

CONTACT PATTERNS BY AGE AND GEOGRAPHY WITH RECURRENT MOBILITY: INFLUENCE OF RELAXING ASSUMPTIONS

Jesse Knight^{1,2}, Huiting Ma¹, Amir Ghasemi³, Mackenzie Hamilton¹, Kevin Brown^{4,5}, and Sharmistha Mishra^{1,2,5,6}

¹MAP Centre for Urban Health Solutions, Unity Health Toronto ²Institute of Medical Science, University of Toronto ³Communications Research Centre Canada, Ottawa ⁴Public Health Ontario, Canada ⁵Dalla Lana School of Public Health, University of Toronto ⁶Division of Infectious Diseases, Department of Medicine, University of Toronto

BACKGROUND

- Contact patterns mediate dynamics of infectious diseases e.g. in transmission models stratified by **age** & geographic **patches** [1]
- Prem et al. [2] project age contact patterns onto 177 countries: “home”, “work”, “school”, & “other” contacts from **POLYMOD**
- Arenas et al. [3] model patch/age contacts due to recurrent **mobility**: repeated daily travel between patches
- We [4] built-upon [3] to integrate age contact patterns from [2], and relax 3 assumptions made in [3]
- We explored the effect of each assumption on modelled contact patterns in the context of **reduced mobility** (April 2020)

RESEARCH QUESTION

How does each assumption below influence patch/age contact patterns?

Overall assumption in [3]: *fixed age pattern for all patches & contact types*
3 component **assumptions**:

- A1.** Contact patterns are equal (averaged) across contact types
- A2.** Contact patterns are not adjusted to per-patch age distributions
- A3.** Contacts at “home” include visitors to the patch

CONTEXT + DATA

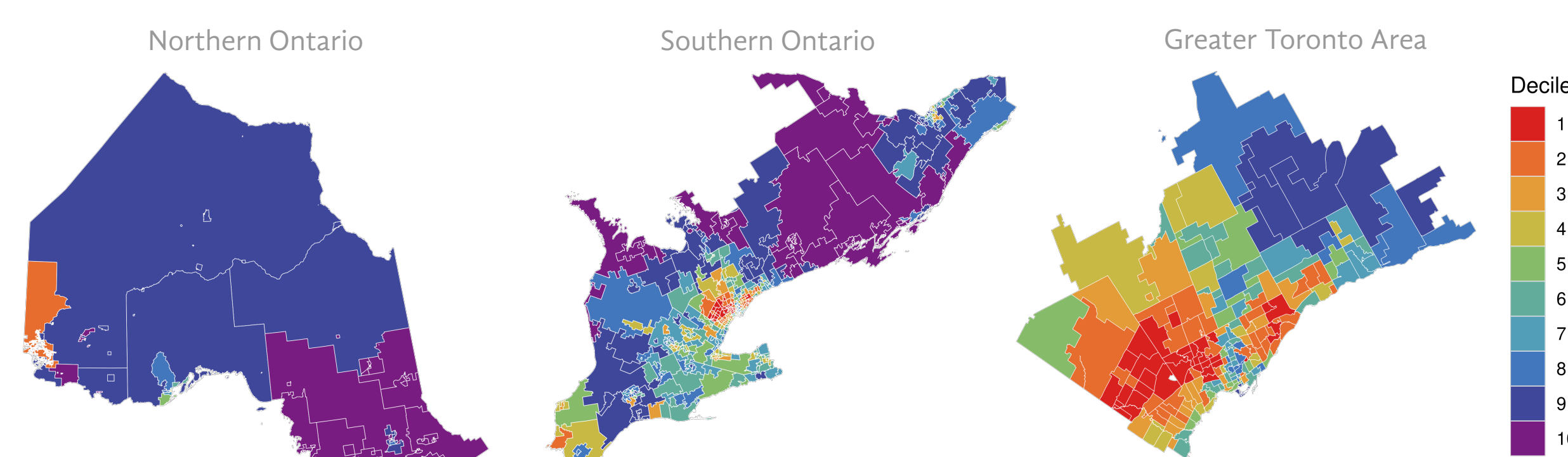


Figure 1. Map of 513 Ontario areas grouped into 10 patches (deciles) by COVID-19 incidence

