

Estimating Local Protective Behavior in Denmark with dynamic MRP

HOPE Project

2020-11-06

The goal of this brief report is to introduce the HOPE project's efforts in estimating COVID-19 protective behavior at local levels in Denmark.

The Data

We are relying on two rolling panel surveys with waves of N = 500. The first is collected by Epinion since March 13, 2020. We collected new waves each day in March, twice a week between April and mid-June, and once a week most recently. Epinion recruits participants from their standing web panel using quotas on age, gender, and region. The contact variables were added to the survey in early April.

The second survey is collected by Gallup since May 13, 2020 with a new wave of 500 respondents on each day. Gallup recruits participants through stratified random sampling based on a database of CPR numbers (Danish social security numbers).

As of 2020-11-06 our sample sizes are:

- Epinion full N = 26,966
- Epinion contact N = 15,955
- Gallup N = 115,725

Variables from the Epinion survey:

- **SumContact:** Total number of non-home contacts - the sum of the four contact variables: Family, Friends, Colleagues, & Strangers. Specifically, respondents are asked for each category to remember "how many people they have been physically close to in the past 24 hours. Physically close is understood here as closer than 2 meters for at least 2 minutes."
- **AvoidCrowds:** A dummy whether the respondent was in a room with more than 10 people the day before.
- **BehavChange:** A four point continuous scale tapping into behaviour change to avoid spreading infection.
- **Handwash:** Number of times respondent washed their hands or used hand sanitizer in the previous 24 hours.

Variables from the Gallup survey:

- **ContactFamily1m:** Number of physical contacts with non co-residing family members.¹
- **ContactFriends1m:** Number of physical contacts with friends.
- **ContactColleagues1m:** Number of physical contacts with colleagues.
- **ContactStrangers1m:** Number of physical contacts with stranger.
- **SumContact1m:** Total number of non-home contacts - the sum of the four contact variables (family, friends, colleagues, strangers).

- **Contact_attention:** An index on compliance with 5 protective behaviors: avoiding physical contact, distancing from elderly and sick, keeping 1-2m distance from others in general, avoiding crowds
- **Hygiene_attention:** An index on compliance with 3 protective behaviors: handwashing, sneezing and coughing in sleeve, ensuring frequent cleaning.

The Method: MRP – Multilevel Regression with Post-stratification.

MRP has been developed as a technique to estimate attitudes on subnational level relying on data from national public opinion surveys. In recent years, it has been validated as a tool for generating reliable and valid subnational estimates of public opinion, which is superior to most naive alternatives (e.g. slicing up data). In a nutshell, MRP relies on both demographic and geographic variables in the modeling process and employs partial pooling (to the extent warranted by the data) in order to improve estimates for smaller units. There many excellent (https://en.wikipedia.org/wiki/Multilevel_regression_with_poststratification) and intuitive (https://scholar.princeton.edu/sites/default/files/jkastellec/files/mrp_primer.pdf) introductions about MRP online, so we refrain from a general introduction here. Instead, we give a brief summary of the analytical steps we took. We implemented MRP relying on the *rstanarm* R library in a fully Bayesian framework.

Stage 1 - Estimating individual level protective behavior with multilevel models

First, we seek to build a model of individual level protective behavior. Our independent variables are the following:

- date_std: Days since median wave. Simple time smoother.
- age_cat: 5year age categories from 20-24 ... to 70+. (11 levels)
- female: participant sex. (2 levels)
- edu_clean: Participant's highest level of education (8 levels)
- region: Participant's place of residence (5 levels).
- round_date: Date of interview².

The R code for the full multilevel model is displayed below. Note that we add both date_std and date_std squared as a time smoother and that we model age conditional on gender.

Moreover, note that the type of regression is conditional on the DV. For count variables (contacts and handwashing) we run negative binomial regressions, for binary variables (avoid crowds of 10+) we run logistic regressions and for the continuous variable (level of behavior change) we run simple linear regression.

```

model <- stan_glmer(
  DV ~ date_std + I(date_std^2) +
    (1 | age_cat:female) +
    (1 | edu_clean) +
    (1 | region) +
    (1 | round_date),
  family = neg_binomial_2,
  data = data_contacts,
  seed = 3012,
  iter = 2000,
  control = list(adapt_delta = 0.99)
)

```

We evaluate the performance of the models with 5-fold cross-validation. These show that out-of-sample predictive performance is generally improved if the time-smoother is added to the model. We explored more complex models for some variables and found that modeling region or age specific time trends does not improve model performance.

