“Health vs Economy”: a false choice of pandemic modelling

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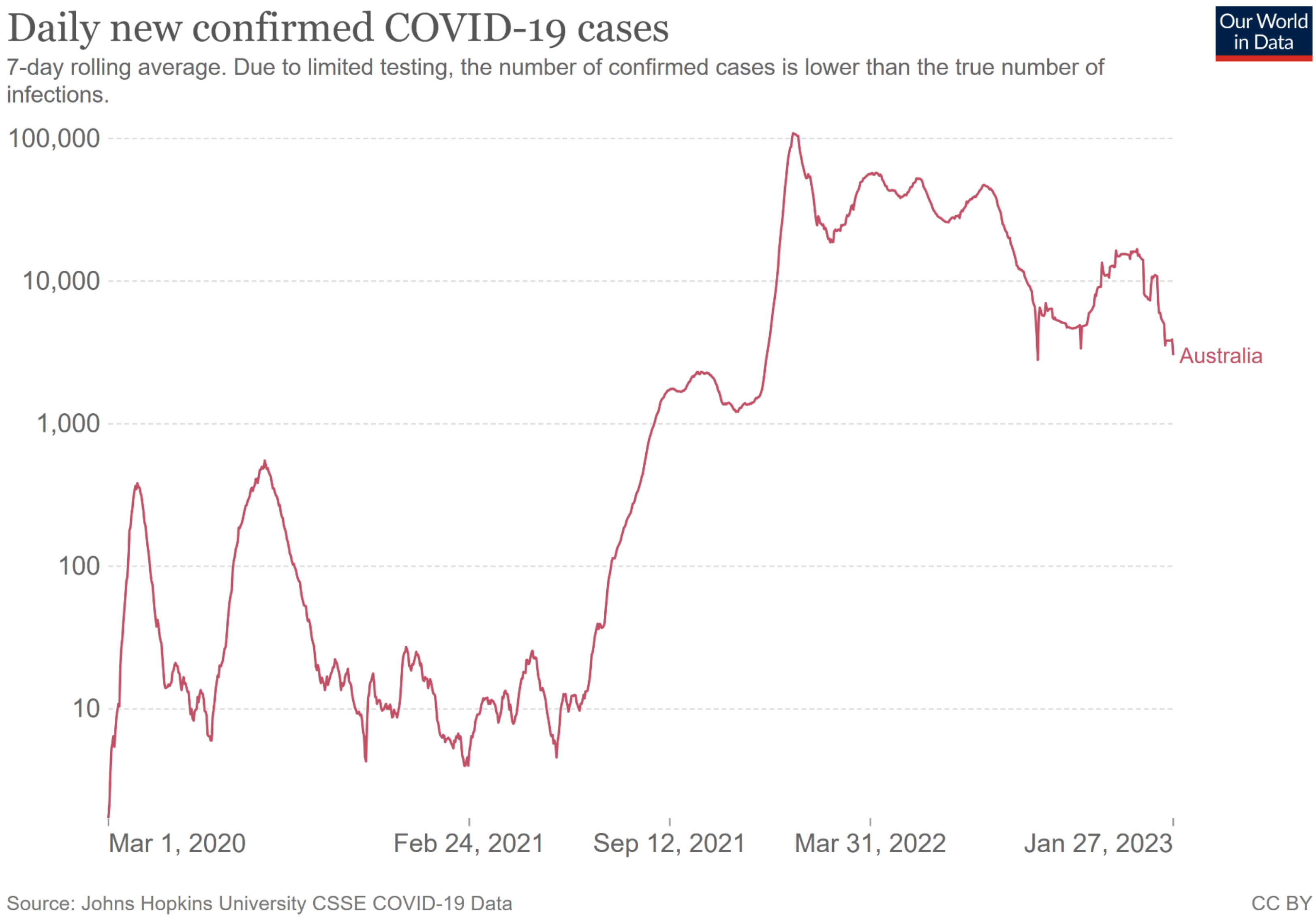
Isaac Newton Institute for Mathematical Sciences (INI)
Newton Gateway to Mathematics, 19 October 2023

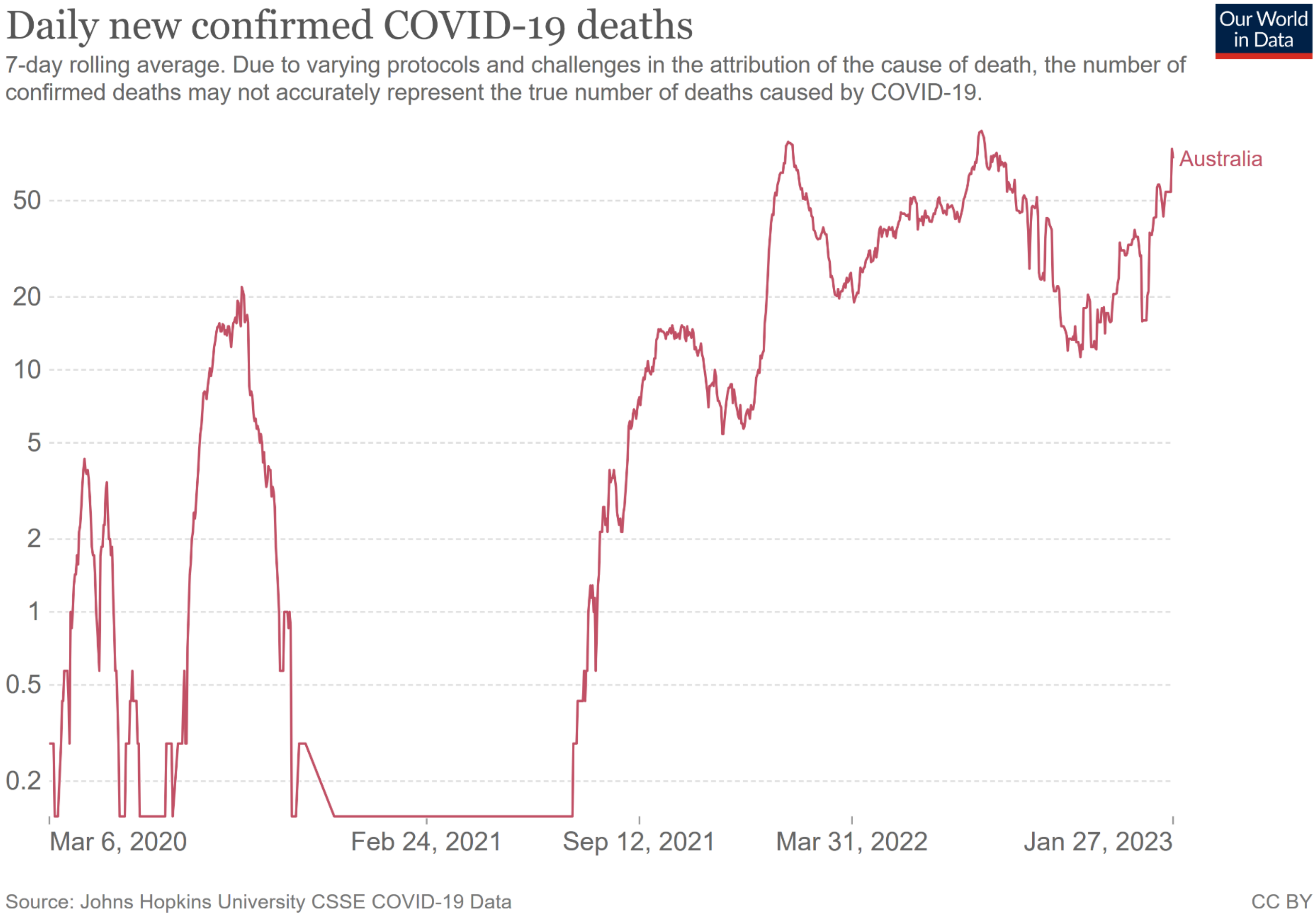
Sources of complexity

- complexity of human behaviour
- socio-economic complexity
- bio-complexity

The COVID-19: four pandemic stages in Australia (incidence, as of January 27, 2023)



The COVID-19: four pandemic stages in Australia (deaths, as of January 27, 2023)



COVID-19 pandemic modelling using ABM

- Large-scale high-resolution agent-based models
  - *demographics*: from census based data to agents
  - *mobility*: travel patterns including long-distance
  - *infection*: epidemiology

- AMTraC-19: **A**gent-based **M**odel of **Tra**nsmission and **C**ontrol of the COVID-**19** pandemic in Australia (~ 24M agents)

- Model calibration and validation during COVID-19 pandemic
  - 1st stage, ancestral (March – June 2020)
  - 2nd stage, ancestral (July – September 2020)
  - 3rd stage, Delta (June – November 2021)
  - 4th stage, Omicron (December 2021 – November 2022)

