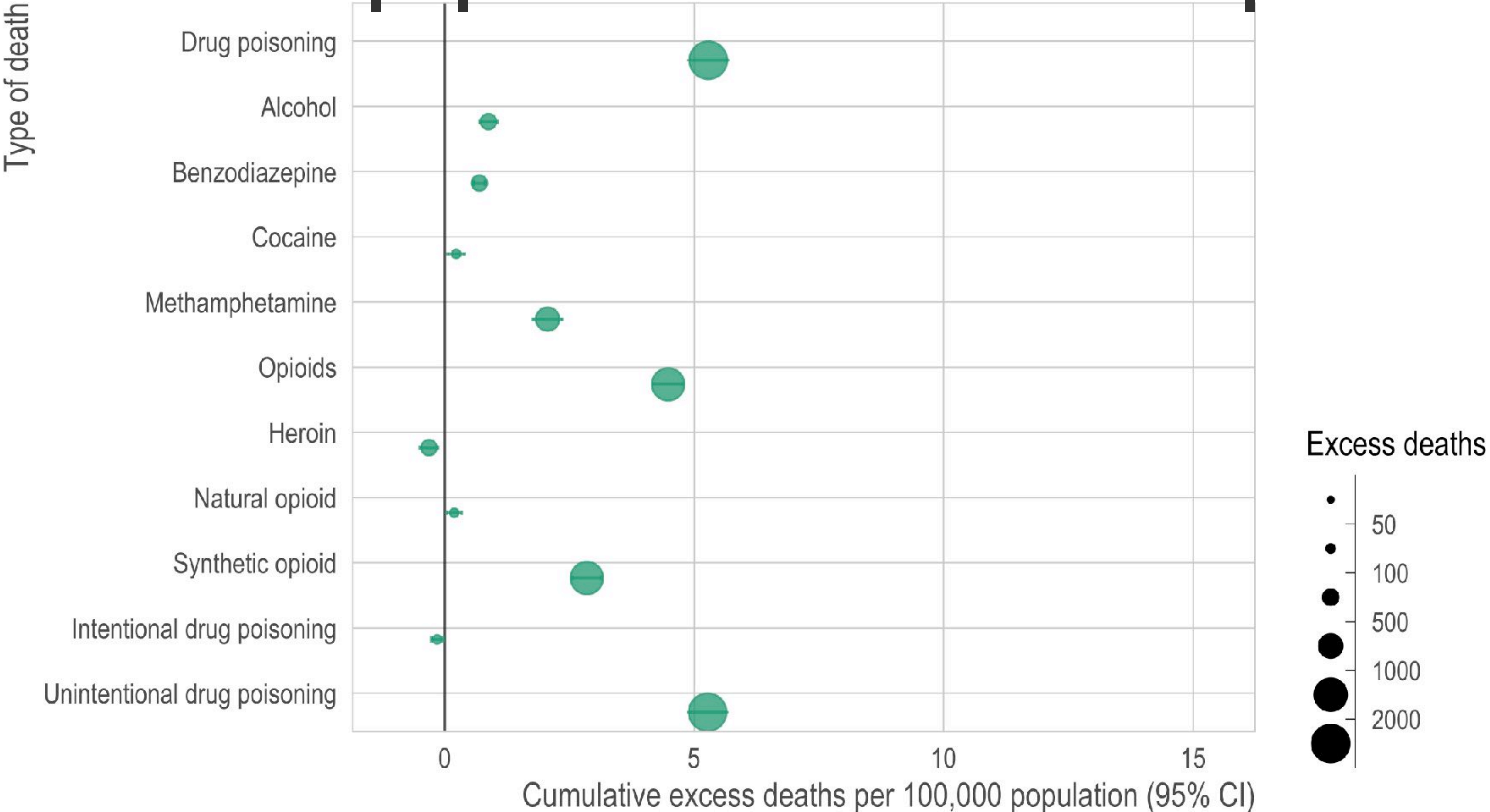
Driven by opioids and methamphetamines



Synthetic opioids were the primary opioid



3. Which populations were most impacted?



Disproportionate impact by race/ethnicity

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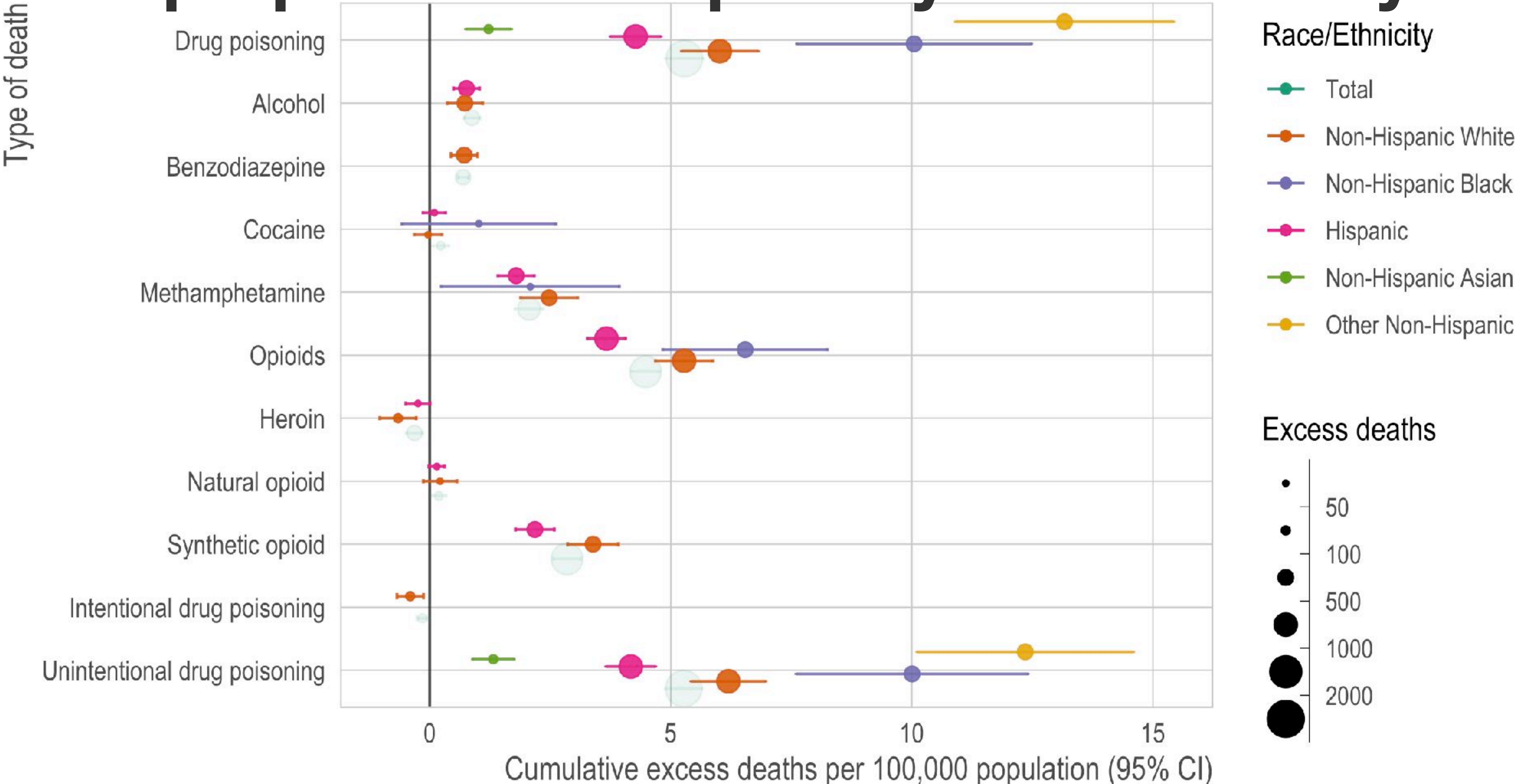

