Occupational Disparities in Excess Mortality Due to External Causes During the Pandemic


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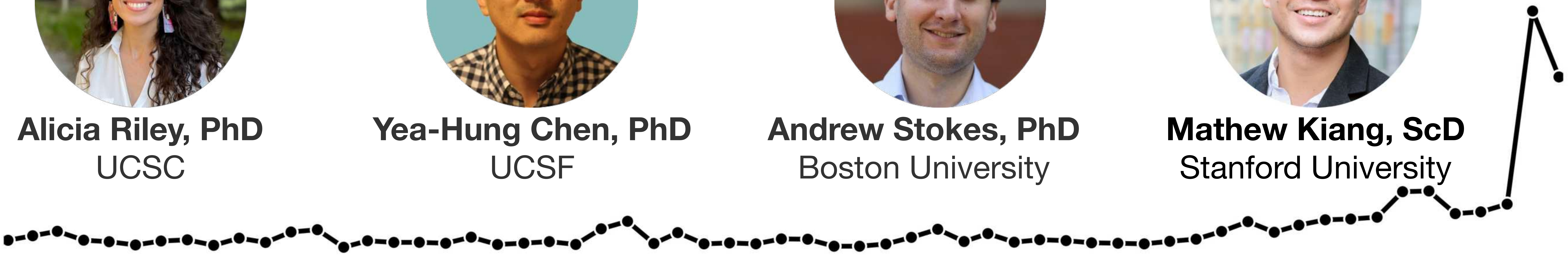


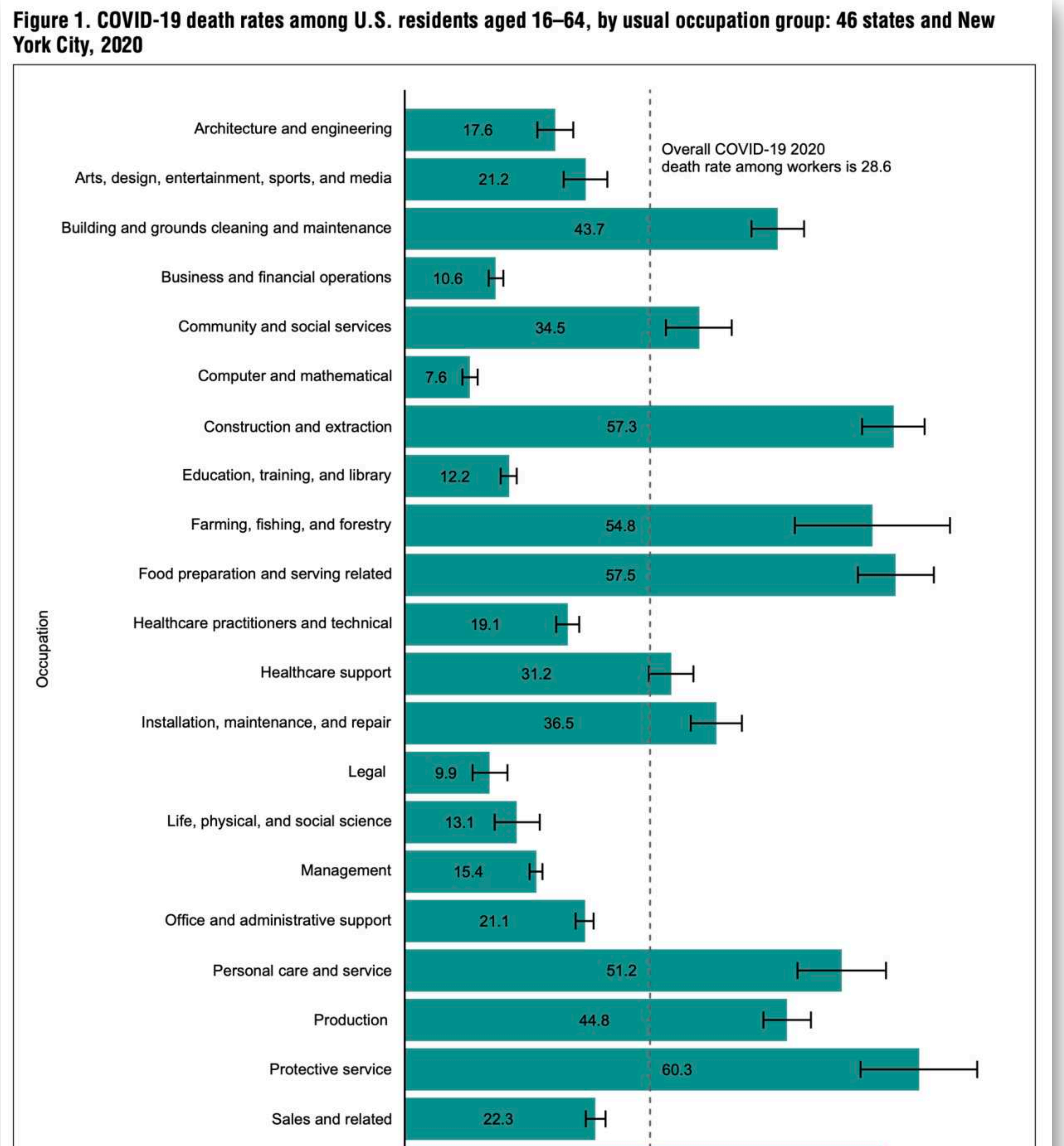
Mortality among 18-64 year old Californians

