

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

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

But Individuals Experience Only **One** Exposure

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

The Three Fundamental Assumptions of Causal Inference

Causal Consistency

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

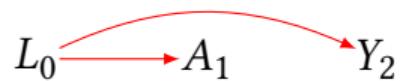
Conditional Exchangeability

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

Positivity

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

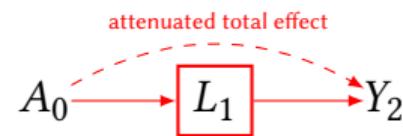
The Common Worry: Confounding by Common Cause



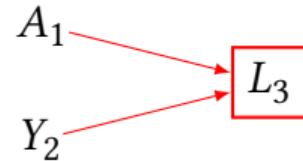
However, There Are Other Worries: Reverse Causation

$$Y_1 \longrightarrow A_2$$

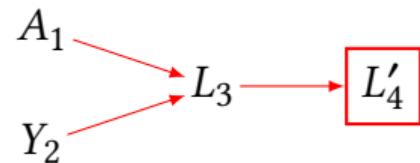
Another Worry is Mediator Bias



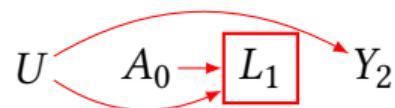
Another Worry is Collider Bias



Another Worry: Collider Bias Proxy



Post Exposure Collider Bias



Another Worry: Unmeasured Common Cause

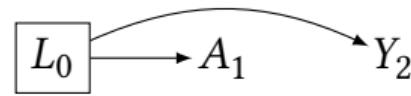
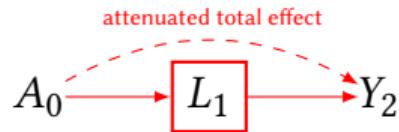


Reverse Causation Solution: Longitudinal Hygiene

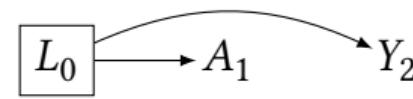
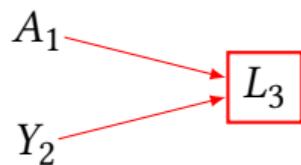
$$Y_1 \longrightarrow A_2$$

$$A_1 \qquad Y_2$$

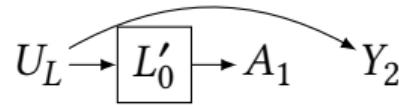
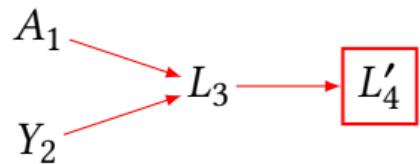
Mediator Bias Solution: Longitudinal Hygiene



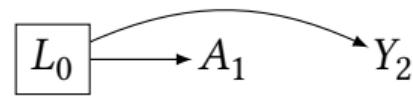
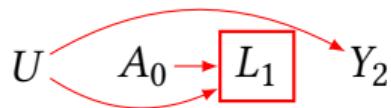
Collider Bias Solution: Longitudinal Hygiene



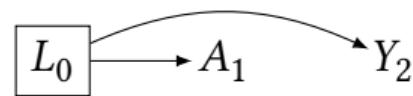
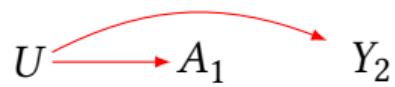
Collider Bias Proxy Solution: Longitudinal Hygiene



Post Exposure Collider Bias **Solution:** Longitudinal Hygiene



Unmeasured Common Cause Solution: Longitudinal Hygiene



Section 2

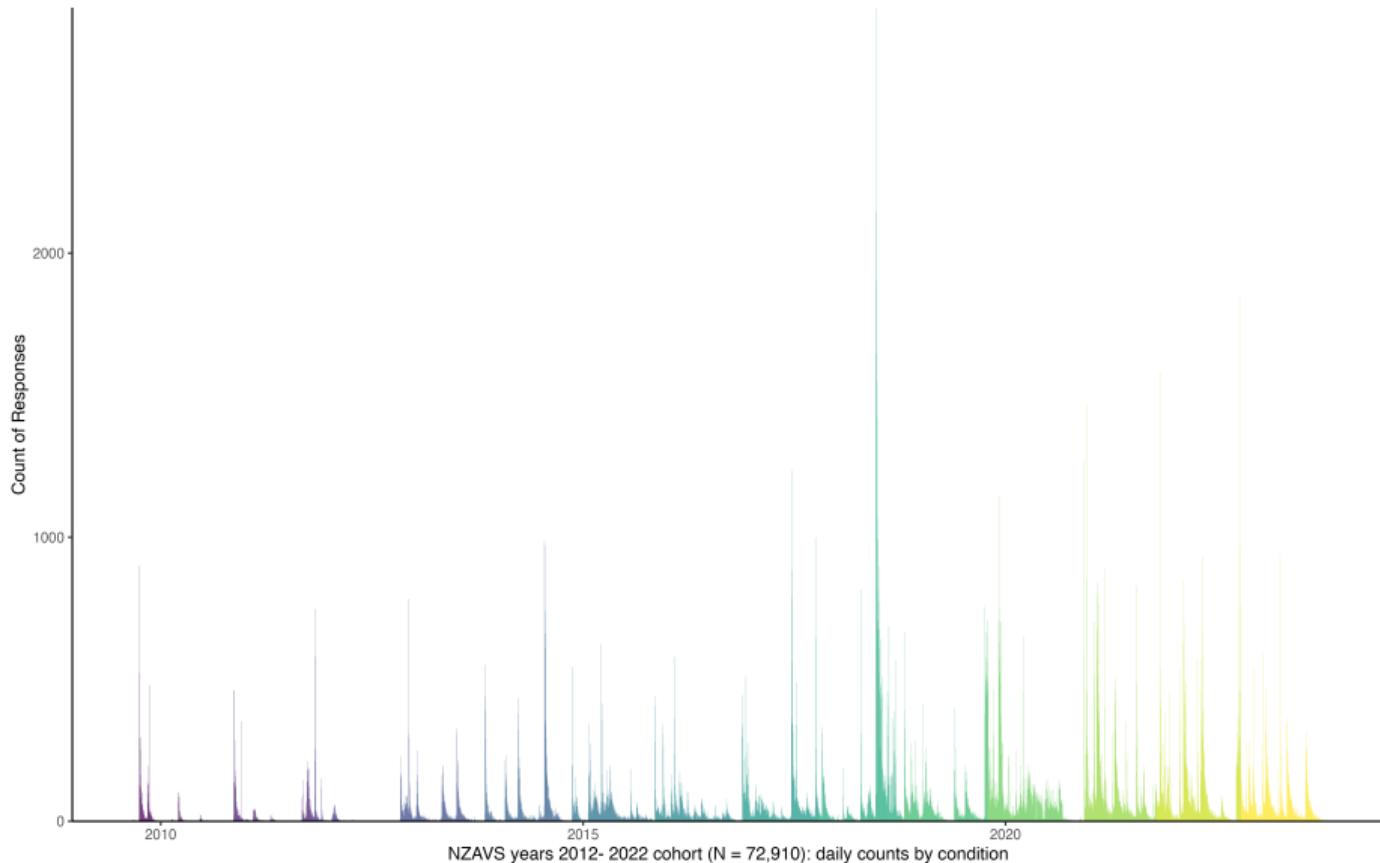
New Zealand Attitudes and Values Study

The New Zealand Attitudes and Values Study: Longitudinally Hygeinic 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 > 72,290,000 unique people, and ~ 38,000 in the longitudinal study

New Zealand Attitudes and Values Study (panel)