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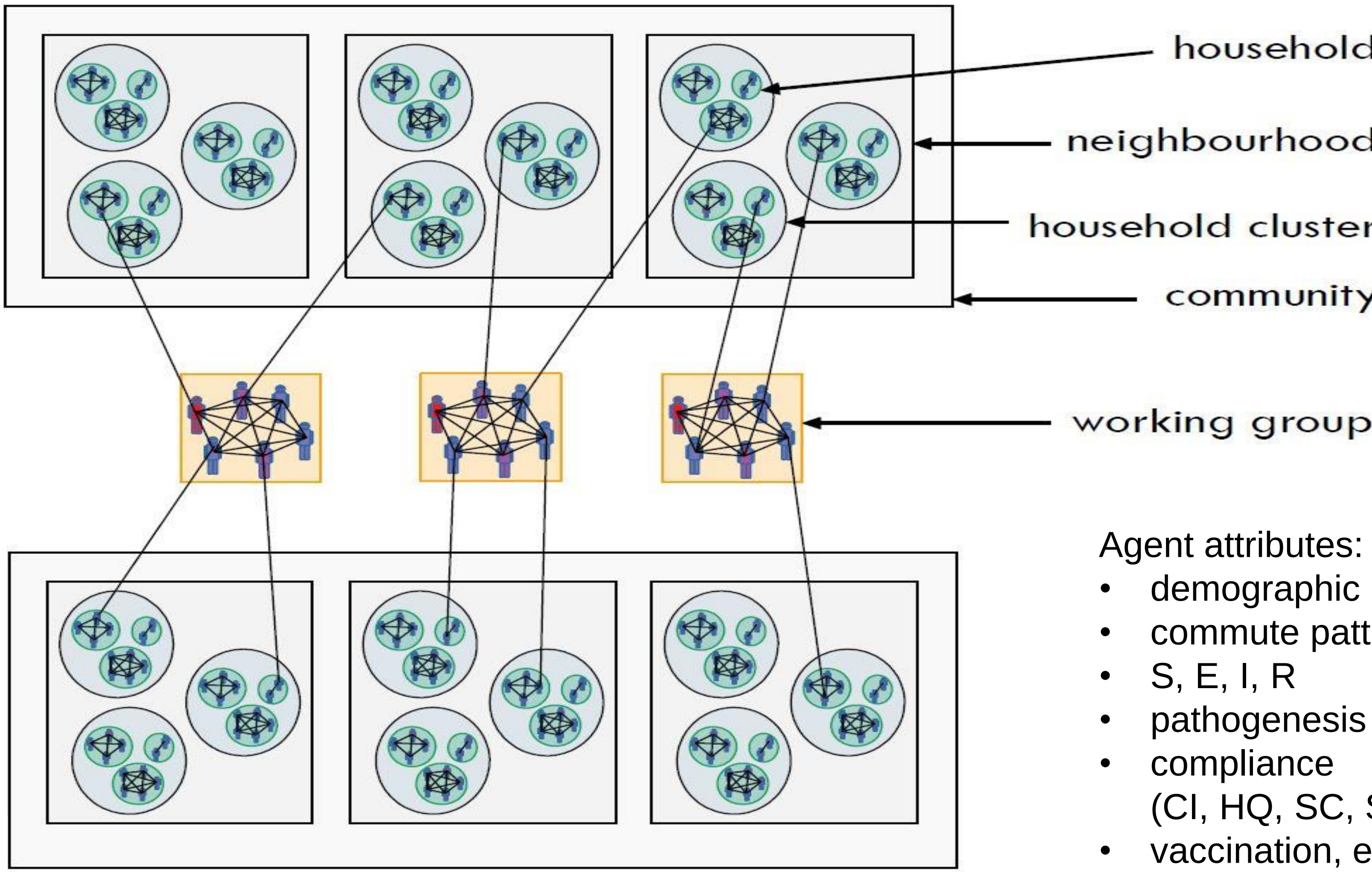
“Same storm, different boats”



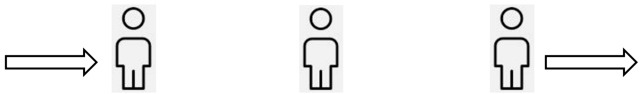
Agent attributes:

- demographic
- commute pattern
- S, E, I, R
- pathogenesis
- compliance (CI, HQ, SC, SD)
- vaccination, etc.

C. Zachreson, K. M. Fair, N. Harding, M. Prokopenko, Interfering with influenza: nonlinear coupling of reactive and static mitigation strategies, *Journal of Royal Society Interface*, 17(165): 20190728, 2020.

Features of AMTraC-19

- ~24M stochastically generated agents (Census, ABS & ACARA data)
- household size and composition vary across different local areas
- commuting patterns between residence and work / study
- flexible infection seeding scenarios
- transmission within mixing contexts
- different symptomatic ratios for children and adults
- vaccination rollout with two vaccines



- vaccine efficacy split across components (infection, symptoms, transmission)
- varying social distancing ("stay-at-home" restrictions)

S. L. Chang, N. Harding, C. Zachreson, O. M. Cliff, M. Prokopenko, Modelling transmission and control of the COVID-19 pandemic in Australia, *Nature Communications*, 11, 5710, 2020.

C. Zachreson, S. L. Chang, O. M. Cliff, M. Prokopenko, How will mass-vaccination change COVID-19 lockdown requirements in Australia? *The Lancet Regional Health – Western Pacific*, 14: 100224, 2021.

Population partitions: residential areas and destination zones

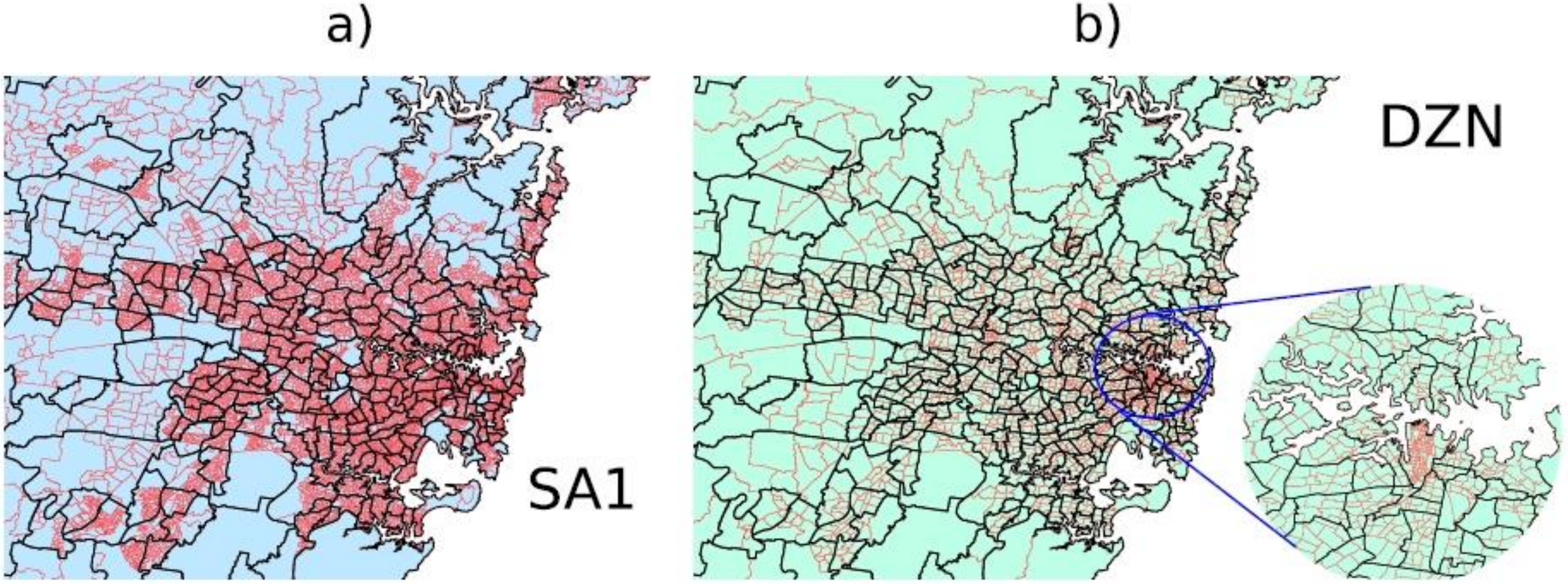
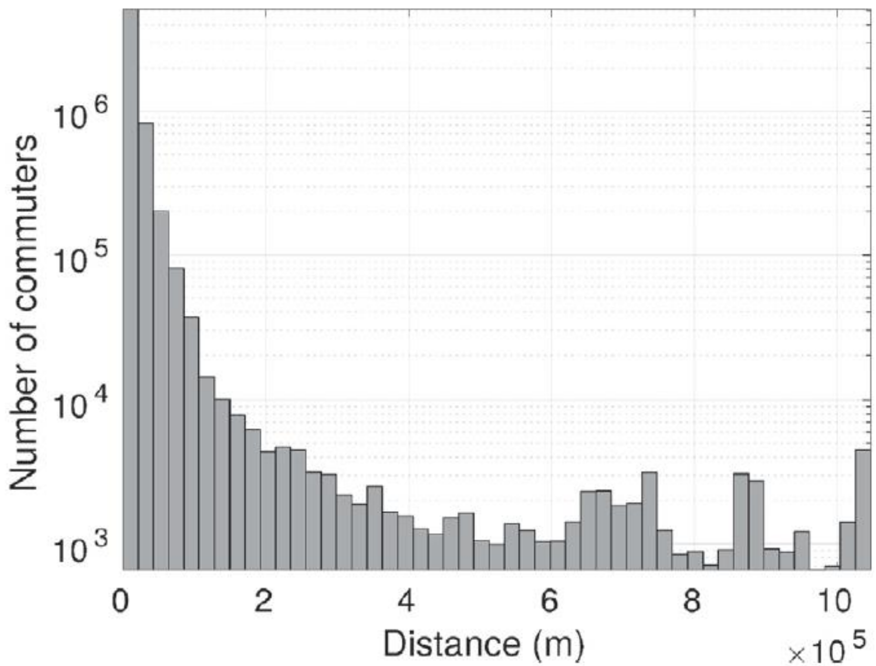


