

Causal Inference in Three-Wave Panel Designs

with illustrations from the New Zealand Attitudes and Values Study

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The Fundamental Problem of Causal Inference: We Require a Counterfactual Contrast

$$Y_{\text{you}}(1) - Y_{\text{you}}(0)$$

1

¹Y denotes the outcome; A denotes a treatment, $Y(a)$ denotes the outcome when $A = a$

But Individuals Experience Only **One** Treatment

$Y_i|A_i = 1 \implies Y_i(0)|A_i = 1$ is counterfactual

Average Treatment Effect in Randomised Controlled Experiments Work From Assumptions

$$\text{Average Treatment Effect} = \left[\begin{array}{c} \left(\underbrace{\mathbb{E}[Y(1)|A=1]}_{\text{observed}} + \underbrace{\mathbb{E}[Y(1)|A=0]}_{\text{unobserved}} \right) \\ - \left(\underbrace{\mathbb{E}[Y(0)|A=0]}_{\text{observed}} + \underbrace{\mathbb{E}[Y(0)|A=1]}_{\text{unobserved}} \right) \end{array} \right]$$

Section 1

The Three Fundamental Assumptions of Causal Inference

Causal Consistency

$$Y_i^{observed}|A_i = \begin{cases} Y_i(a^*) & \text{if } A_i = a^* \\ Y_i(a) & \text{if } A_i = a \end{cases}$$

Conditional Exchangeability

$$Y(a) \coprod A|L \quad \text{or equivalently} \quad A \coprod Y(a)|L$$

2

² L denotes measured covariates.

Positivity

$$0 < Pr(A = a | L = l) < 1$$

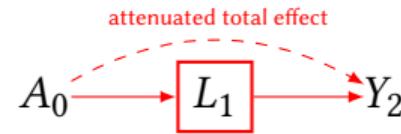
The Typical Worry: Confounding by Common Cause



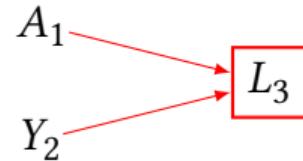
However, There Are Other Worries: Reverse Causation

$$Y_1 \longrightarrow A_2$$

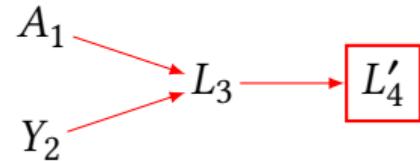
Another **Worry** is Mediator Bias



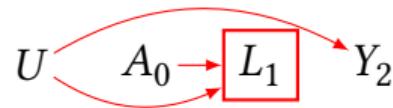
Another **Worry** is Collider Bias



Another **Worry** is Collider Bias Proxy



Yet Another Worry is Post Exposure Collider Bias



3

³U denotes and unmeasured confounder of $A \rightarrow Y\}$

Another **Worry** are Unmeasured Common Causes (U)

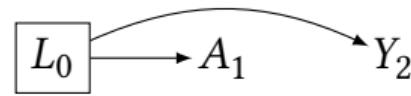
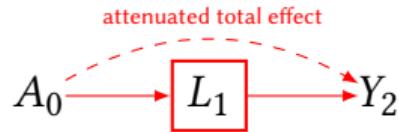


Reverse Causation Strategy: Longitudinal Hygiene

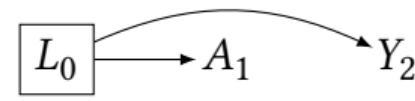
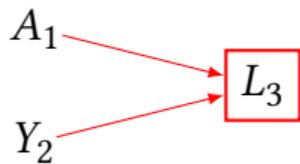
$$Y_1 \longrightarrow A_2$$

$$A_1 \qquad Y_2$$

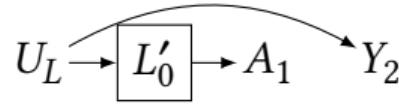
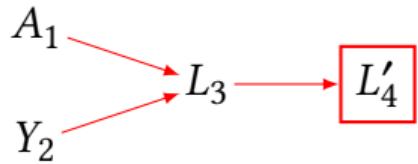
Mediator Bias Strategy: Longitudinal Hygiene



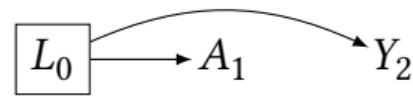
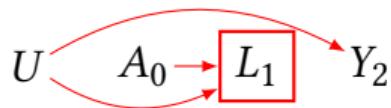
Collider Bias Strategy: Longitudinal Hygiene



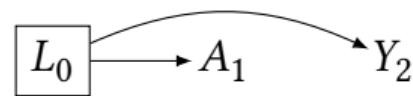
Collider Bias Proxy Strategy: Longitudinal Hygiene



Post Exposure Collider Bias Strategy:Longitudinal Hygiene



Unmeasured Common Cause Strategy: Longitudinal Hygiene



Section 2

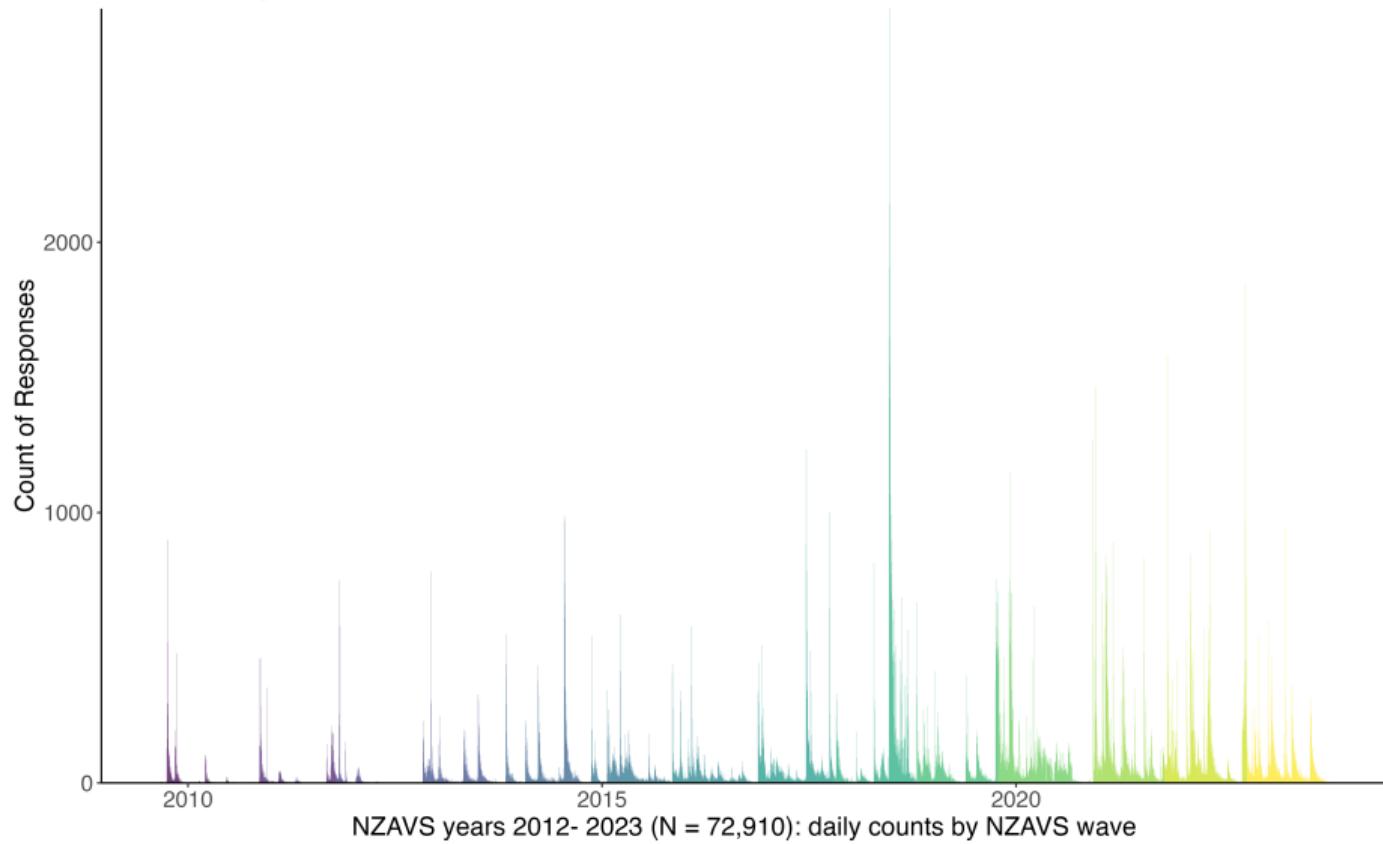
New Zealand Attitudes and Values Study (NZAVS)

NZAVS Longitudinally Hygienic Data Collection

- Planned 20-year longitudinal study, currently in its 14th year.
- Sample frame is drawn randomly from NZ Electoral Roll.
- Postal questionnaire (coverage; retention ~ 80%)
- Large multidisciplinary research team (40 +)
- Focus on personality, social attitudes, values, religion, employment, prejudice ...
- Current sample contains 72910 unique individuals, and ~ 38,000 in the longitudinal study