4. Where were these excess deaths?

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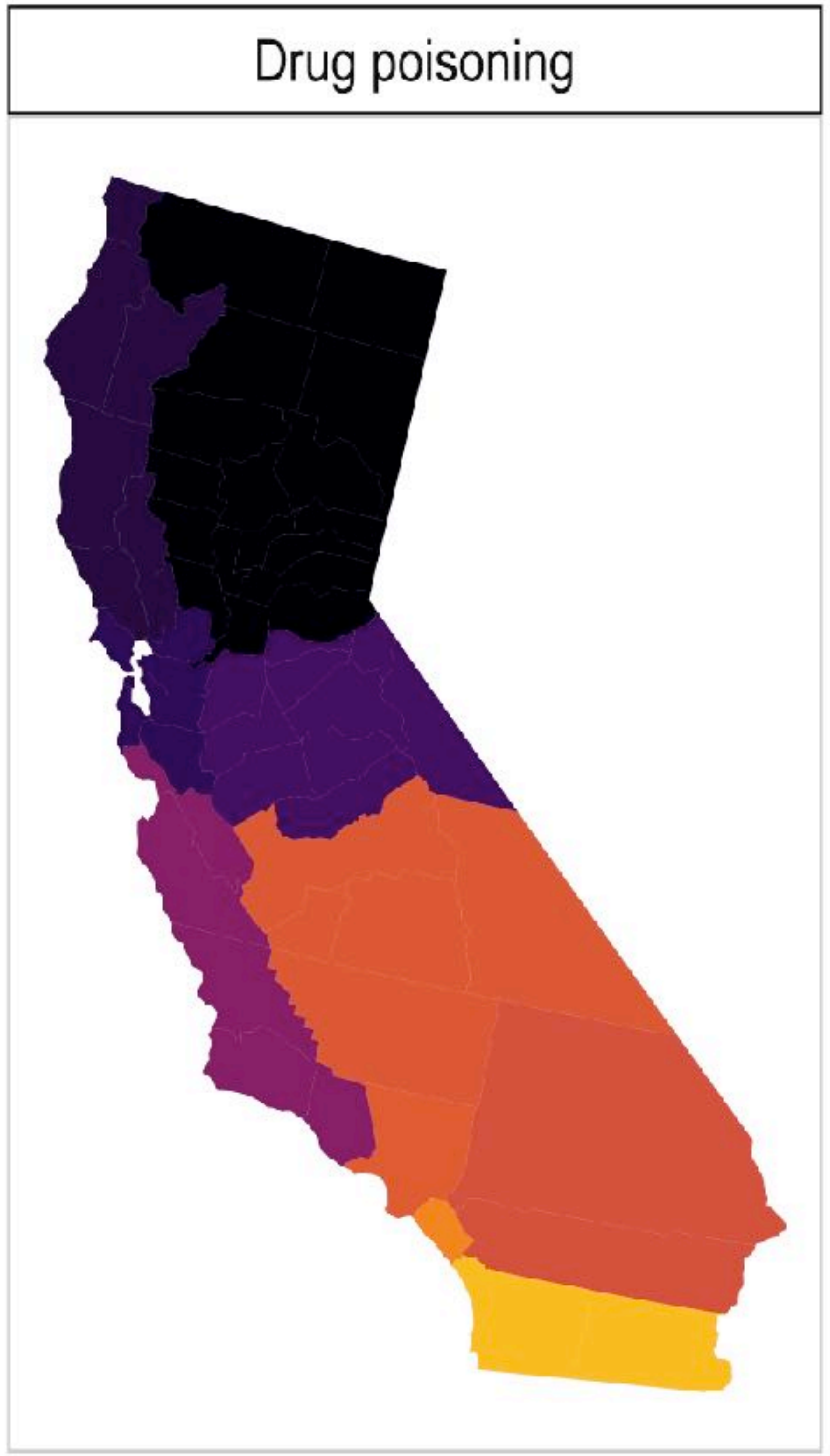
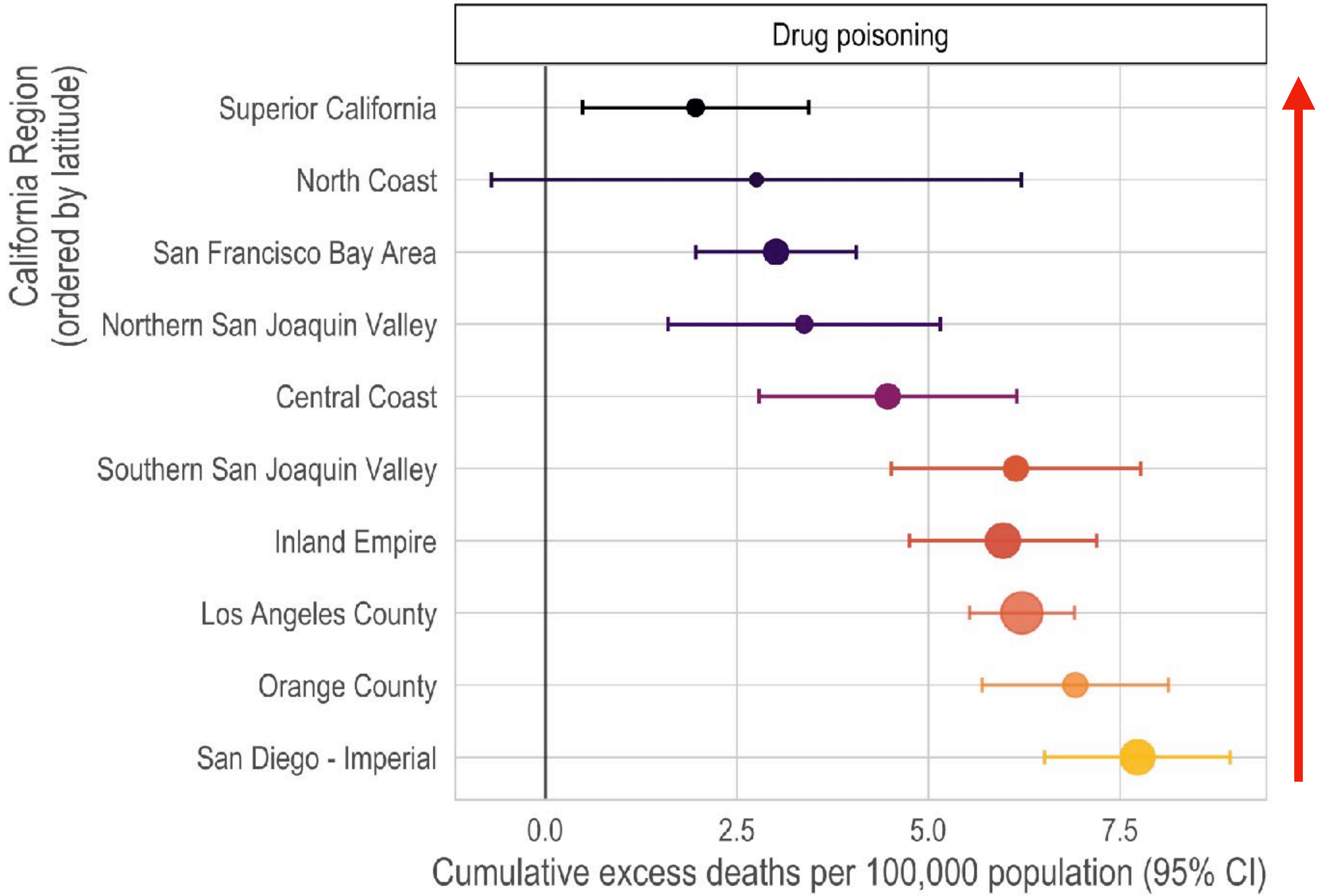
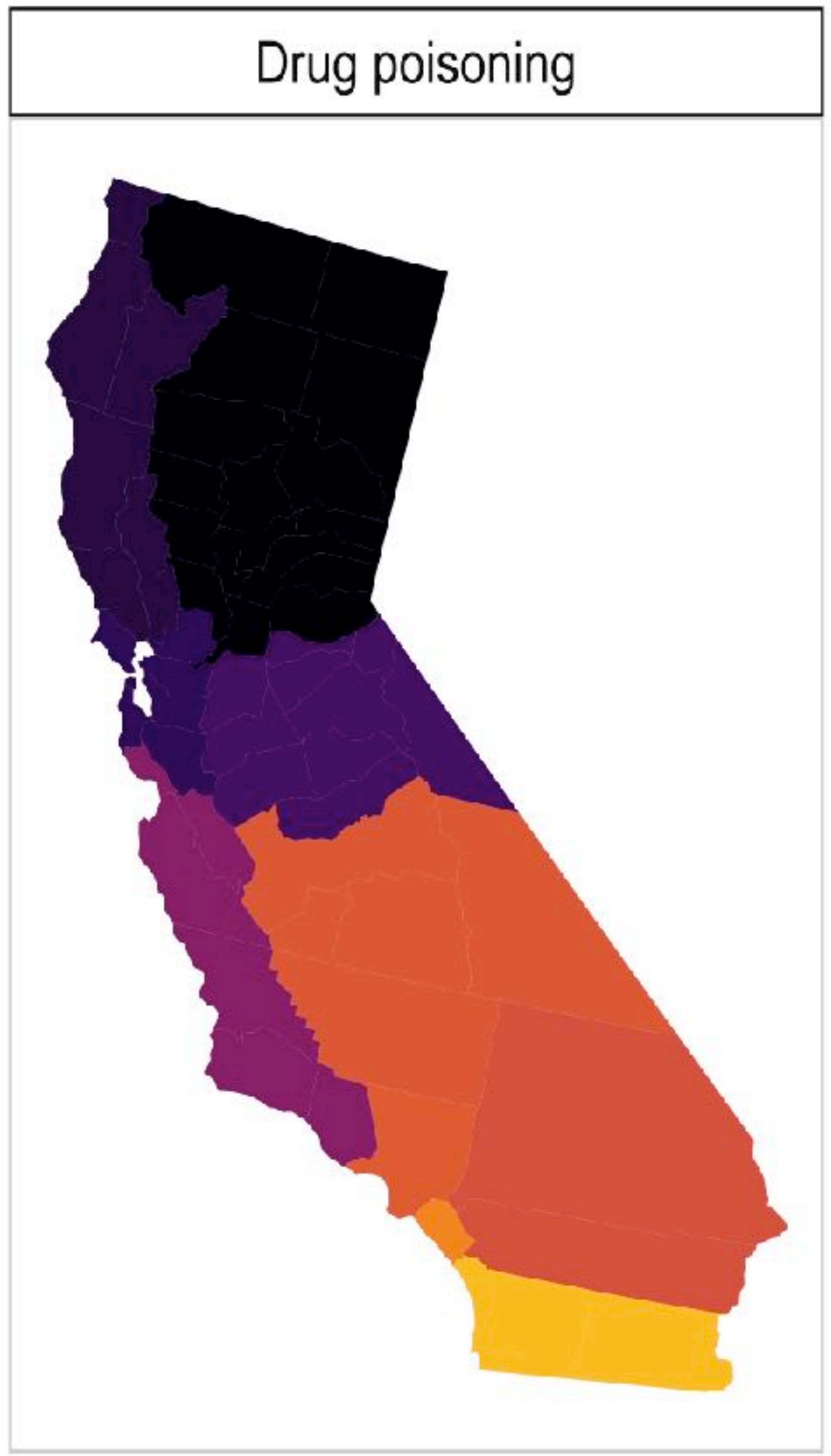