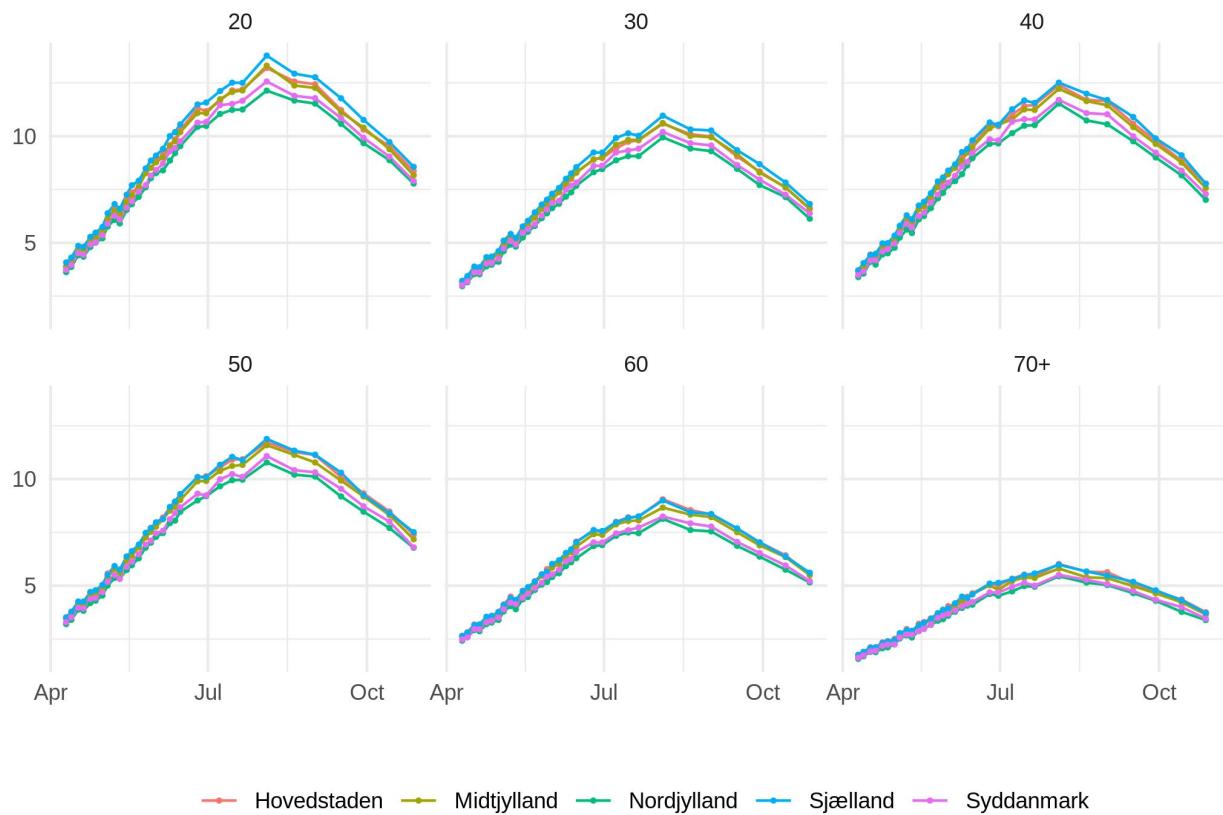
Stage 2 - Simulation and Post-stratification

As the multilevel model informs us about the ‘effects’ of various demographic factors, we can next simulate the outcome for every type of person in our model. In other words, we predict the expected outcome for every possible combination of age, sex, education, and region. ($11 * 2 * 8 * 5 = 880$). Next, we rely on census data from the Statistics Denmark (<https://www.statistikbanken.dk/statbank5a/default.asp?w=1440>) to weigh the frequency of each type of respondent in each region.³ We repeat this procedure for every day in our data. (We assume population distribution does not change between our dates.) We then aggregate these for region \times 10 year age groups and estimate 50% and 90% credible intervals based on the posterior distributions.