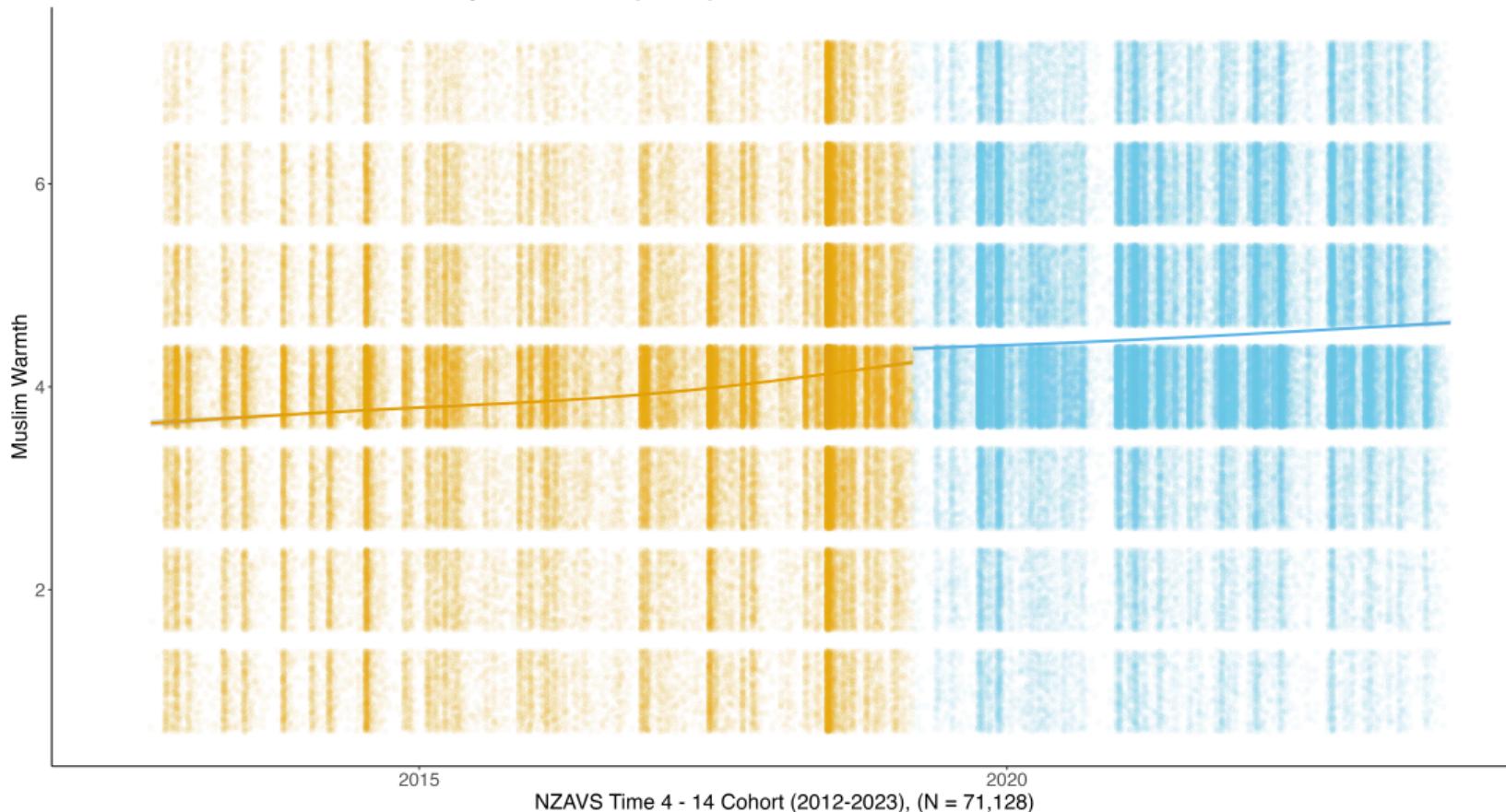
New Zealand Attitudes and Values Study (panel)

N = 72,910; years 2012-2023



BIG EVENTS

Muslim Warmth Pre/Post Mosque Attacks (GAM)



NZAVS Time 4 - 14 Cohort (2012-2023), (N = 71,128)

Institutional Trust

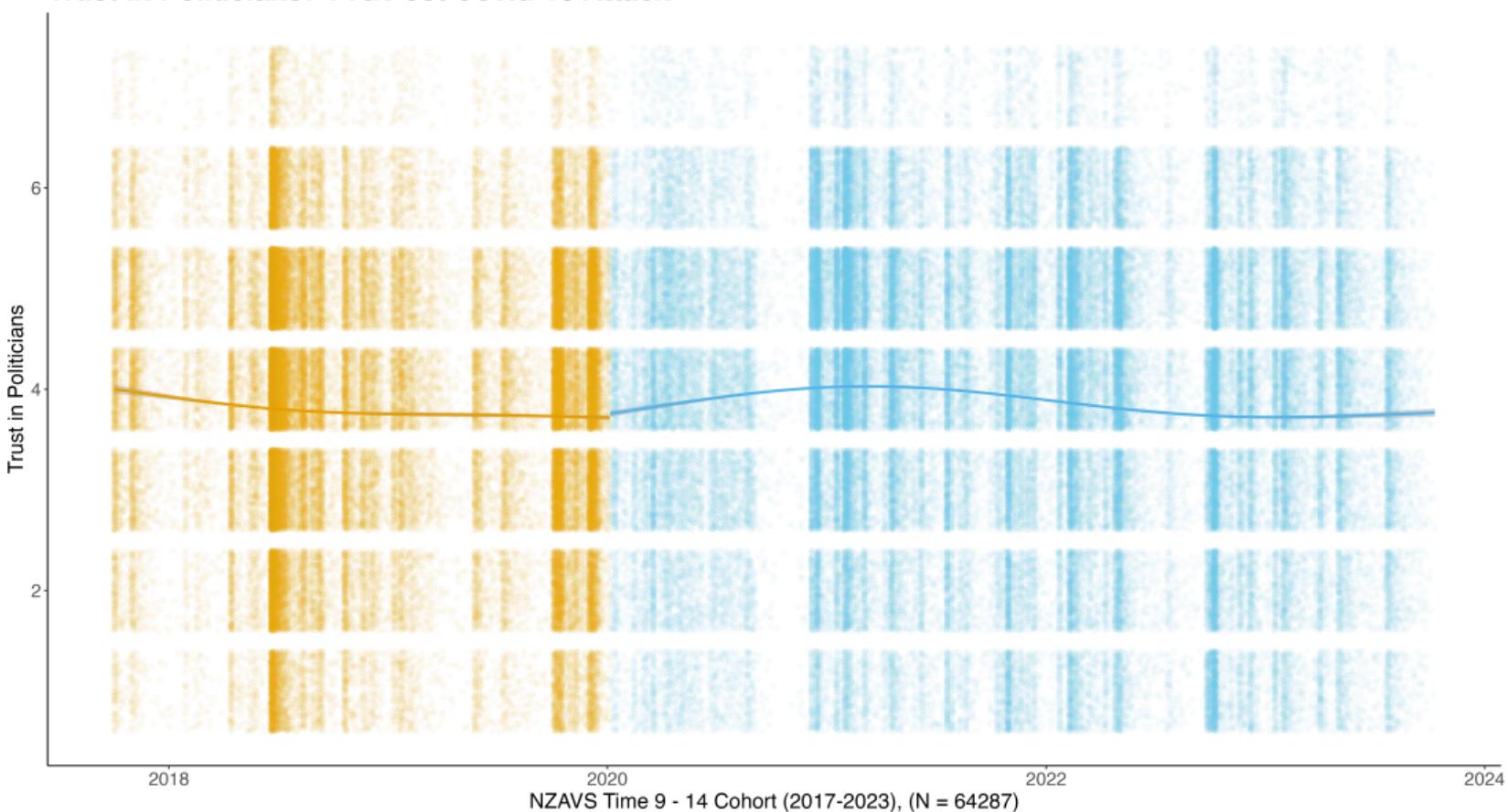
COVID-19 Government response - “I trust the Government to make sensible decisions about how to best manage COVID-19 in New Zealand.” - “The New Zealand government response to COVID-19.”

Trust in politicians - “Politicians in New Zealand can generally be trusted.”