South-to-north spatial gradient

South-to-north spatial gradient

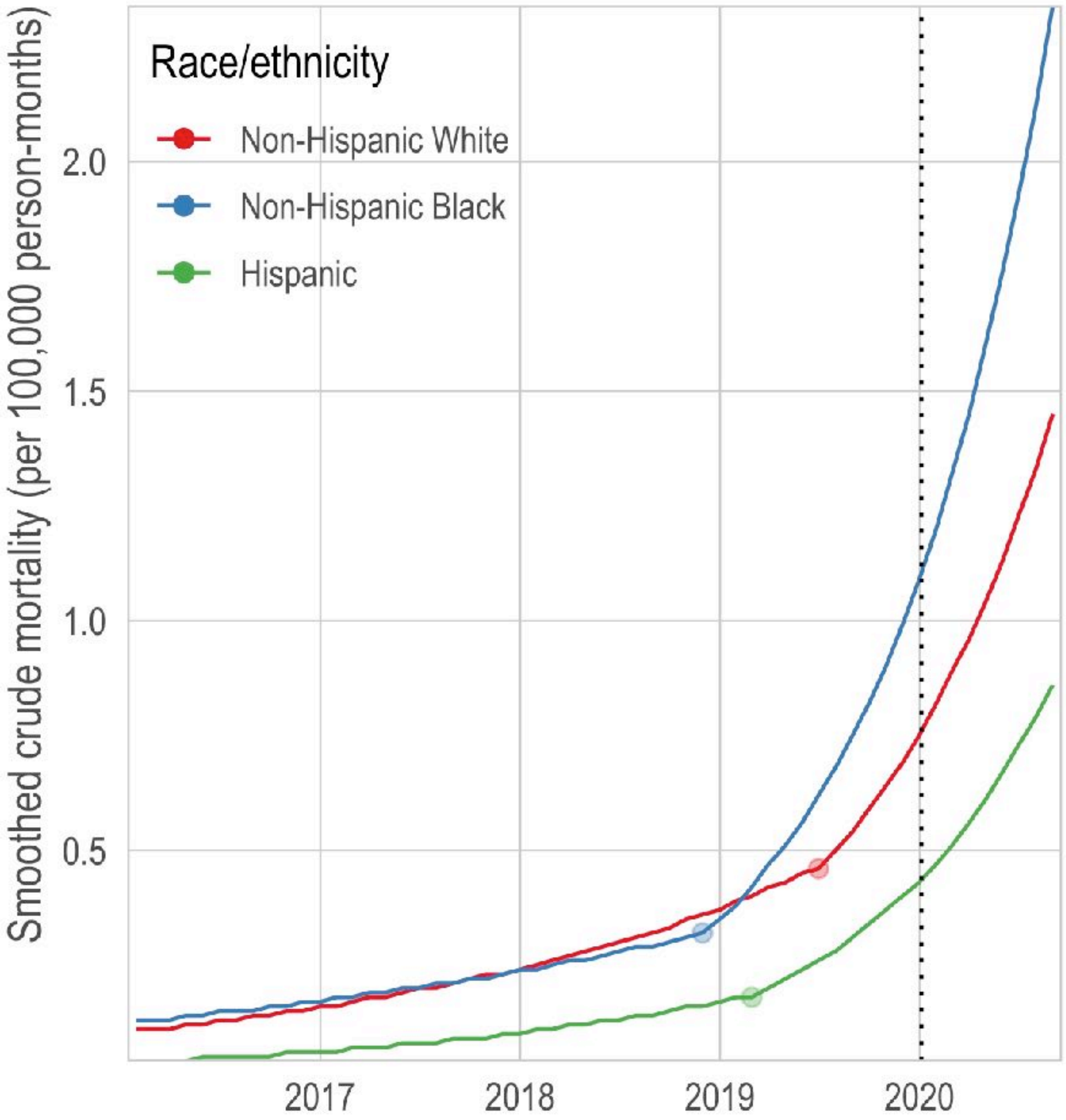




South-to-north spatial gradient

Important limitations and caveats

- Fundamental, and untestable, modeling assumptions
- Synthetic opioid-related mortality was accelerating before COVID-19
- Lots of variation in reporting quality on death certificates
- Model does not account for changes in substance use (e.g., polysubstance use)



Key Results

1. **2,084 (1925 to 2243)** excess fatal drug overdoses.

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3. Disproportionately impacted the **non-Hispanic Black** and **Other non-Hispanic** populations (as well as those with **only a high school degree)**.

Key Results

1. **2,084 (1925 to 2243)** excess fatal drug overdoses.
2. Excess fatal drug overdoses were **unintentional**, driven by **methamphetamine** and **opioids** (especially **synthetic opioids**).
3. Disproportionately impacted the **non-Hispanic Black** and **Other non-Hispanic** populations as well as those with **only a high school degree**.
4. A strong **south-to-north spatial gradient**.

Thank you

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Acknowledgements

- **Ayesha Mahmud** (Berkeley) and participants at the Department of Demography Brown Bag
- Funding from **NIDA** (R00DA051534)

California Department of PublicHealth

UCSF

NIDA

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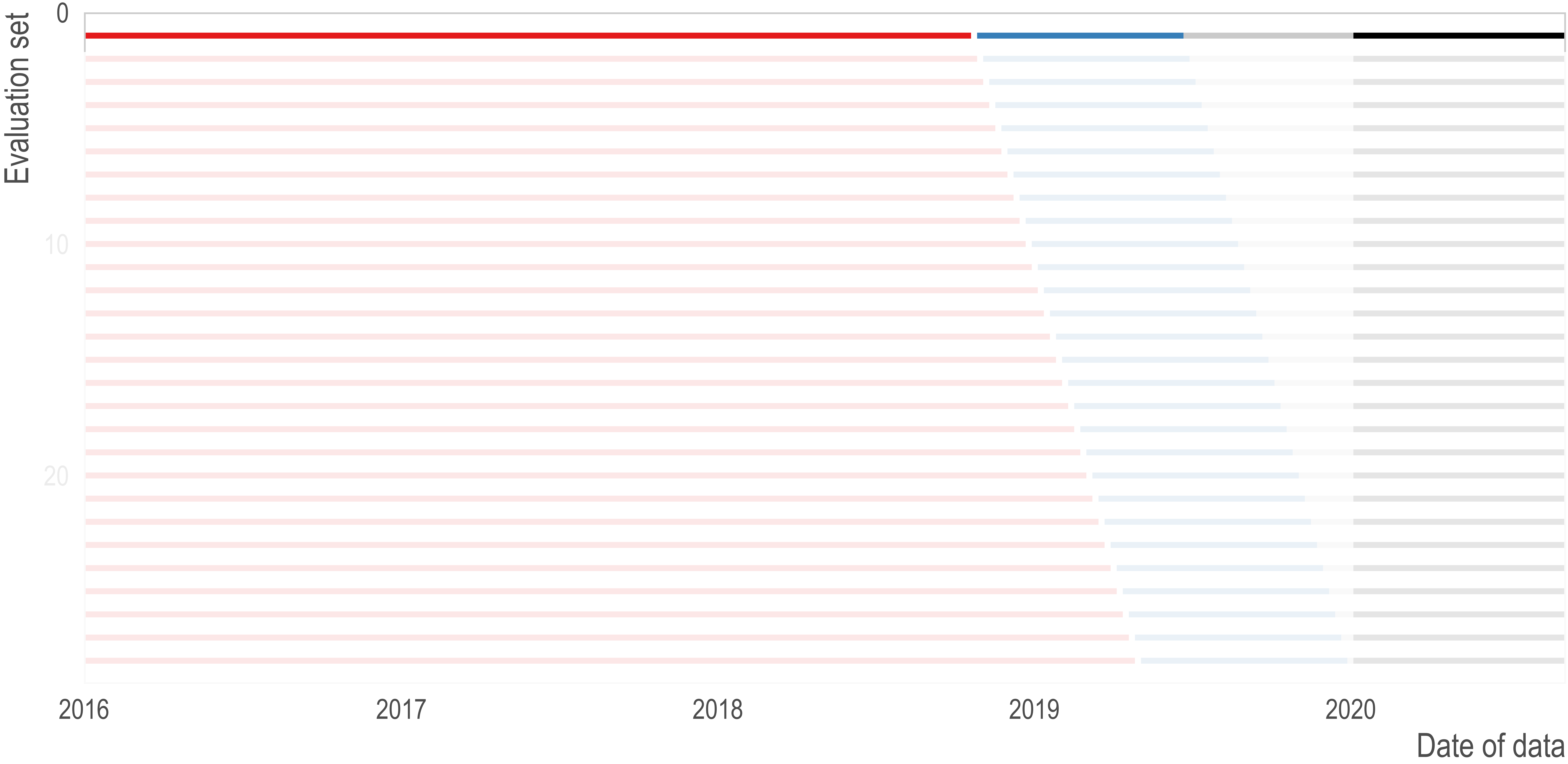
Additional Slides

TS-CV – The optimal baseline model



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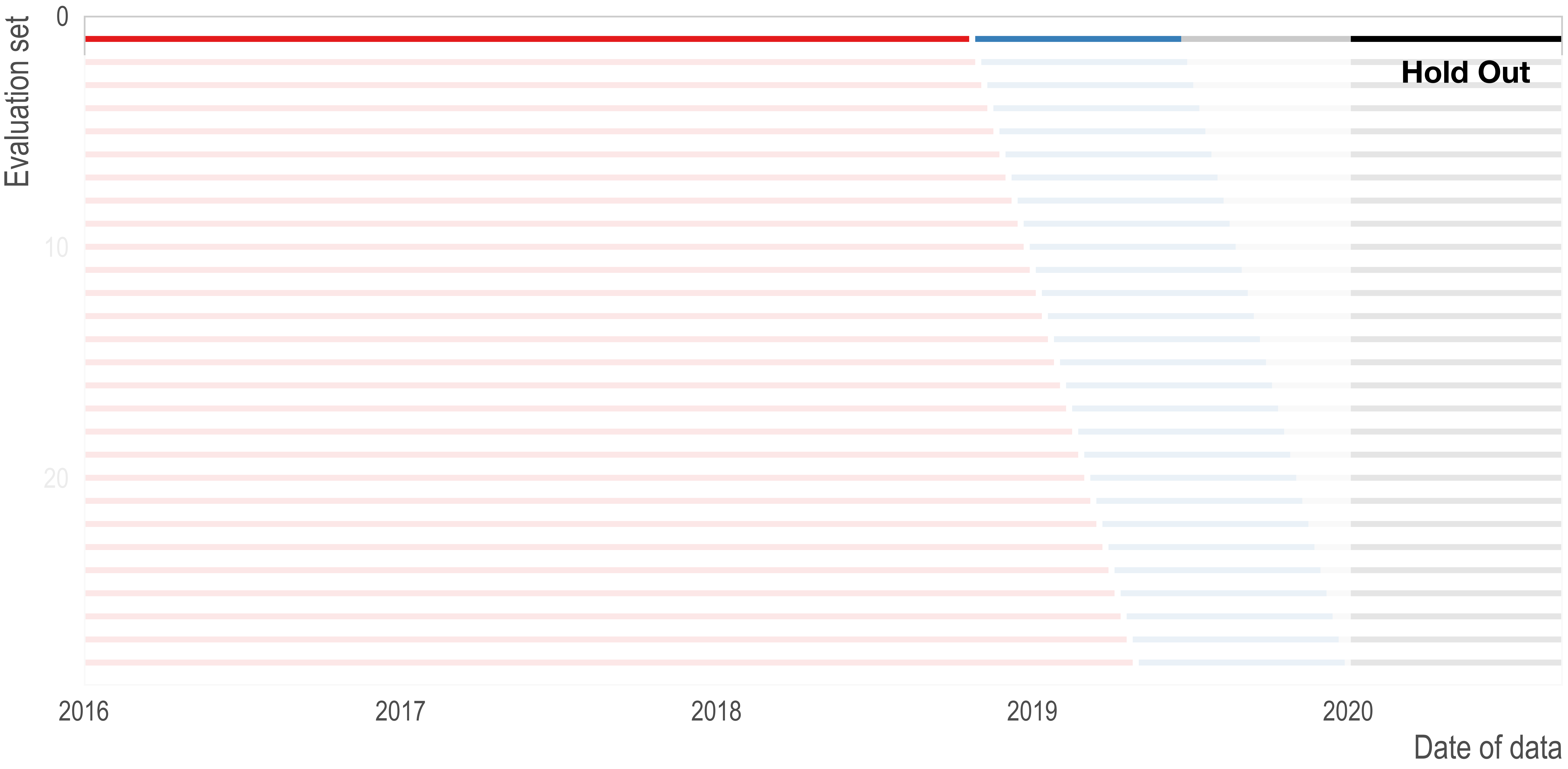