Substantial variation by occupation

Substantial variation by occupation

Primarily driven by SARS-CoV-2 infection

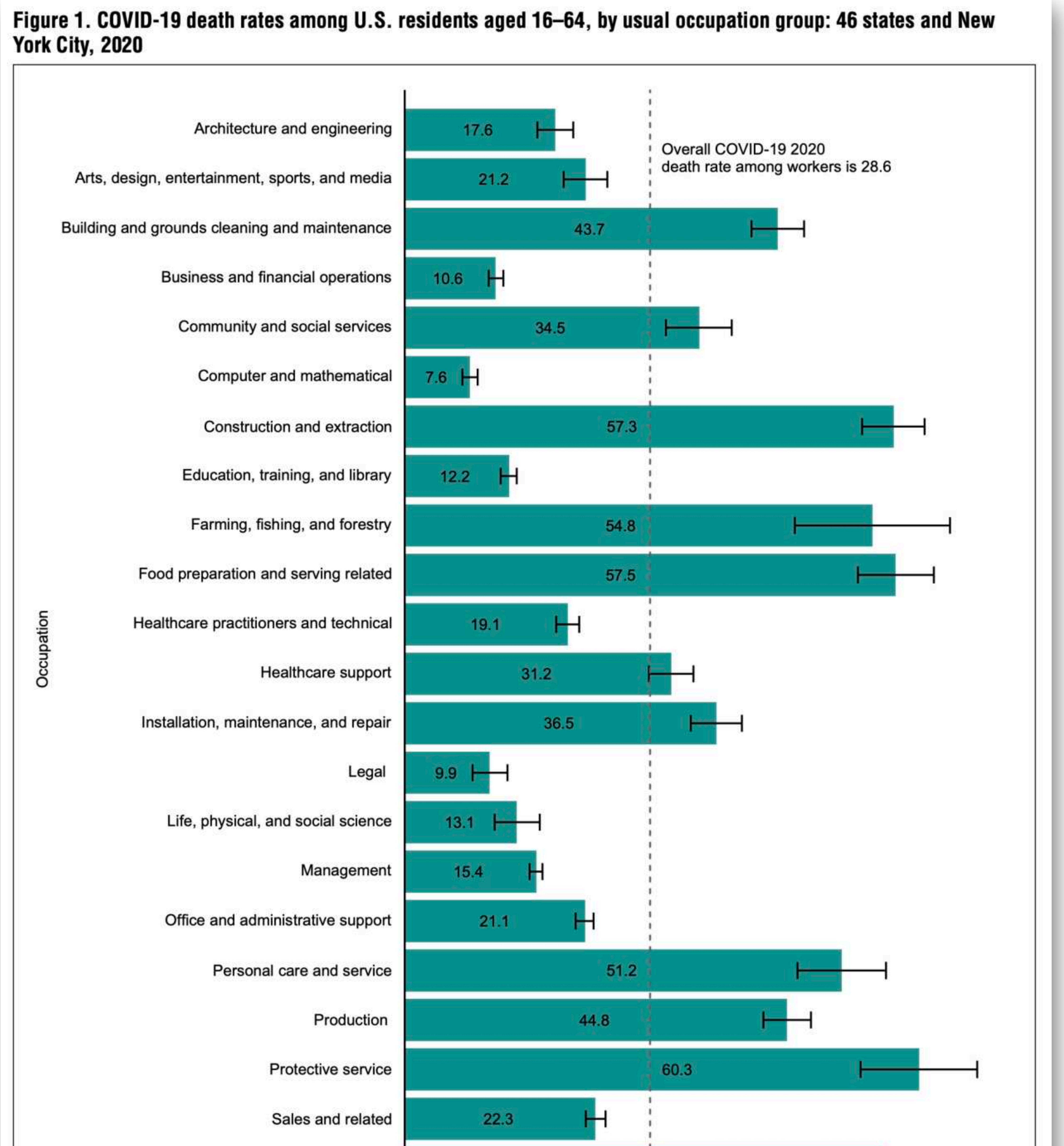
- Pandemic era policies focused on *direct impact* of COVID-19



NVSR Report 2022 "COVID-19 Mortality by Usual Occupation and Industry: 46 States and New York City, United States, 2020"

Primarily driven by SARS-CoV-2 infection

- Pandemic era policies focused on *direct impact* of COVID-19
- Differential exposure and risk of infection at the workplace
  - Workplace protections
  - Remote work options
  - Place-based ventilation and filtration



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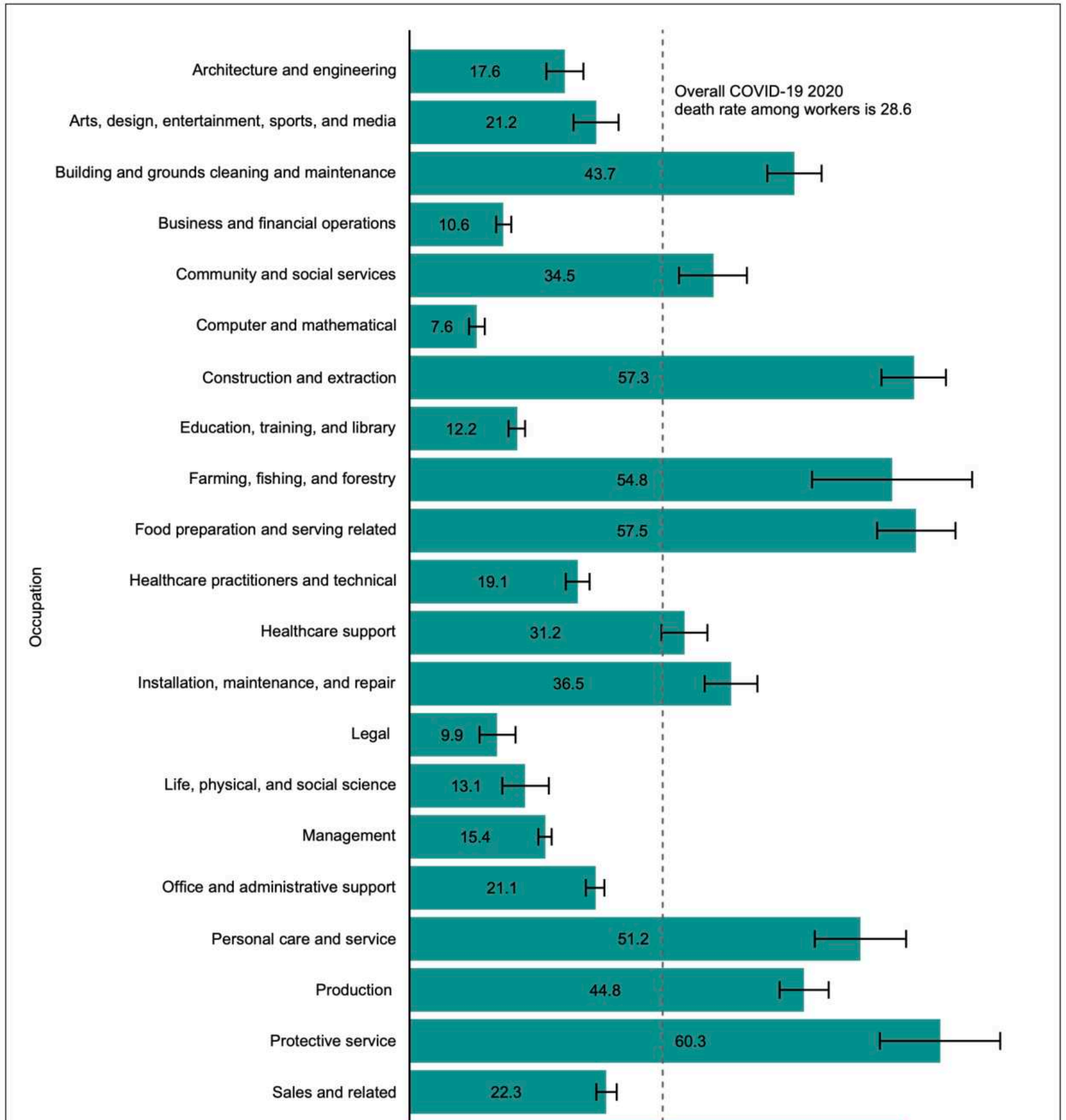
Primarily driven by SARS-CoV-2 infection

- Pandemic era policies focused on *direct impact* of COVID-19
- Differential exposure and risk of infection at the workplace
    - Workplace protections
    - Remote work options
    - Place-based ventilation and filtration
- Differential access to care once infected
    - Paid sick leave
    - Health insurance
    - Precarious work

Figure 1. COVID-19 death rates among U.S. residents aged 16–64, by usual occupation group: 46 states and New York City, 2020



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But not entirely due to SARS-CoV-2

- More excess deaths than COVID-19 deaths
  - Some of this is undiagnosed COVID
- Also likely due to *indirect effects* of the pandemic:
  - Mental health declines, loss of access to health care, financial instability, etc.

Table 1. Excess mortality among Californians 18–65 years of age, by occupational sector, March through November 2020.