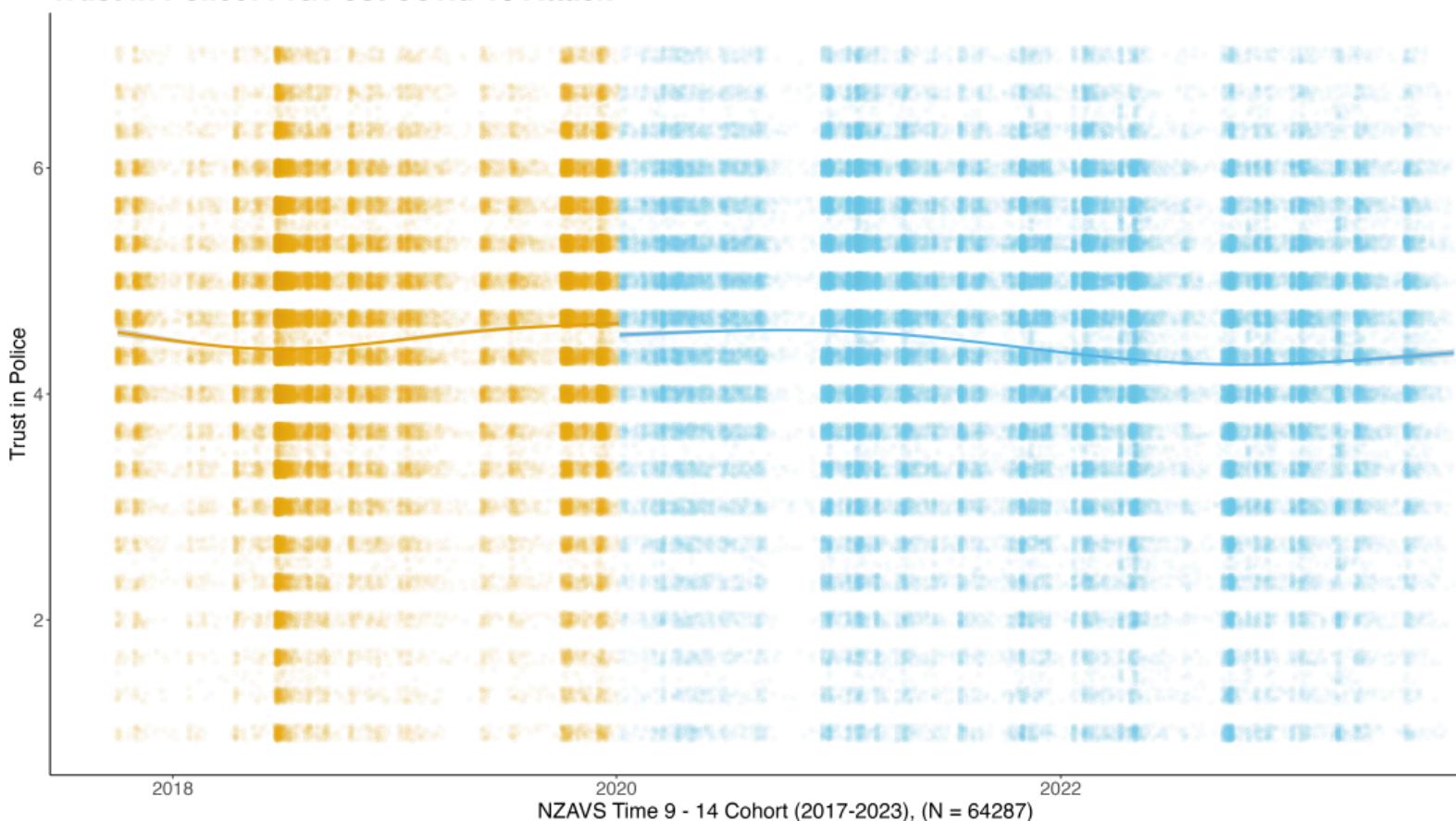
Institutional trust in police - “People’s basic rights are well protected by the New Zealand Police.” - “There are many things about the New Zealand Police and its policies that need to be changed.” - “The New Zealand Police care about the well-being of everyone they deal with.”

General tendency to believe in conspiracies - “I think that the official version of major world events given by authorities often hides the truth.”

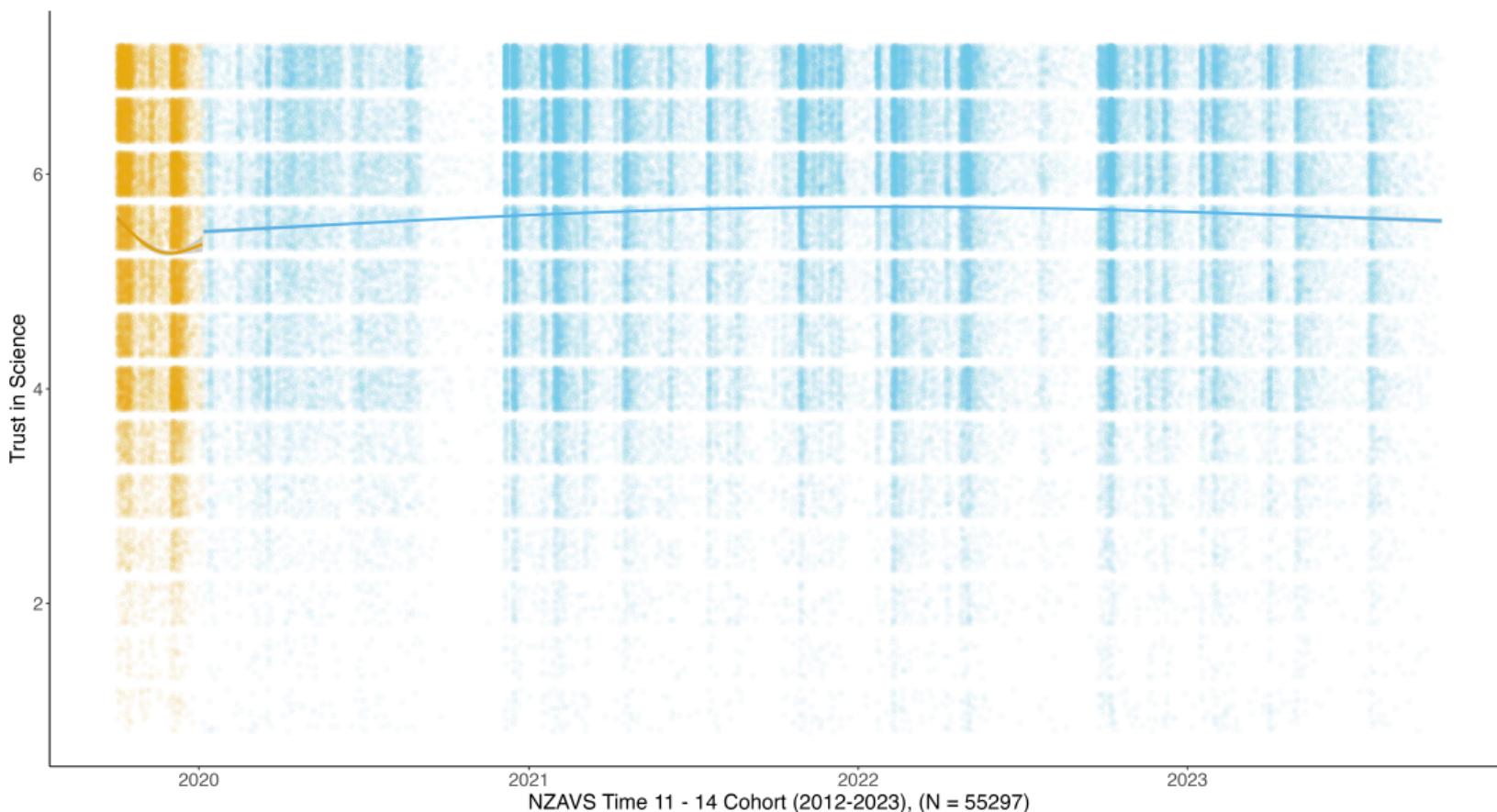
Trust in Politicians: Pre/Post Covid-19 Attack



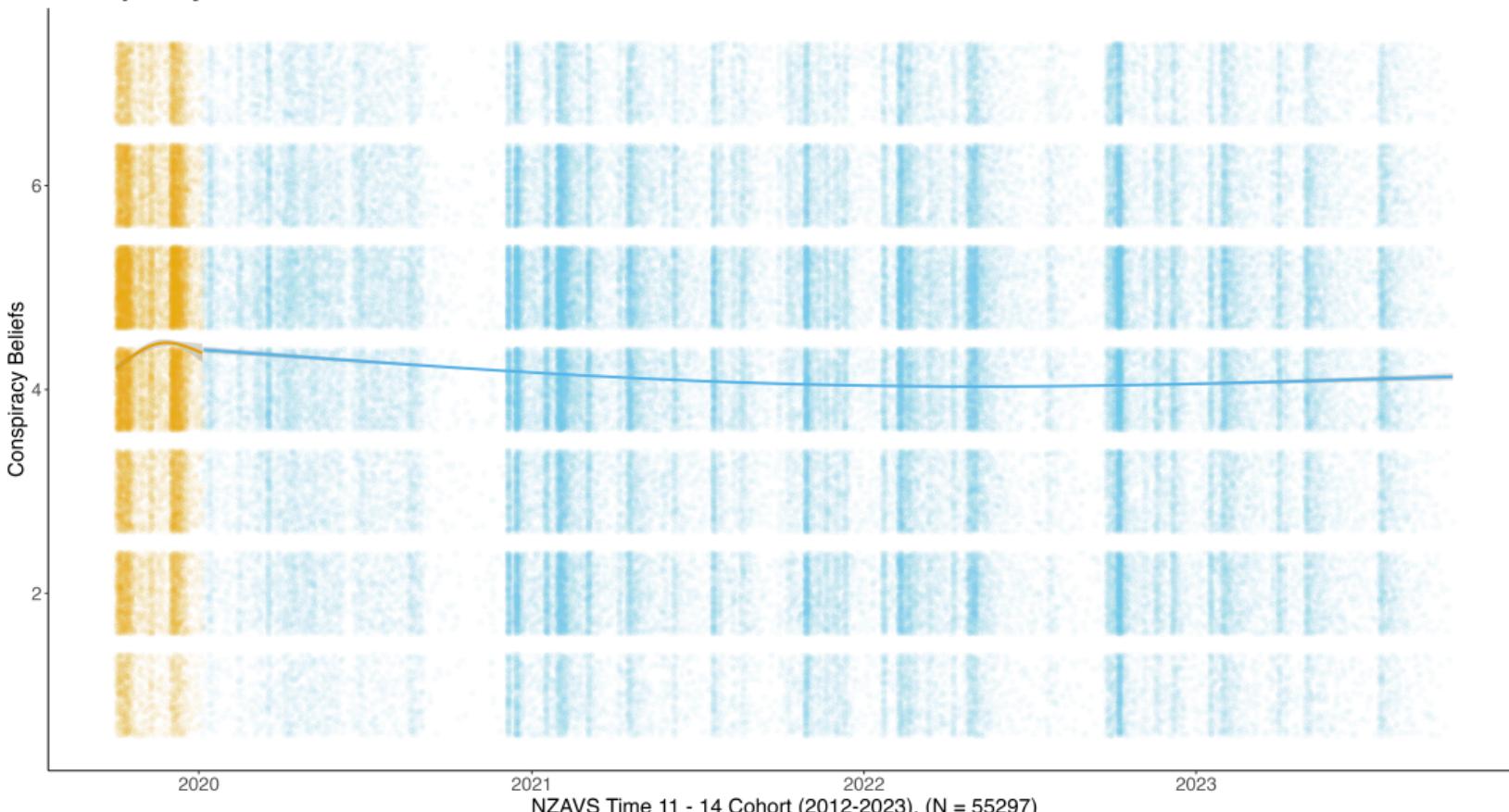
Trust in Police: Pre/Post Covid-19 Attack