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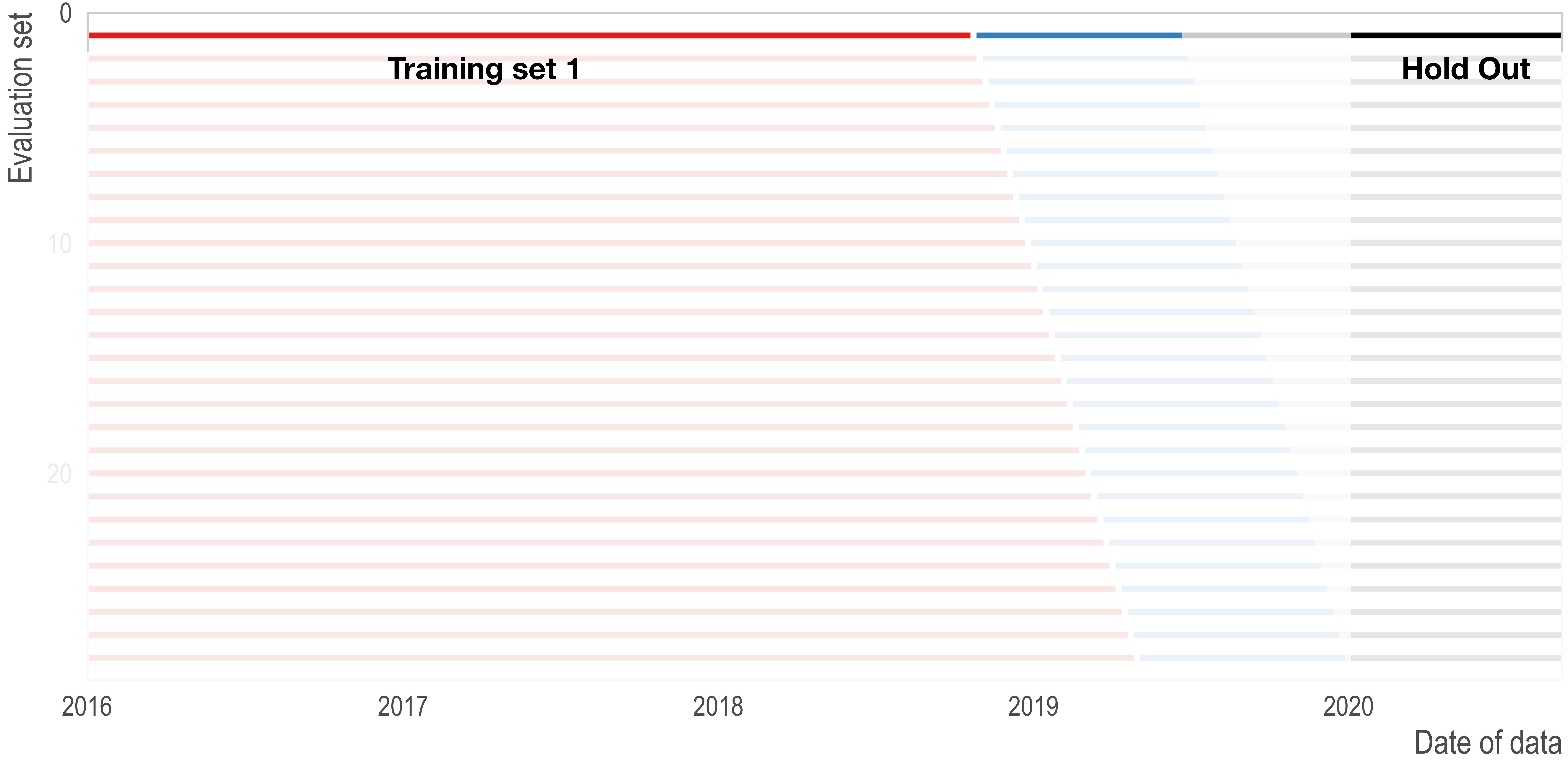

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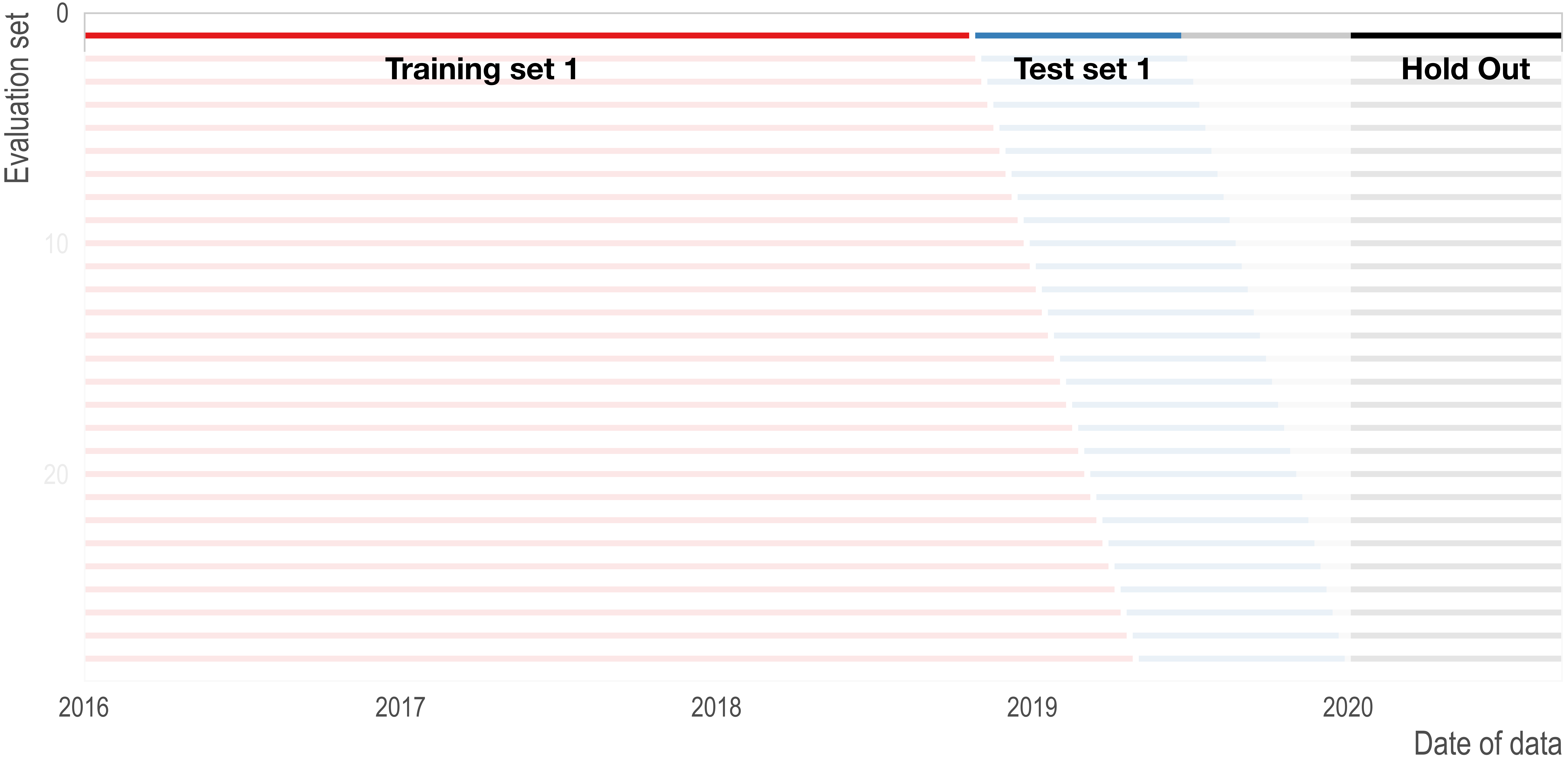