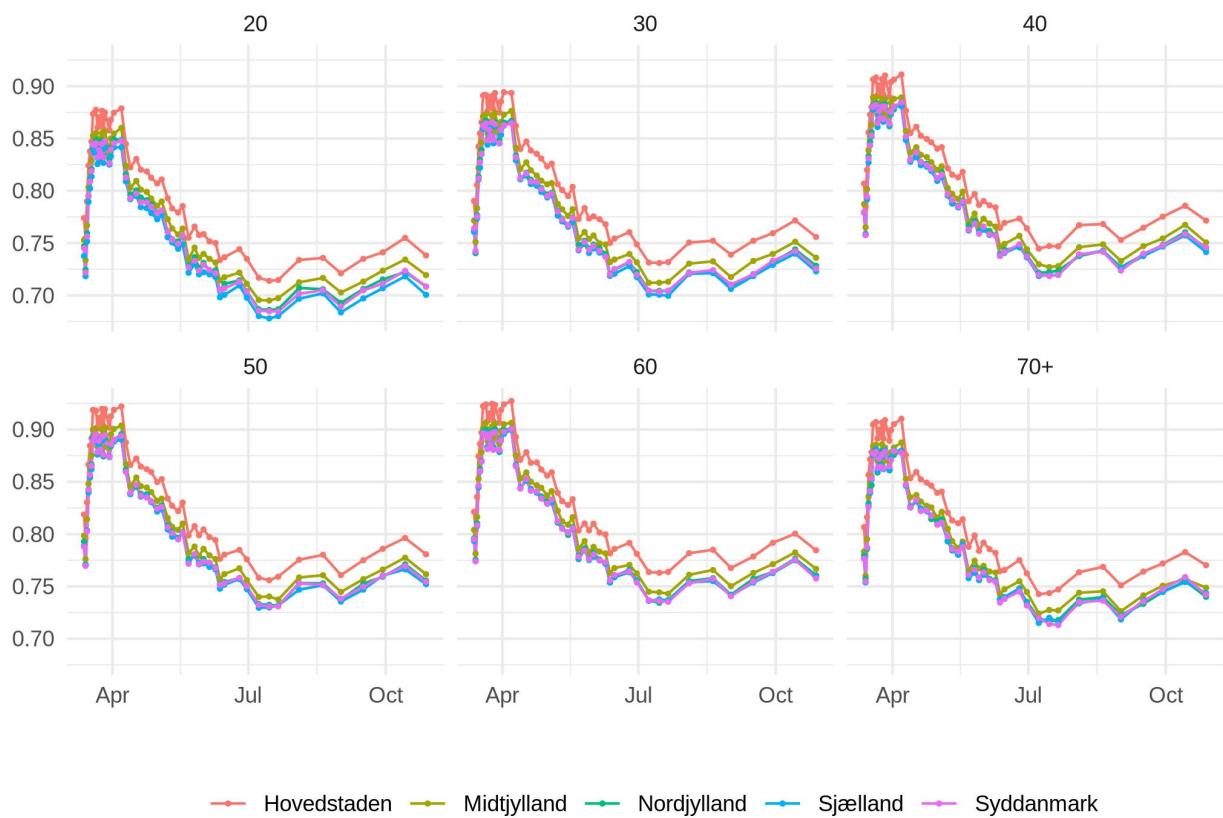
Results

The plots below show our main results: the level of protective behavior for every age group in every region for every date in our data. We omitted credible intervals, which would be highly overlapping given the limited variation by region.

