

# Disentangling the Multifaceted Drivers of Disease Transmission: A Bayesian Hierarchical Model of Climate, Air Quality, and Contact Patterns in Hong Kong

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## Background

The COVID-19 pandemic underscored the need to understand how transmission is shaped by multiple factors, including NPIs, weather, air quality and contact patterns. Many existing models either oversimplify these interdependencies or assess only limited combinations, risking the loss of key interaction effects. Using contact tracing data<sup>[1,2]</sup>, we assess how NPIs, meteorological conditions and air quality influence SARS-CoV-2 transmission. Our multidimensional analysis quantifies age-specific transmission, spatial heterogeneity across districts, and setting-specific clusters.

## Methods

We model the impact of weather (ultraviolet(UV), absolutely humidity (AH)), air quality (ozone (O<sub>3</sub>), respirable suspended particulates (RSP)) and Non-Pharmaceutical Interventions (NPIs) on SARS-COV-2 transmission as  $\beta_t = \exp(\beta_{UV} * UV + \beta_{AH} * AH + \beta_{O_3} * O_3 + \beta_{RSP} * RSP + \beta_{NPI} * NPIs)$ .

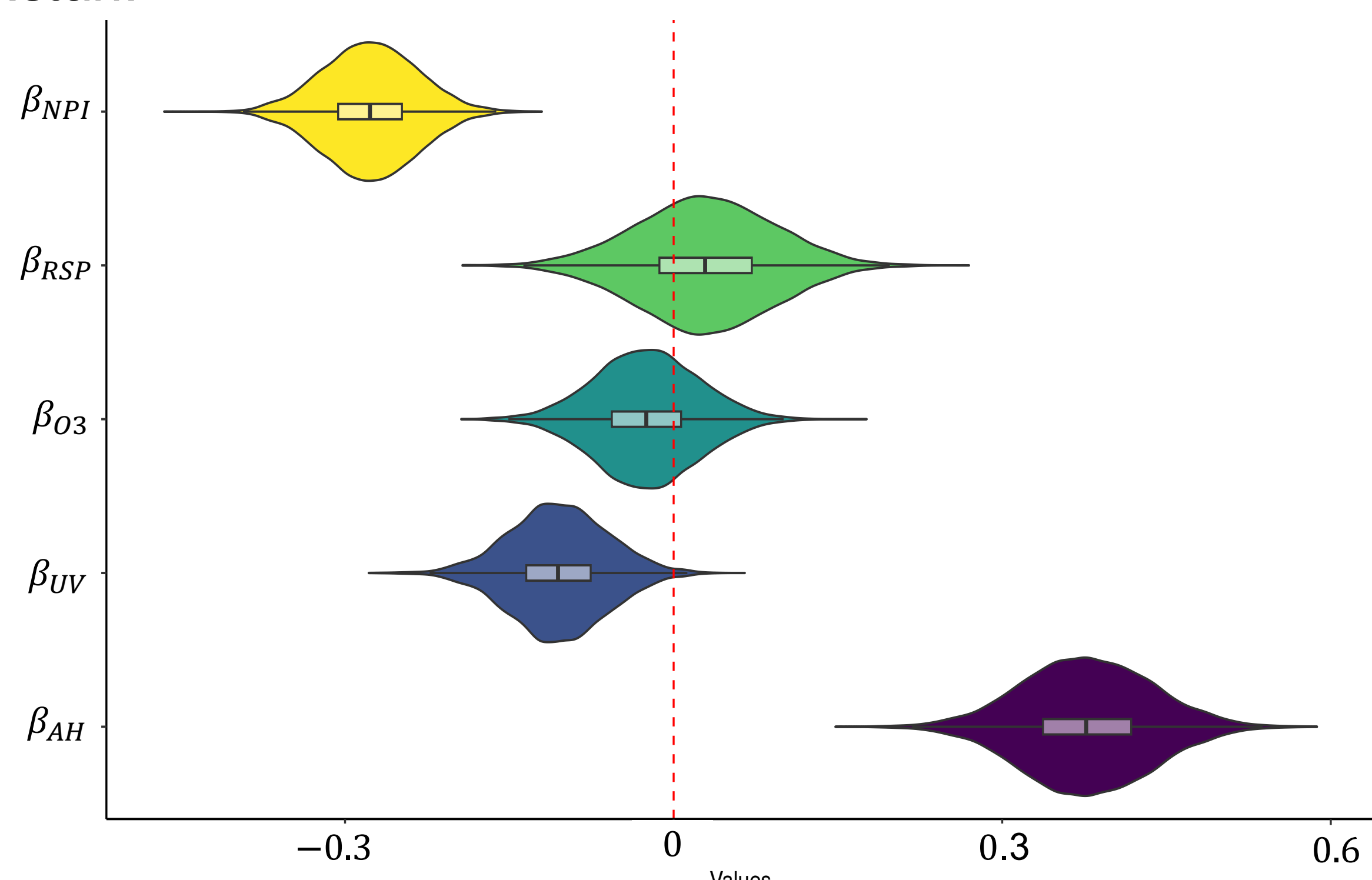
Let  $C$ ,  $A$ ,  $D$  be the contact matrix across cluster settings, age groups, and districts, respectively, we define the infection cases in specific cluster  $c$ , age group  $a$ , district  $d$  as,

$$\begin{aligned}\eta_c(i, t) &= \beta_t * \sum_l C_{i,l} * \eta_c(l, t) \\ \eta_a(j, t) &= \beta_t * \sum_l A_{j,l} * \eta_a(l, t) \\ \eta_d(k, t) &= \beta_t * \sum_l D_{k,l} * \eta_d(l, t)\end{aligned}$$