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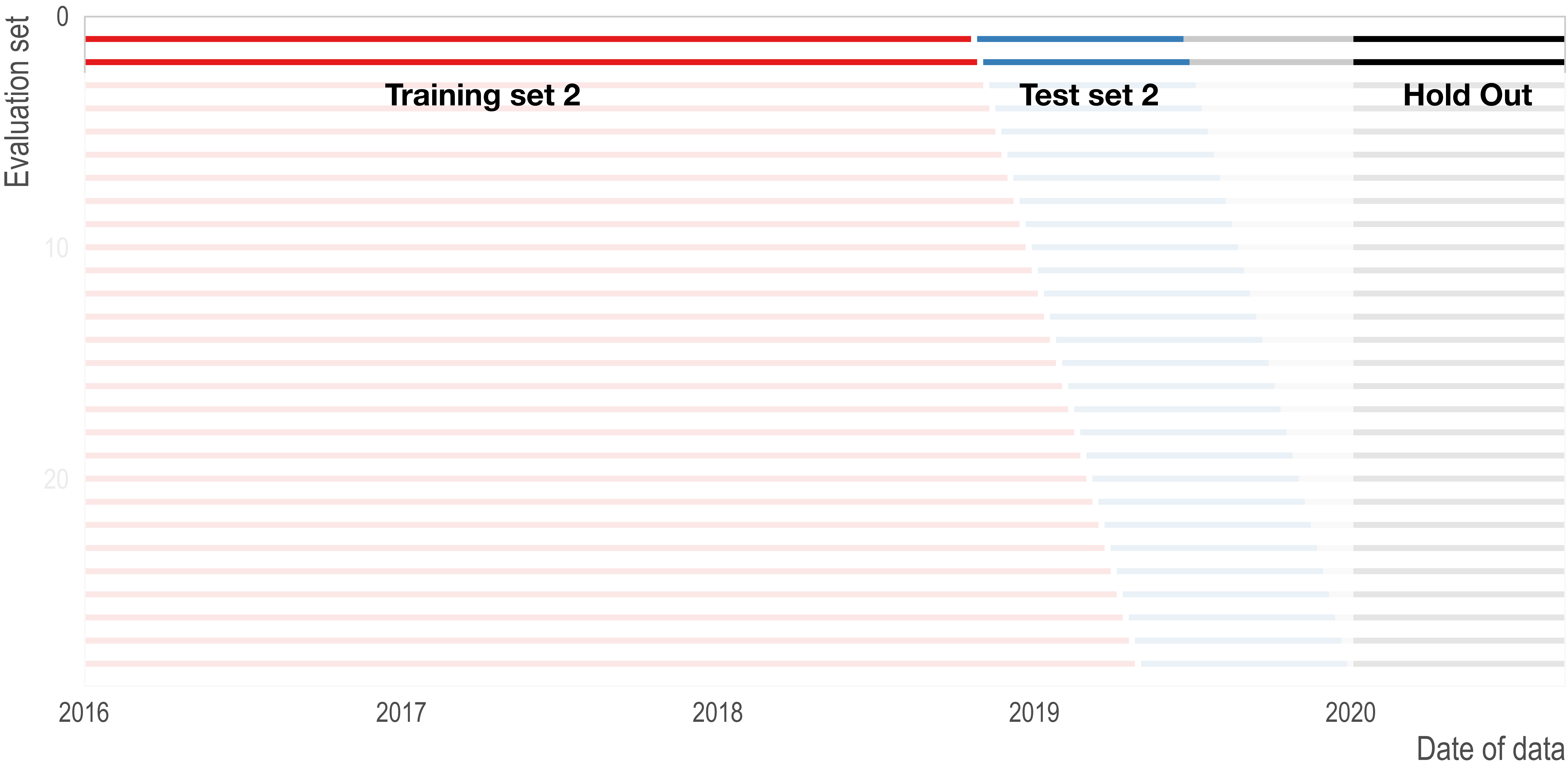

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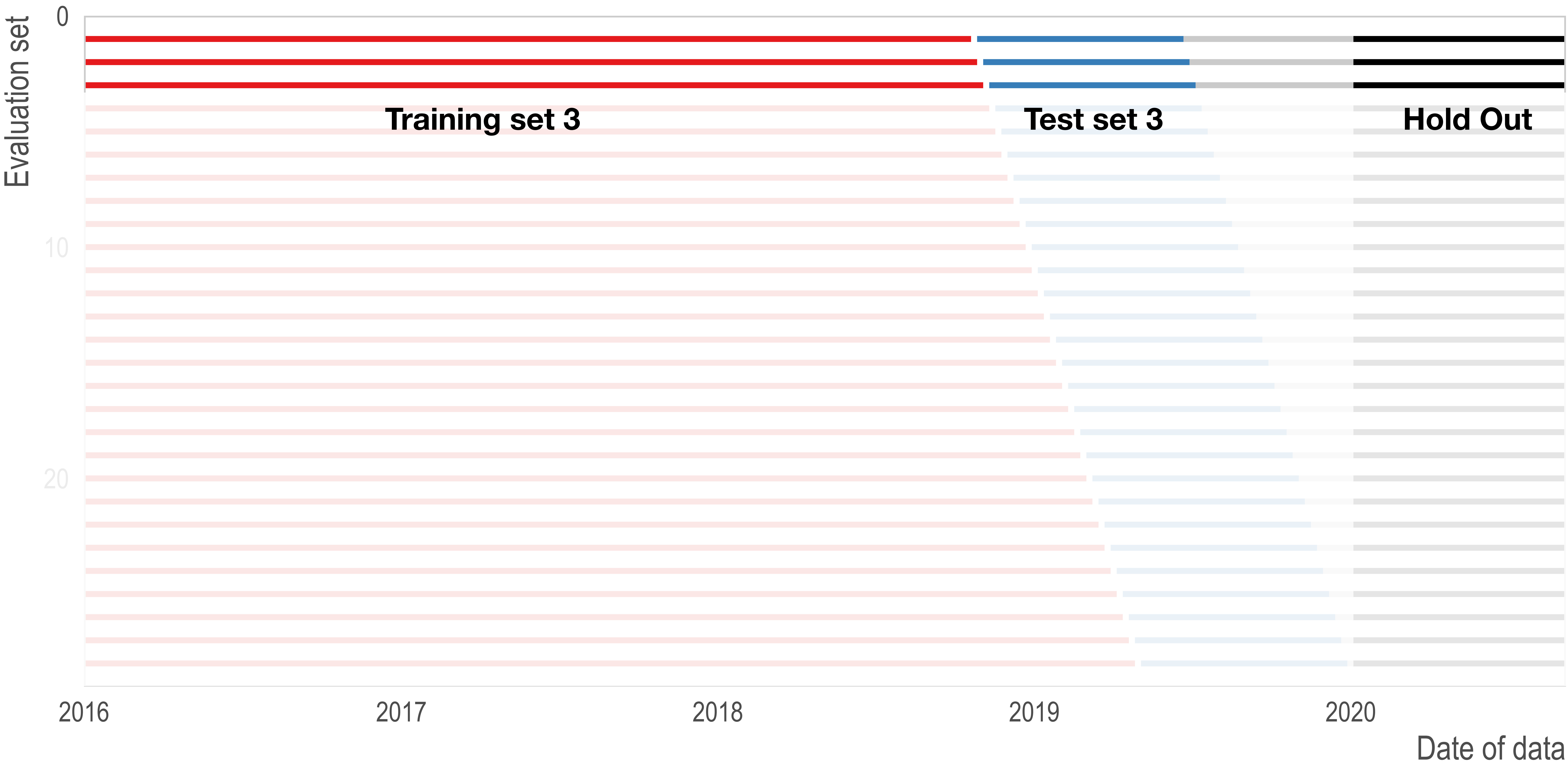