Notation: g : self patch a : self age group y : contact type
 g' : other patch a' : other age group

Main Output: $C_{gag'a'y}$: # daily contacts of type- y per-person formed from patch/age ga to patch/age $g'a'$

Context: 513 Ontario areas grouped into 10 patches by COVID-19 incidence (Figure 1) & population stratified into 5-year age groups

Data:

- Population distribution by age and patch $P_{ga} \leftarrow$ Census [5] (Figure 3)
- Mobility matrix $B_{gg'}$ \leftarrow Cell phone data [6]
% residents who travelled from g to g' daily, including within-patch & % reduced mobility during t = April 2020 vs Jan–Feb 2020 (REF)
- Age contact patterns $C_{aa'y} \leftarrow$ Prem et al. [2]
daily type- y contacts per-person from age group a to a'

METHODS

Estimating $C_{gag'a'y}$: # daily type- y contacts per-person from patch/age ga to patch/age $g'a'$:

- Define two types of “mixing pools” (Figure 2):
 - Home pools:** can only contact other residents of this patch
 - Travel pools:** can contact anybody currently present
- For each contact type y & patch g^* :
 - Population from g' present in travel pool: $P_{g'a}^{g^*} = B_{g'g^*} P_{g'a}$
 - Adjust age contact patterns $C_{aa'y}$ to $P_{g'a}^{g^*}$ per [7]
 - Assume random mixing by patch gg' within pool
- Assume reduced mobility \rightarrow reduced non-home contacts
- Sum contacts from all patch g^* pools \rightarrow Total contacts $C_{gag'a'y}$

