Inference under Superspreading: Determinants of SARS-CoV-2 Transmission in Germany

Patrick Schmidt
University of Zurich

Outline

About me

Paper presentation

- Motivation
- Model
- Challenges
- Results

Short CV

- Studies of Mathematics, Statistics, and Economics
- PhD in Econometrics
  (causal inference, computational statistics, decision-theory)
- Statistical consultant
  (impact evaluation and survey research for World Bank)
- PostDoc in Psychometrics
  (Bayesian, longitudinal data, measurement, epidemiology)
- Visiting Professor in Econometrics

Experience

- statistical programming
- structural estimation
- causal inference
- survey measurements

Outline

About me

Paper presentation

- Motivation
- Model
- Challenges
- Results

Inference under superspreading

Schmidt, P. W. (2024). Inference under superspreading: Determinants of SARS-CoV-2 transmission in Germany.
Statistics in Medicine, 43(10):1933–1954

Motivation

- Goal: Understand determinants of SARS-CoV-2 transmission

Motivation

- Goal: Understand determinants of SARS-CoV-2 transmission
- Method: Structural model on surveillance data with Bayesian inference
  1. Estimate infection dynamic based on cases
  2. Explain infection dynamic with covariates

Motivation

- Seminal contributions that estimate effects of interventions:
  - Flaxman et al. (Nature, 2020)
  - Brauner et al. (Science, 2021)

Motivation

- Seminal contributions that estimate effects of interventions:
  - Flaxman et al. (Nature, 2020)
  - Brauner et al. (Science, 2021)
- Is there anything to add?

Motivation

- Seminal contributions that estimate effects of interventions:
  - Flaxman et al. (Nature, 2020)
  - Brauner et al. (Science, 2021)
- Is there anything to add?

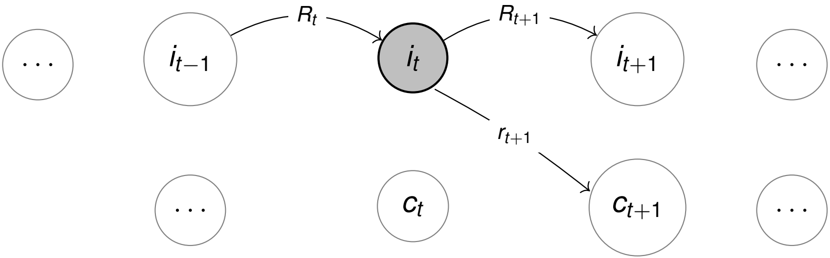
× reporting delay $\rightarrow$ symptom onset data

× superspreading $\rightarrow$ model uncertainty

× confounding of determinants $\rightarrow$ more covariates

Toy model

- simplified: generation time and incubation fixed
- i_t infections at time t (unobserved)
- c_t cases with symptom onset at time t (observed)
- R_t reproductive number at time t
- r_t ascertainment rate at time t



Toy model

- Transmission:
$$i_t \sim NB(i_{t-1} R_t, i_{t-1} \Psi).$$

Toy model

- Transmission:
$$i_t \sim NB(i_{t-1} R_t, i_{t-1}\Psi).$$
- Measurement:
$$c_t \sim Poisson(r_t i_{t-1}).$$

Toy model

- Transmission:
$$i_t \sim NB(i_{t-1} R_t, i_{t-1} \Psi).$$
- Measurement:
$$c_t \sim Poisson(r_t i_{t-1}).$$
- Effect model:
$$R_t = R_0 \prod_{j=1}^{J} (1 + \beta_j x_{j,t}),$$

with covariates x_t.

Challenge: Superspreading

- Transmission:

$$i_t \sim NB(i_{t-1}R_t, i_{t-1}\Psi).$$

Challenge: Superspreading

- Transmission:
$$i_t \sim NB(i_{t-1}R_t, i_{t-1}\Psi).$$

- Consistent with individual model of superspreading (Lloyd-Smith et al., 2005), where secondary infections are given by
$$NB(R_t, \Psi).$$

- Assumption: Secondary infections independent given R_t.

Challenge: Superspreading

- Transmission model $i_t \sim NB(i_{t-1}R_t, i_{t-1}\Psi)$ is different from $i_t \sim NB(i_{t-1}R_t, \Psi)$.

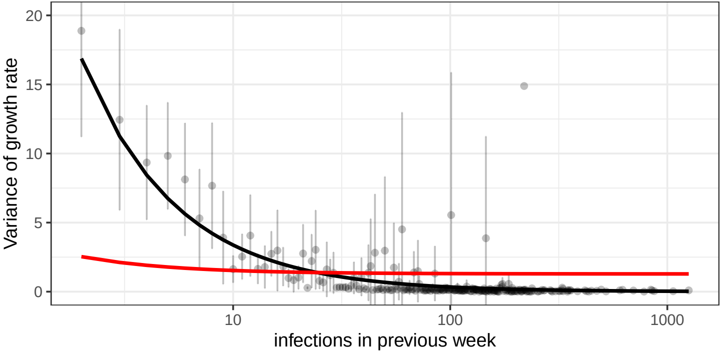


Figure: Mean estimate of empirical variance of weekly growth rates.

Challenge: Confounding

- Previous studies use only non-pharmaceutical interventions (Brauner et al., 2021; Flaxman et al., 2020).