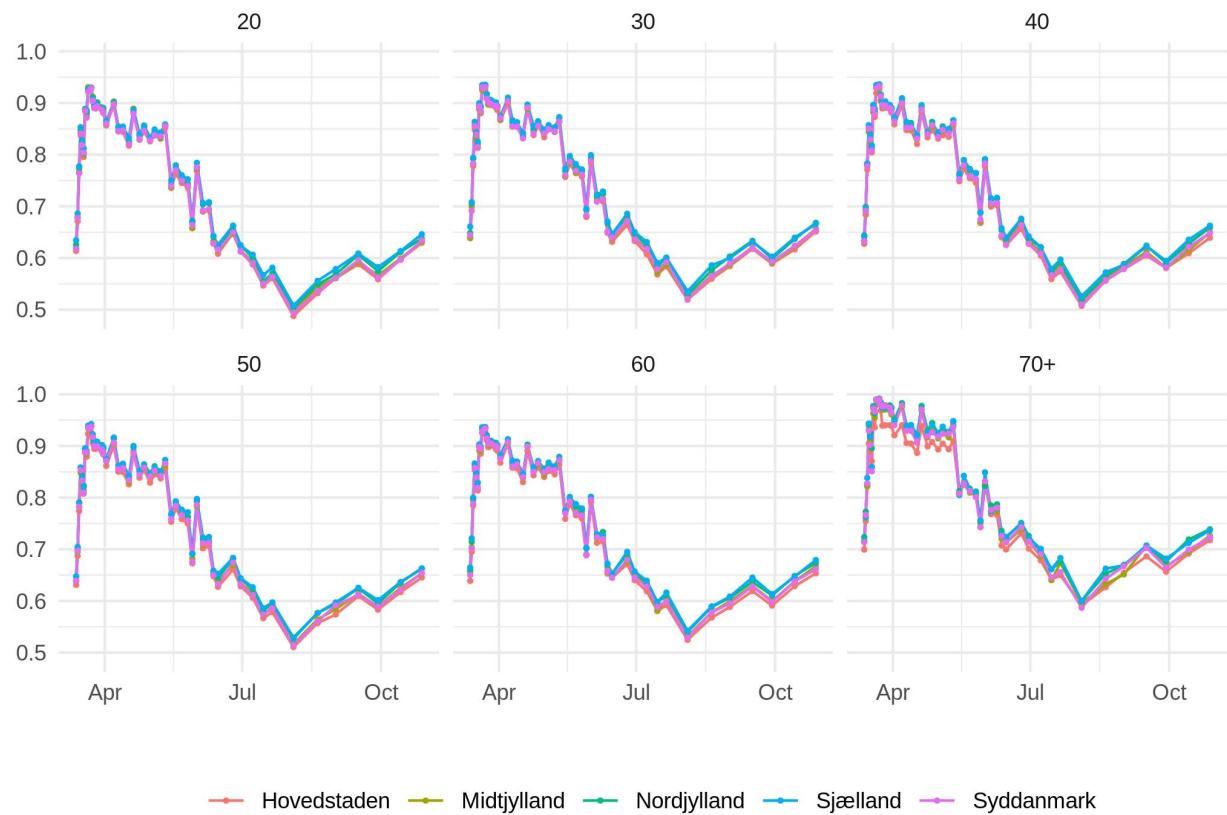
Sum of contacts outside of household