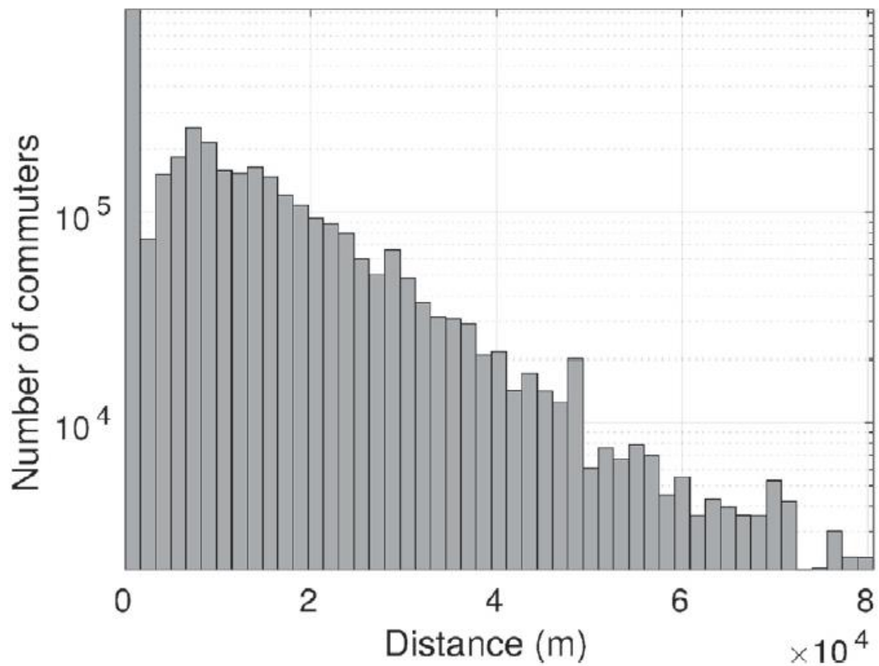
Fig. 1 Maps of the Greater Sydney region illustrating the distribution of population partitions. (**a**) A map of the Greater Sydney region showing SA2 (black) and SA1 (red) population partitions. (**b**) A map of the same area showing SA2 (black) and DZN (red) partitions. The inset in (**b**) zooms in on the Sydney central business district to illustrate the much denser packing of DZN partitions in that area.

K. M. Fair, C. Zachreson, M. Prokopenko, Creating a surrogate commuter network from Australian Bureau of Statistics census data, *Scientific Data*, 6, 150, 2019.

Australian Census: travel-to-work data (mobility)



(a) Workers



(b) Students

Fig. B1. Commute distance distributions.

International air traffic

Airport code	State	City	Passengers
SYD	NSW	Sydney	40884
MEL	VIC	Melbourne	25859
BNE	QLD	Brisbane	14250
PER	WA	Perth	11449
OOL	QLD	Gold Coast	3022
ADL	SA	Adelaide	2214
CNS	QLD	Cairns	1874
DRW	NT	Darwin	597
TSV	QLD	Townsville	105

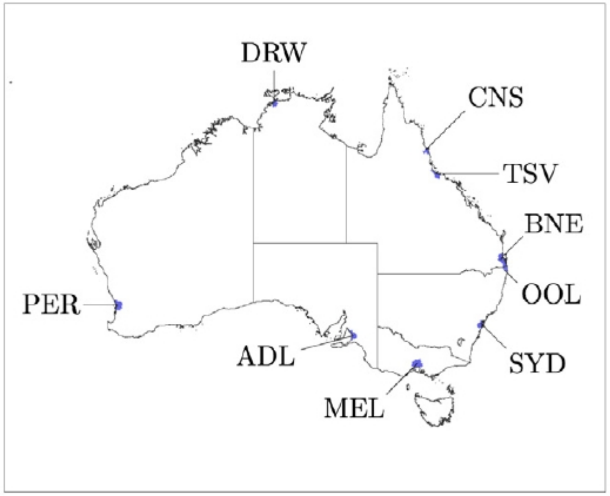


Fig. 3. Daily incoming passengers per Australian international airport obtained from BITRE [30] along with a map detailing the airport locations.

O. M. Cliff, N. Harding, M. Piraveenan, E. Y. Erten, M. Gambhir, M. Prokopenko, Investigating Spatiotemporal Dynamics and Synchrony of Influenza Epidemics in Australia: An Agent-Based Modelling Approach, *Simulation Modelling Practice and Theory*, 87, 412-431, 2018.

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Social Distancing (SD): “stay-at-home” restrictions

Table 2 The micro- and macro-distancing parameters: macro-compliance levels and context-dependent micro-distancing levels.

Strategy	Macro-distancing	Micro-distancing contacts		
	Compliance levels	Household	Community	Workplace/school
No intervention	100%	100%	100%	100%
Case isolation	70%	100%	25%	25%
Home quarantine	50%	200%	25%	25%
School closure (children)	100%	150%	150%	0%
School closure (parents)	25 or 50%	150%	150%	0%
Social distancing	0–100%	100%	50%	0%

$$p_i(n) = 1 - \prod_{g \in G_i(n)} \left[\prod_{j \in A_g \setminus i} \left(1 - p^g_{j \to i}(n)\right) \right]$$

$$p_i(n) = 1 - \prod_{g \in G_i(n)} \left[1 - F_g(i) \left(1 - \prod_{j \in A_g \setminus \{i\}} \left(1 - F_g(j)\, p^g_{j \to i}(n)\right) \right) \right]$$

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Modelling vaccination rollout

- Efficacy for susceptibility (VEs): impacts immunity in those susceptible to the virus (reduces the probability of becoming infected if exposed)

- Efficacy for disease (VEd): impacts the expression of illness in those who are vaccinated and subsequently become infected (reduces the probability of expressing symptoms if infected)

- Efficacy for infectiousness (VEi): impacts the potential for vaccinated individuals to transmit the virus if infected (reduces the force of infection produced by infected individuals who are vaccinated)

$$VE = VEd + VEs - VEs \times VEd \qquad VEi = \sim 0.5$$

for example:

$$0.91 = 0.7 + 0.7 - 0.7 \times 0.7$$
$$0.92 = 0.8 + 0.6 - 0.8 \times 0.6$$

$$0.75 = 0.5 + 0.5 - 0.5 \times 0.5$$
$$0.65 = 0.5 + 0.3 - 0.5 \times 0.3$$

C. Zachreson, S. L. Chang, O. M. Cliff, M. Prokopenko, How will mass-vaccination change COVID-19 lockdown requirements in Australia? *The Lancet Regional Health – Western Pacific*, 14: 100224, 2021.

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Vaccination components

$$p_i(n) = 1 - \prod_{g \in G_i(n)} \left[\prod_{j \in A_g \setminus i} (1 - p^g_{j \to i}(n)) \right]$$

$$p_i(n) = 1 - \prod_{g \in G_i(n)} \left[1 - F_g(i) \left(1 - \prod_{j \in A_g \setminus \{i\}} (1 - F_g(j)\ p^g_{j \to i}(n)) \right) \right]$$

$$p_i(n) = 1 - \prod_{g \in G_i(n)} \left[1 - (1 - VE^s_i) F_g(i) \left(1 - \prod_{j \in A_g \setminus i} (1 - (1 - VE^t_j) F_g(j)\ p^g_{j \to i}(n)) \right) \right]$$

$$p^d_i(n) = (1 - VE^d_i)\ \sigma_{a|c}\ p_i(n)$$

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Balance health and socioeconomic consequences: challenges

- how to objectively model and quantify the health and economic costs in comparative terms?

- how to remove the bias created by subjective perspectives of policy- and decision-makers?