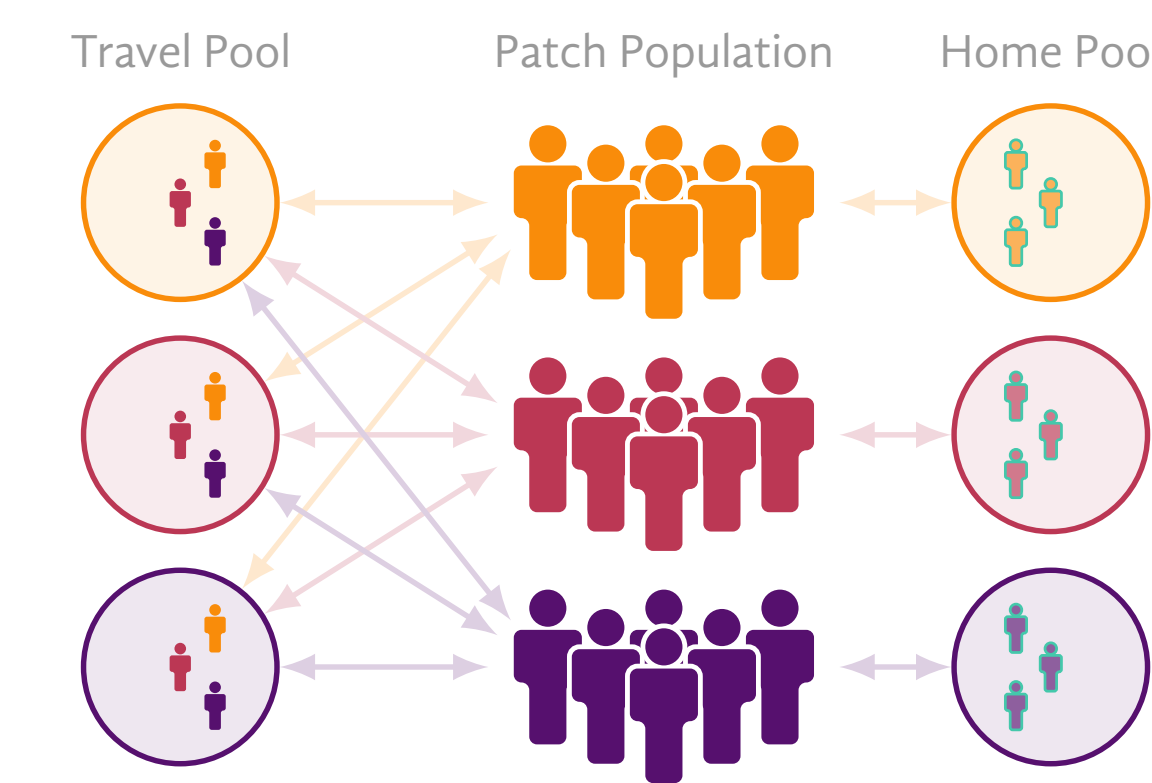


Figure 2. Illustration of travel vs home mixing pools for 3 toy patches

Experiment: We estimated & compared (subtracted) $C_{gag'a'y}$ under different sets of assumptions:

- (A1+A2+A3) subtract (A2+A3) \rightarrow assumption A1 effect
- (A2+A3) subtract (A3) \rightarrow assumption A2 effect
- (A3) subtract (·) \rightarrow assumption A3 effect

We aggregated $C_{gag'a'y}$ across patches/ages to show overall patterns by age aa' or patch gg'

RESULTS

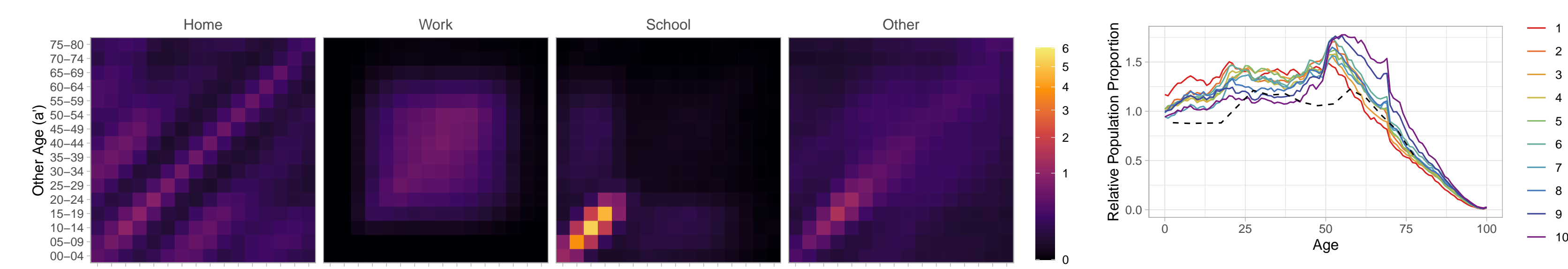


Figure 3. Relative age distribution by patch (colours [5]) and overall (dotted [2])