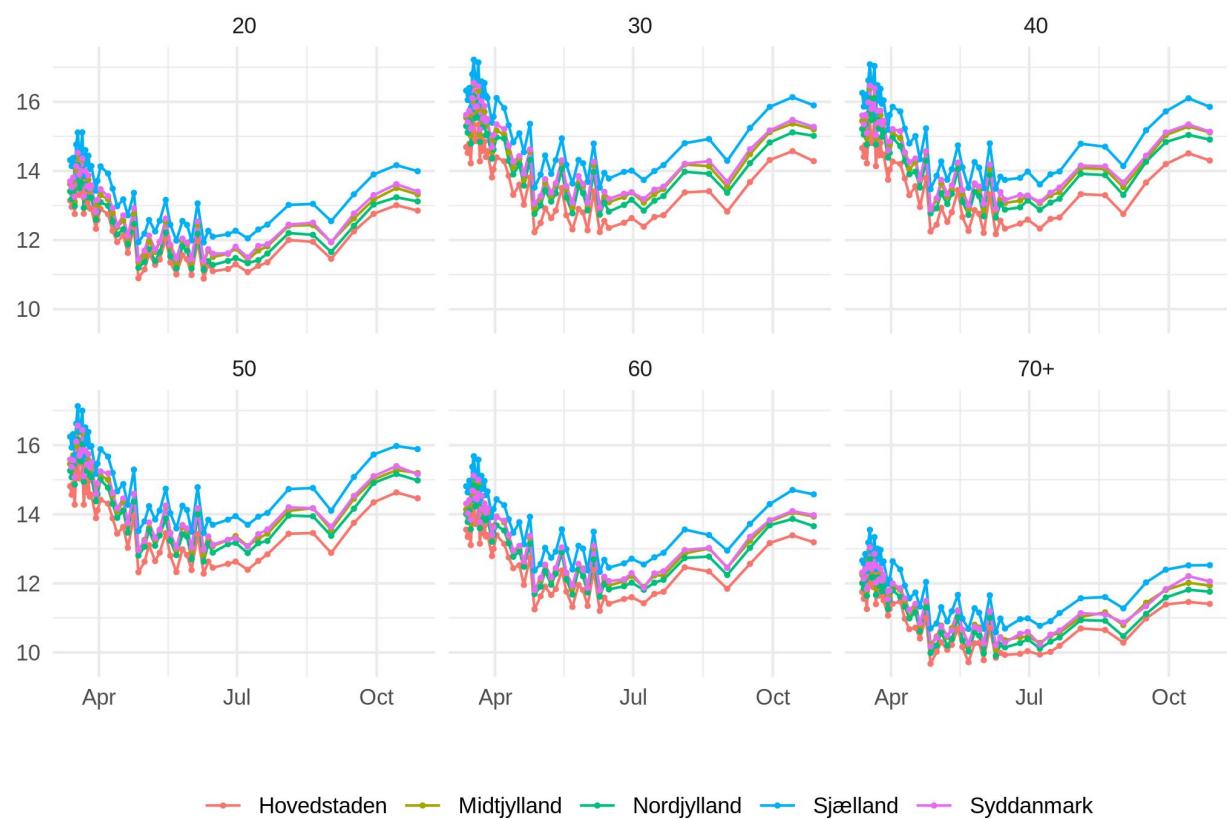
Extent of behavioral change to fight COVID-19