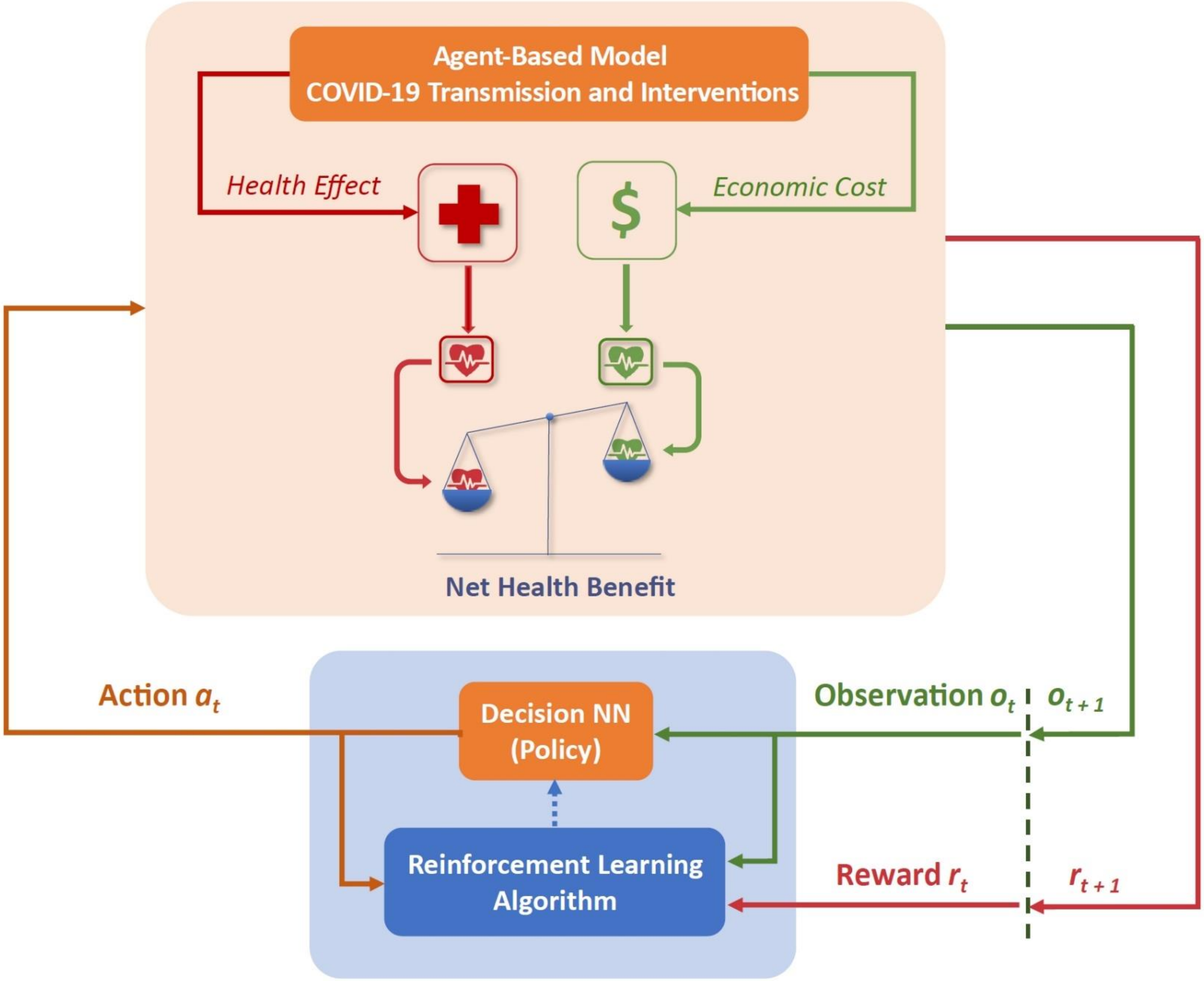
- how to account for the diversity of demographics and human behaviour?

Q. D. Nguyen, M Prokopenko, Optimising cost-effectiveness of pandemic response under partial intervention measures, *Scientific Reports*, 12: 19482, 2022.

Balance health and socioeconomic consequences: approach

- how to objectively model and quantify the health and economic costs in comparative terms?
  - the Net Health Benefit (NHB)
- how to remove the bias created by subjective perspectives of policy- and decision-makers?
  - a reinforcement learning (RL) algorithm dynamically optimising feasible interventions
- how to account for the diversity of demographics and human behaviour?
  - an agent-based model (ABM) based on comprehensive demographic (census) data