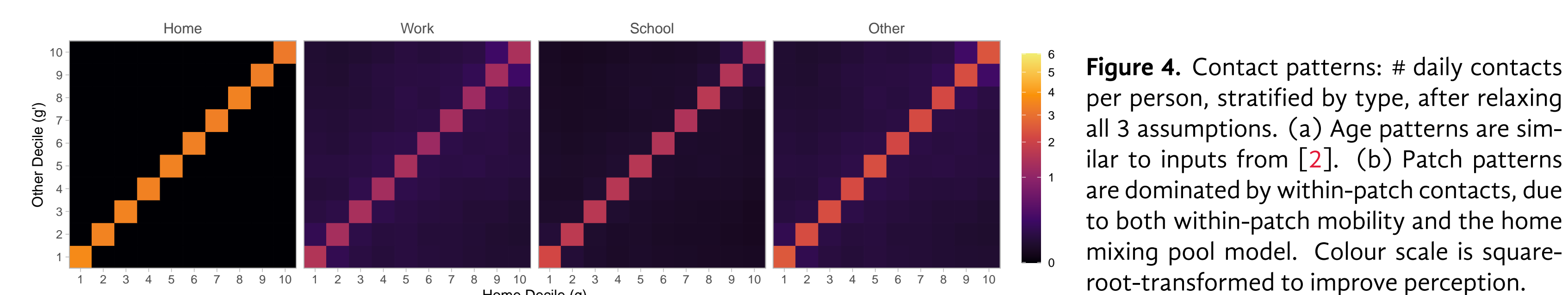


Figure 4. Contact patterns: # daily contacts per person, stratified by type, after relaxing all 3 assumptions. (a) Age patterns are similar to inputs from [2]. (b) Patch patterns are dominated by within-patch contacts, due to both within-patch mobility and the home mixing pool model. Colour scale is square-root-transformed to improve perception.

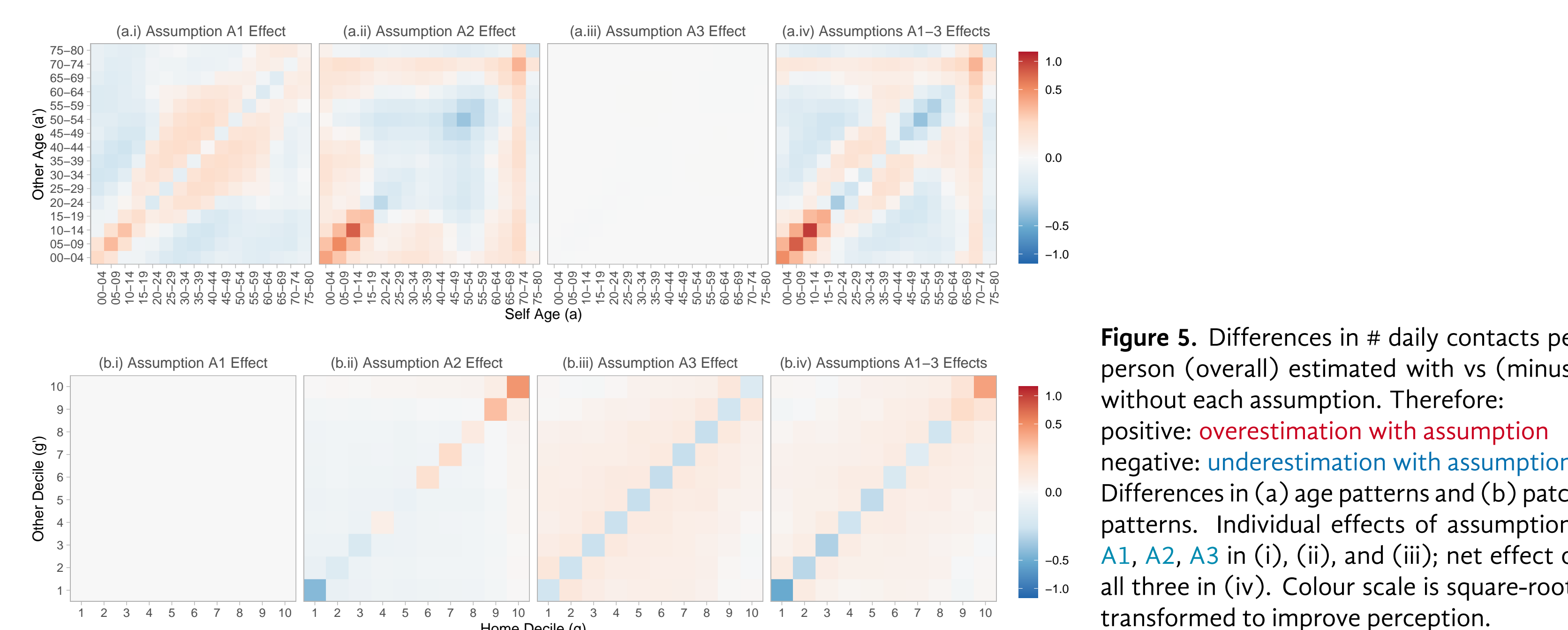


Figure 5. Differences in # daily contacts per person (overall) estimated with vs (minus) without each assumption. Therefore: positive: **overestimation with assumption**; negative: **underestimation with assumption**. Differences in (a) age patterns and (b) patch patterns. Individual effects of assumptions A1, A2, A3 in (i), (ii), and (iii); net effect of all three in (iv). Colour scale is square-root-transformed to improve perception.