	Excess deaths	COVID-19 deaths	Per-capita excess[a]	Relative excess[b]
Entire state	11,628 (10,779–12,468)	5,813	46 (43–49)	1.22 (1.20–1.24)
Facilities	2,119 (1,711–2,518)	1,093	83 (67–98)	1.23 (1.18–1.29)
Food or agriculture	1,424 (1,248–1,596)	691	75 (66–85)	1.39 (1.32–1.45)
Government or community	567 (459–673)	328	24 (20–29)	1.17 (1.13–1.20)
Health or emergency	611 (541–680)	395	30 (27–34)	1.17 (1.15–1.19)
Manufacturing	700 (662–738)	539	61 (57–64)	1.24 (1.23–1.26)
Retail	601 (521–678)	263	38 (33–43)	1.21 (1.18–1.24)
Transportation or logistics	1,649 (1,453–1,842)	772	91 (81–102)	1.31 (1.26–1.36)
Not essential	1,335 (1,077–1,590)	744	17 (14–20)	1.12 (1.09–1.14)
Unemployed or missing	2,397 (2,139–2,653)	988	59 (52–65)	1.25 (1.22–1.28)

Chen Y-H, Glymour M, Riley A, Balmes J, Duchowny K, Harrison R, et al. (2021) Excess mortality associated with the COVID-19 pandemic among Californians 18–65 years of age, by occupational sector and occupation: March through November 2020. PLoS ONE 16(6): e0252454. https://doi.org/10.1371/journal. pone.0252454

Research questions

1. How much did external causes of death contribute to overall (non-COVID-19) excess mortality?

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2. What are the occupational disparities in excess deaths from external causes?

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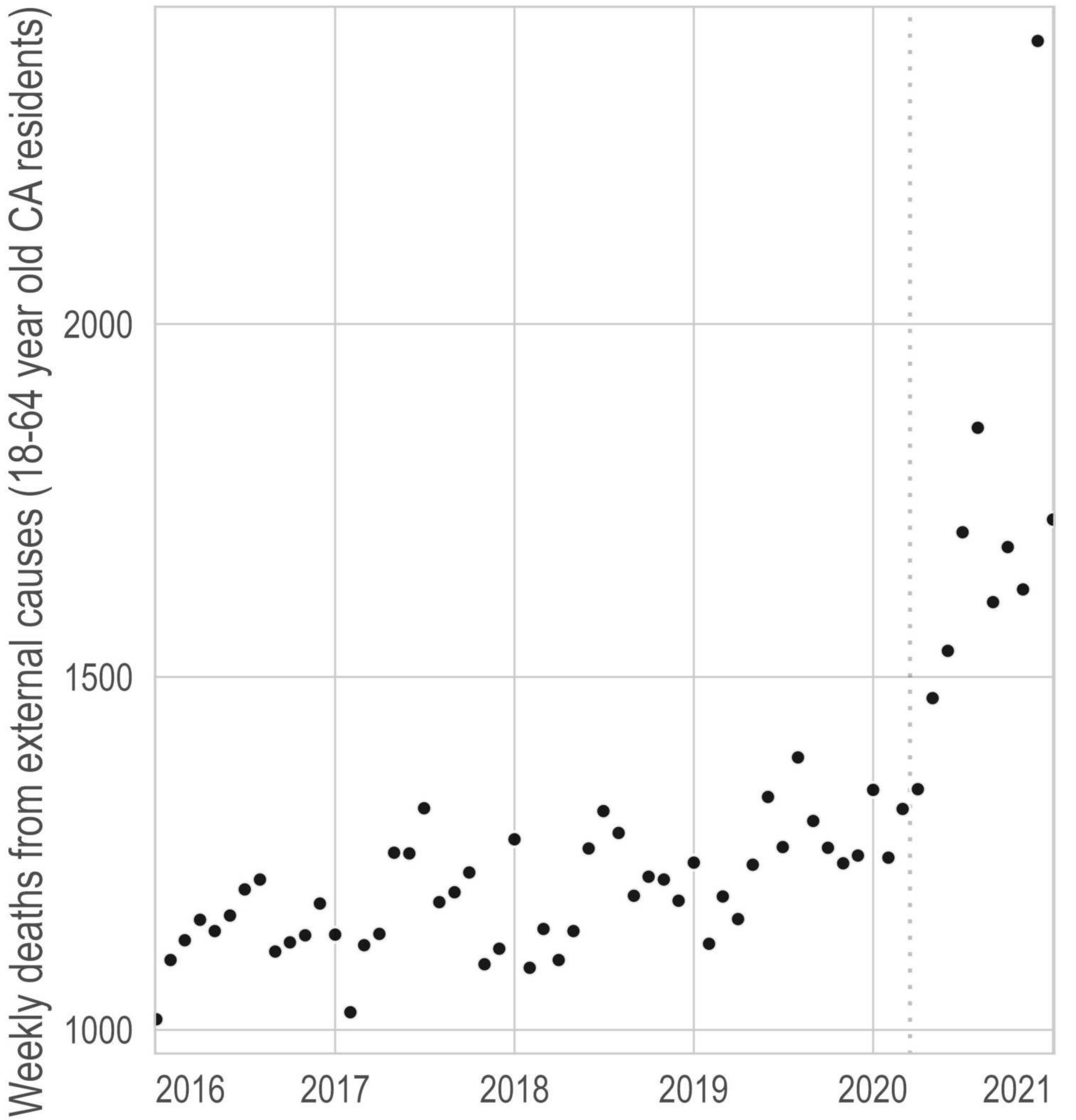
1. How much did external causes of death contribute to overall (non-COVID-19) excess mortality?

2. What are the drivers of occupational disparities in excess deaths from external causes?

Data – Description

- **77,878** deaths from external causes among 18-64 year old California residents from Jan 1, 2016 through Jan 2021 (N~1.3 million total)
- Contains age, sex, usual occupation (free text), and cause of death
- 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, "A Flexible Statistical Framework for Estimating Excess Mortality." *Epidemiology*. doi: 10.1097/EDE.0000000000001445.

Methods – Creating a counterfactual model

- Assume deaths per month are Poisson distributed

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Methods – Creating a counterfactual model

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- The expected number of deaths at month *t* is a function of:

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Methods – Creating a counterfactual model

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

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Methods – Creating a counterfactual model

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

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Methods – Creating a counterfactual model

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

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  - Long-term trend
  - Seasonal trend
  - Weekday effect
- An "event effect"

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Constraining the model space

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

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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

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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