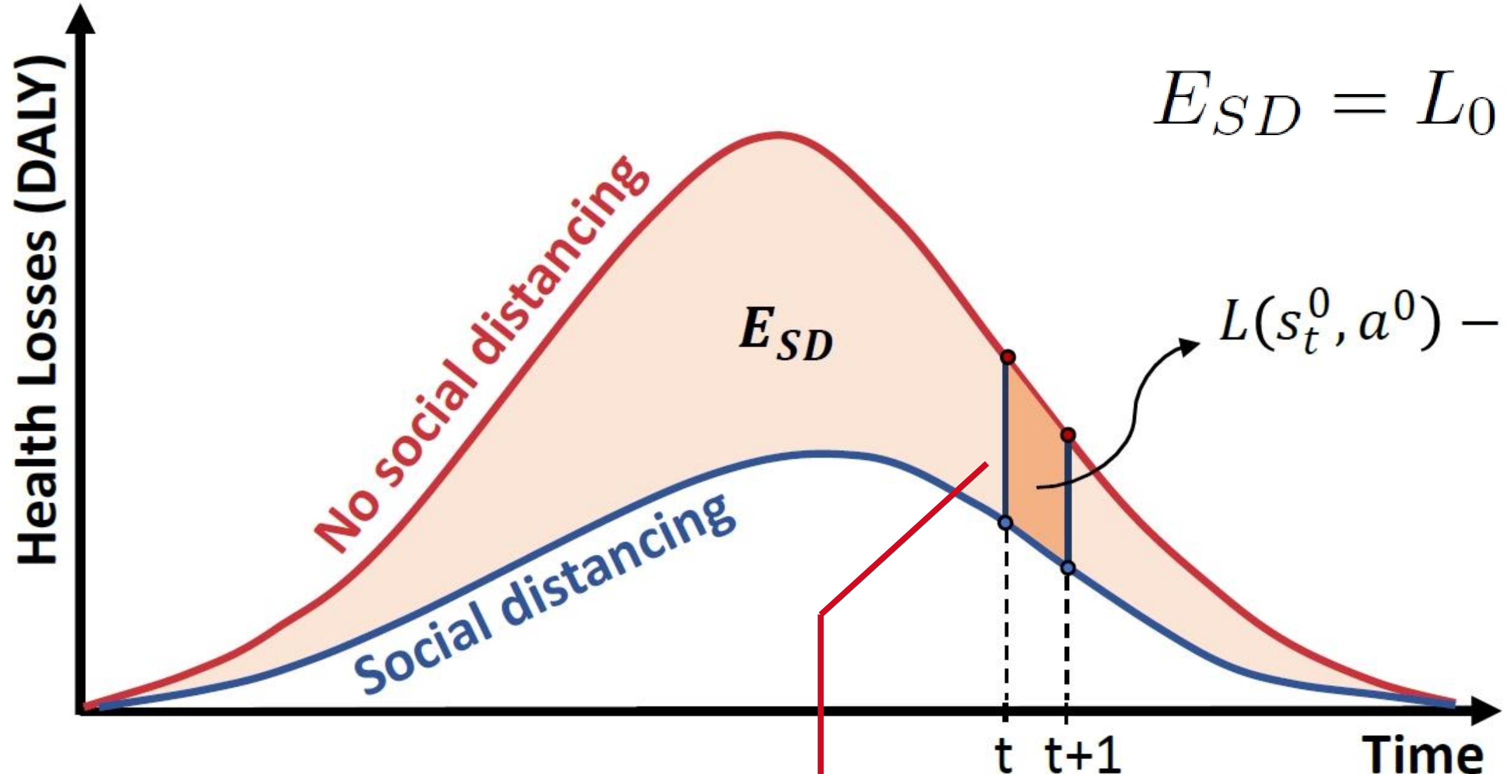
Optimisation: RL with ABM in the loop



Disability-Adjusted Life Years (DALY) and Health effects

$$\text{DALY} = \text{YLL} + \text{YLD}$$

$$E_{SD} = L_0 - L_{SD}$$

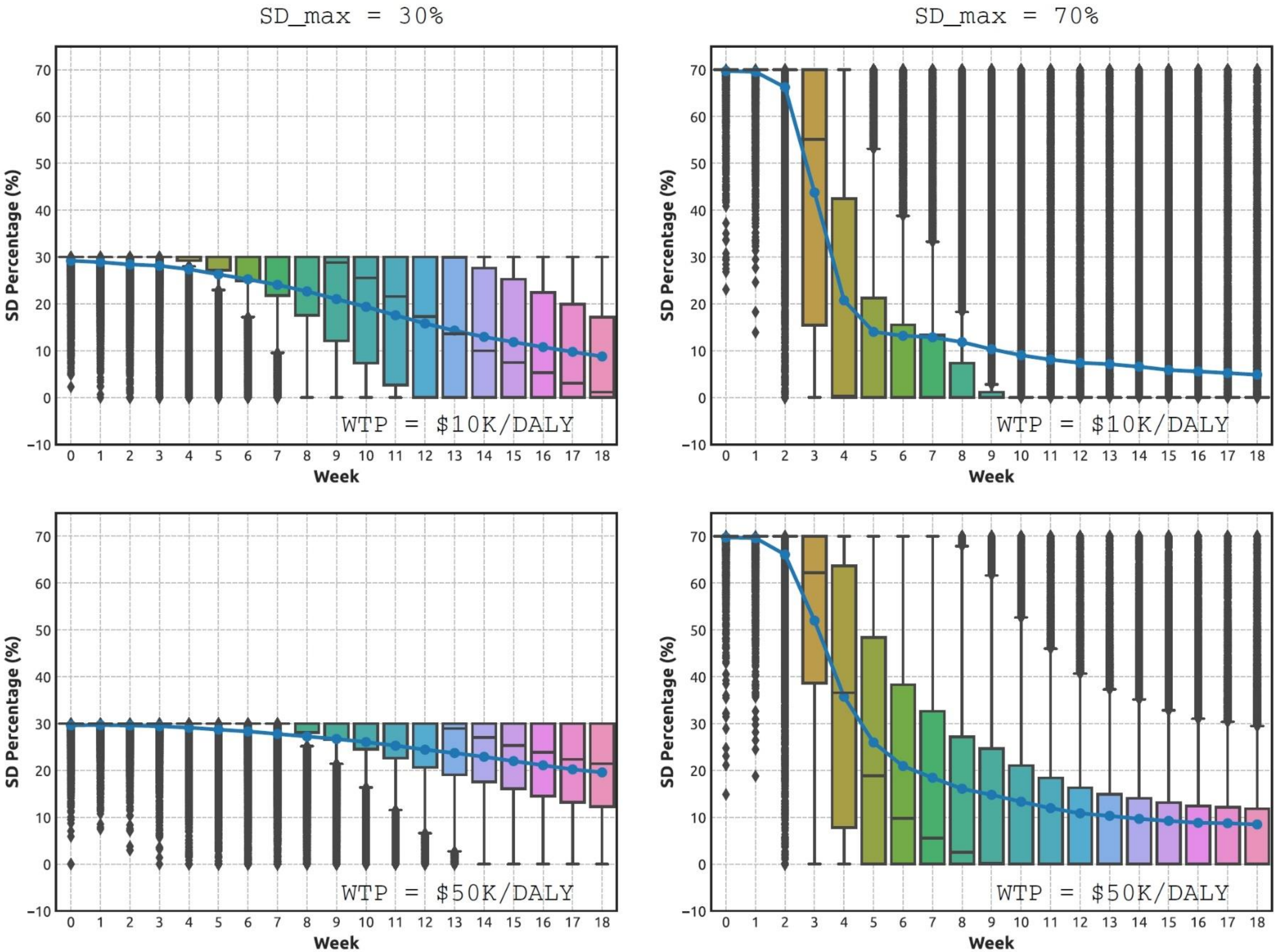


$$L(s_t^0, a^0) - L(s_t, a_t)$$

$$\text{NHB} = \mu_{E_{SD}} - \frac{\mu_{C_{SD}}}{\lambda}$$

Willingness to pay (WTP)

Adaptive SD strategies



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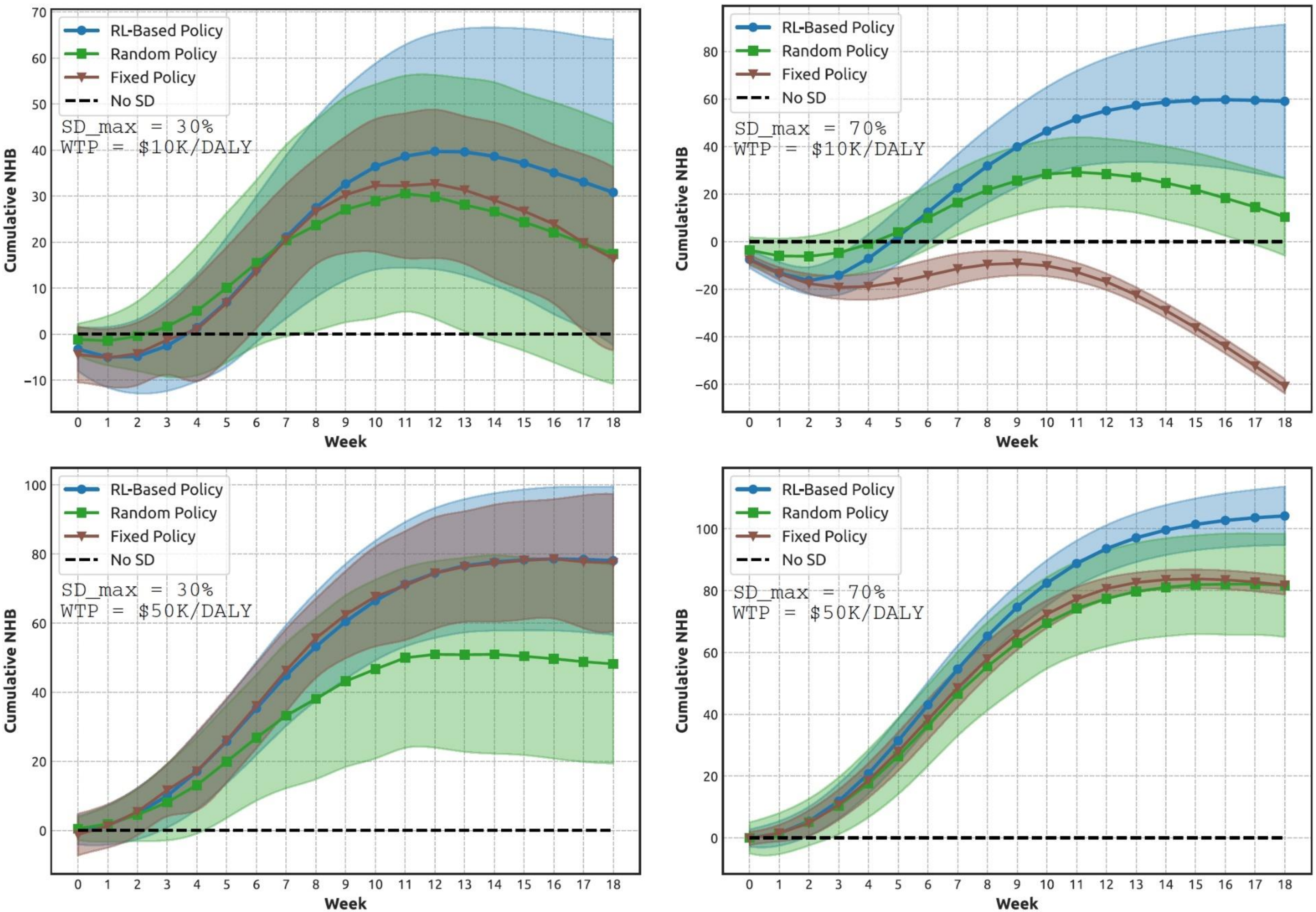
Comparison: adaptive vs fixed | random | zero-SD