N = 72,910; years 2012-2022

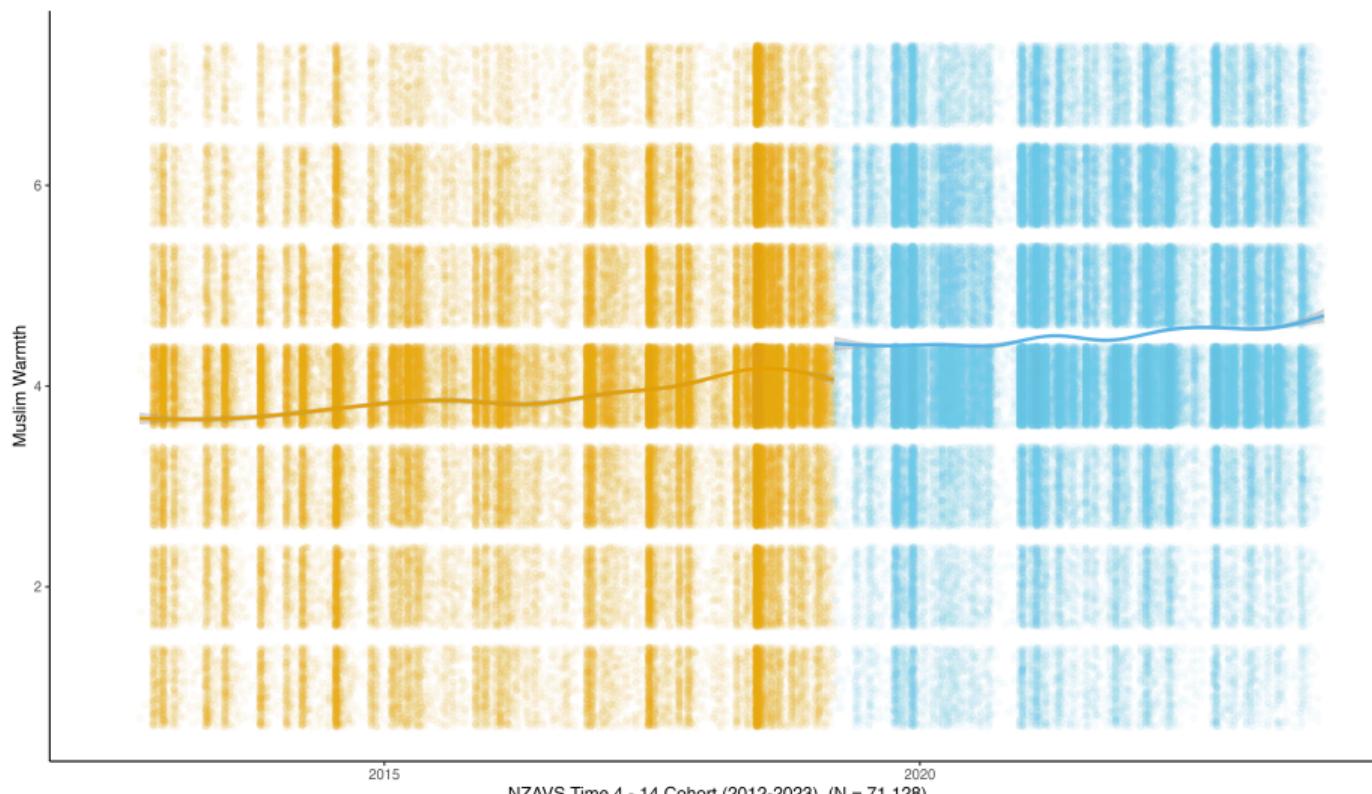


BIG EVENTS

Discontinuity at attacks (GAM)

Boost to Warmth increase in the years following the attacks: FULL SAMPLE

attack_condition 0 1



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.”

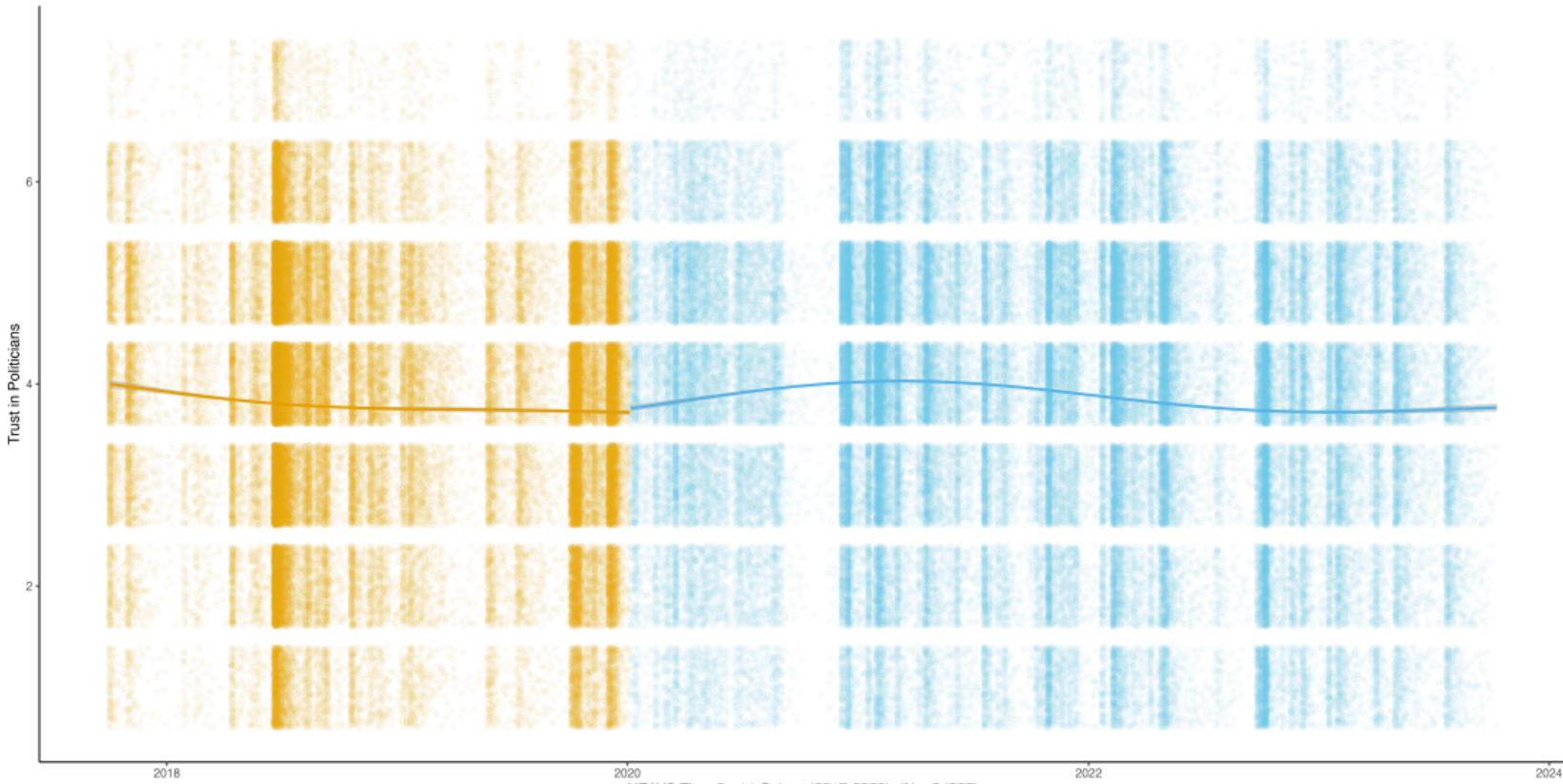
Trust in politicians - “Politicians in New Zealand can generally be trusted.”

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.”

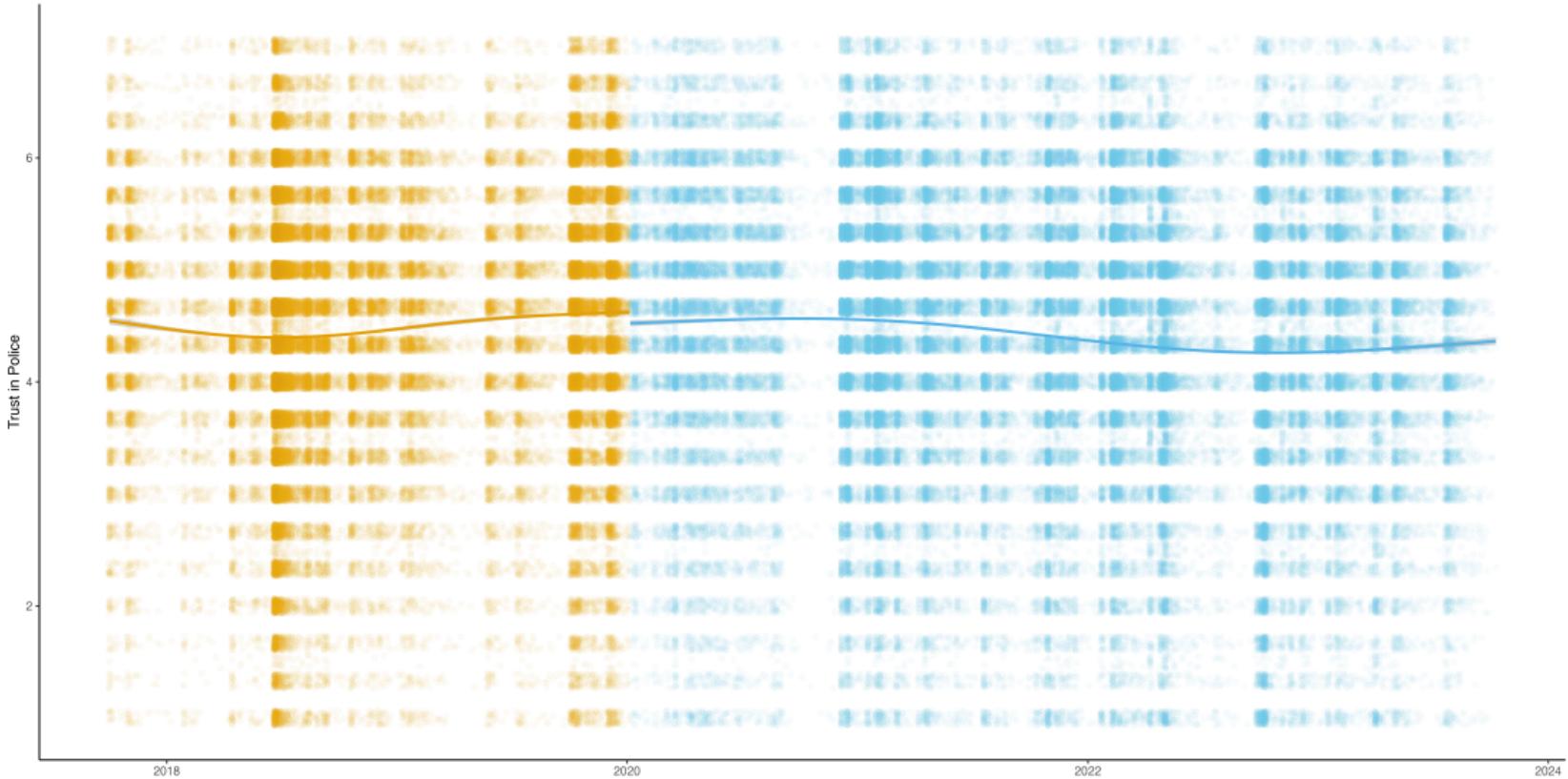
Trust in Politicians: Pre/Post Covid-19 Attack