Deaths from external causes

Select baseline model using TS-CV

Our baseline model

Long term trend

Seasonal trend

Expected deaths after March 2020

Observed deaths after March 2020

Observed deaths after March 2020

Focusing on Apr 2020 through Jan 2021

Excess deaths per month

Cumulative excess deaths over time

Excess deaths from external causes

1. How many excess deaths?

2. Occupational disparities?

In general, higher among men

And those 18 to 39 years of age

3. Primarily driven by (drug) poisoning

Opioids and meth are most involved drugs

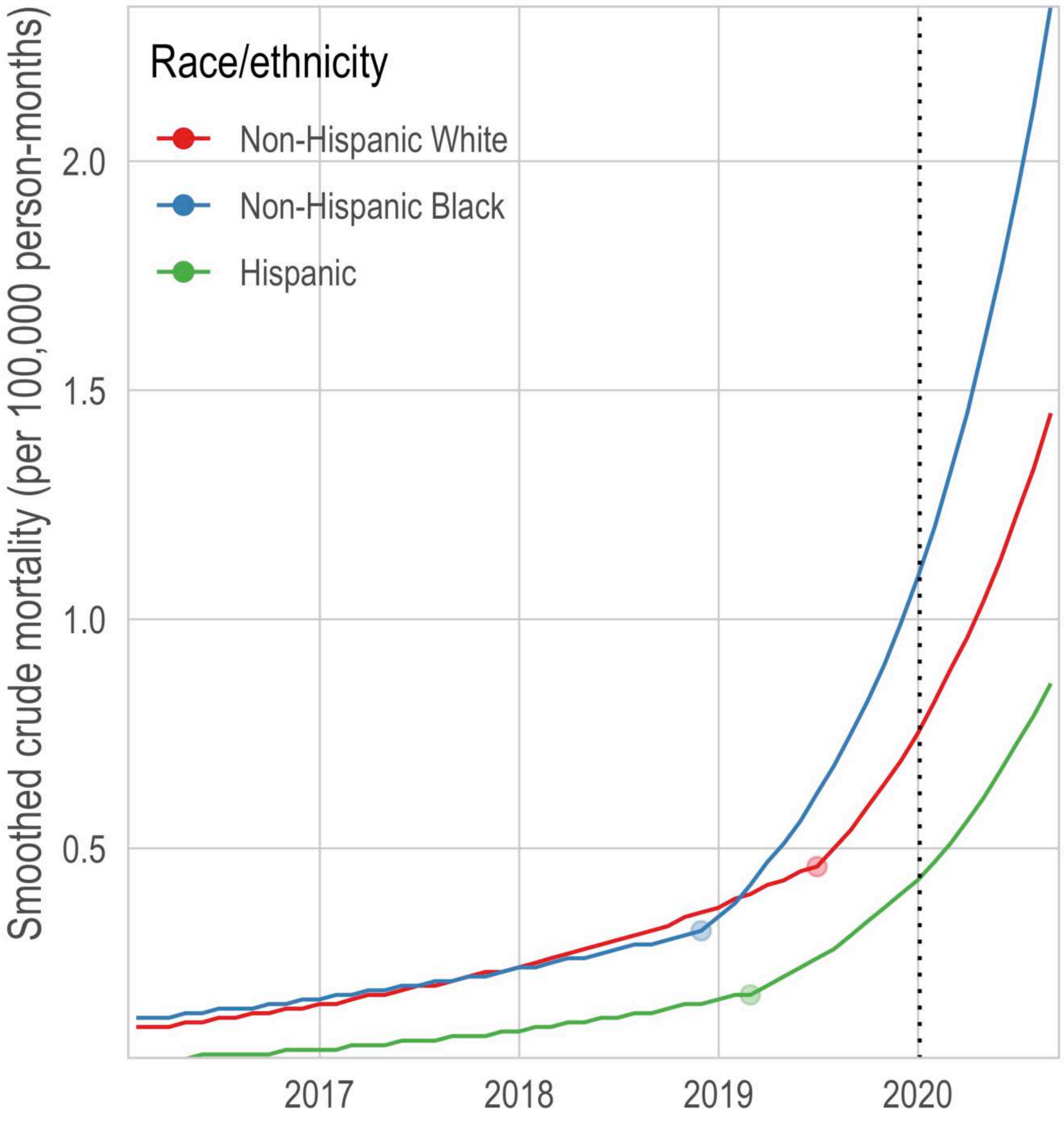
By selected causes and occupations

By selected causes and occupations

By selected causes and occupations

Important limitations and caveats

- Fundamental, and untestable, modeling assumptions
- Drug-related mortality was accelerating before COVID-19
- Lots of variation in reporting quality on death certificates
- Denominator is difficult to measure



Key Results

1. **Over 4,000** excess deaths among working age Californians
2. Highest among **construction** and **transportation workers**
3. **Males and 18-39 y/o higher** within occupations
4. Driven by **drug poisonings**, especially opioids and meth
5. But **variation across major causes and occupations**

Thank you

Yea-Hung Chen, PhD (UCSF)
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Alicia Riley, PhD (UCSC)
Mathew Kiang, ScD (Stanford)
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Acknowledgements

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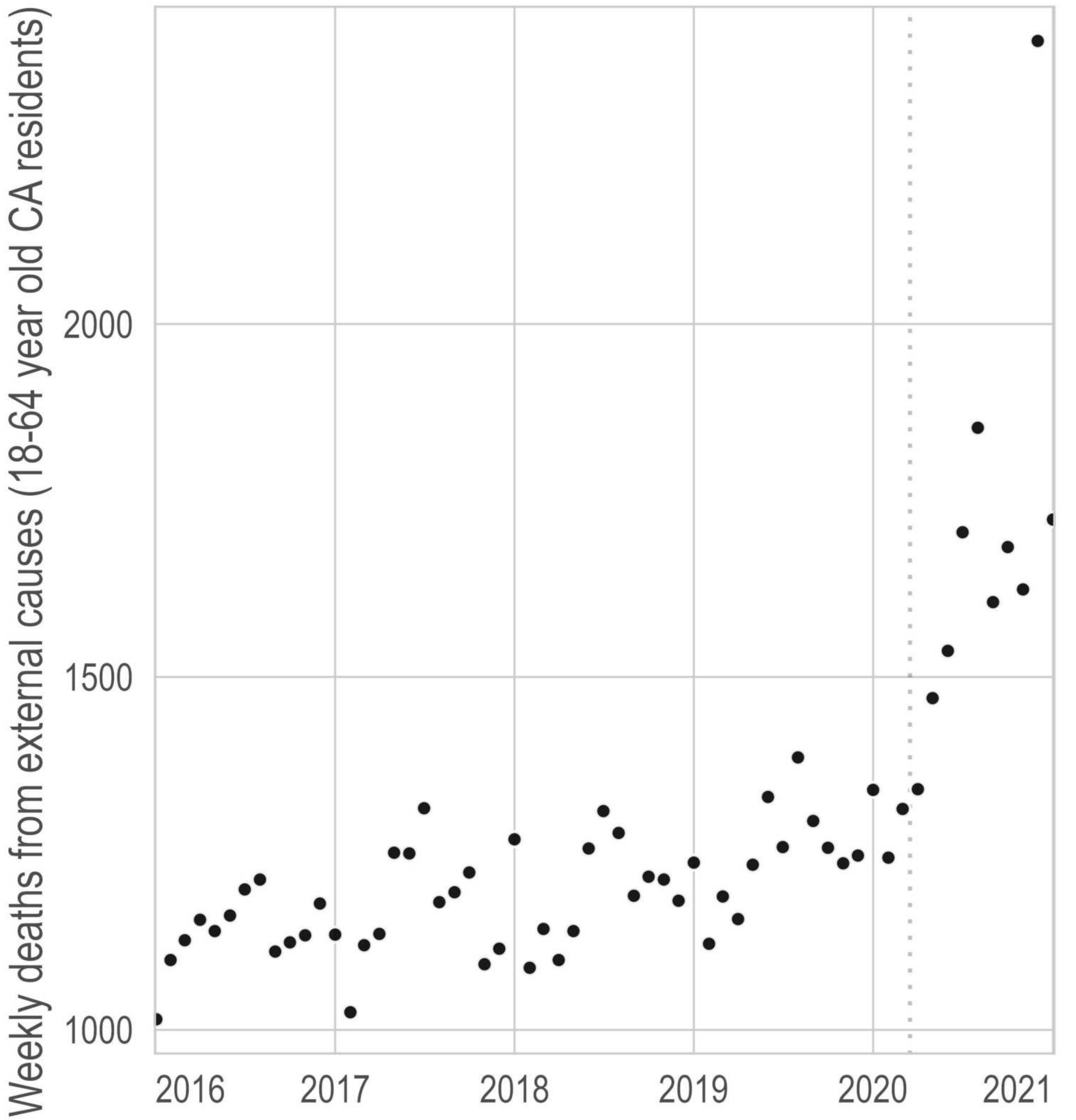
Additional Slides