Then, we use the observed weekly case counts for each stratum (setting, age group, district) were assumed to follow a Negative Binomial distribution, which accounts for potential overdispersion commonly observed in infectious disease count data. The likelihood is defined as:

$$\begin{aligned}Y_d(i, t) &\sim NB(\eta_d(i, t), \phi) \\ Y_s(j, t) &\sim NB(\eta_s(j, t), \phi) \\ Y_a(k, t) &\sim NB(\eta_k(k, t), \phi)\end{aligned}$$

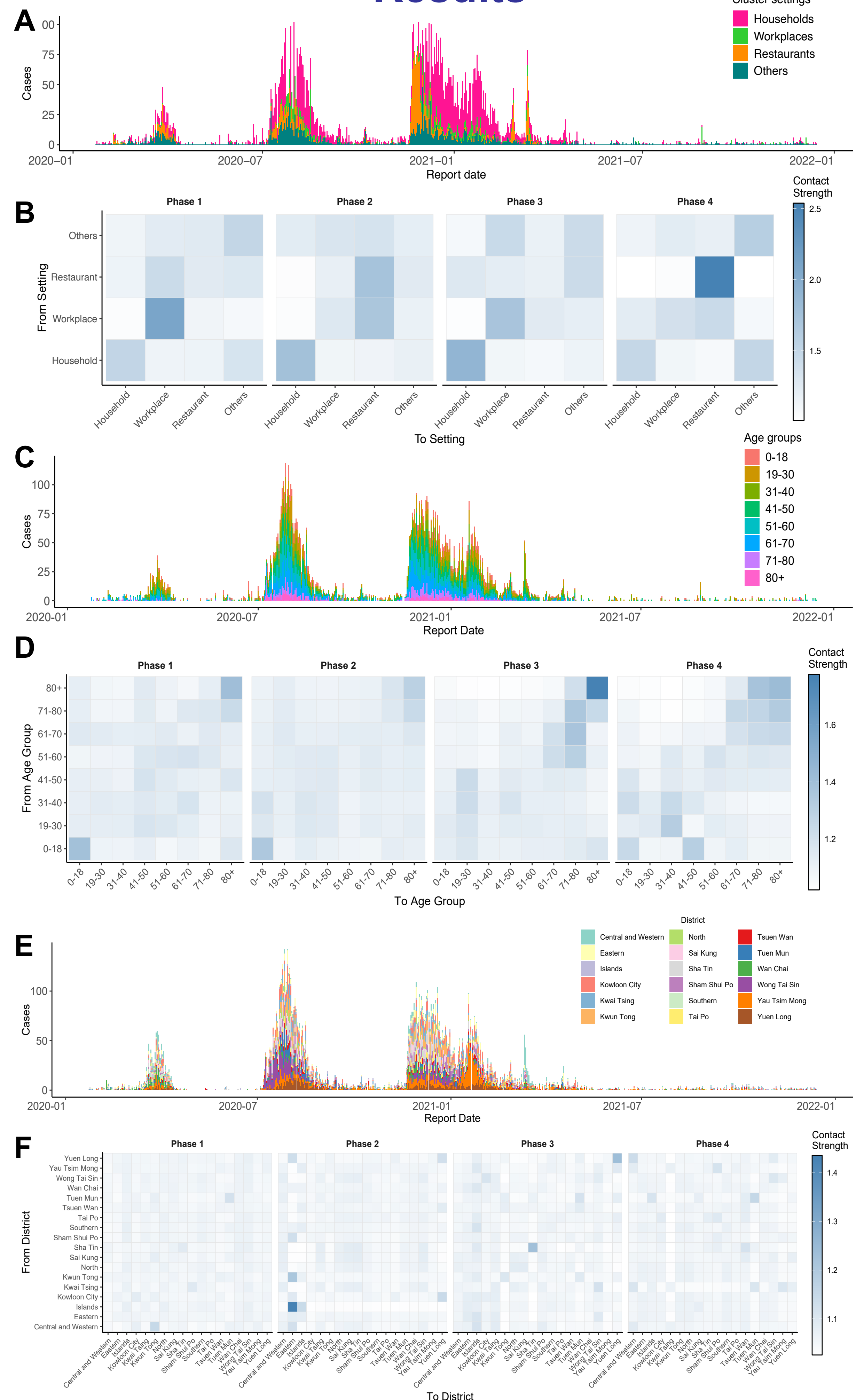
Posterior inference was conducted via HMC sampling in *Rstan*.



**Figure 1. The impact of weather, air quality and NPI on SARS-CoV-2 transmission.**

P2.068, Contact: dongw21@hku.hk (Dong WANG) If your work touches Epidemiology, Mathematical Modeling, Complex Network, Geographic and Spatial Analytics, Bayesian Hierarchical Modeling, Genomic Epidemiology, and Analysis of Collective Behavior, please consider hiring me for Post-doc, or any relevant Research position). Thank you!

## Results



**Figure 2. The documented infection cases for different categories and the derived contact pattern across cluster settings, age groups and districts.**

## Discussion / Advertisement

This study provides a data-driven method to investigate the synergistic impact of NPIs, climate variables, air quality and social gatherings on epidemic transmission, and estimate the age-stratified, geographically-distributed, and setting-specific contact pattern.

## References

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[2] Moritz U. G. Kraemer *et al.*, spatiotemporal invasion dynamics of SARS-CoV-2 lineage B.1.1.7 emergence. *Science* **373**, 889-895(2021). DOI:10.1126/science.abj0113

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