covid_19_attack 0 1



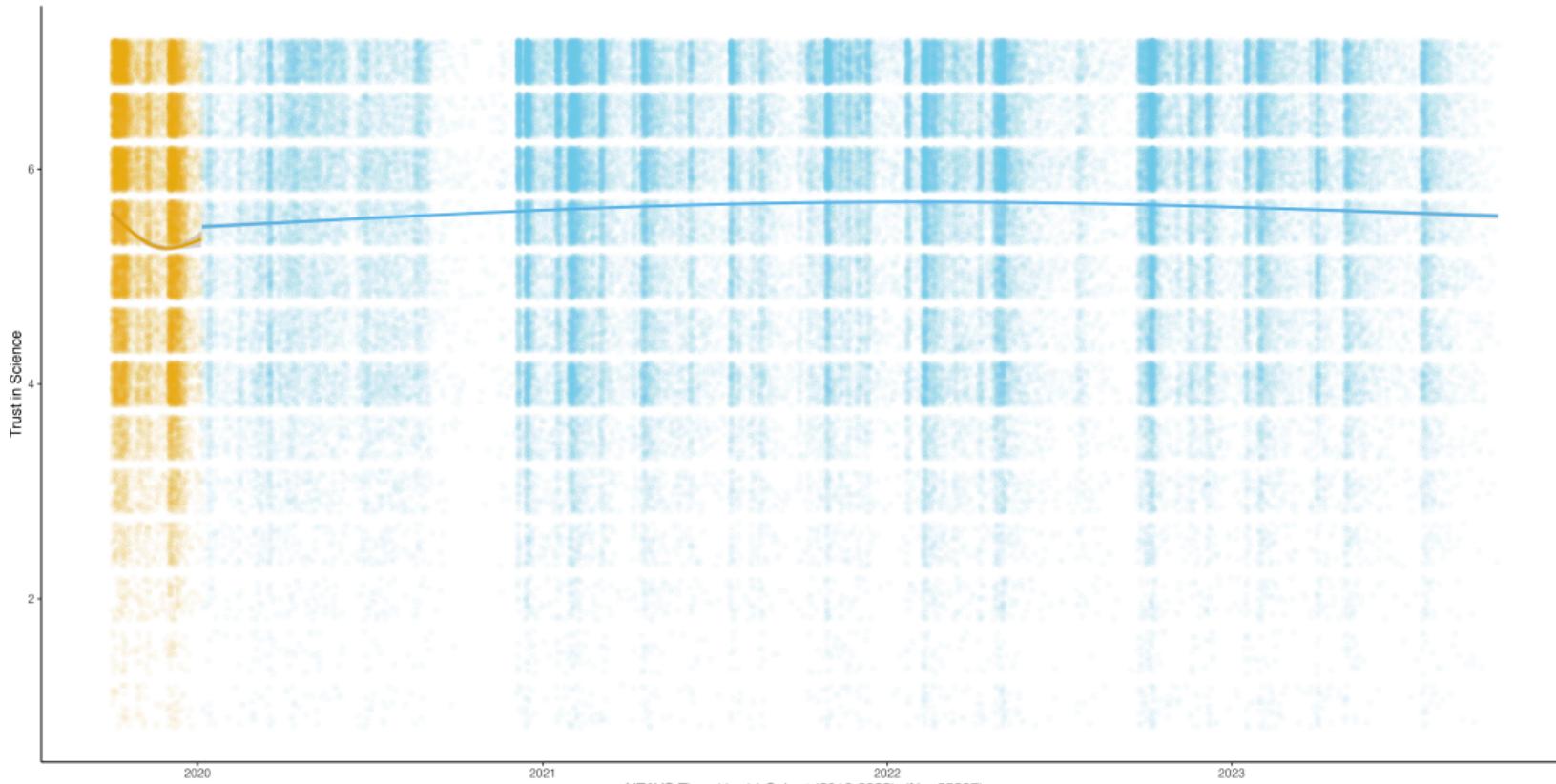
NZAVS Time 9 - 14 Cohort (2017-2023), (N = 64287)

Trust in Police: Pre/Post Covid-19 Attack

covid_19_attack 

Trust in Science: Pre/Post Covid-19 Attacks

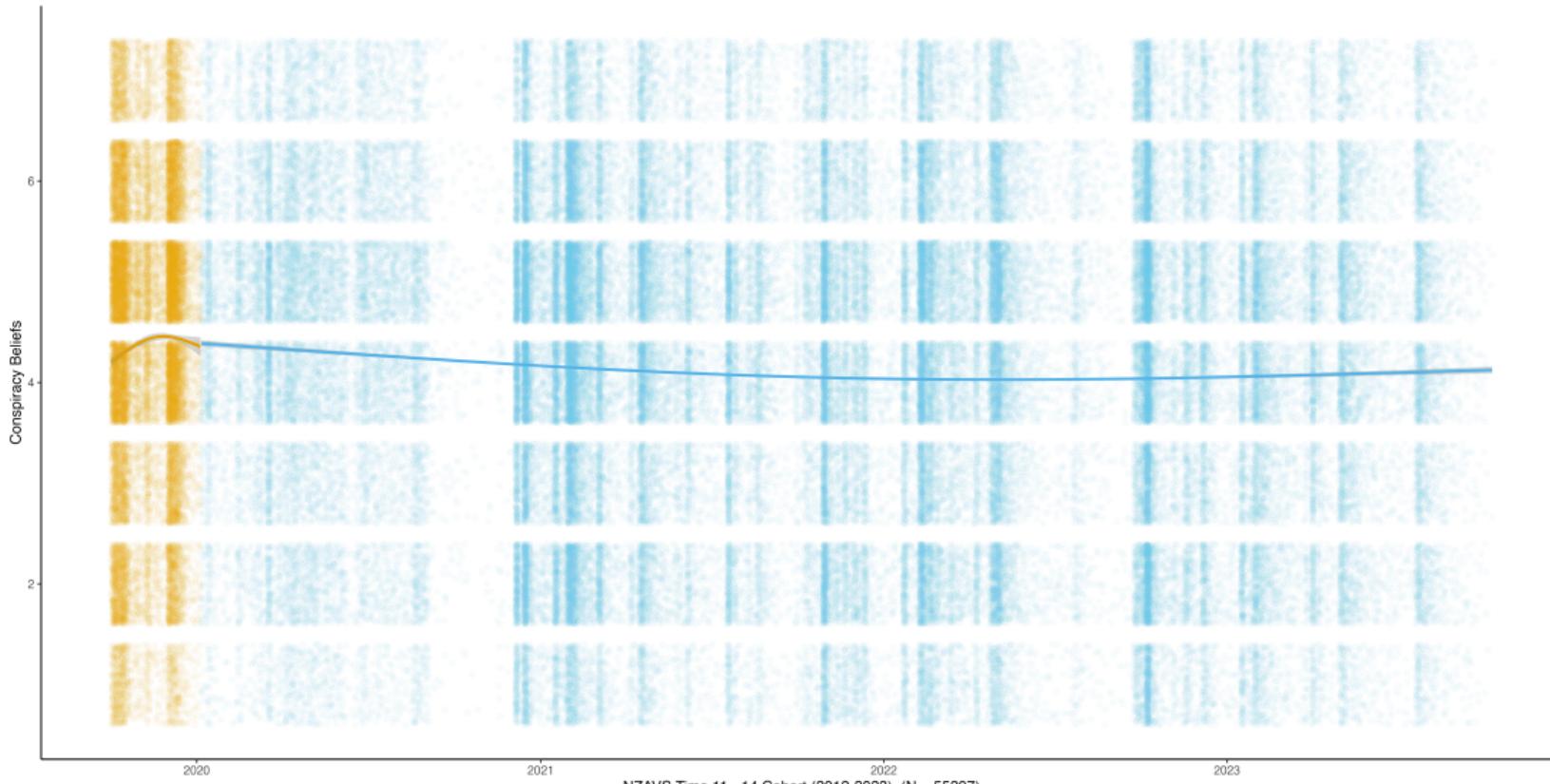
covid_19_attack 0 1



NZAVS Time 11 - 14 Cohort (2012-2023), (N = 55297)