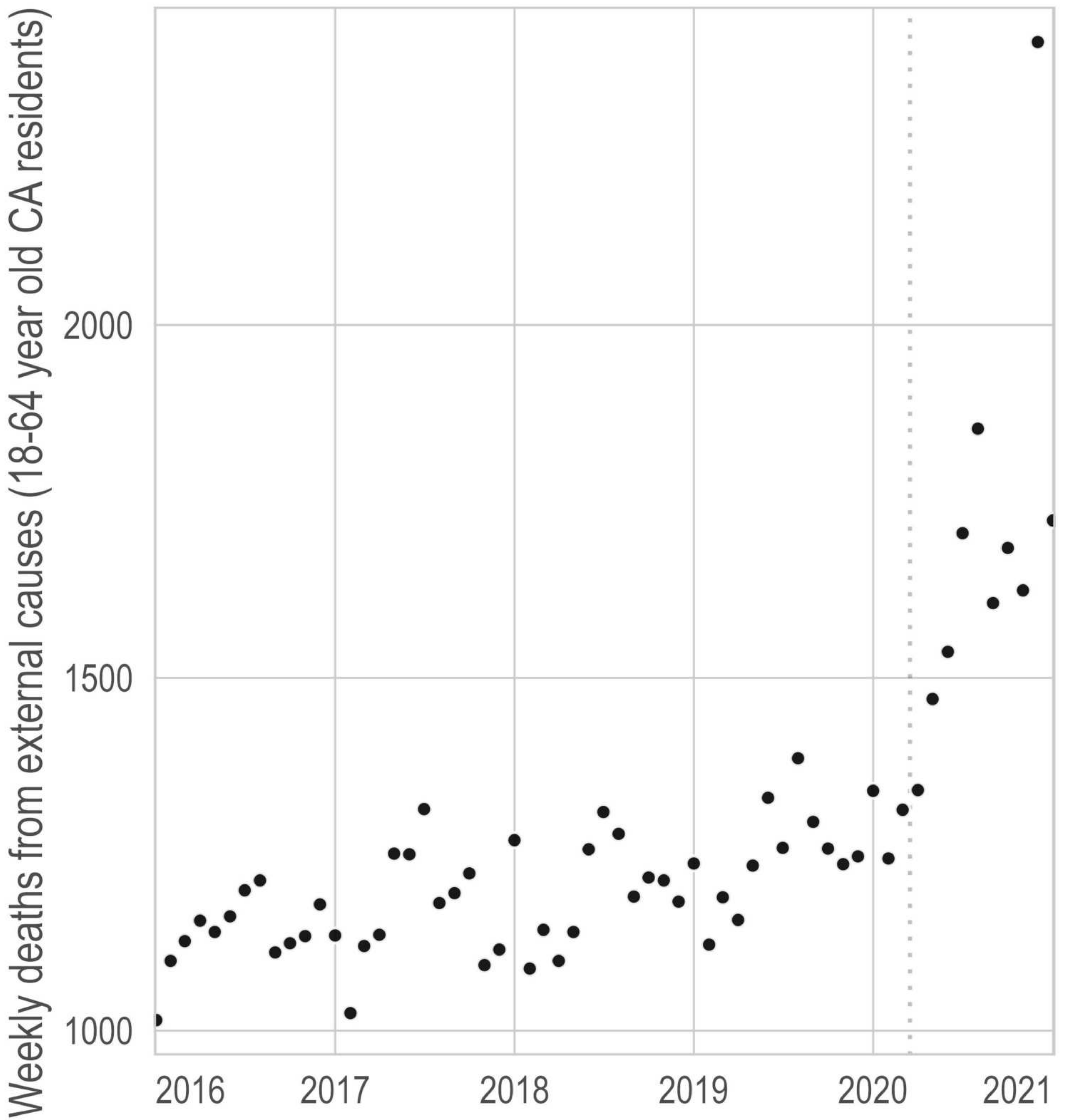
Data – Description

- Death certificates in California from Jan 1, 2016 through Jan 2021 (N ~ 1.3 million)
- Subset to 18-64 year old residents (N = 352,987)
- Focus on external causes of death (N = 77,878)
- Contains age, sex, usual occupation (free text), and cause of death
- Population estimates from US Census Bureau public use microdata