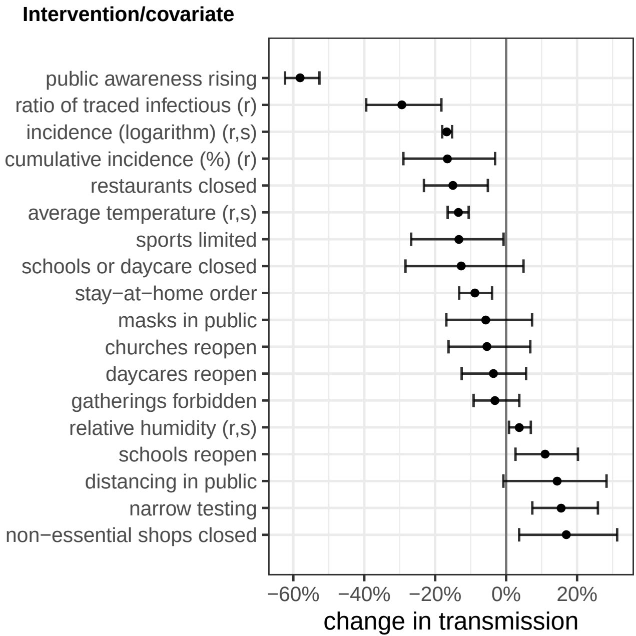
Challenge: Confounding

- Previous studies use only non-pharmaceutical interventions (Brauner et al., 2021; Flaxman et al., 2020).

- This work further includes:
  - temperature, humidity
  - information on incidence
  - ratio of traced infectious
  - public awareness rising

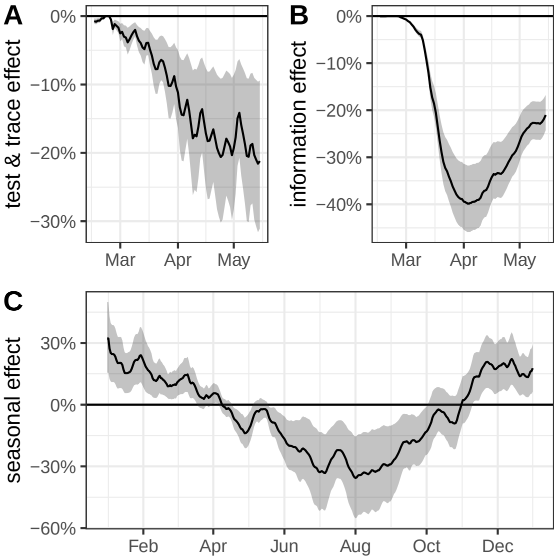
Data and Estimation

- German Covid-19 surveillance data by RKI with date of symptom onset
- DWD daily weather information
- Daily location-specific policy interventions from state legislative orders
- Estimation is based on cases in the 111 most impacted counties
- MCMC sampling implemented with JAGS (Plummer, 2019)



Intervention/covariate
public awareness rising
ratio of traced infectious (r)
incidence (logarithm) (r,s)
cumulative incidence (%) (r)
restaurants closed
average temperature (r,s)
sports limited
schools or daycare closed
stay−at−home order
masks in public
churches reopen
daycares reopen
gatherings forbidden
relative humidity (r,s)
schools reopen
distancing in public
narrow testing
non−essential shops closed
−60%
−40%
−20%
0%
20%
change in transmission

Results: Total effects



Inference conclusions

- Difficult task and many pitfalls remain unmentioned here.

Inference conclusions

- Difficult task and many pitfalls remain unmentioned here.
- Data on symptom onset can improve inference.

Inference conclusions

- Difficult task and many pitfalls remain unmentioned here.
- Data on symptom onset can improve inference.
- Individual superspreading can be incorporated in models on aggregated cases.

Inference conclusions

- Difficult task and many pitfalls remain unmentioned here.
- Data on symptom onset can improve inference.
- Individual superspreading can be incorporated in models on aggregated cases.
- Transmission driven by policy interventions, seasonality, and behavioral adaptation to local risk.

Conclusions of a non-epidemiologist

- Some opinions are supported by the data
  - ✓ Public awareness rising had impact
  - ✓ Behavior adapts to virus spread irrespective of policy interventions
  - ✓ Seasonal variation important driver
  - ✓ Test and trace had relatively strong impact

- Some opinions are not supported by the data
  - × Distancing/curfew/mask mandates had strong impact
  - × Only interventions cause economic and social costs

References I

Brauner, J. M., Mindermann, S., Sharma, M., Johnston, D., Salvatier, J., Gavenčiak, T., Stephenson, A. B., Leech, G., Altman, G., Mikulik, V., et al. (2021). Inferring the effectiveness of government interventions against covid-19. *Science*, 371(6531).

Flaxman, S., Mishra, S., Gandy, A., Unwin, H. J. T., Mellan, T. A., Coupland, H., Whittaker, C., Zhu, H., Berah, T., Eaton, J. W., et al. (2020). Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature*, 584(7820):257–261.

Lloyd-Smith, J. O., Schreiber, S. J., Kopp, P. E., and Getz, W. M. (2005). Superspreading and the effect of individual variation on disease emergence. *Nature*, 438(7066):355–359.

Plummer, M. (2019). *rjags: Bayesian Graphical Models using MCMC*. R package version 4-10.

References II

Schmidt, P. W. (2024). Inference under superspreading: Determinants of SARS-CoV-2 transmission in Germany. *Statistics in Medicine*, 43(10):1933–1954.