Conspiracy Beliefs: Pre/Post Covid-19 Attacks

covid_19_attack 0 1



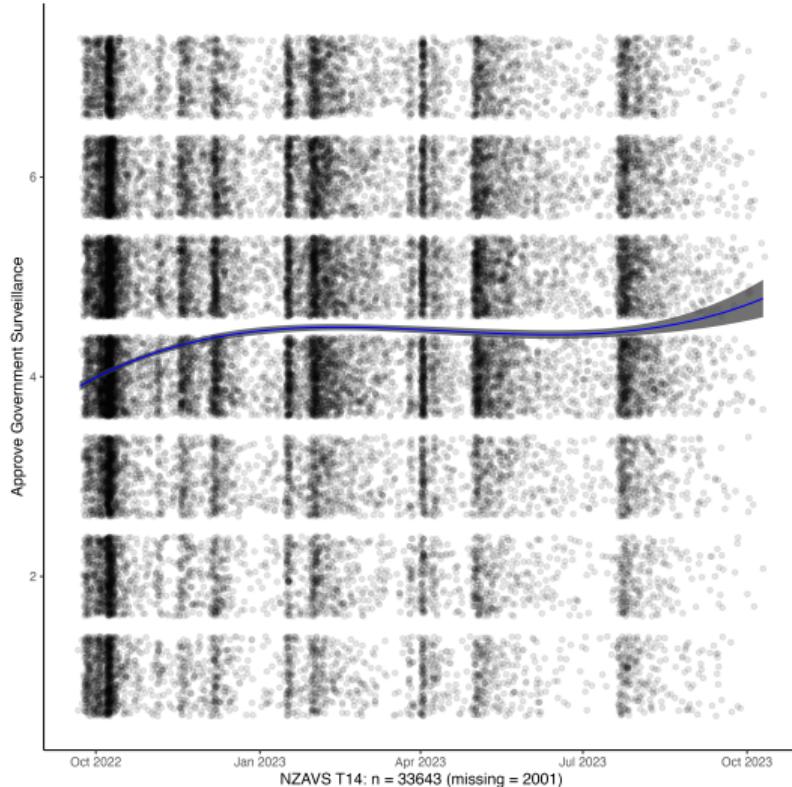
Regulate Artificial Intelligence?

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)

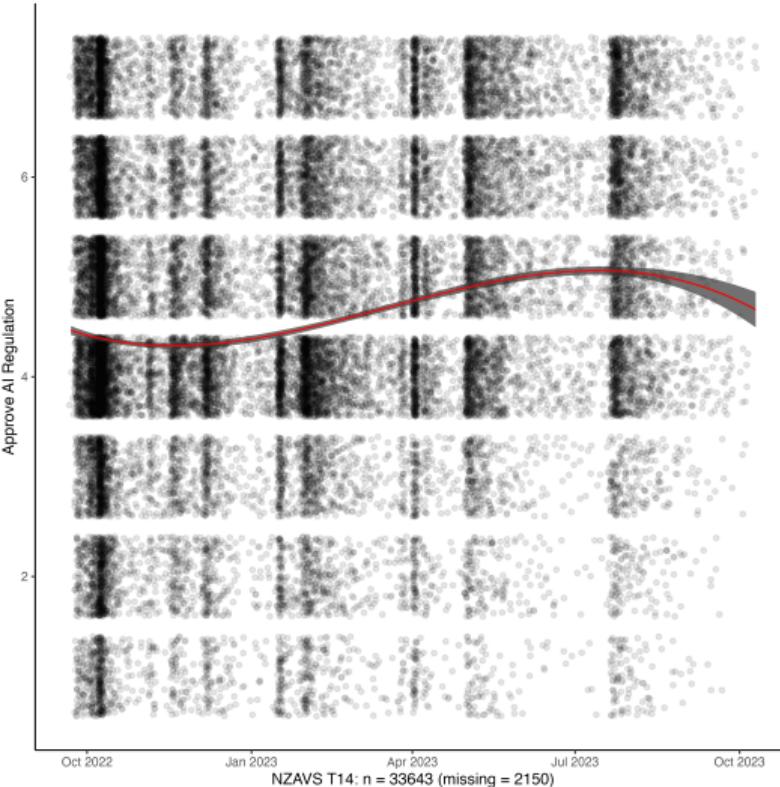
A

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

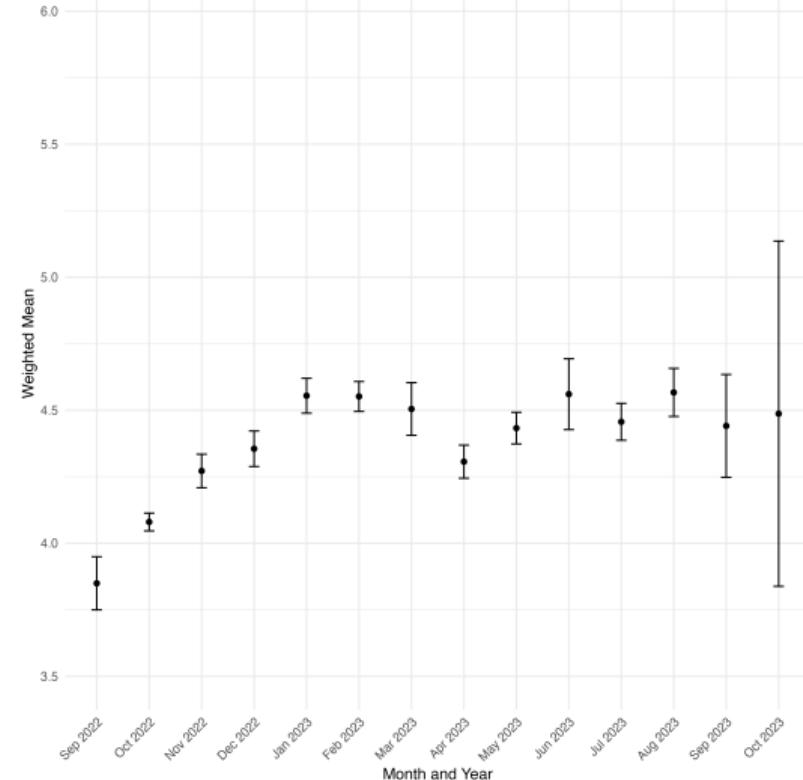


Weighted Monthly Marginal Means: Comparisons of Attitudes to New Zealand Government Interventions

NZAVS Time 14 (n=33643)