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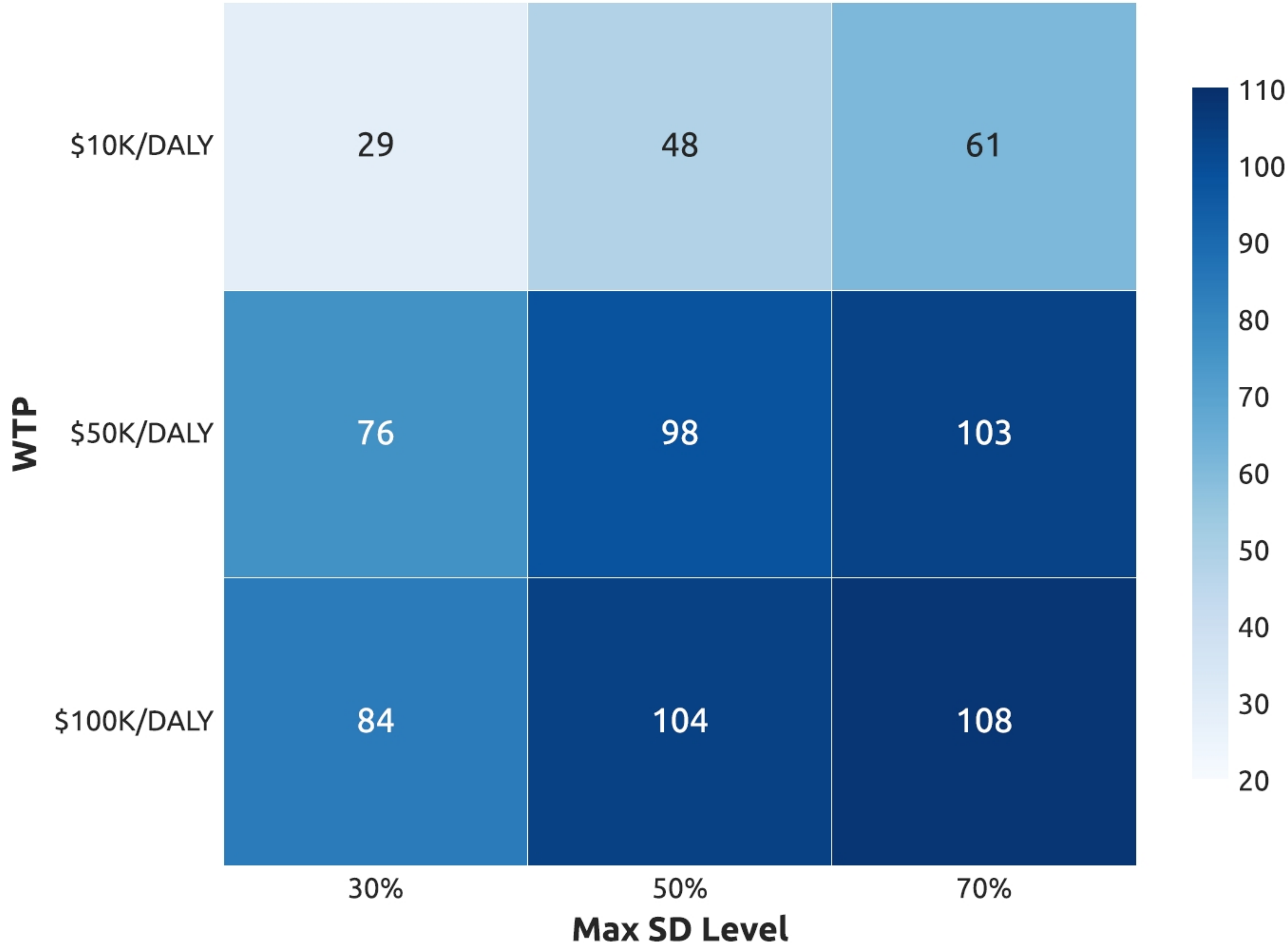
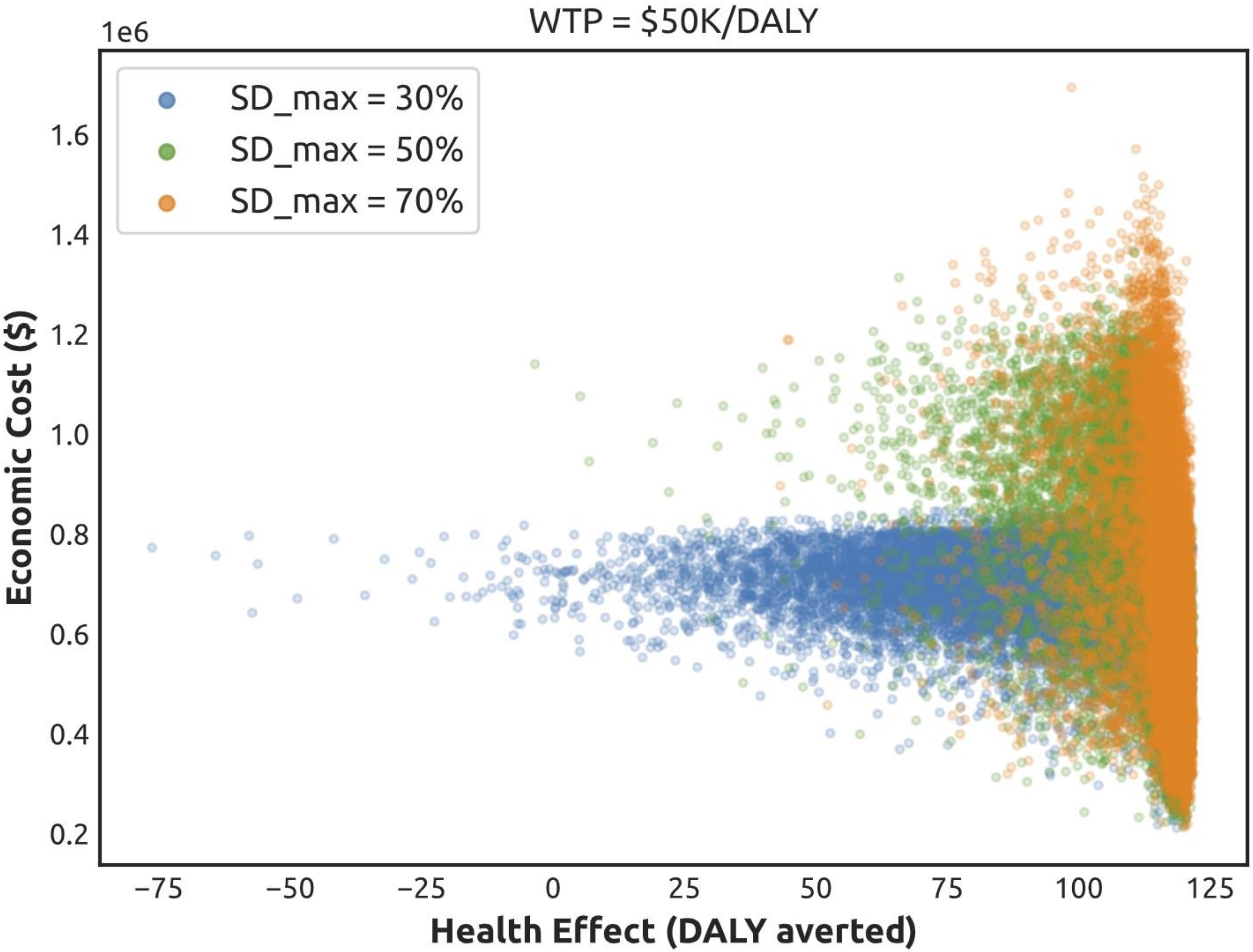
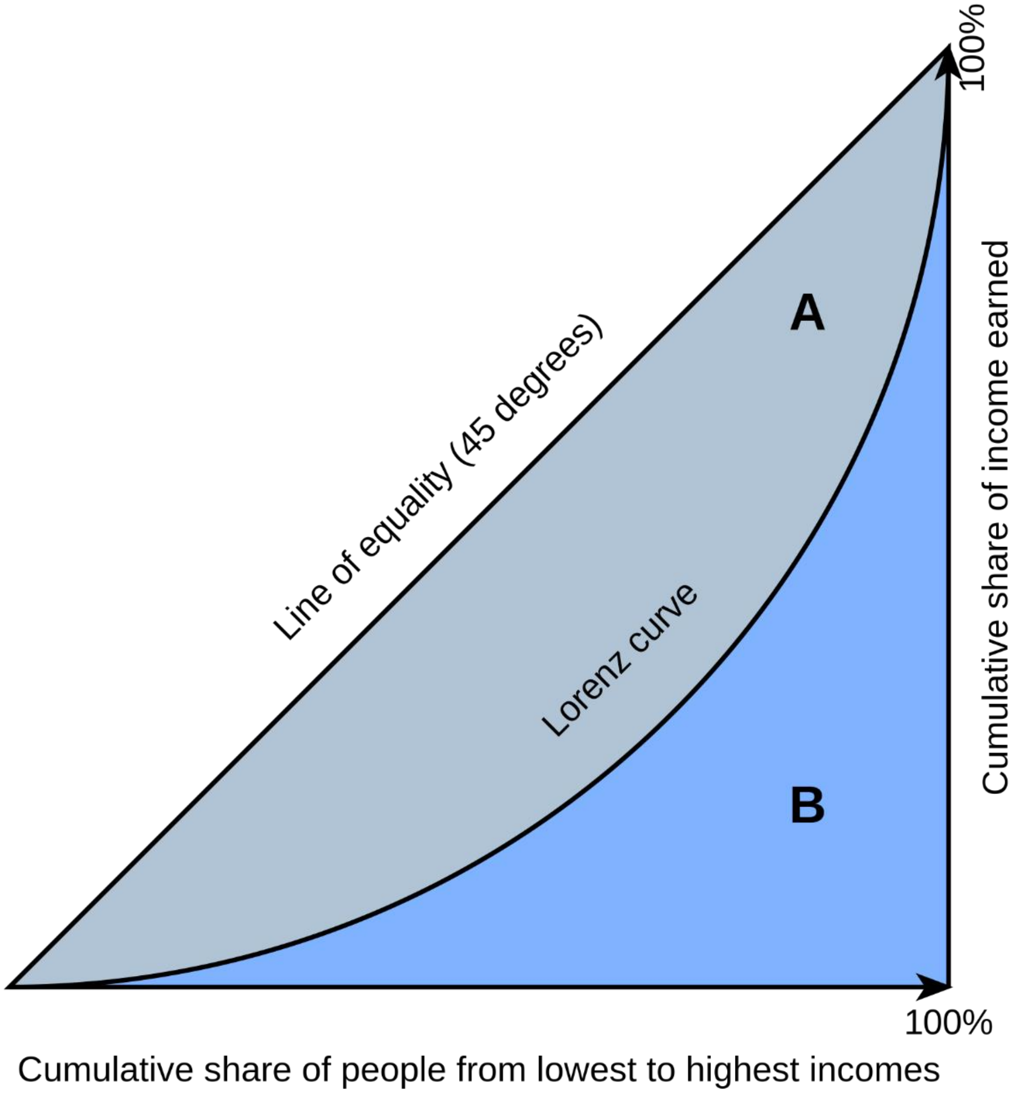
Cumulative NHB generated by adaptive SD strategies