Trust in Science: Pre/Post Covid-19 Attacks



Conspiracy Beliefs: Pre/Post Covid-19 Attacks



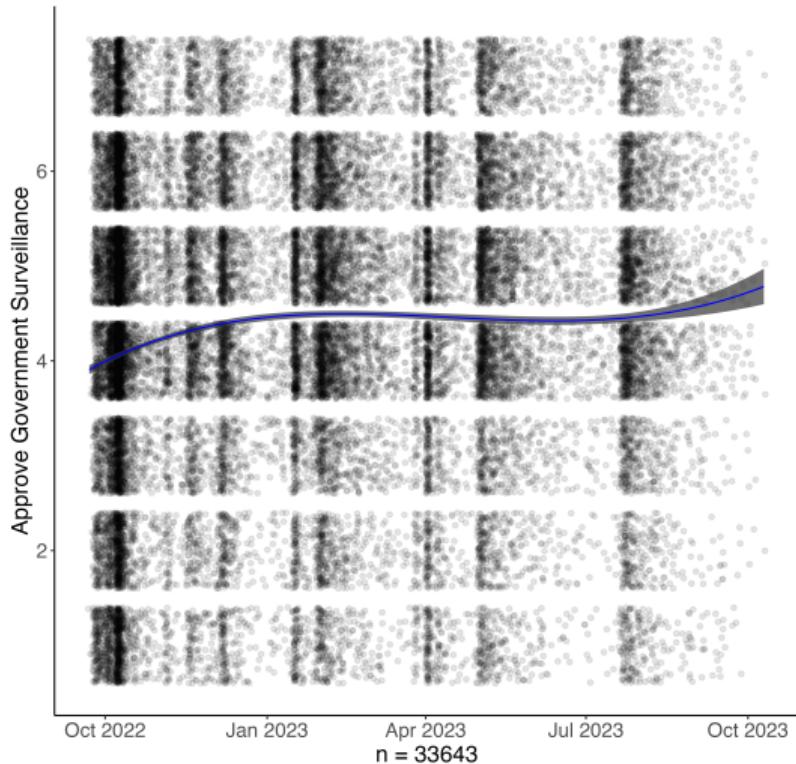
Regulate Gov't Surveillance vs Regulate AI

Comparison of Attitudes to New Zealand Government Interventions from 2022-SEP-22 to 2023-OCT-10

Generalised Additive Model: 3-knot splines weighted to NZ Census Age/Gender/Ethnicity NZAVS (n=33643)

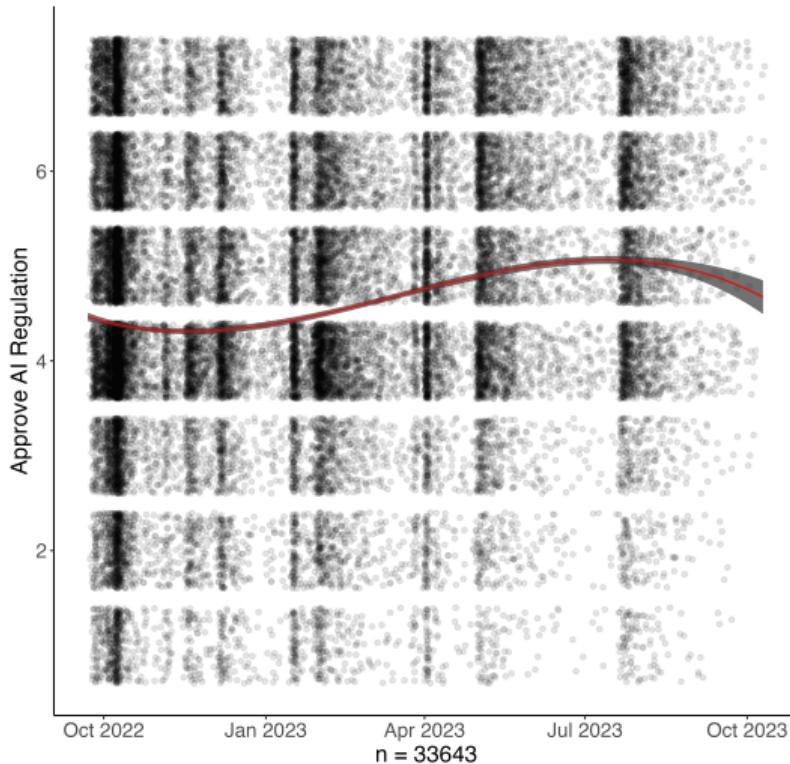
A

Collection of telephone and internet data by the New Zealand Government as part of anti-terrorism efforts



B

Strict regulation limiting the development and use of Artificial Intelligence

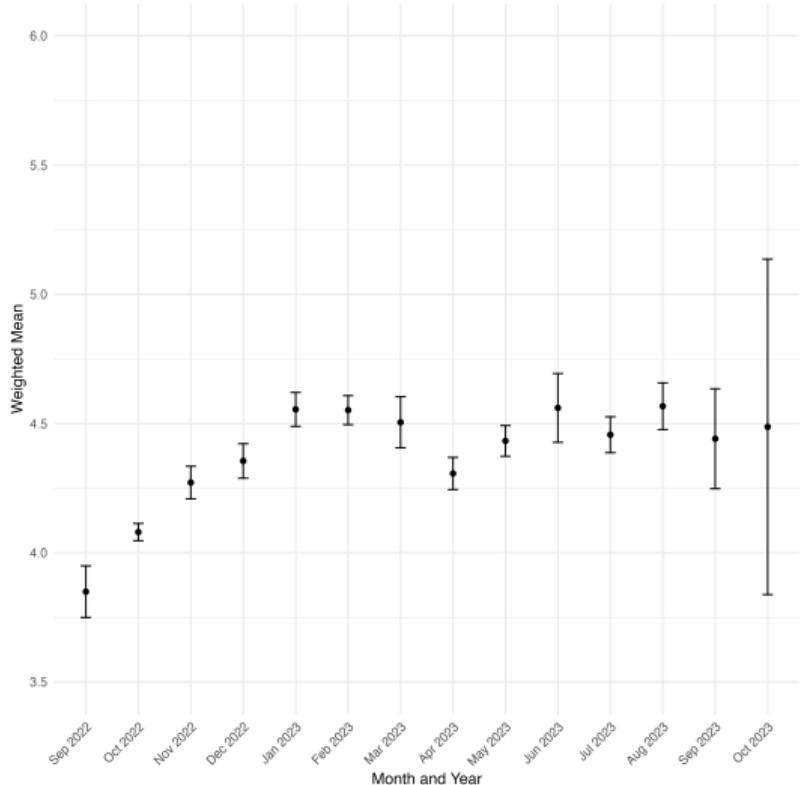


Weighted Monthly Marginal Means: Comparisons of Attitudes to New Zealand Government Interventions

NZAVS Time 14 (n=33643)