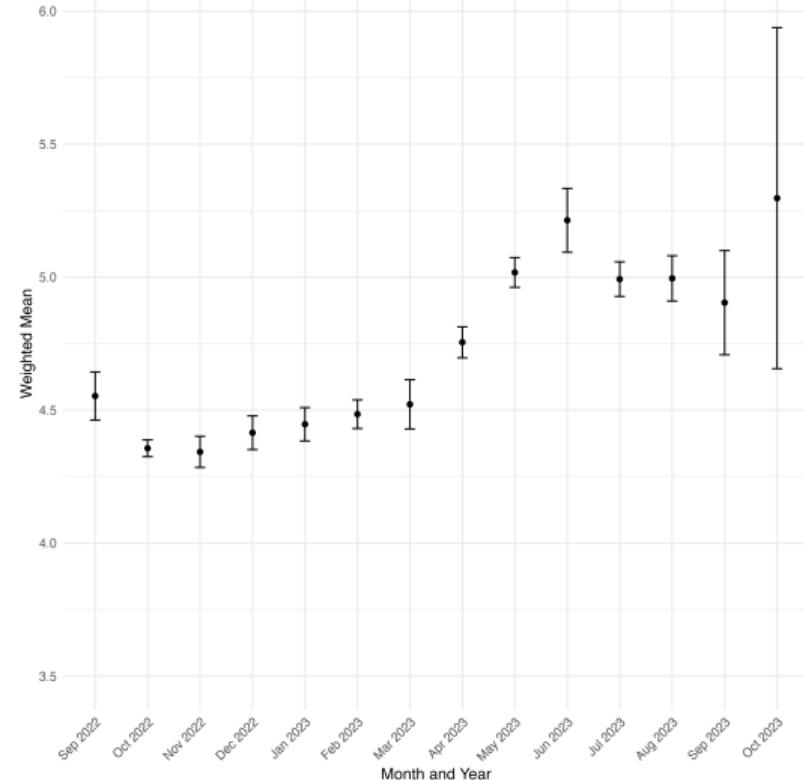
A

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



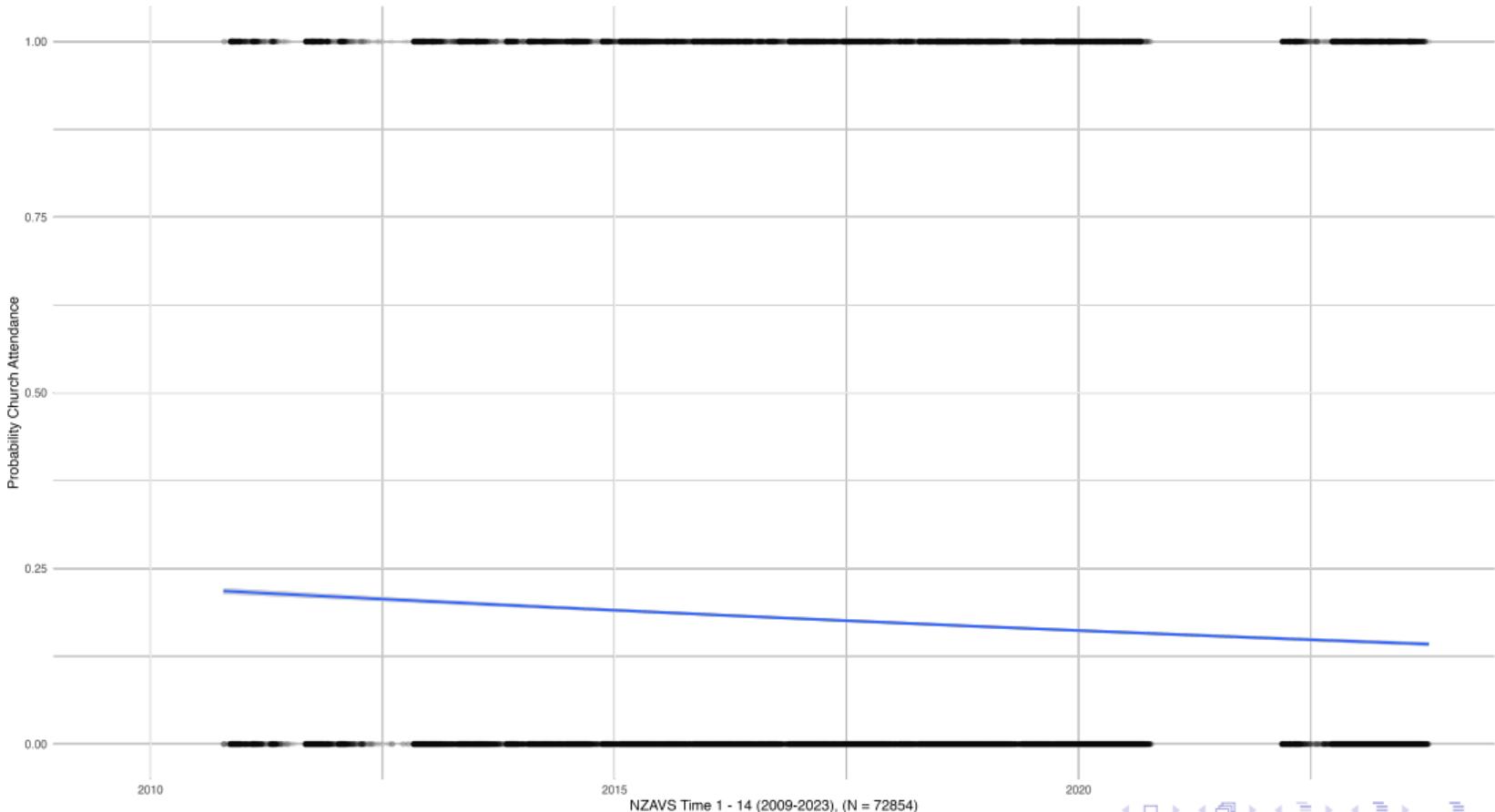
B

Self-regulation limiting the development and use of Artificial Intelligence



Consider Gradual Events

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



Worked Example: Casual 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

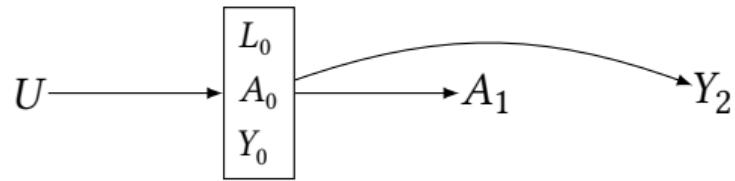
Intervention

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

Contrast:

$$f(A) = 0$$

Key Graph

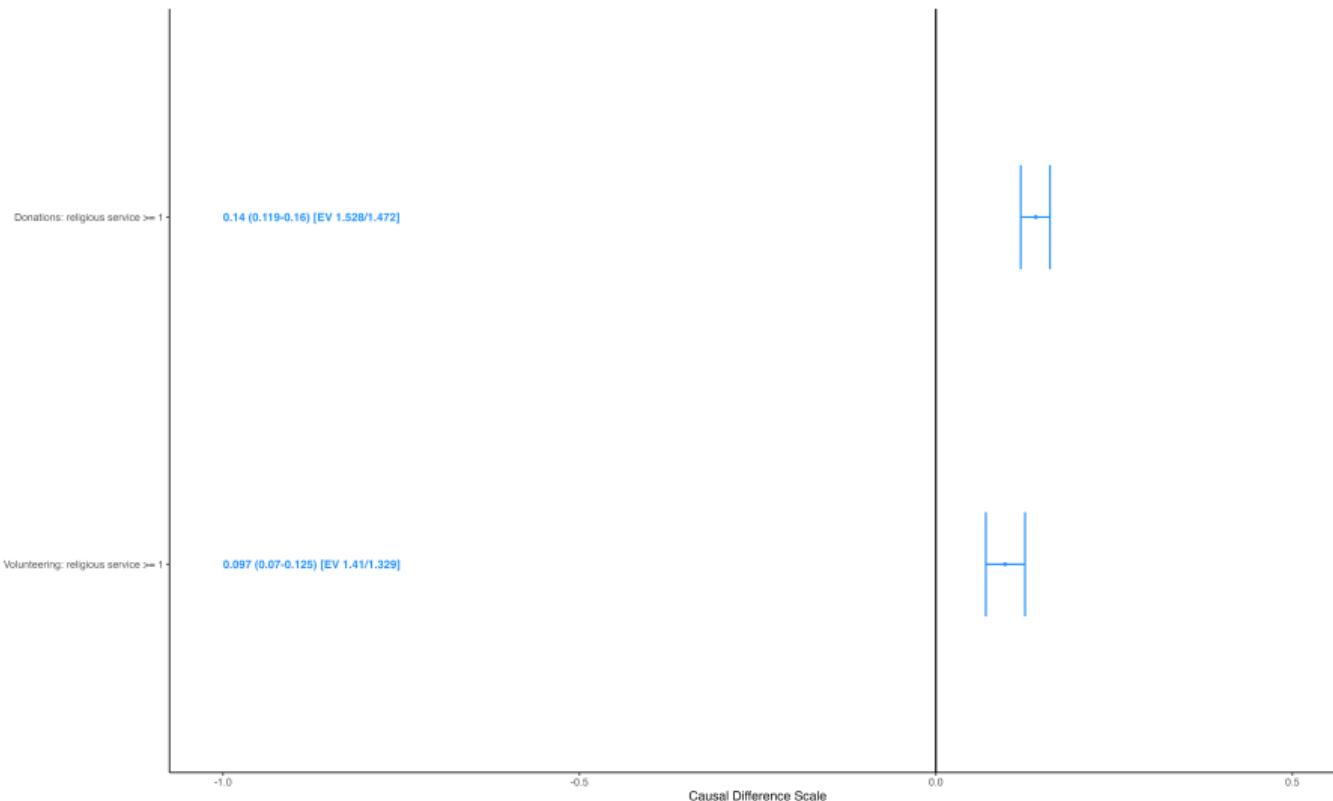


Religious Service Outcomes

Religious service effect on reported donations and volunteering

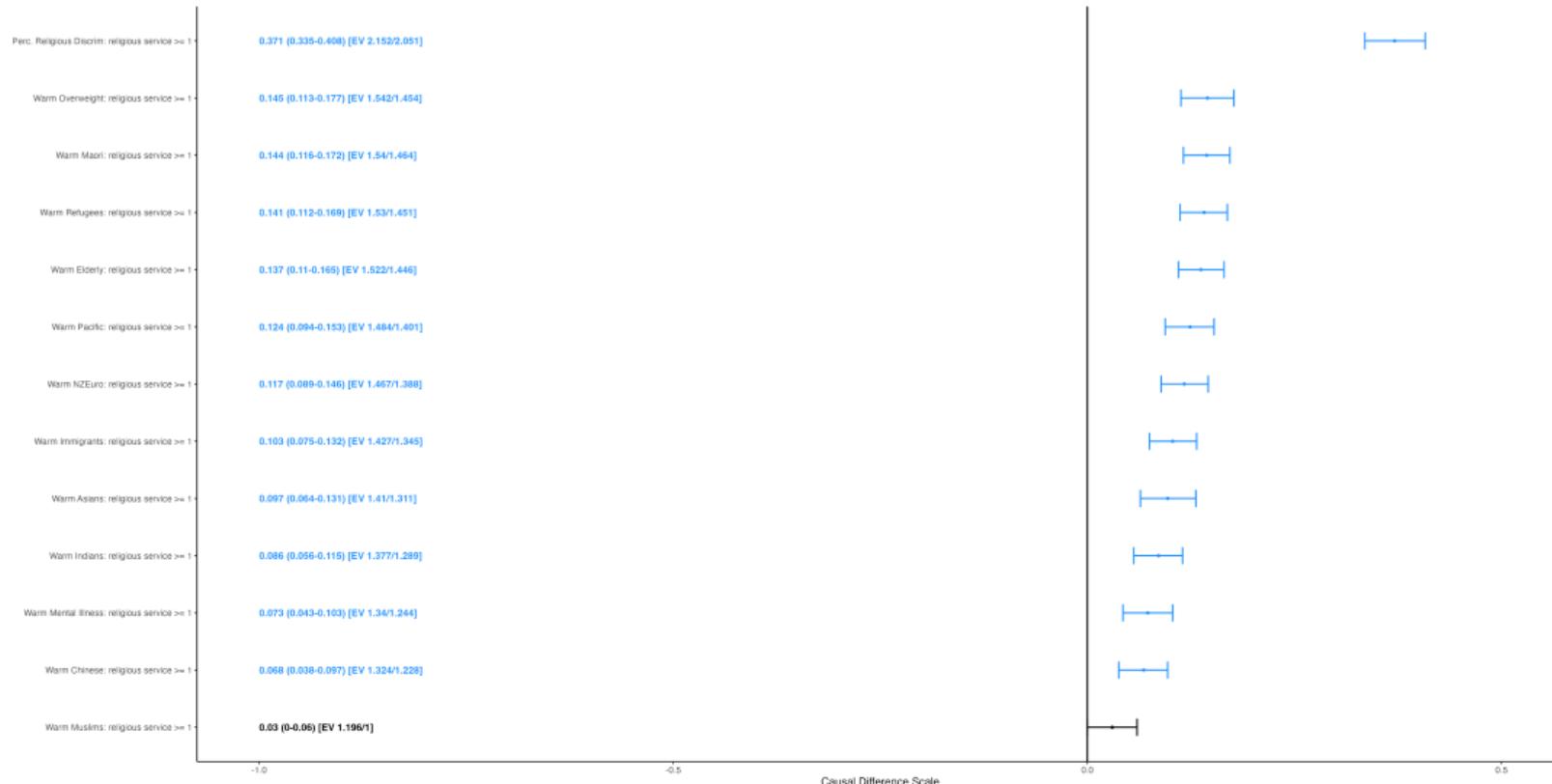
 $\geq 1 \times$ weekly religious service attendance

Reliability positive



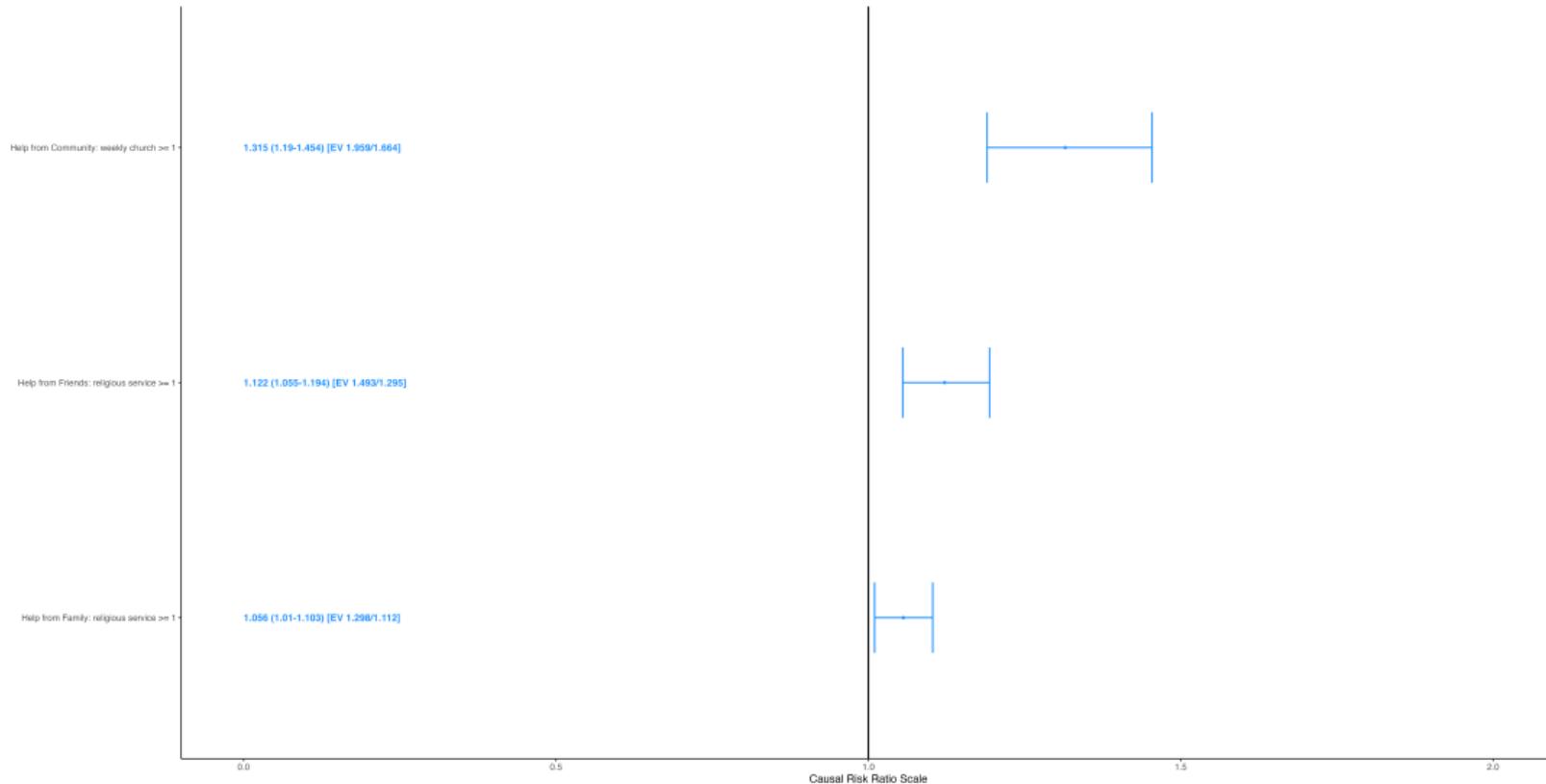
Religious service effect on minority-group attitudes
 $\geq 1 \times$ weekly religious service attendance