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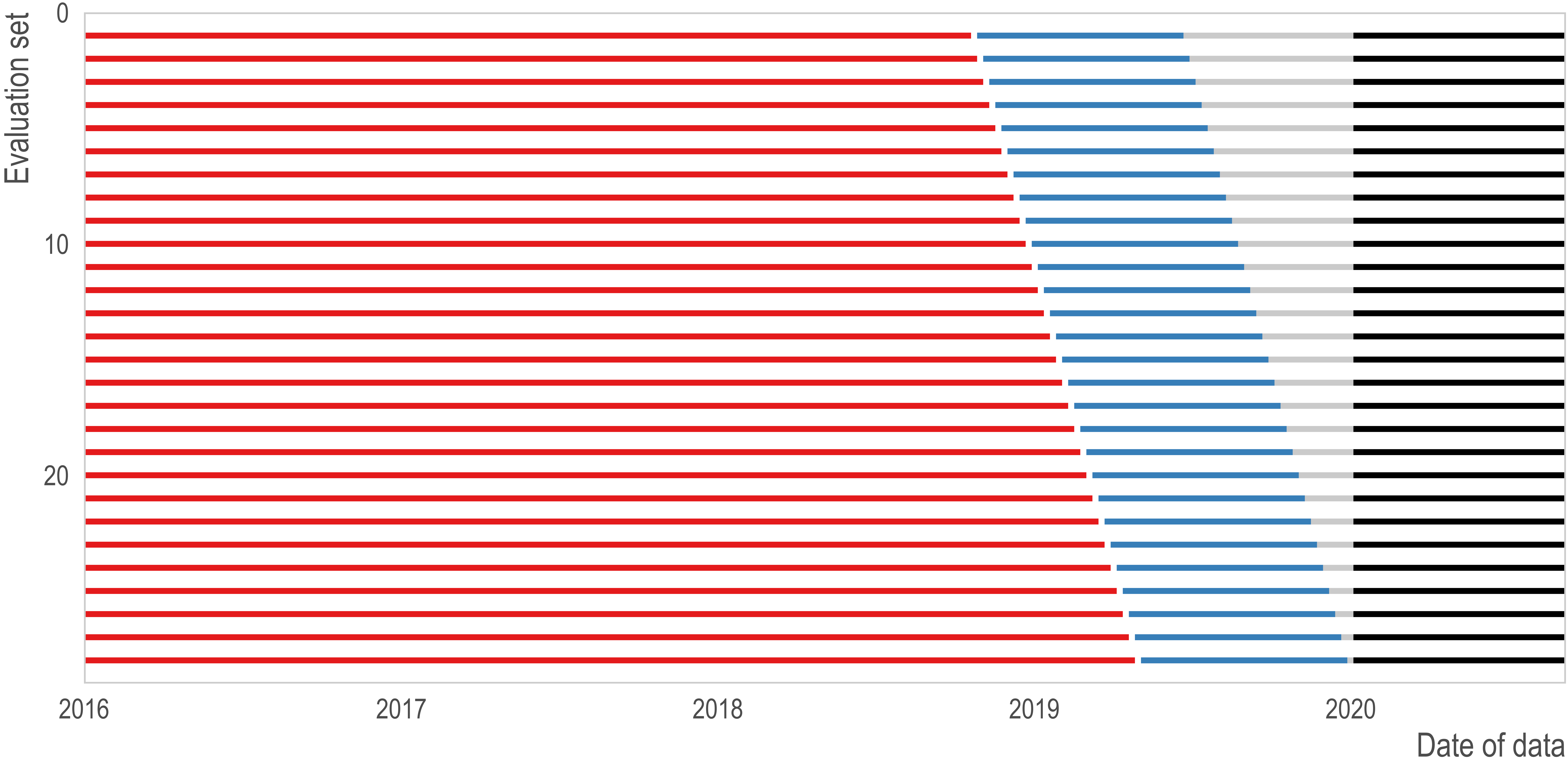
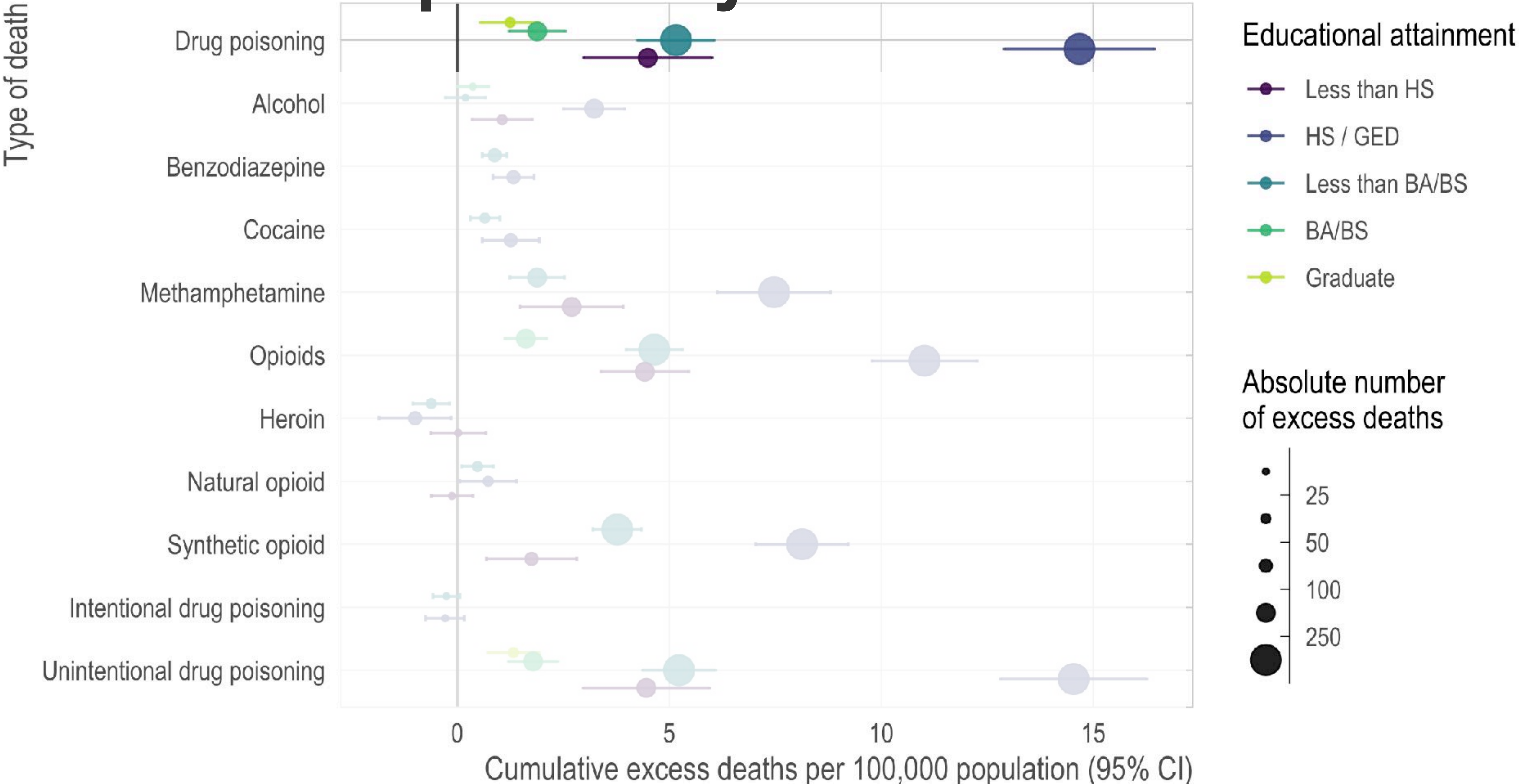