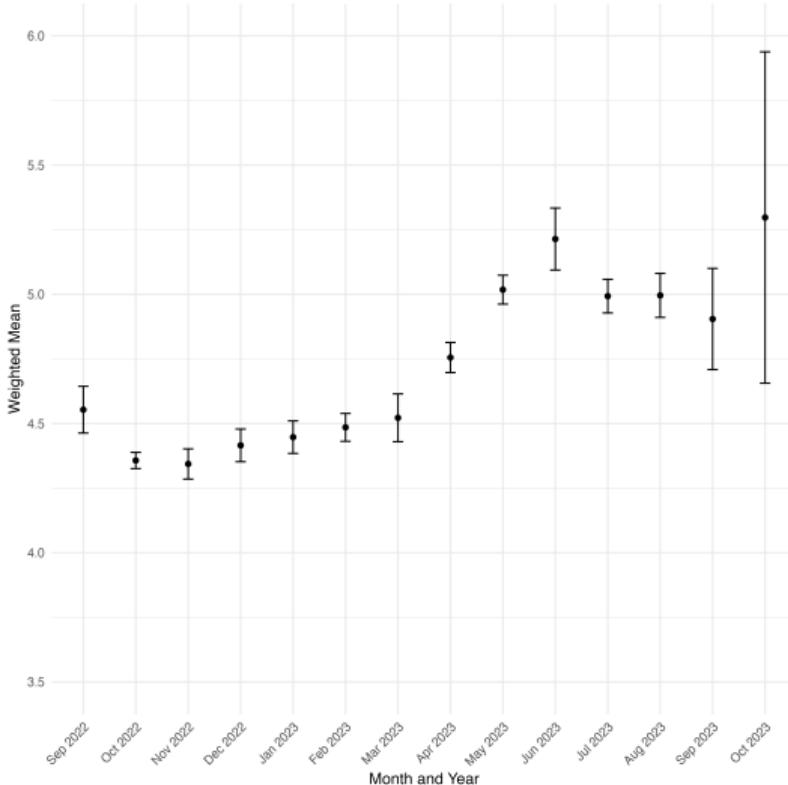
A

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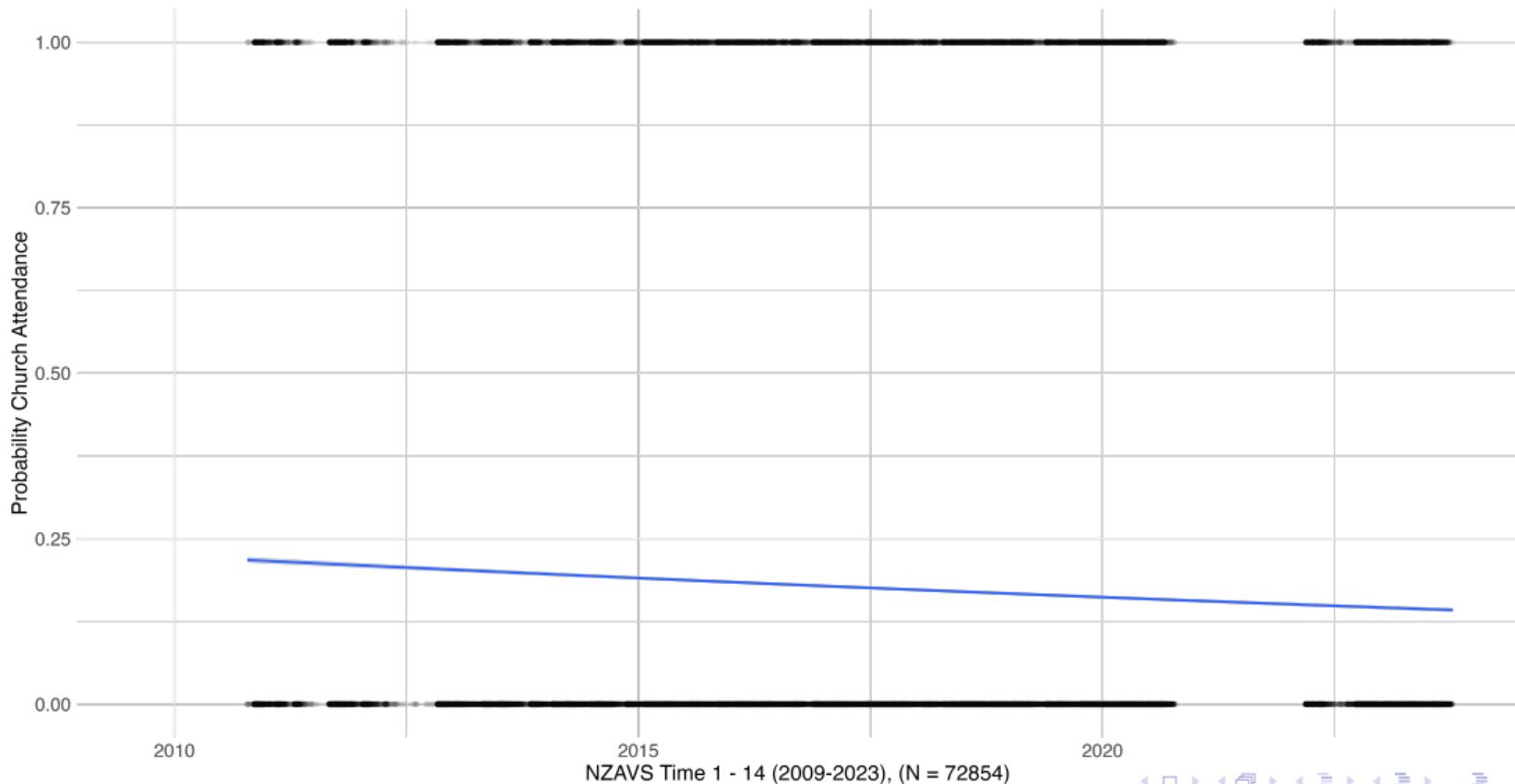
B

Strict regulation limiting the development and use of Artificial Intelligence



Consider Gradual Events

Probability of Church Attendance in New Zealand: Years 2009 - 2023



NZAVS Time 1 - 14 (2009-2023), (N = 72854)

Worked Example: causal Effects of Religious Service on Prosociality

Intervention

$$f(A = a^*) = \begin{cases} 4 & \text{if } A < 4 \text{ monthly religious service attendance} \\ \tilde{A} & \text{if } A \geq 4 \text{ monthly religious service attendance} \end{cases}$$

Contrast

$$f(A) = 0$$

Shift Intervention: Socializing

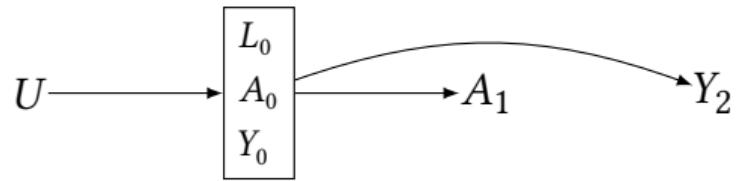
Intervention

$$f(A) = \begin{cases} 1.4 & \text{if } A \leq 1.4 \text{ hours socialising with community} \\ \tilde{A} & \text{if } A > 1.4 \text{ hours socialising with community} \end{cases}$$

Contrast:

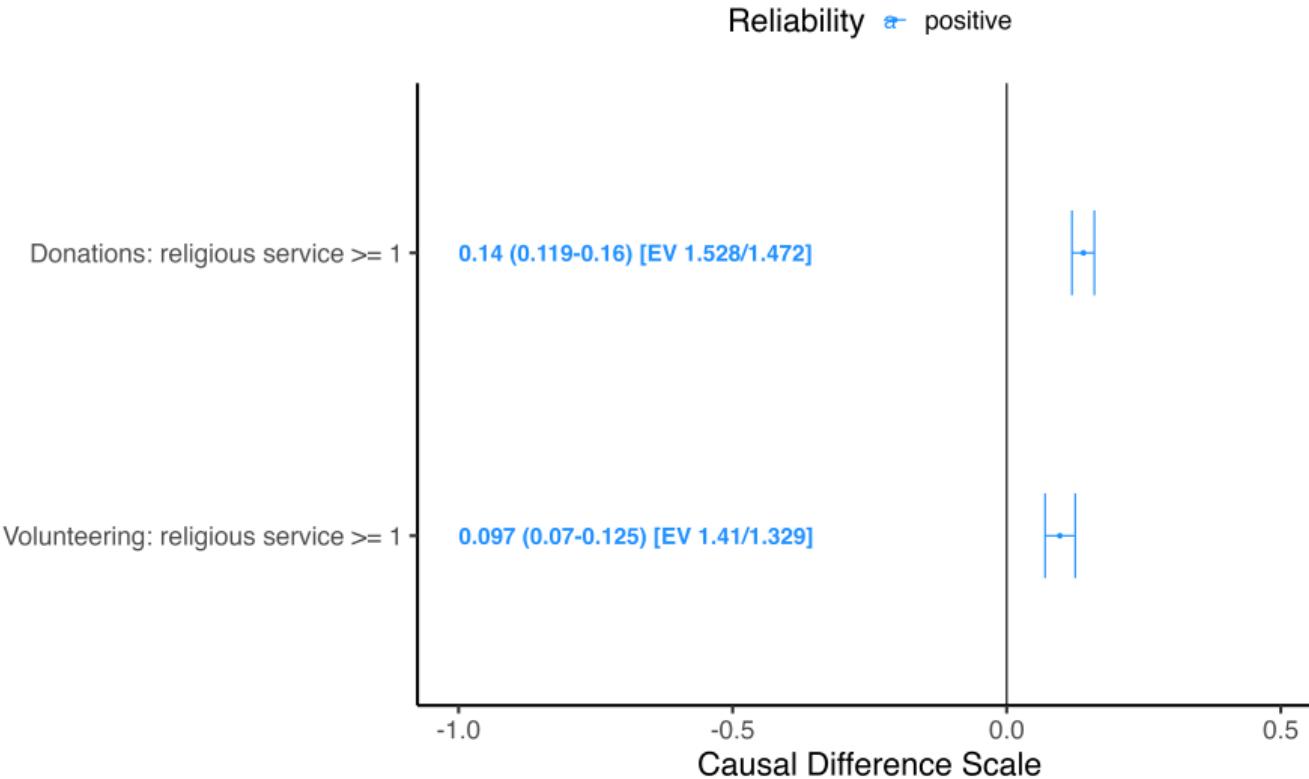
$$f(A) = 0$$

Key Graph



Religious Service Outcomes

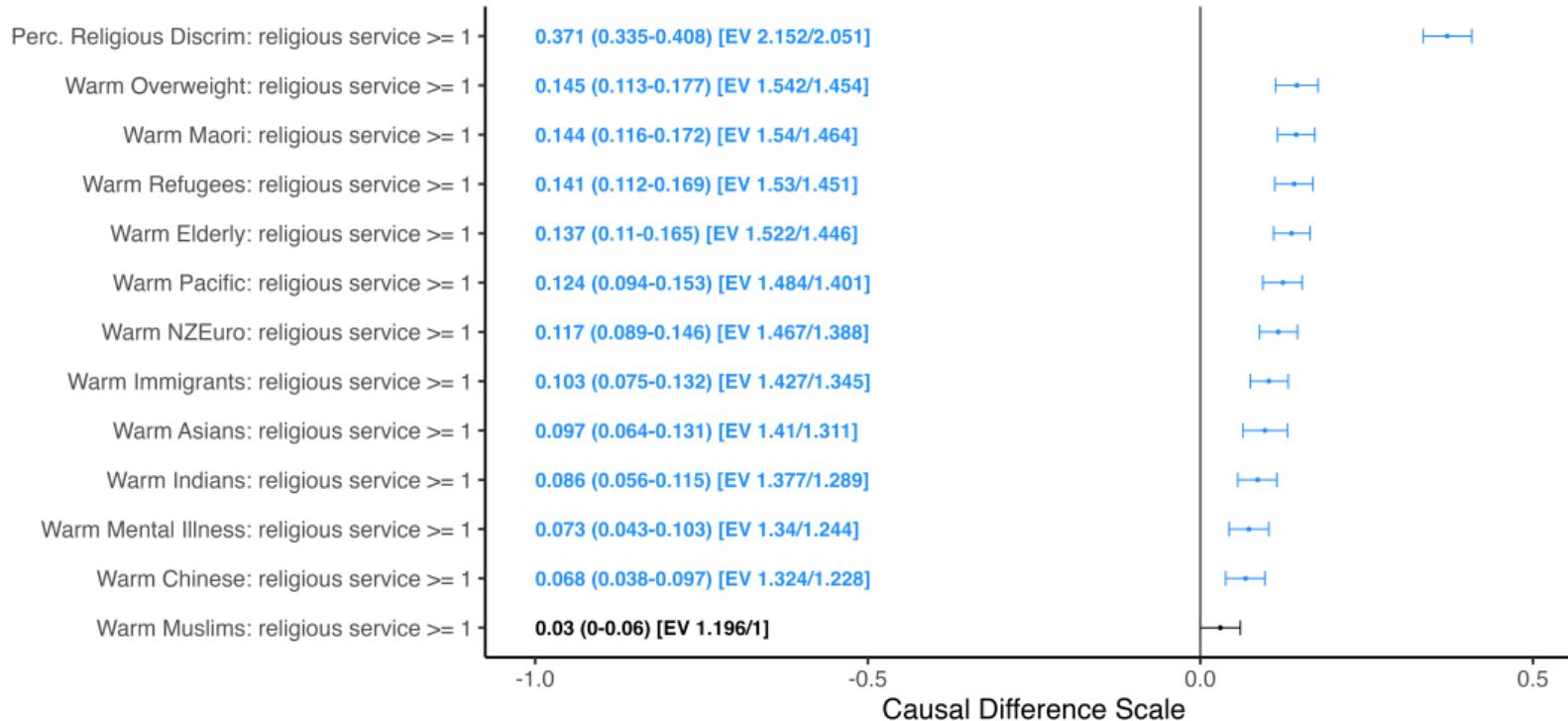
Religious service: donations and volunteering >= 1 x weekly religious service attendance



Religious service: Warmth

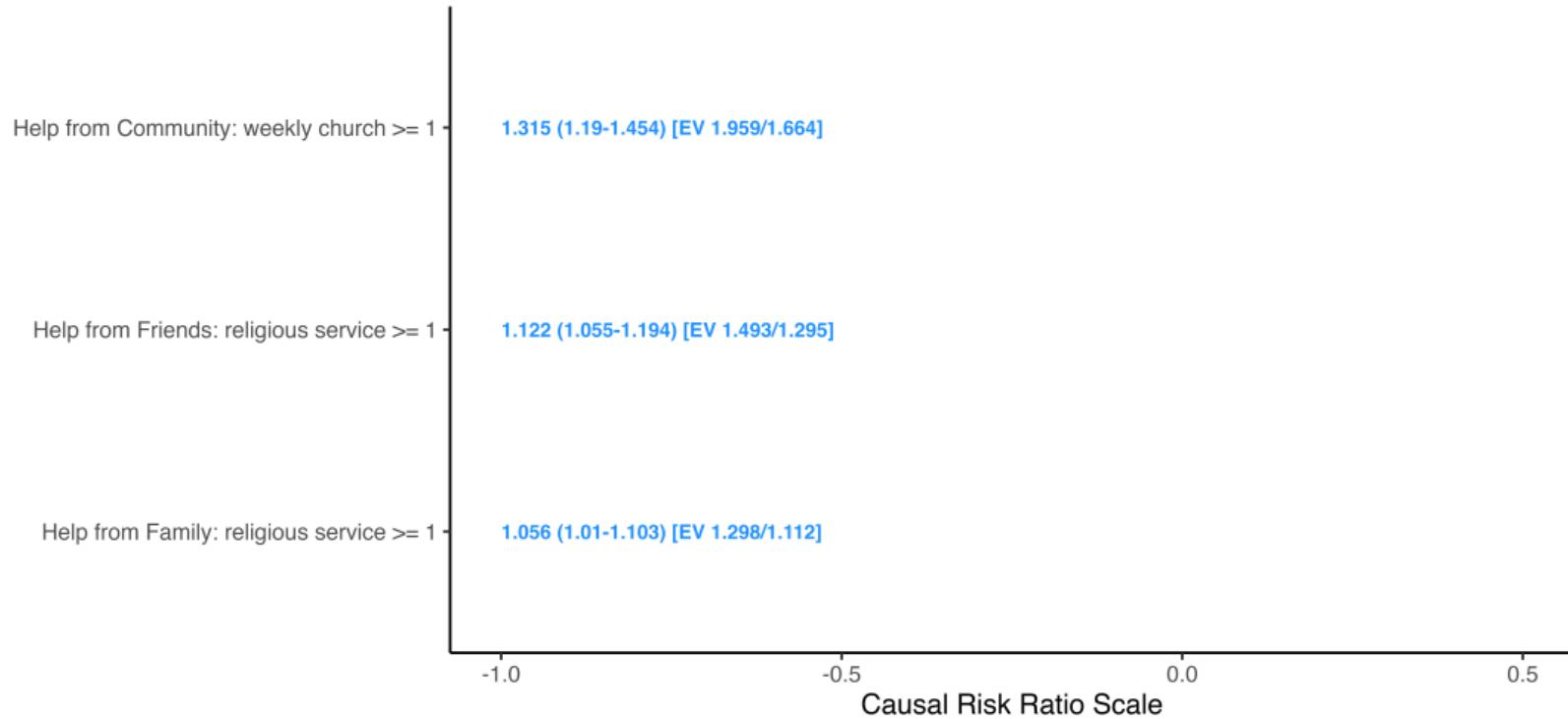
$\geq 1 \times$ weekly service attendance