Reliability positive zero_crossing



Religious service effect on help received**>= 1 x weekly service attendance**

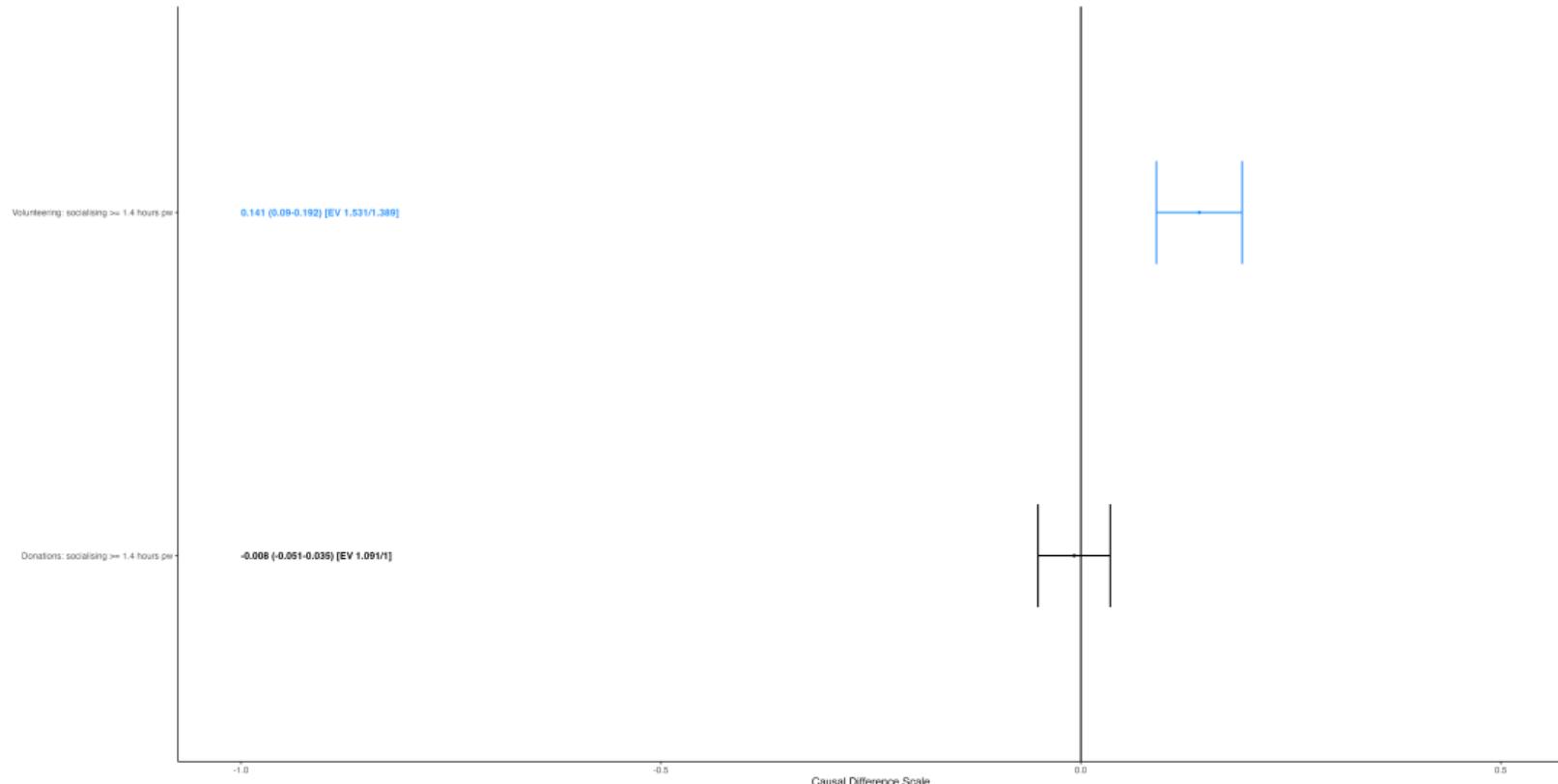
Reliability positive



Socializing Outcomes

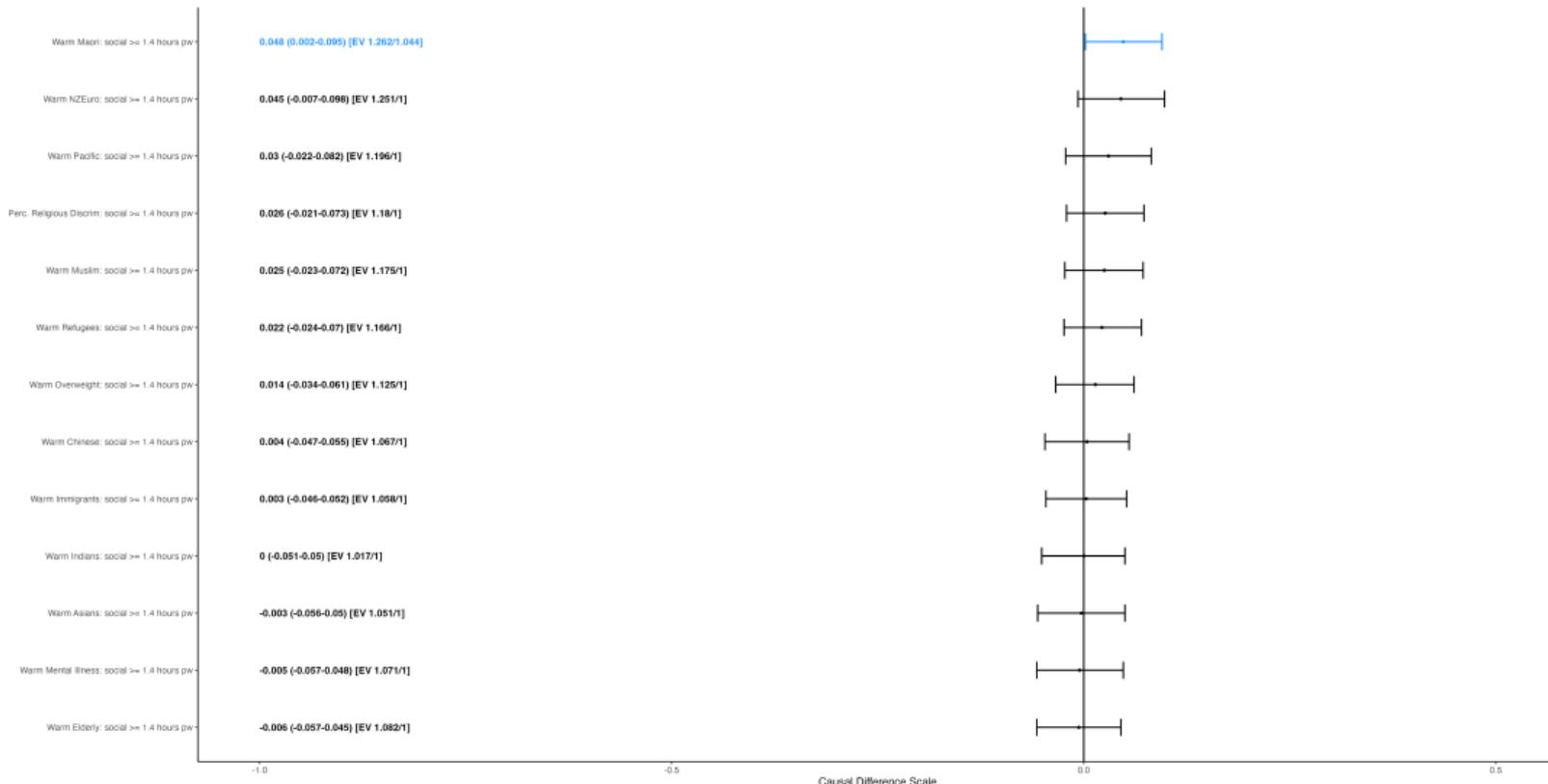
Socialising effect on charity
 $\geq 1.4 \times$ weekly hours socialising

Reliability ↗ positive ↘ zero_crossing

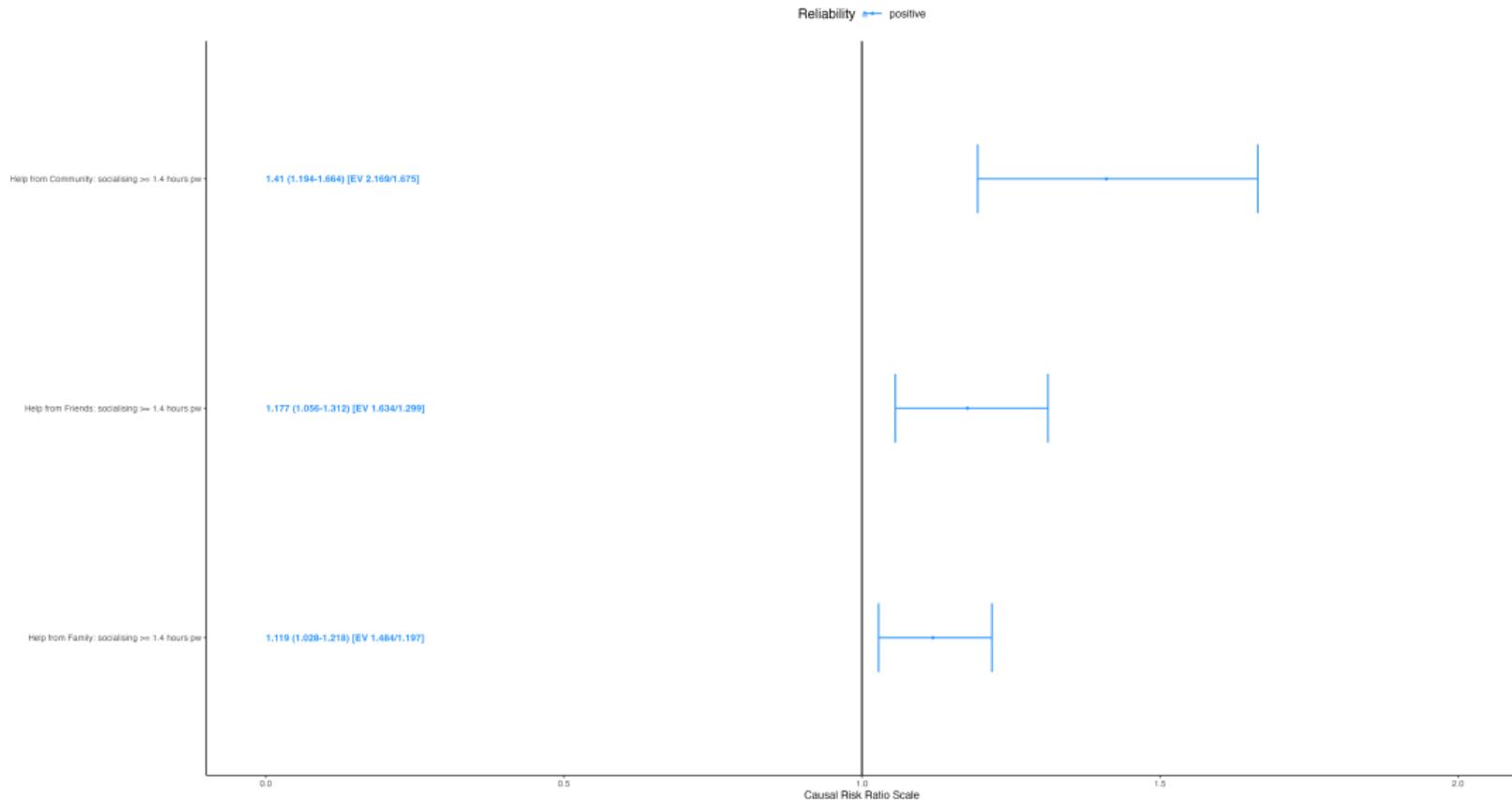


Socialing effect on prejudice/acceptance **$\geq 1.4 \times$ weekly hours socialising**