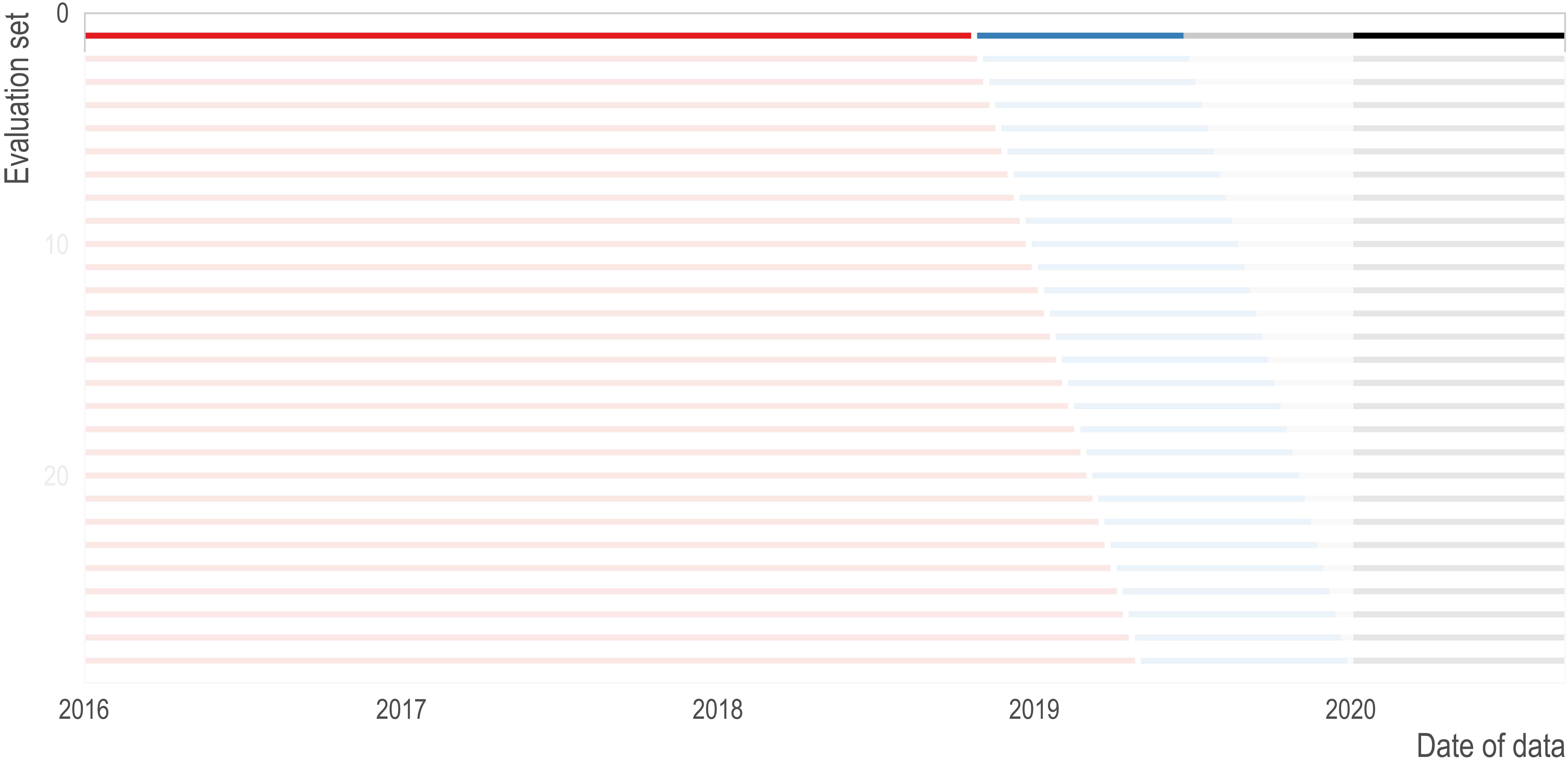


Data – Processing

- Usual occupation (free text) converted to 2012 Industry and Occupation codes using NIOCCS and reviewed by research team
- Aggregated to monthly mortality
- Dropped subgroups with unreliable sample size (CoV > .30)



TS-CV – The optimal baseline model



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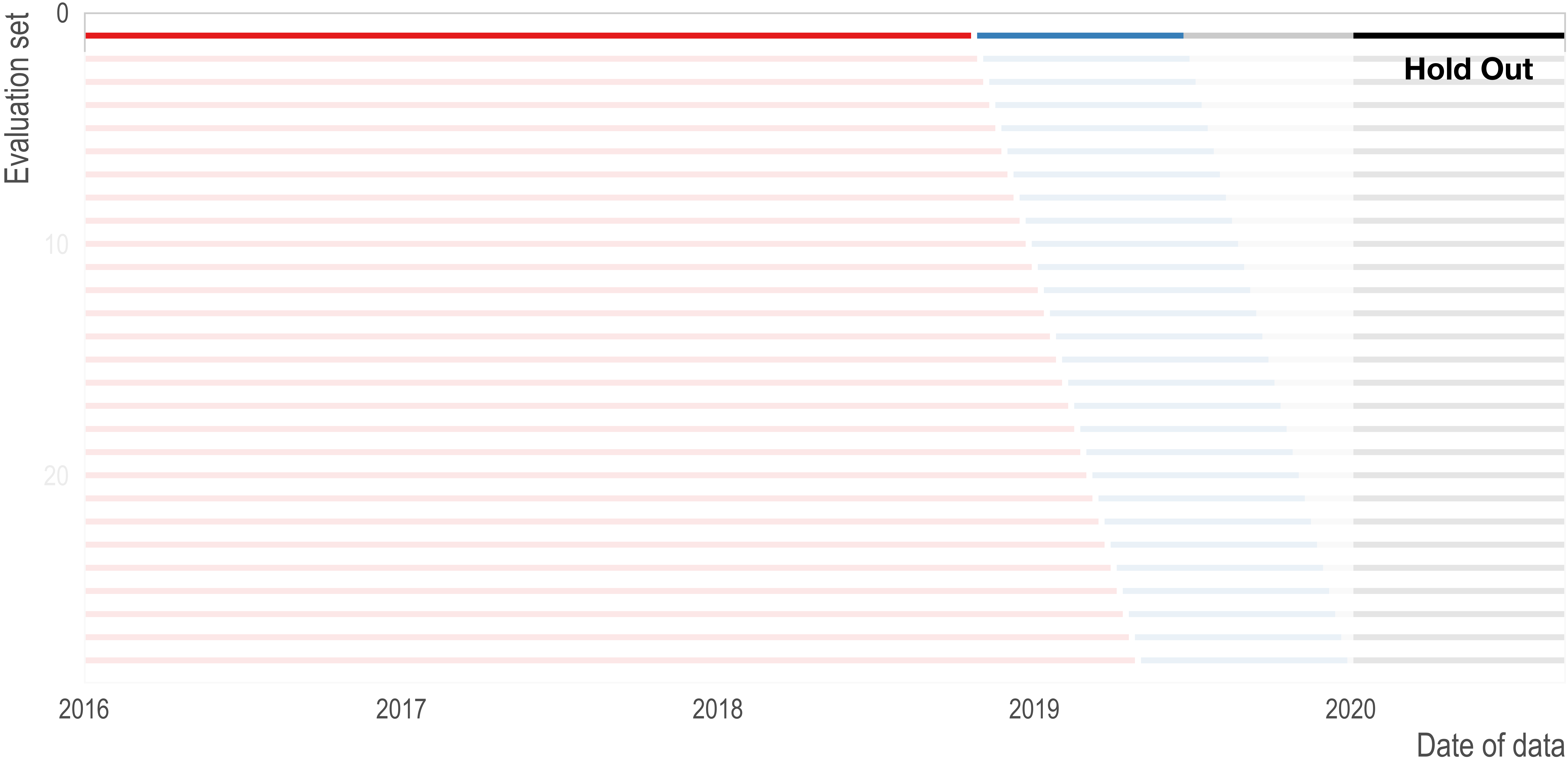