Reliability ↗ positive ↙ zero_crossing



Religious Service: Help Received >= 1 x weekly service attendance

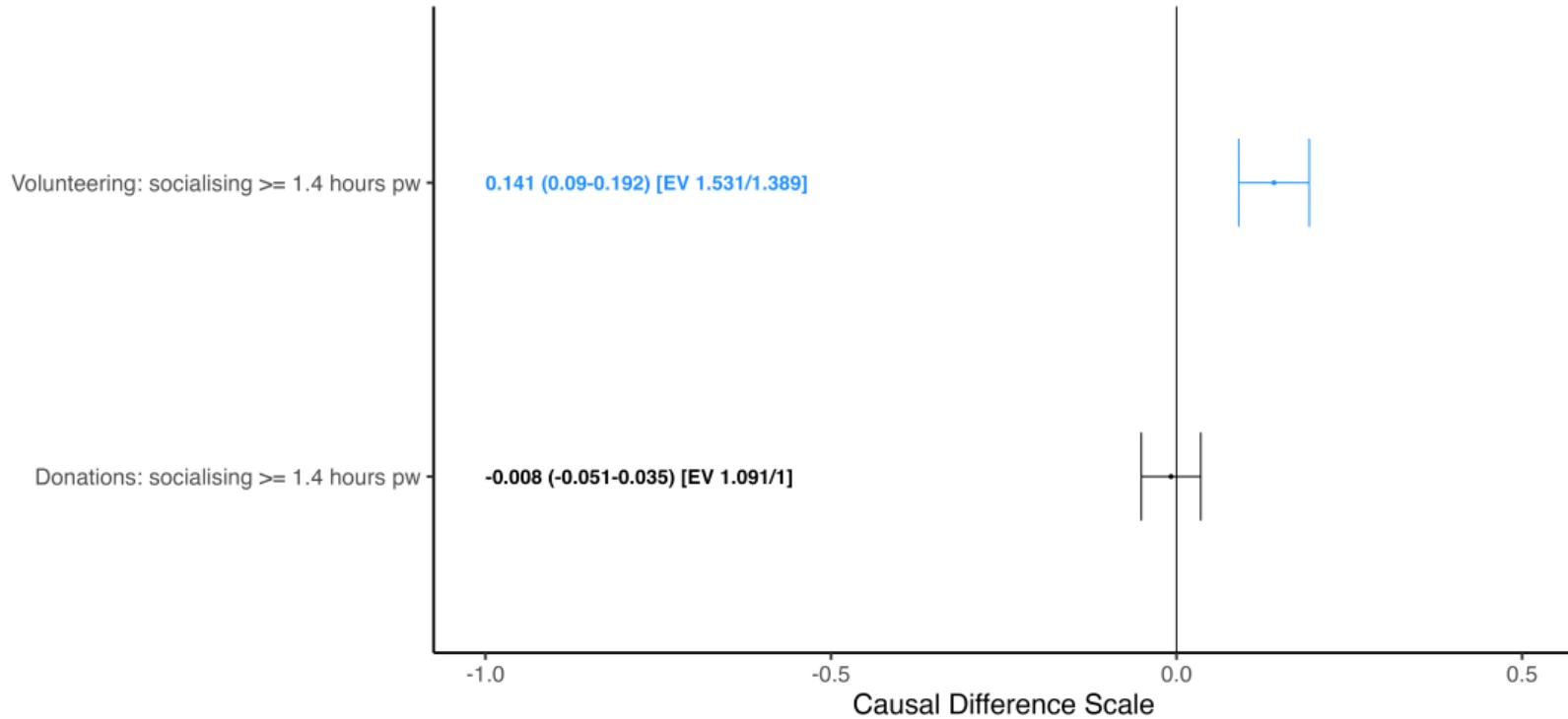
Reliability ↗ positive



Socializing Outcomes

Socialising effect on charity >= 1.4 x weekly hours socialising

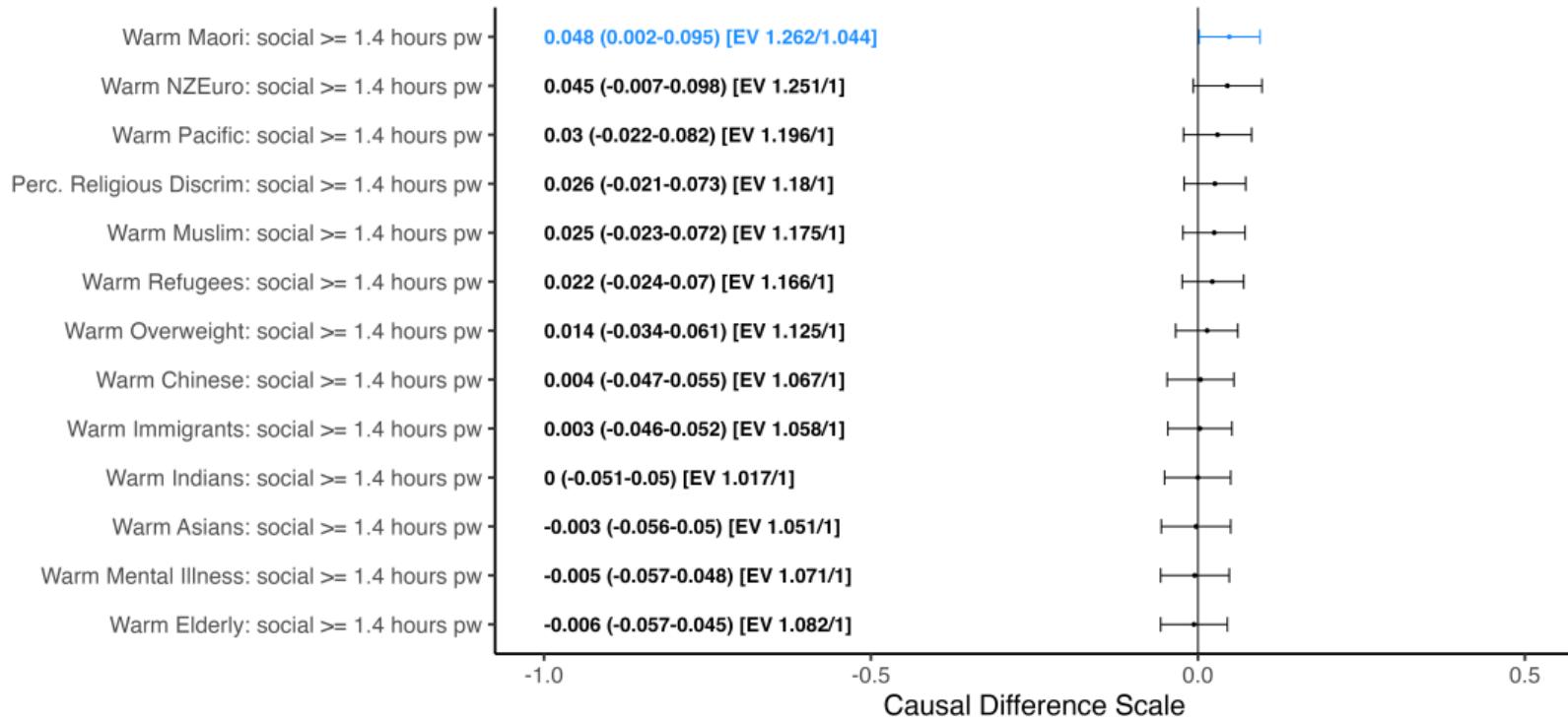
Reliability ↗ positive ↙ zero_crossing



Socialing effect on prejudice/acceptance

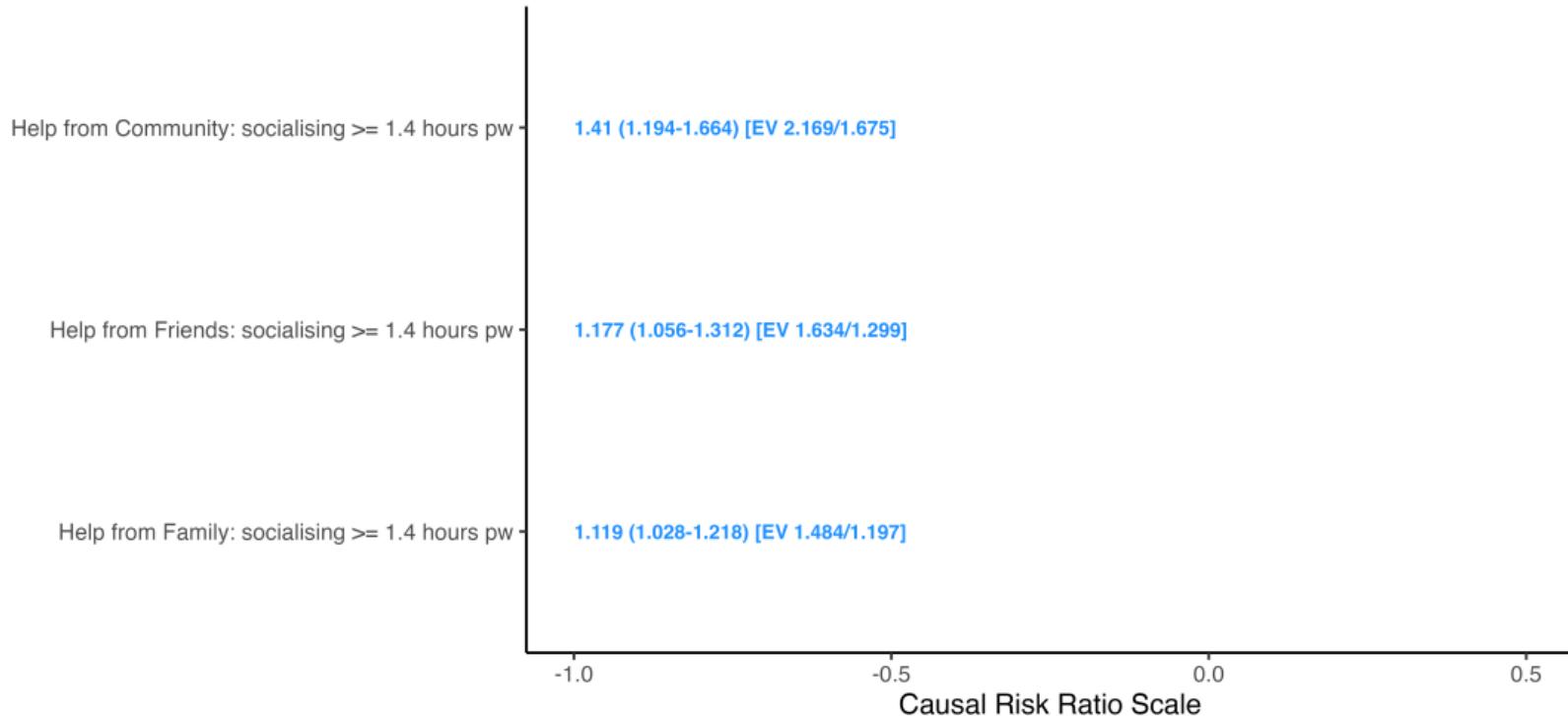
$\geq 1.4 \times$ weekly hours socialising

Reliability ↗ positive ↘ zero_crossing



Socialising effect on help received >= 1.4 x weekly hours socialising

Reliability ↗ positive



Results

- Causal effects of religious service attendance on the economy are considerable, in expectation they represent ~ **0.048%** of New Zealand's 2021 annual government budget.
- Notably, cross-sectional associations are four times stronger, but these associations are **uninterpretable**
- Results underscore the importance of investigating gradual cultural change.

Summary

- ① To move beyond association to causality requires time, literally.

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Summary

- ① To move beyond association to causality requires time, literally.
- ② Big events ≠ big effect sizes.
- ③ Long-term effects unclear.
- ④ Long-term change might be more important for planning.