Non-linear pattern by education



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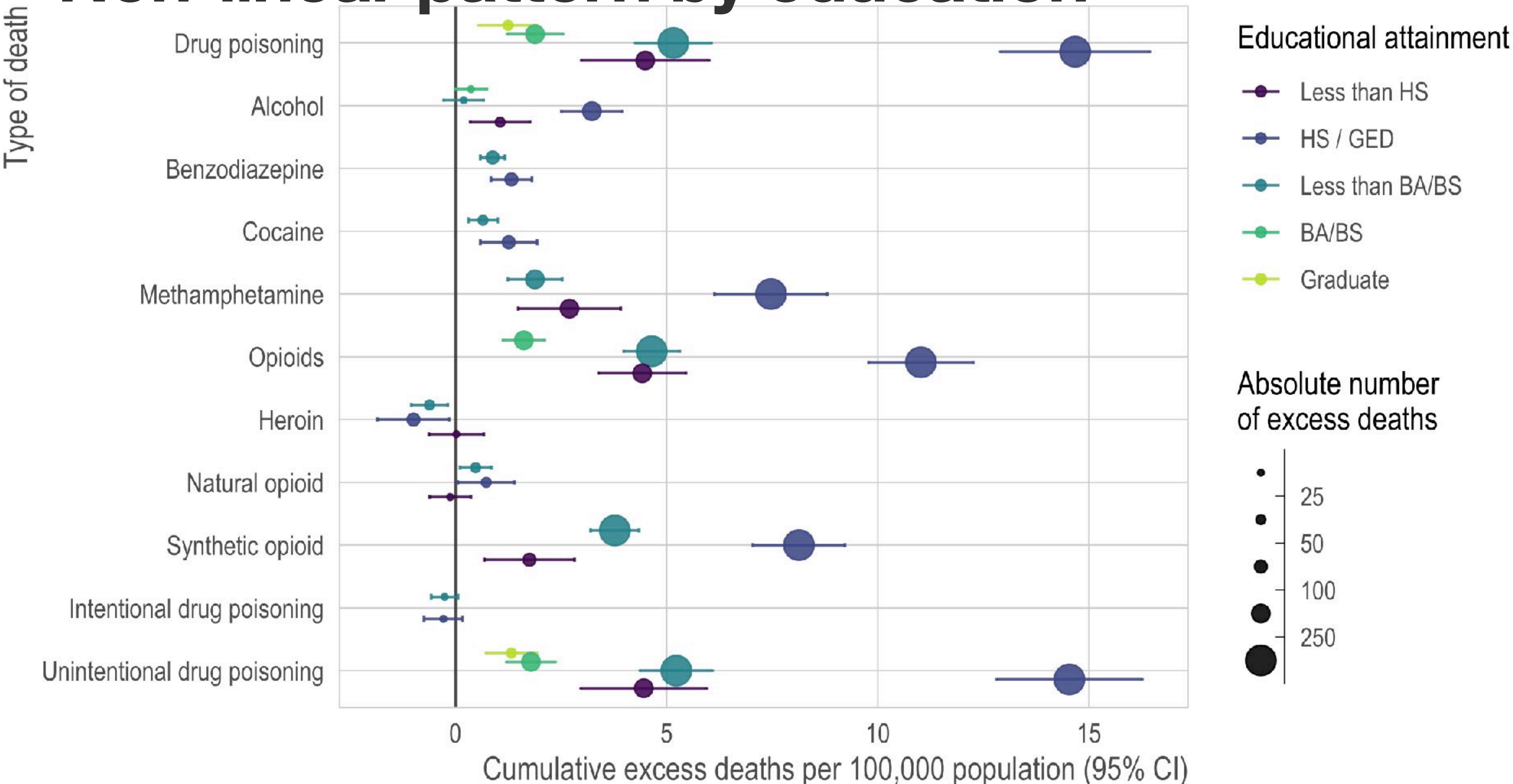
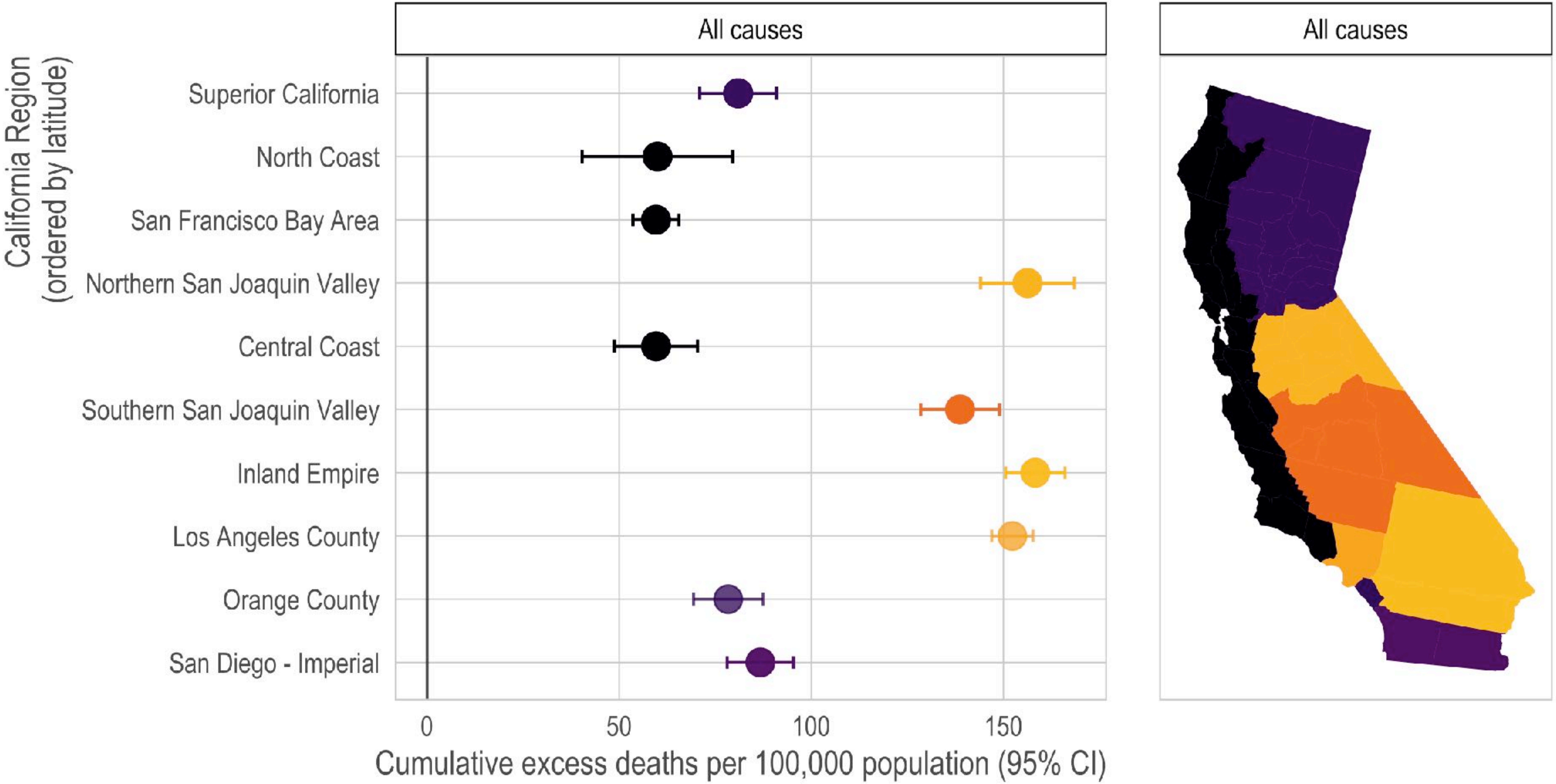
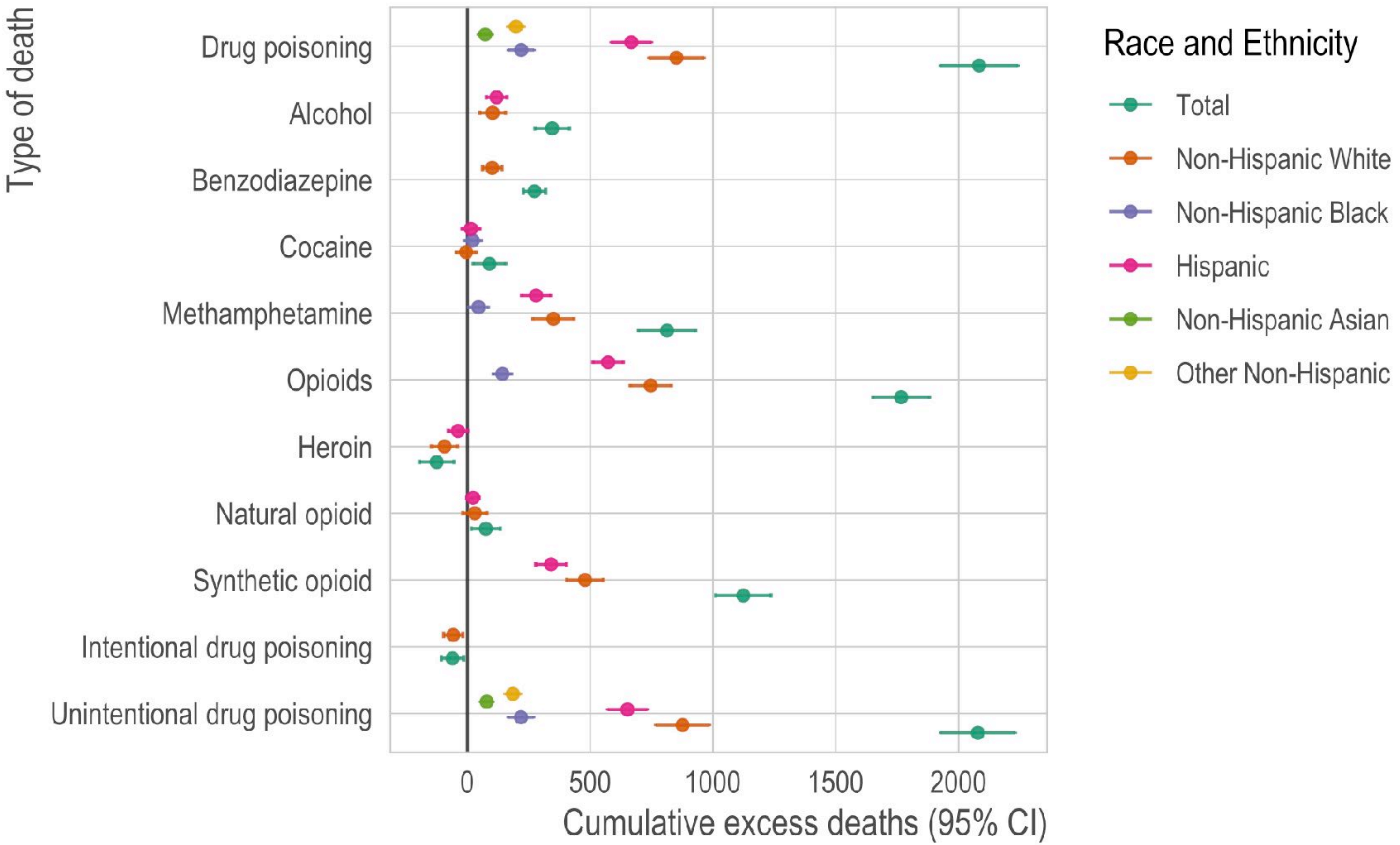
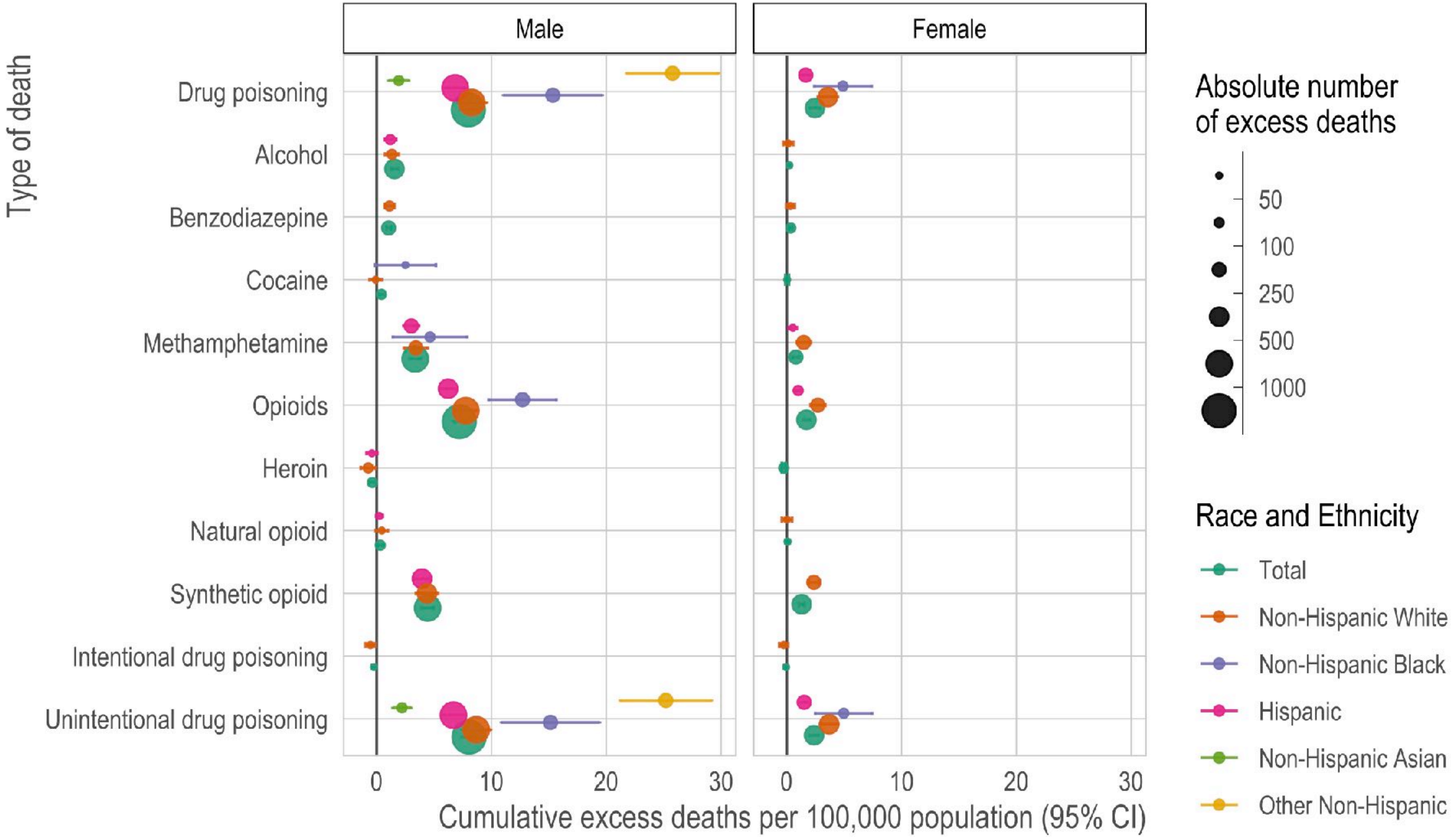