Not being in a room with 10+ people



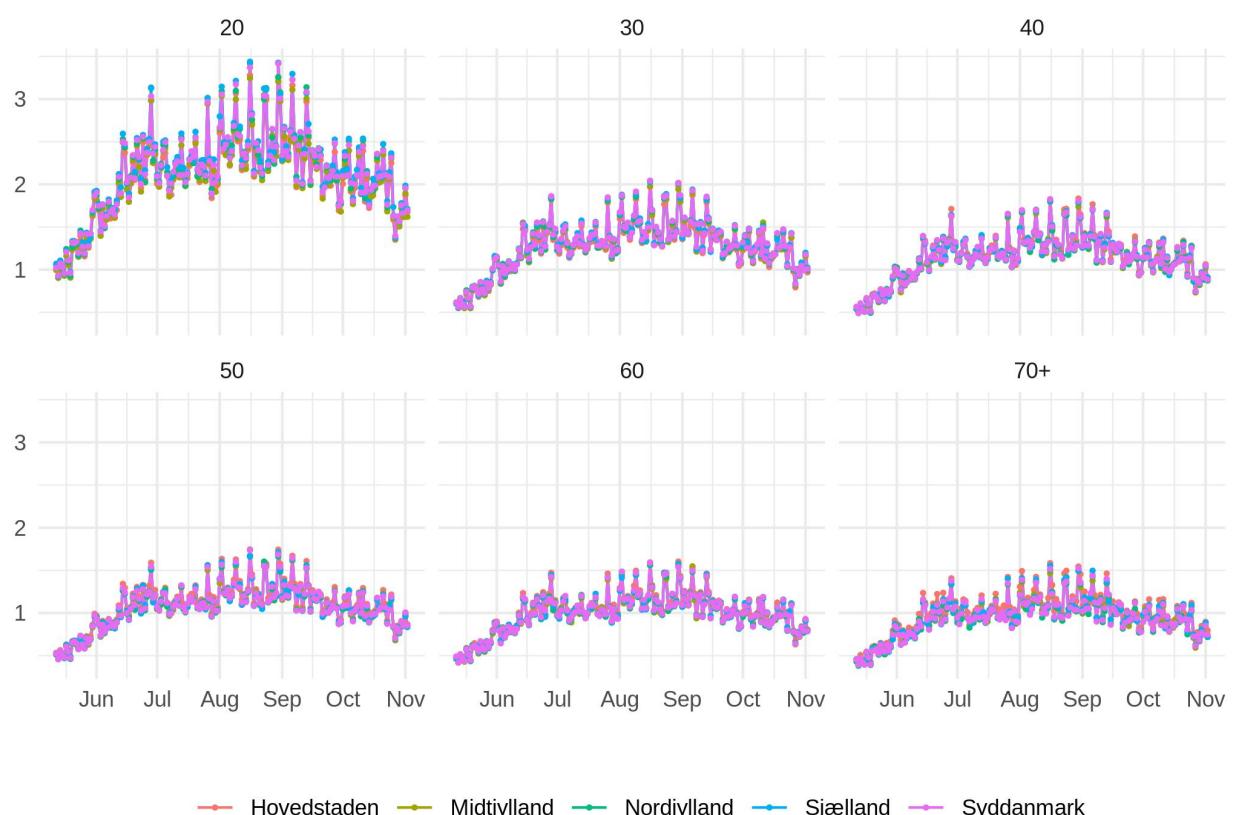
Number of handwashes



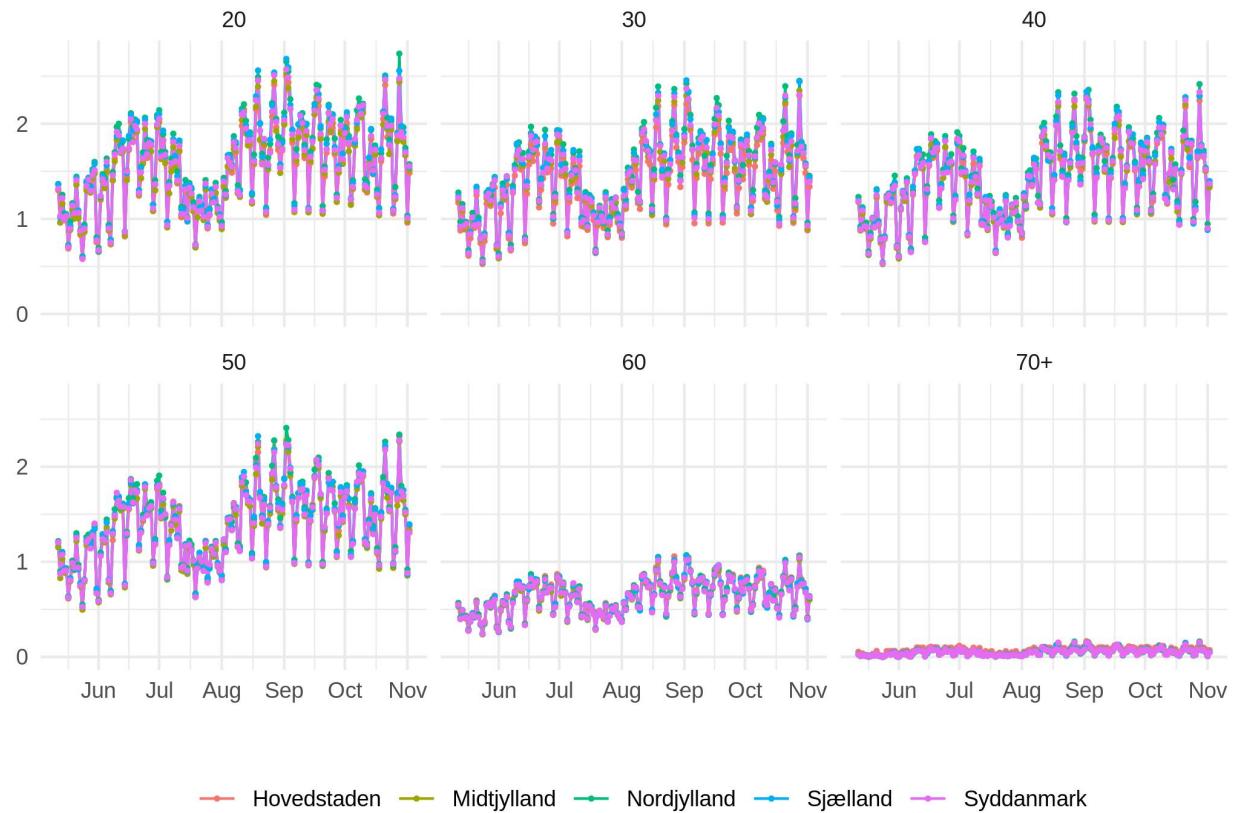