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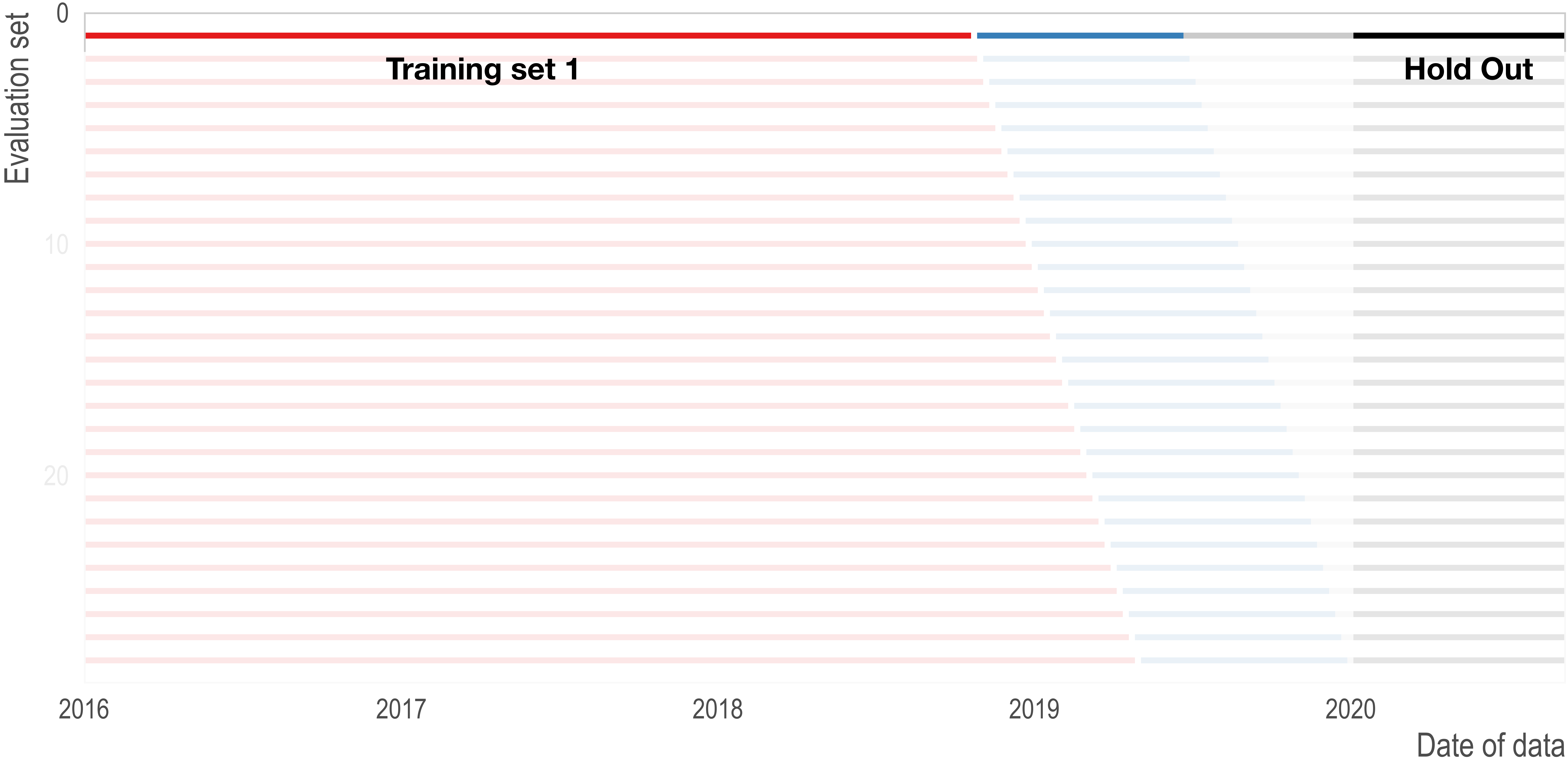

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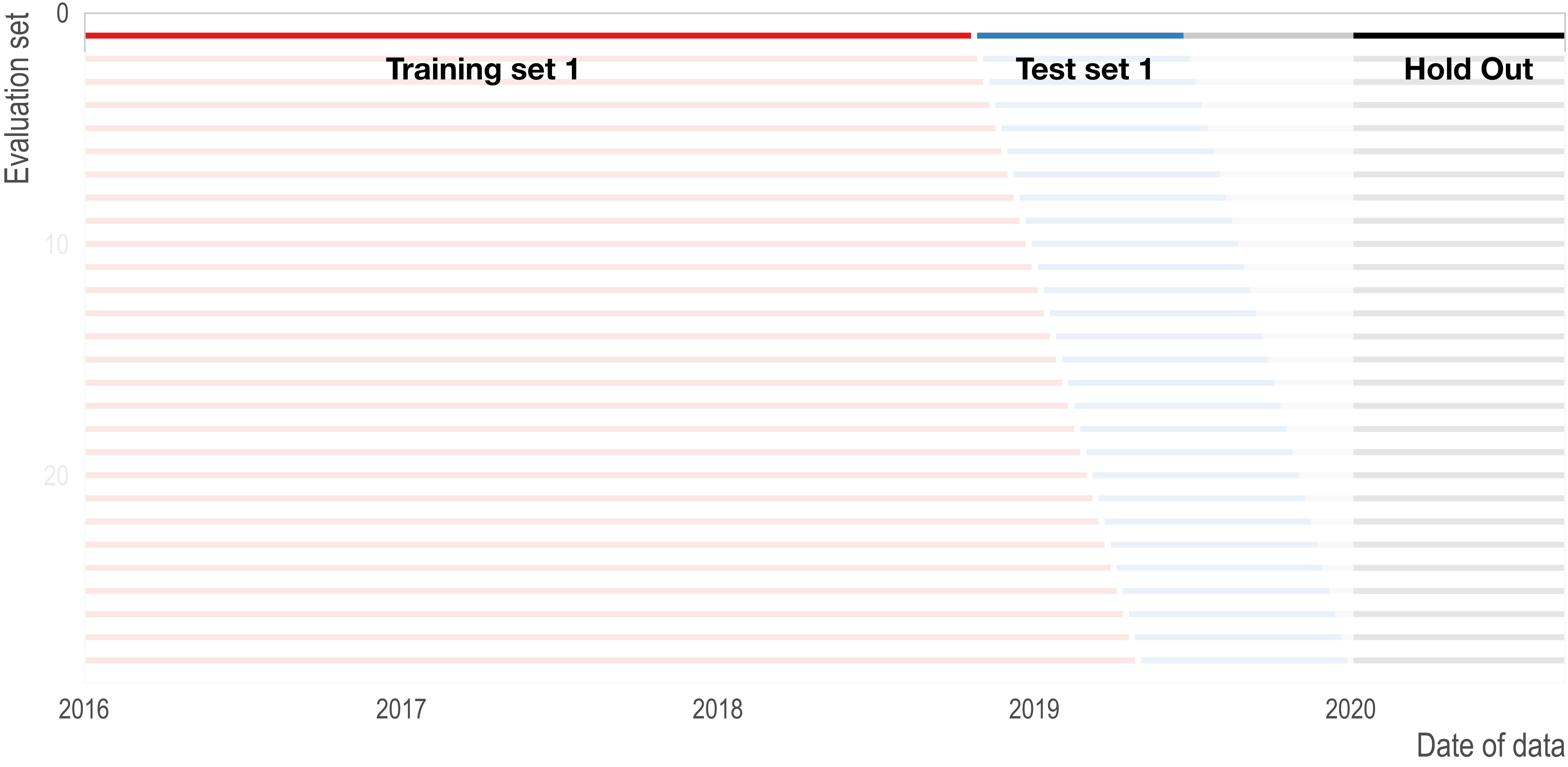