Reliability positive zero_crossing



Socialising effect on help received
 $\geq 1.4 \times$ weekly hours socialising



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.
- These results underscores the importance of investigating the consequences of gradual change in cultural engagement.
- **What do you think we should be focussing on?**

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)
- TRT Grant 0418
- Max Planck Institute for Evolutionary Anthropology
- Victoria University
- University of Canterbury
- 72,290 NZAVS participants

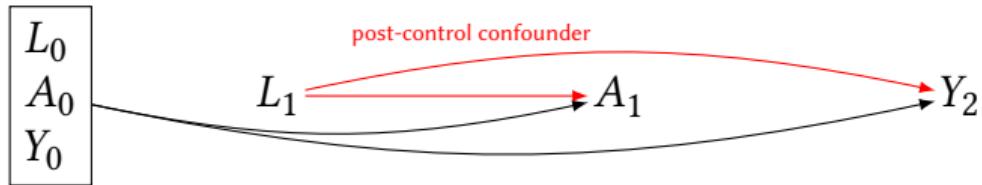




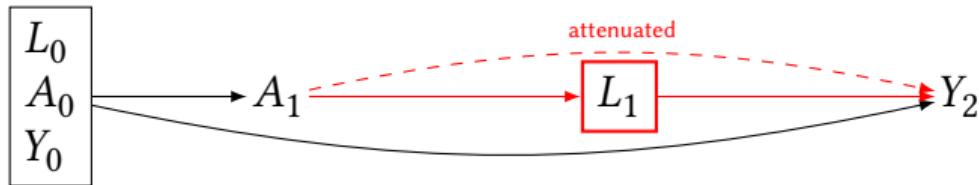
Extra Slides

Longitudinal Data Bring Their Own Problems

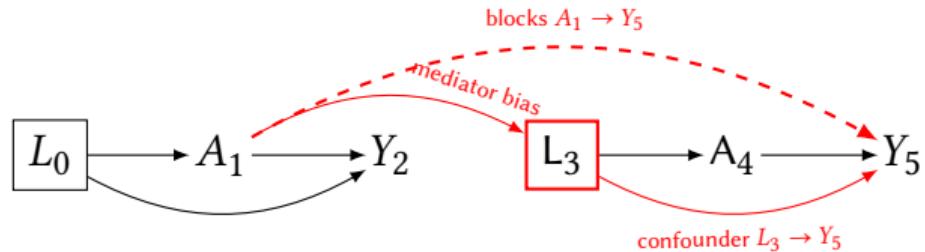
Timing of Confounder



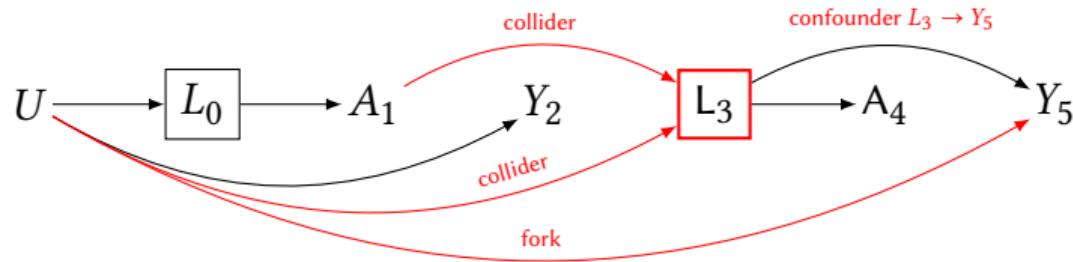
Timing of Mediator



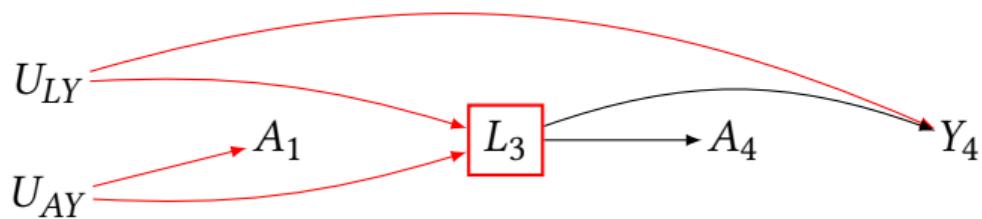
Treatment Confounder Bias



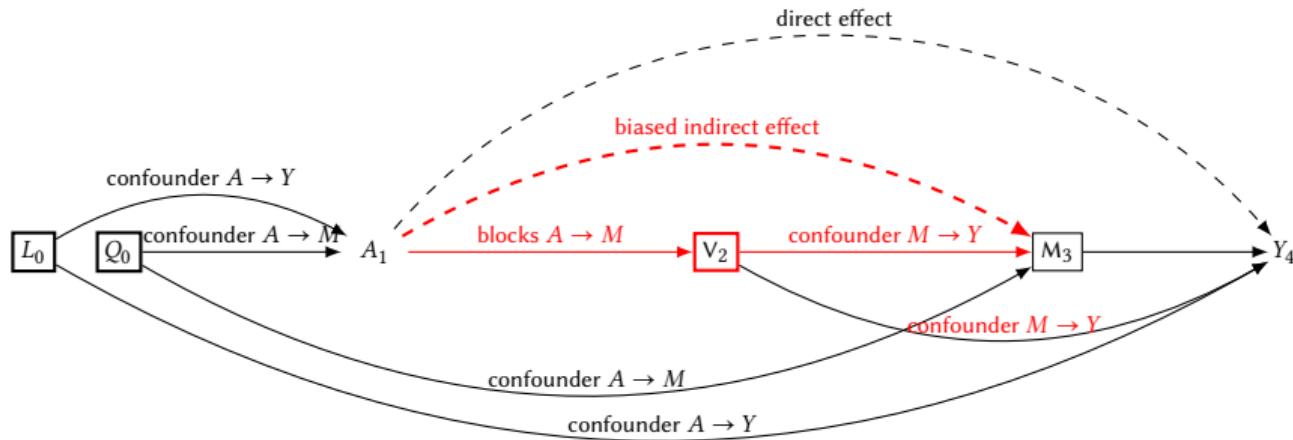
Treatment Confounder Feedback



Treatment Confounder Feedback Variation



Mediation



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

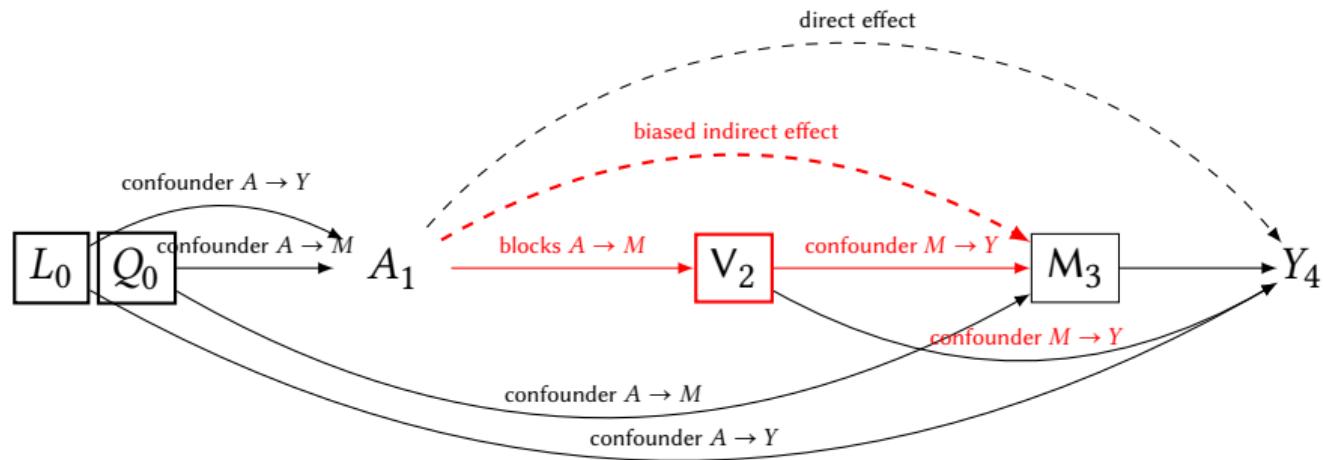
Natural Indirect Effect (NIE): is the effect of the exposure on the outcome that is mediated. To obtain these quantities we must compare the potential outcome Y under treatment, where the mediator assumes its natural level under treatment with the potential outcome when the mediator assumes its natural 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

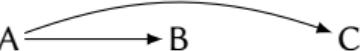
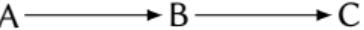
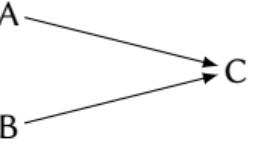
Symbol

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.	$A \not\perp\!\!\!\perp B C$