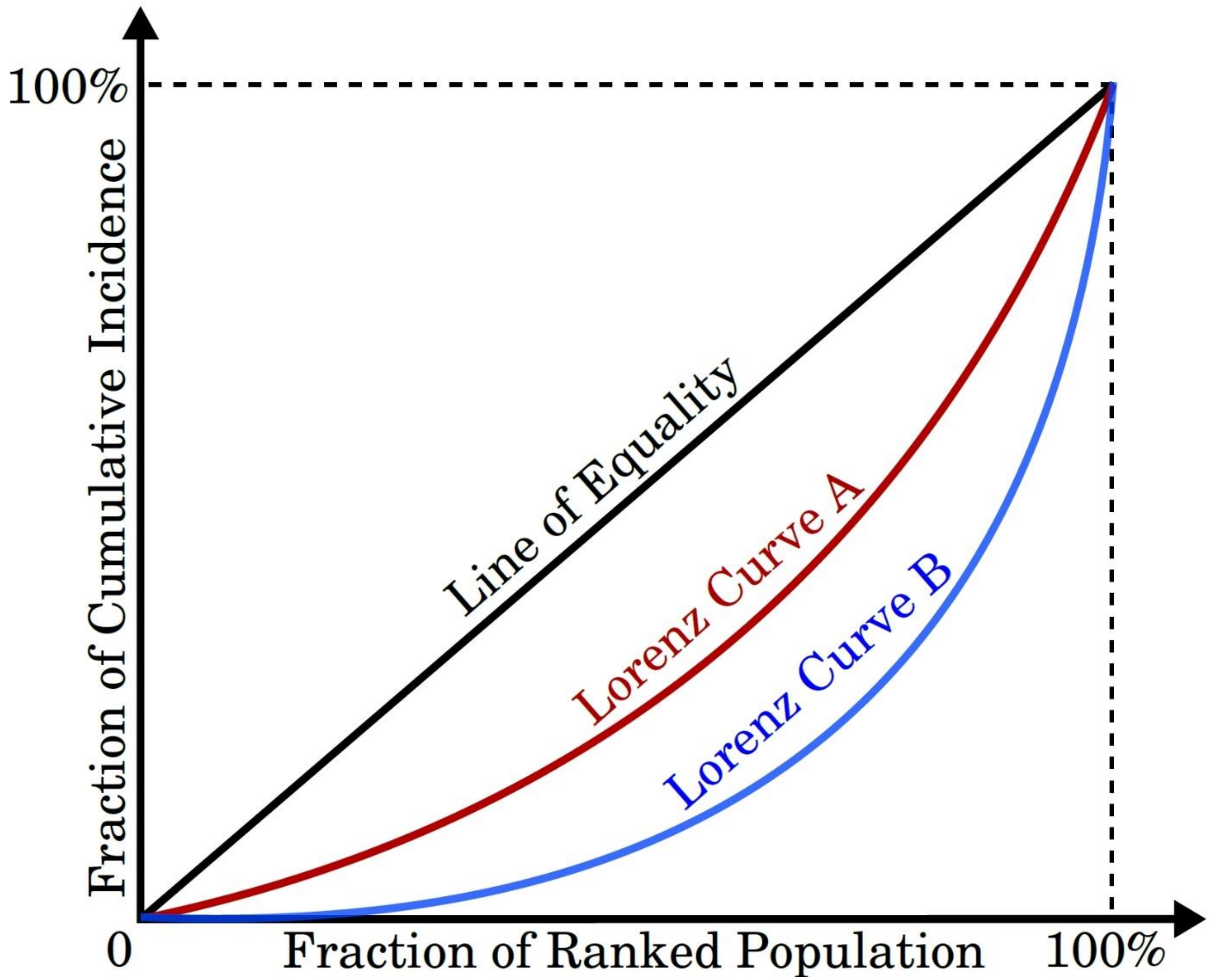
Phase diagram of the NHB dynamics: health effects vs economic costs



Inequality of wealth distribution



Pandemic inequality: pandemic Lorenz curves



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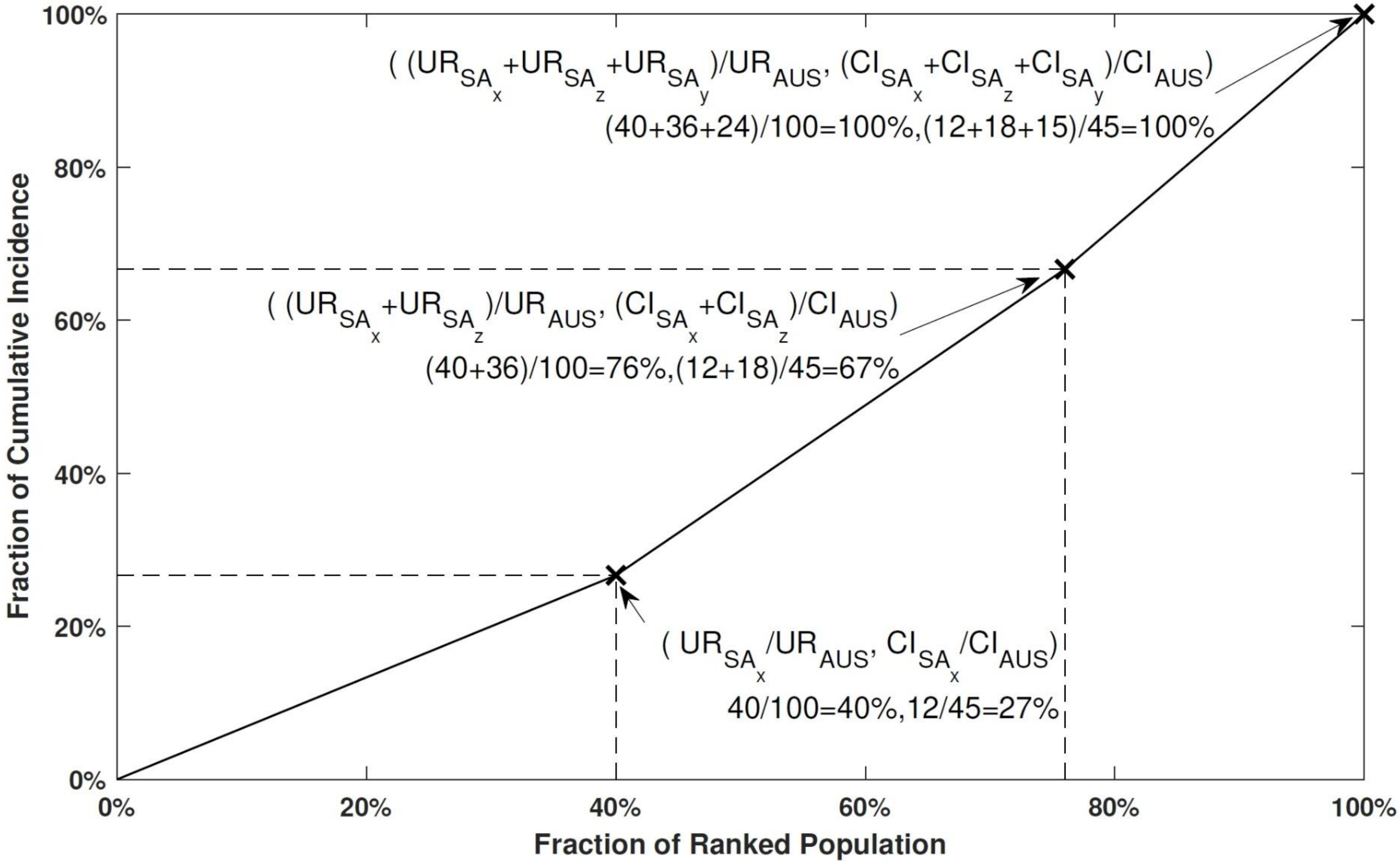

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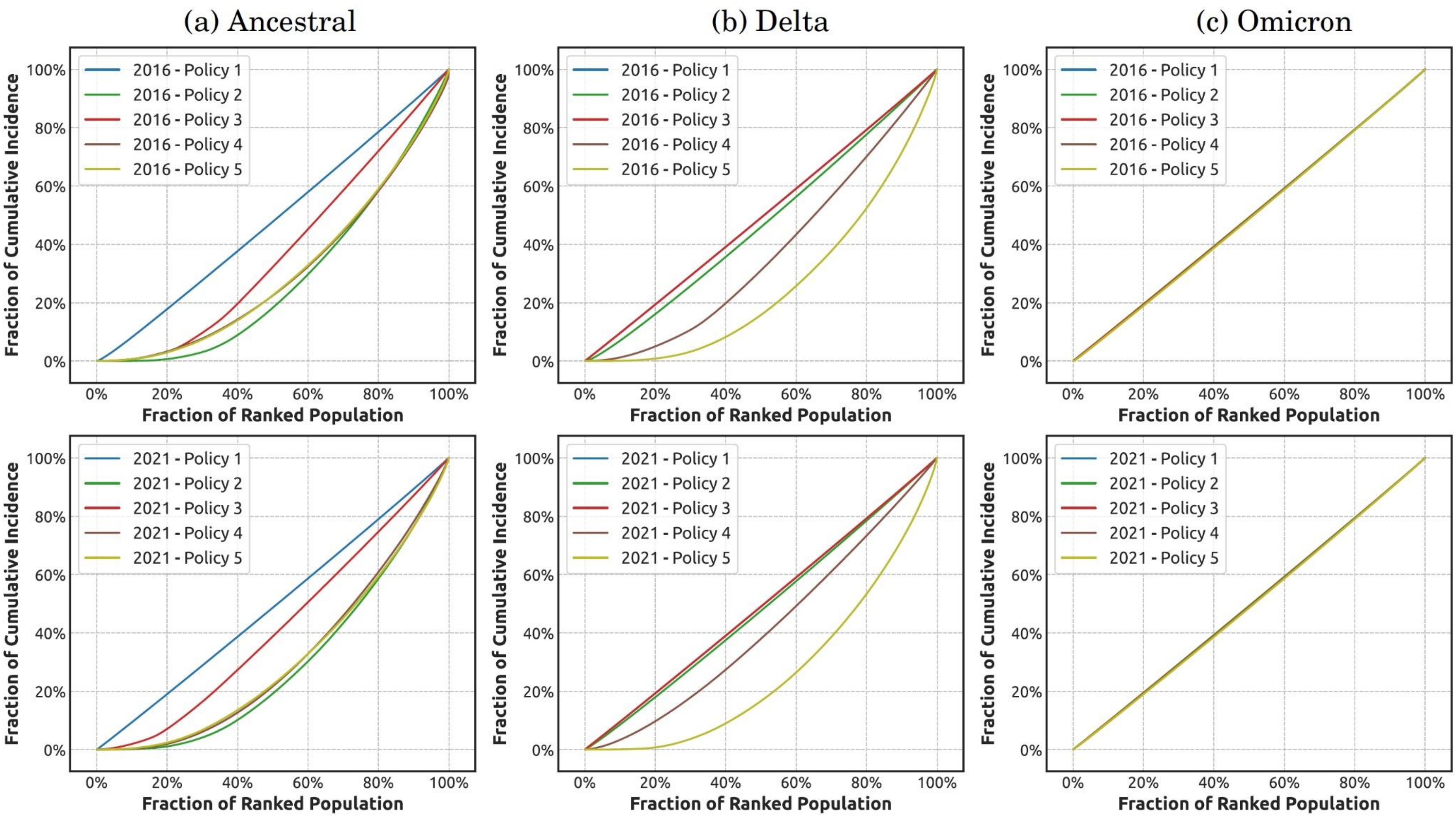