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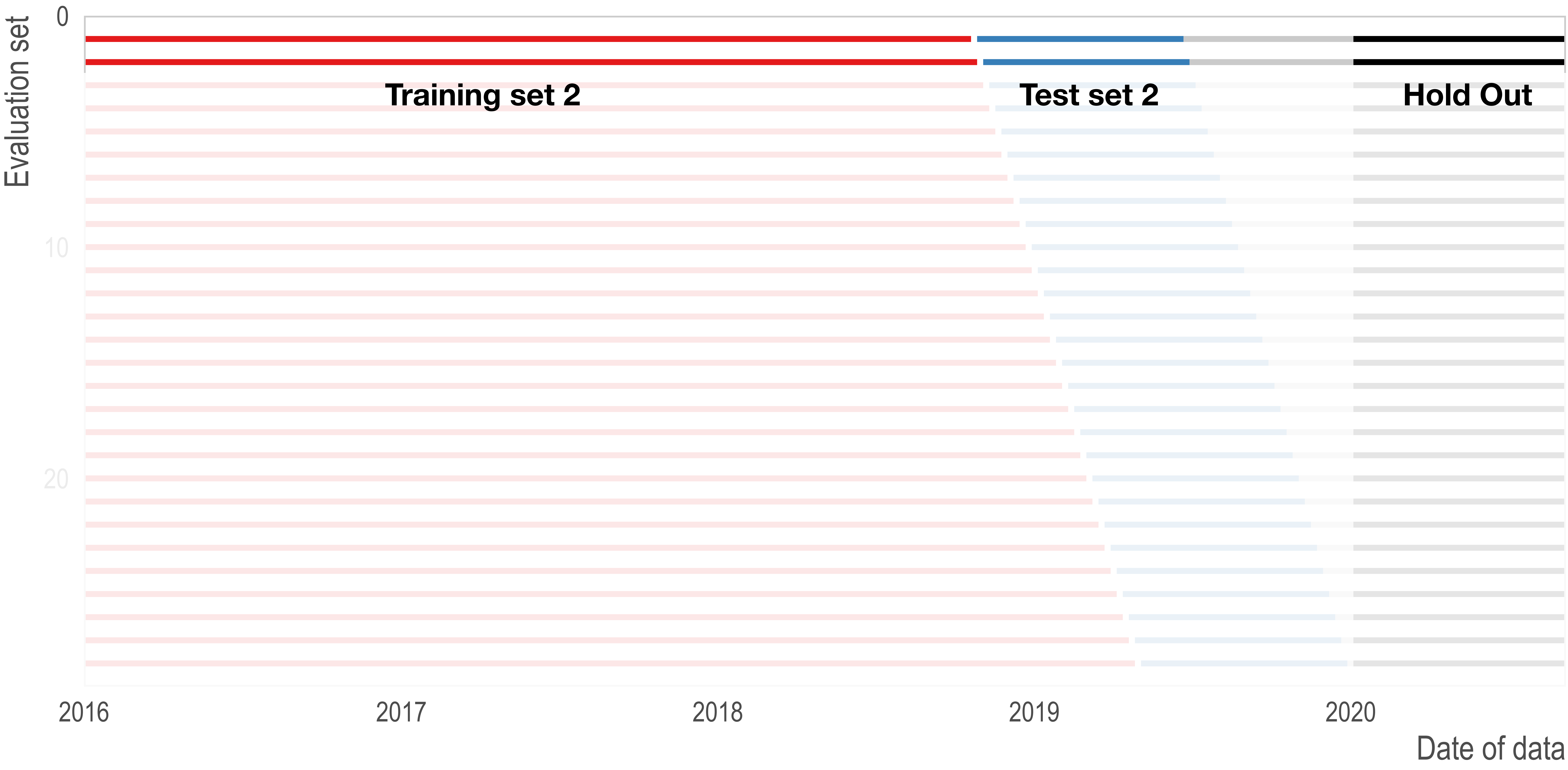

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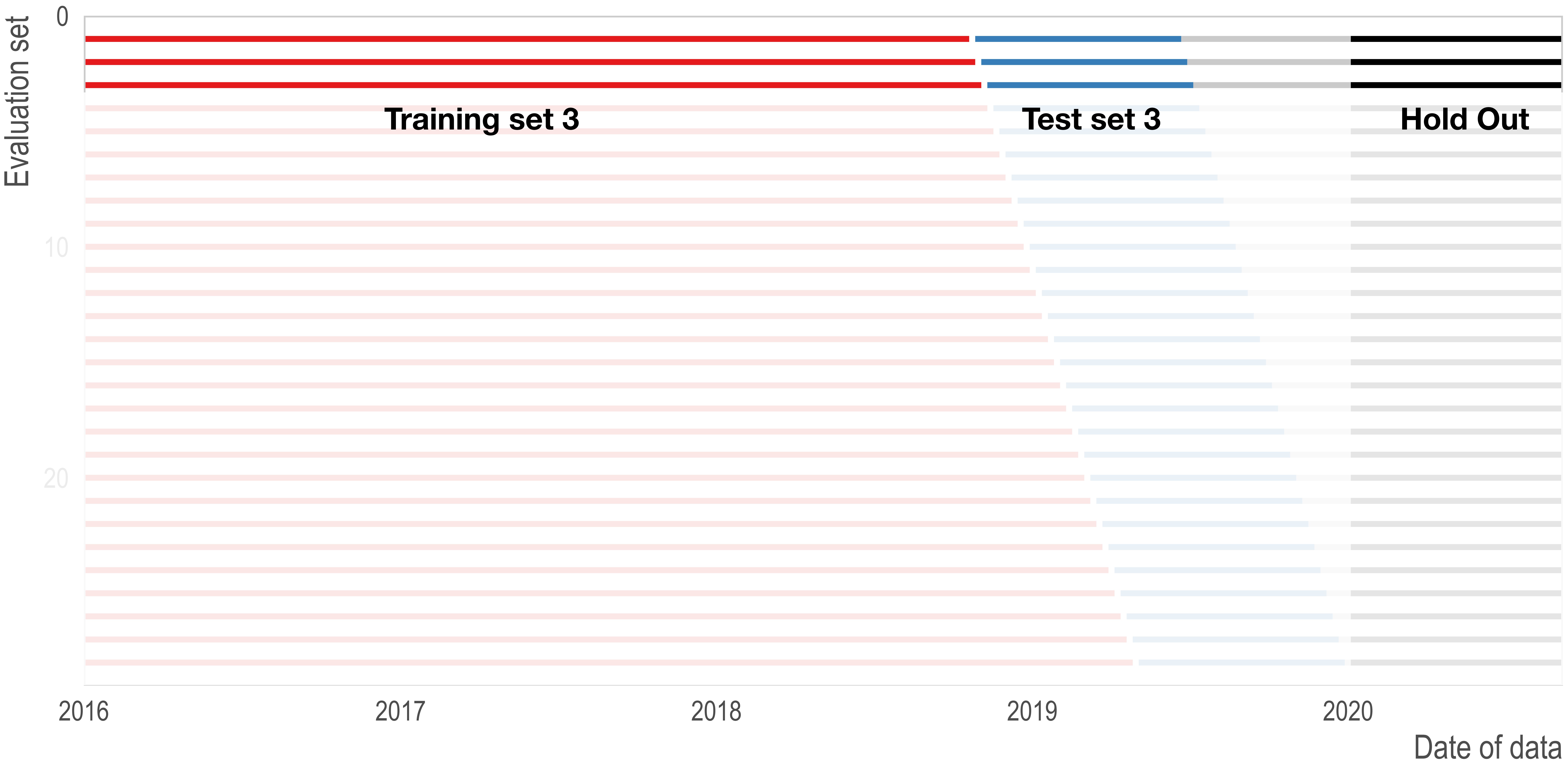

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