SUMMARY OF ASSUMPTION EFFECTS

- A1.** If contact patterns averaged across types (Figure 5.i)
 - \rightarrow overestimate like-with-like age patterns from school/work
 - \rightarrow underestimate inter-generational contacts from home
- A2.** If contact patterns not locally age-adjusted (Figure 5.ii)
 - \rightarrow overestimate contacts with smaller age groups
 - \rightarrow underestimate contacts with larger age groups
- A3.** If contacts at home can include patch visitors (Figure 5.iii)
 - \rightarrow overestimate contacts formed with other patches
 - \rightarrow underestimate contacts formed within same patch

INTERPRETATION

- Fixing age patterns for all patches & contact types **may underestimate intergenerational home contacts** during reduced mobility
- Not adjusting contact patterns to per-patch age distributions **may over/underestimate overall contacts in different patches**
- Predominance of home contacts & within-patch mobility may result in **relatively few contacts between patches**
- Assumptions about contact patterns may influence model-based evaluations of **patch/age-targeted interventions** for infectious diseases
- Our approach to estimate contact patterns **integrates empiric contact patterns and mobility data**, and thus reduces the required assumptions

THANKS

Kristy Yiu, Gary Moloney, Linwei Wang, Yue Chen, Ruth Mwatelah, and Collin McGuire for helpful discussions and technical support; Prem et al. [2] for open-sourcing analysis code and numerical results.



REFERENCES

- Sharmistha Mishra et al. “A Vaccination Strategy for Ontario COVID-19 Hotspots and Essential Workers”. In: *Science Briefs of the Ontario COVID-19 Science Advisory Table 2.26* (Apr. 2021). doi: [10.47326/ocsat.2021.02.26.1.0](https://doi.org/10.47326/ocsat.2021.02.26.1.0).
- Kiesha Prem et al. “Projecting contact matrices in 177 geographical regions: An update and comparison with empirical data for the COVID-19 era”. In: *PLoS Computational Biology* 17.7 (July 2021). doi: [10.1371/journal.pcbi.1009098](https://doi.org/10.1371/journal.pcbi.1009098).
- Alex Arenas et al. “Modeling the Spatiotemporal Epidemic Spreading of COVID-19 and the Impact of Mobility and Social Distancing Interventions”. In: *Physical Review X* 10.4 (Dec. 2020), p. 041055. doi: [10.1103/PhysRevX.10.041055](https://doi.org/10.1103/PhysRevX.10.041055).
- Jesse Knight et al. “Adaptive data-driven age and patch mixing in contact networks with recurrent mobility”. In: *medRxiv* (Oct. 2021). doi: [10.1101/2021.09.29.21264319](https://doi.org/10.1101/2021.09.29.21264319).
- Statistics Canada. *Table 98-400-X2016008*. 2016.
- Amir Ghasemi et al. “Impact of a nighttime curfew on overnight mobility”. In: *medRxiv* (Apr. 2021). doi: [10.1101/2021.04.04.21254906](https://doi.org/10.1101/2021.04.04.21254906).
- Sergio Arregui et al. “Projecting social contact matrices to different demographic structures”. In: *PLoS Computational Biology* 14.12 (Dec. 2018), e1006638. doi: [10.1371/journal.pcbi.1006638](https://doi.org/10.1371/journal.pcbi.1006638).

All project code & most data are available at: github.com/mishra-lab/age-patch-mobility-mixing