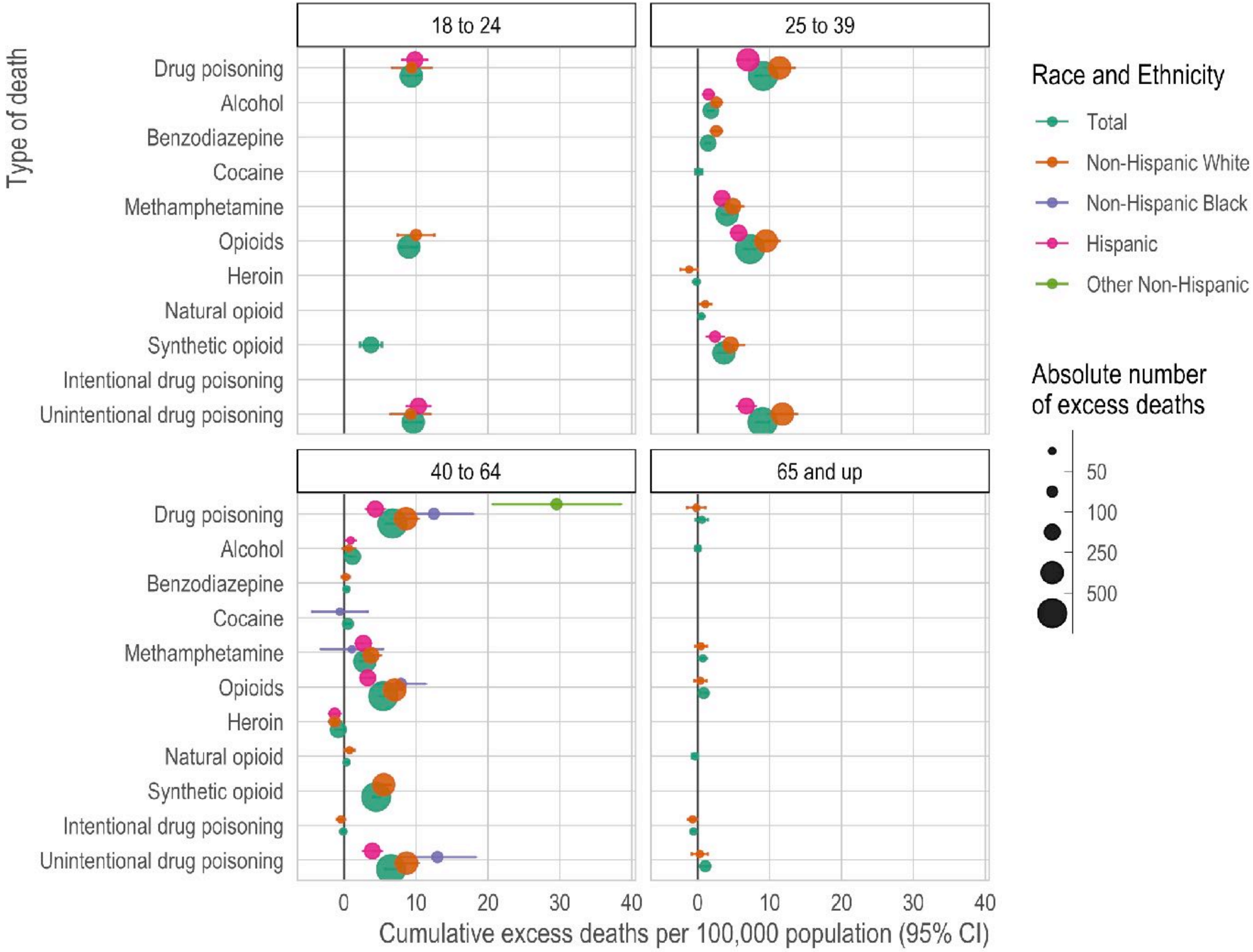
No spatial gradient for all-cause excess

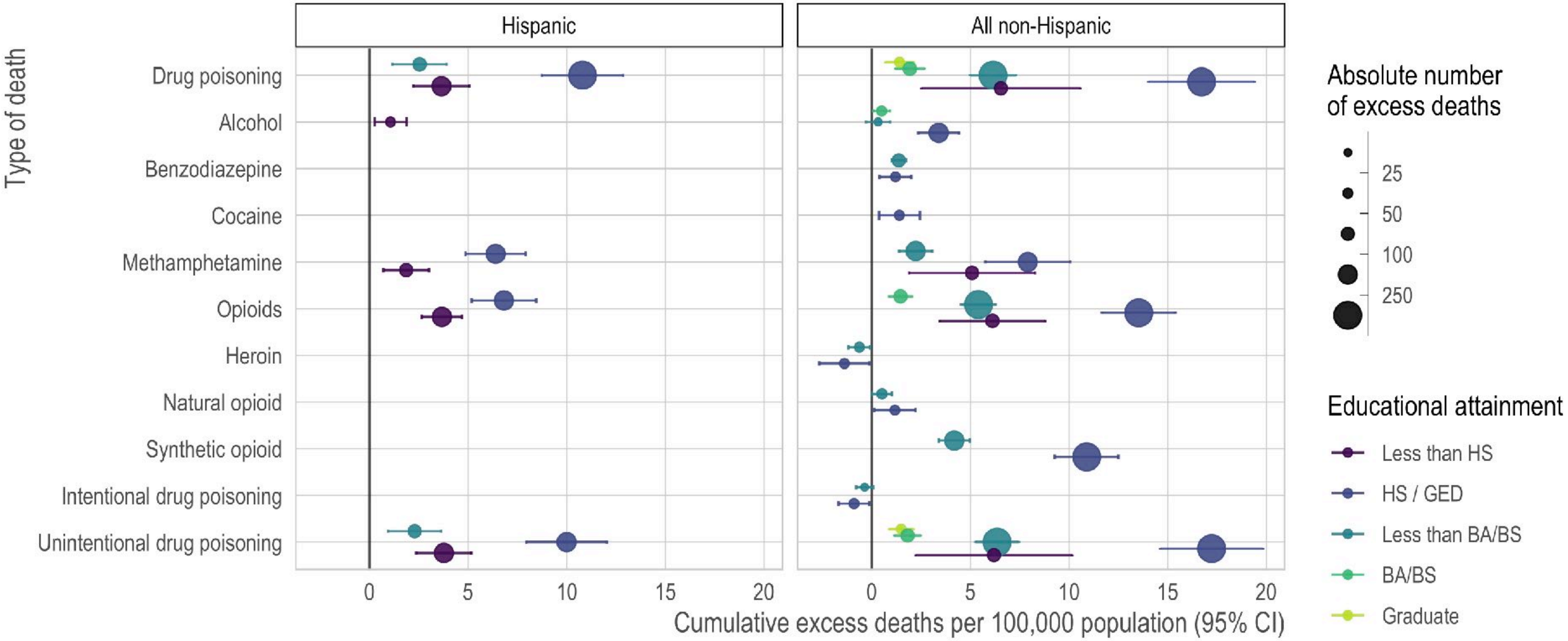



Type of death
Drug poisoning
Alcohol
Benzodiazepine
Cocaine
Methamphetamine
Opioids
Heroin
Natural opioid
Synthetic opioid
Intentional drug poisoning
Unintentional drug poisoning
0
500
1000
1500
2000
Cumulative excess deaths (95% CI)
Race and Ethnicity
Total
Non-Hispanic White
Non-Hispanic Black
Hispanic
Non-Hispanic Asian
Other Non-Hispanic



Male
Female
Type of death
Drug poisoning
Alcohol
Benzodiazepine
Cocaine
Methamphetamine
Opioids
Heroin
Natural opioid
Synthetic opioid
Intentional drug poisoning
Unintentional drug poisoning
0
10
20
30
Cumulative excess deaths per 100,000 population (95% CI)
Absolute number of excess deaths
50
100
250
500
1000
Race and Ethnicity
Total
Non-Hispanic White
Non-Hispanic Black
Hispanic
Non-Hispanic Asian
Other Non-Hispanic


18 to 24
25 to 39
40 to 64
65 and up
Type of death
Drug poisoning
Alcohol
Benzodiazepine
Cocaine
Methamphetamine
Opioids
Heroin
Natural opioid
Synthetic opioid
Intentional drug poisoning
Unintentional drug poisoning
0
10
20
30
40
Cumulative excess deaths per 100,000 population (95% CI)
Race and Ethnicity
Total
Non-Hispanic White
Non-Hispanic Black
Hispanic
Other Non-Hispanic
Absolute number of excess deaths
50
100
250
500



Hispanic
All non-Hispanic
Type of death
Drug poisoning
Alcohol
Benzodiazepine
Cocaine
Methamphetamine
Opioids
Heroin
Natural opioid
Synthetic opioid
Intentional drug poisoning
Unintentional drug poisoning
0
5
10
15
20
Cumulative excess deaths per 100,000 population (95% CI)
Absolute number of excess deaths
25
50
100
250
Educational attainment
Less than HS
HS / GED
Less than BA/BS
BA/BS
Graduate


Alcohol
Benzodiazepine
Cocaine
Heroin
Natural opioid
Synthetic opioid
California Region (ordered by latitude)
Superior California
North Coast
San Francisco Bay Area
Northern San Joaquin Valley
Central Coast
Southern San Joaquin Valley
Inland Empire
Los Angeles County
Orange County
San Diego - Imperial
-1
0
1
2
3
Cumulative excess deaths per 100,000 population (95% CI)
Absolute number of excess deaths
10
25
50
100
250


By race and ethnicity
Total
Non-Hispanic White
Non-Hispanic Black
Hispanic
Type of death
Drug poisoning
Alcohol
Benzodiazepine
Cocaine
Methamphetamine
Opioids
Heroin
Natural opioid
Synthetic opioid
Intentional drug poisoning
Unintentional drug poisoning
0
1000
2000
0
500
1000
0
100
200
300
0
250
500
750
Cumulative excess deaths (95% CI)
Estimation method
Main (Poisson weekly)
Poisson monthly
ARIMA

By educational

Excess fatal drug poisonings per 100,000
20
10
0
-10