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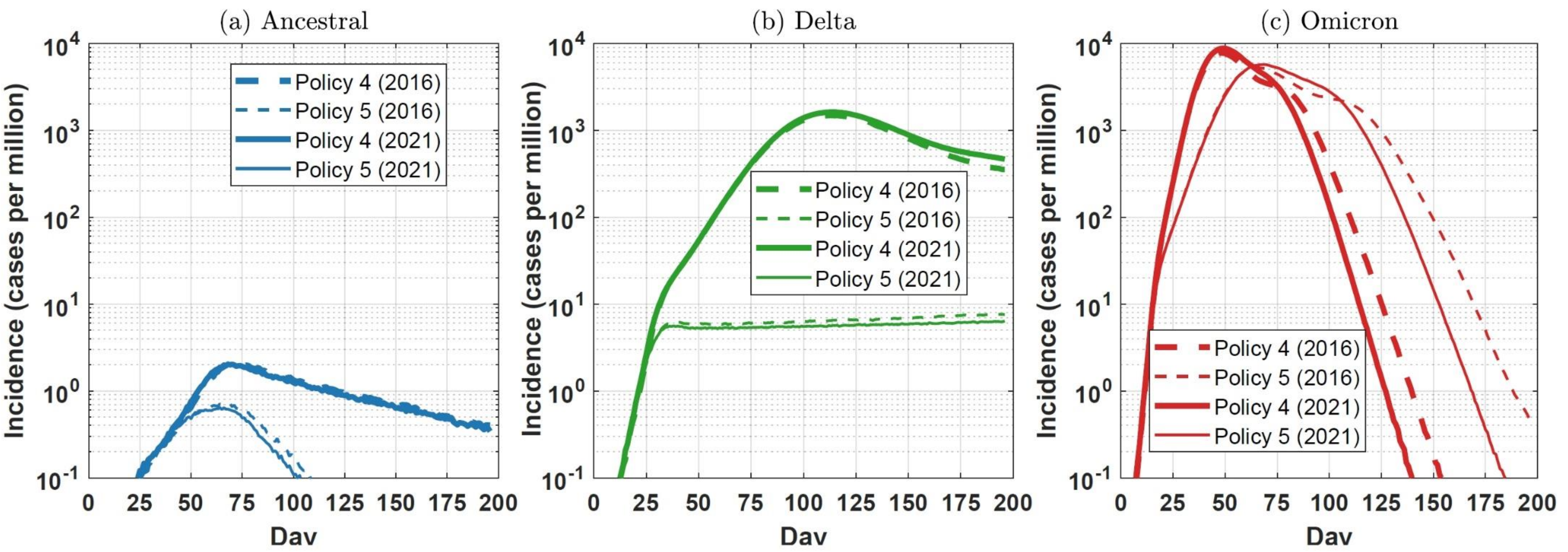
Effect of school closures



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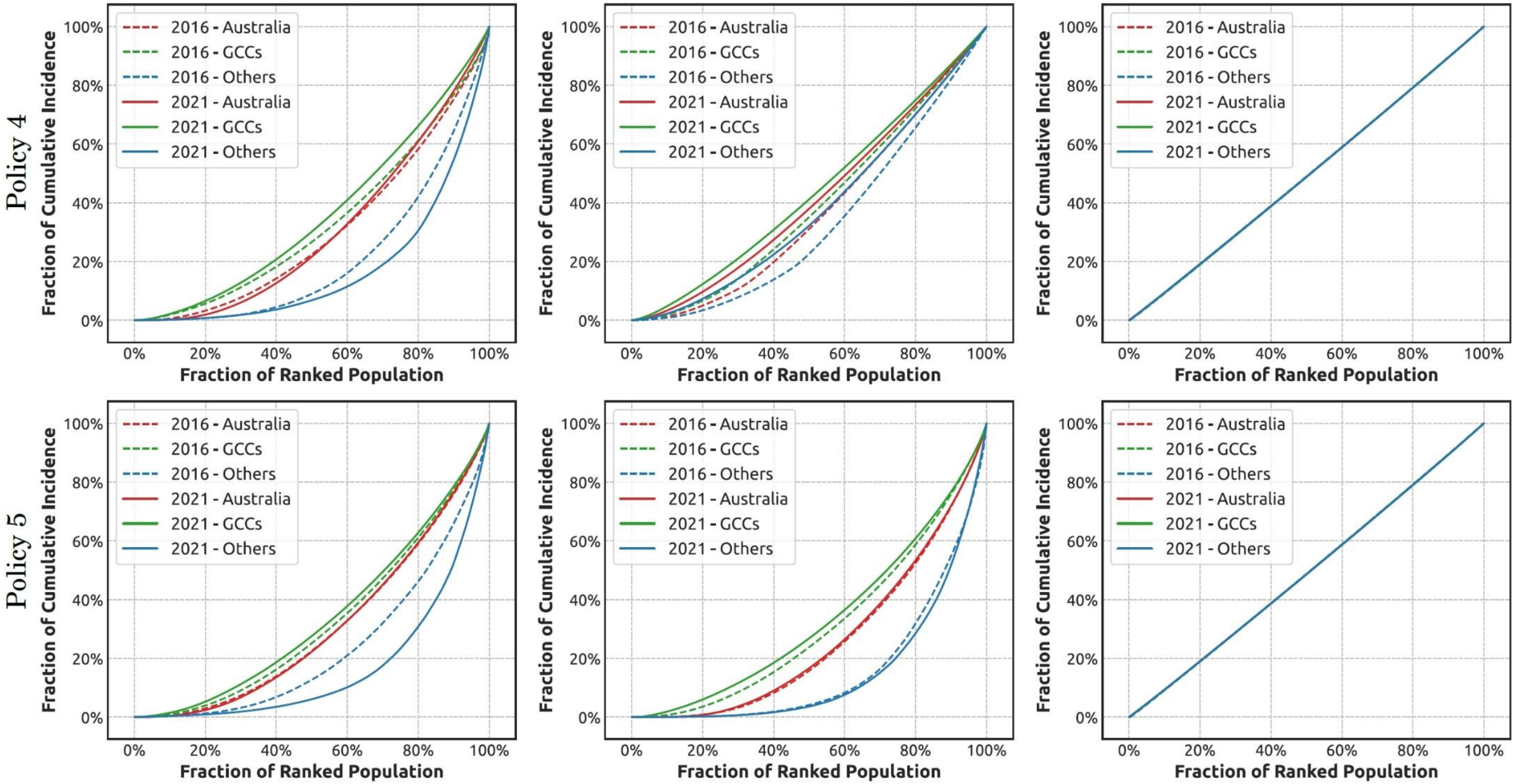
Pandemic inequality: urban vs regional



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Challenges and feedback loops

- complexity of human behaviour:
  - tipping points in social distancing (SD) compliance / adoption
  - highly-transmissible variants strongly amplify small changes in SD adoption
  - vaccine uptake and SD levels are uneven across demographics
- socio-economic complexity:
  - subjective perspectives of policy- and decision-makers
  - capacity limits of testing, tracing, isolation, quarantine measures
  - balance of health and economic costs
- bio-complexity:
  - emergence and evolution of sub-lineages
  - vaccination efficacy diminishes over time
- recurrent waves

AMTraC-19 open source

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December 14, 2021

Software Open Access

AMTraC-19 Source Code: Agent-based Model of Transmission and Control of the COVID-19 pandemic in Australia

Chang, Sheryl L.; Harding, Nathan; Zachreson, Cameron; Cliff, Oliver M.; Prokopenko, Mikhail

The software implements an agent-based model for a fine-grained computational simulation of the COVID-19 pandemic in Australia. This model is calibrated to reproduce several features of COVID-19 transmission, including its age-dependent epidemiological characteristics. The individual-based epidemiological model accounts for mobility (worker and student commuting) patterns and human interactions derived from the Australian census and other national data sources. The high-precision simulation comprises approximately 24 million stochastically generated software agents and traces various scenarios of the COVID-19 pandemic in Australia. The software has been used to evaluate various intervention strategies, including (1) non-pharmaceutical interventions, such as restrictions on international air travel, case isolation, home quarantine, school closures, and stay-at-home restrictions with varying levels of compliance (i.e., "social distancing"), and (2) pharmaceutical interventions, such as pre-pandemic vaccination phase and progressive vaccination rollout.

The paper describing the model and the scenarios investigated with AMTRaC-19 (v7_7d):

S. L. Chang, C. Zachreson, O. M. Cliff, M. Prokopenko, Simulating transmission scenarios of the Delta variant of SARS-CoV-2 in Australia, *Frontiers in Public Health*, 10, 10.3389/fpubh.2022.823043, 2022.

Please cite it, as well as other publications referenced below, when using the software.

The dataset generated during this study is also available on Zenodo:

Publication date:
December 14, 2021

DOI:
DOI 10.5281/zenodo.5778218

Keyword(s):
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