Thanks

- Chris G. Sibley (NZAVS lead Investigator)
- Templeton Religion Trust Grant 0418
- Max Planck Institute for Evolutionary Anthropology: Department Linguistic and Cultural Evolution
- Victoria University
- University of Canterbury
- 72,910 NZAVS participants

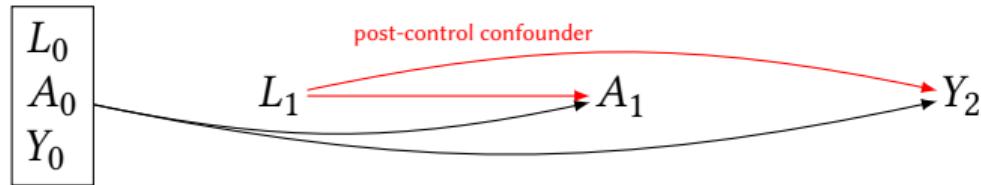




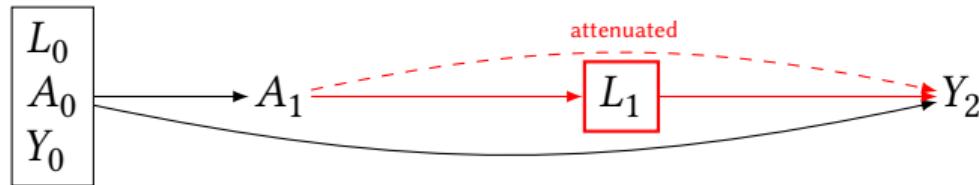
Extra Slides

Longitudinal Data Bring Their Own Problems

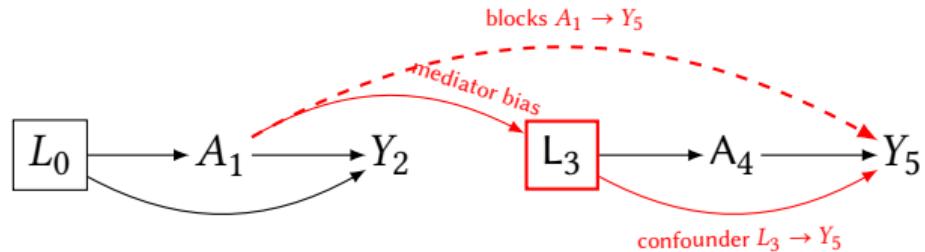
Timing of Confounder



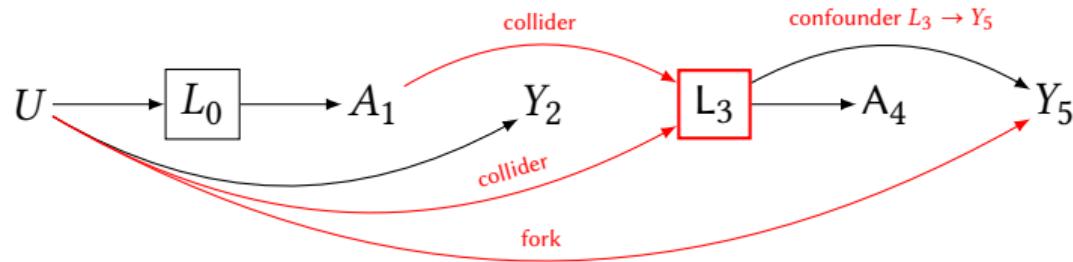
Timing of Mediator



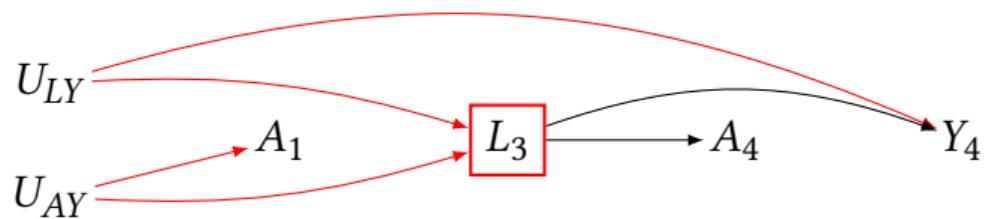
Treatment Confounder Bias



Treatment Confounder Feedback



Treatment Confounder Feedback Variation



Mediation

Total Effect

$$TE = \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)]$$

Total Effect Considering Mediator

$$TE = \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)]$$

$$\mathbb{E}[Y(1)] = \mathbb{E}[Y(1, M(1))]$$

Natural Direct Effect

Natural Direct Effect (NDE) is the effect of the treatment on the outcome while maintaining the mediator at the level it would have been if the treatment had *not* been applied:

$$NDE = \mathbb{E}[Y(1, M(0))] - \mathbb{E}[Y(0, M(0))]$$

Natural Indirect Effect

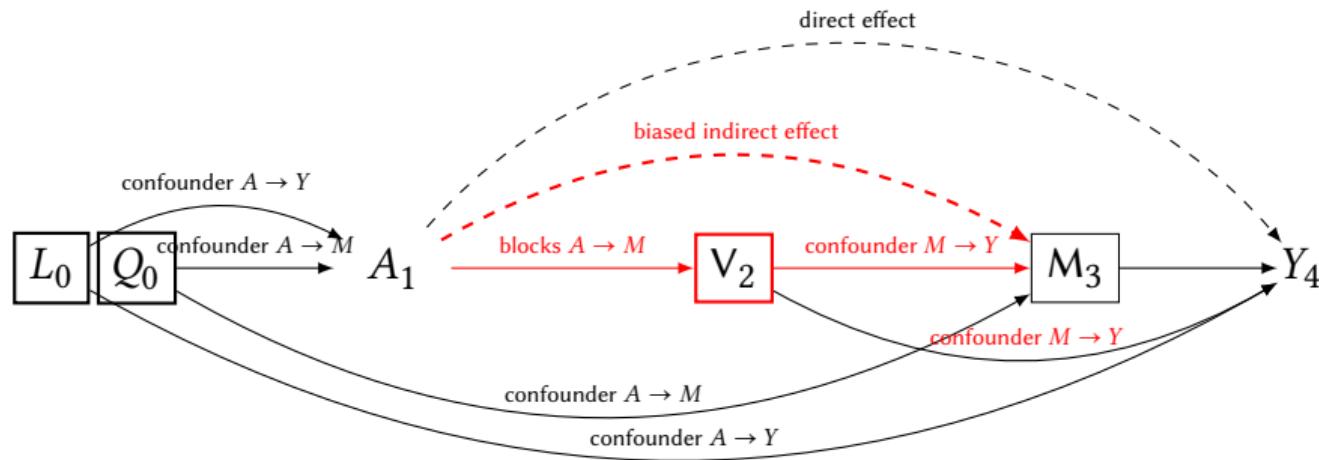
Natural Indirect Effect (NIE): is the effect of the exposure on the outcome that is mediated. To obtain these quantities we must compare the potential outcome Y under treatment, where the mediator assumes its natural level under treatment with the potential outcome when the mediator assumes its natural value under no treatment is given:

$$NIE = \mathbb{E}[Y(1, M(1))] - \mathbb{E}[Y(1, M(0))]$$

Decomposition

$$\text{Total Effect (TE)} = \underbrace{\left\{ \mathbb{E}[Y(1, M(1))] - \mathbb{E}[Y(1, M(0))] \right\}}_{\text{Natural Indirect Effect (NIE)}} + \underbrace{\left\{ \mathbb{E}[Y(1, M(0))] - \mathbb{E}[Y(0, M(0))] \right\}}_{\text{Natural Direct Effect (NDE)}}$$

Why Mediation is Difficult



Interaction

Interaction: simplifies to

$$\underbrace{\mathbb{E}[Y(1, 1)]}_{\text{joint exposure}} - \underbrace{\mathbb{E}[Y(1, 0)]}_{\text{only A exposed}} - \underbrace{\mathbb{E}[Y(0, 1)]}_{\text{only B exposed}} + \underbrace{\mathbb{E}[Y(0, 0)]}_{\text{neither exposed}} \neq 0$$

Key

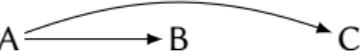
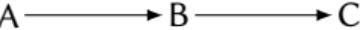
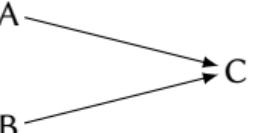
Symbol

X	Any variable.
A	The treatment or, equivalently, the exposure.
Y	The outcome.
$Y(a)$	The potential outcome when $A = a$.
L	Measured confounder(s): typically comprises a set of variables.
U	Unmeasured confounder.
Z	Effect-modifier (or ‘moderator’) of A on Y .
M	Mediator of A on Y .
\bar{X}	Sequential variables, e.g. $\bar{A} = \{A_1, A_2, A_3\}; \bar{L} = \{L_0, L_1, L_2\}$.
\mathcal{R}	Denotes randomisation into treatment event.

Two variables

1	Causality Absent	A B	A and B have no causal effect on each other.	$A \perp\!\!\!\perp B$ (independent)
2	Causality	$A \longrightarrow B$	A causally affects B, and they are associated.	$A \not\perp\!\!\!\perp B$ (dependent)

Three variables

3	Fork		A causally affects both B and C; B and C are conditionally independent given A.	$B \perp\!\!\!\perp C A$
4	Chain		C is affected by B which is, in turn, affected by A; A and C are conditionally independent given B.	$A \perp\!\!\!\perp C B$
5	Collider		C is affected by both A and B, which are independent; conditioning on C induces association between A and B.	$A \not\perp\!\!\!\perp B C$