Contact with family within 1m



Contact with friends within 1m



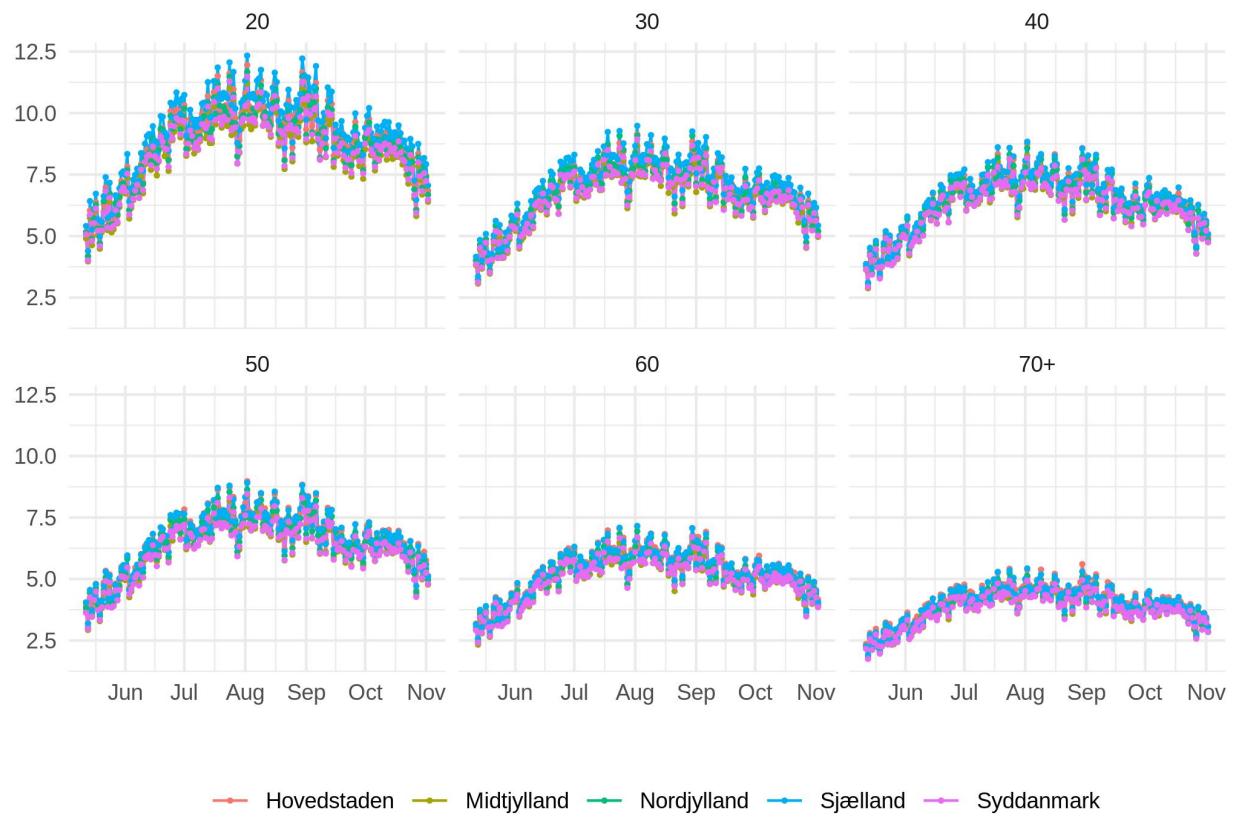
Contact with colleagues within 1m



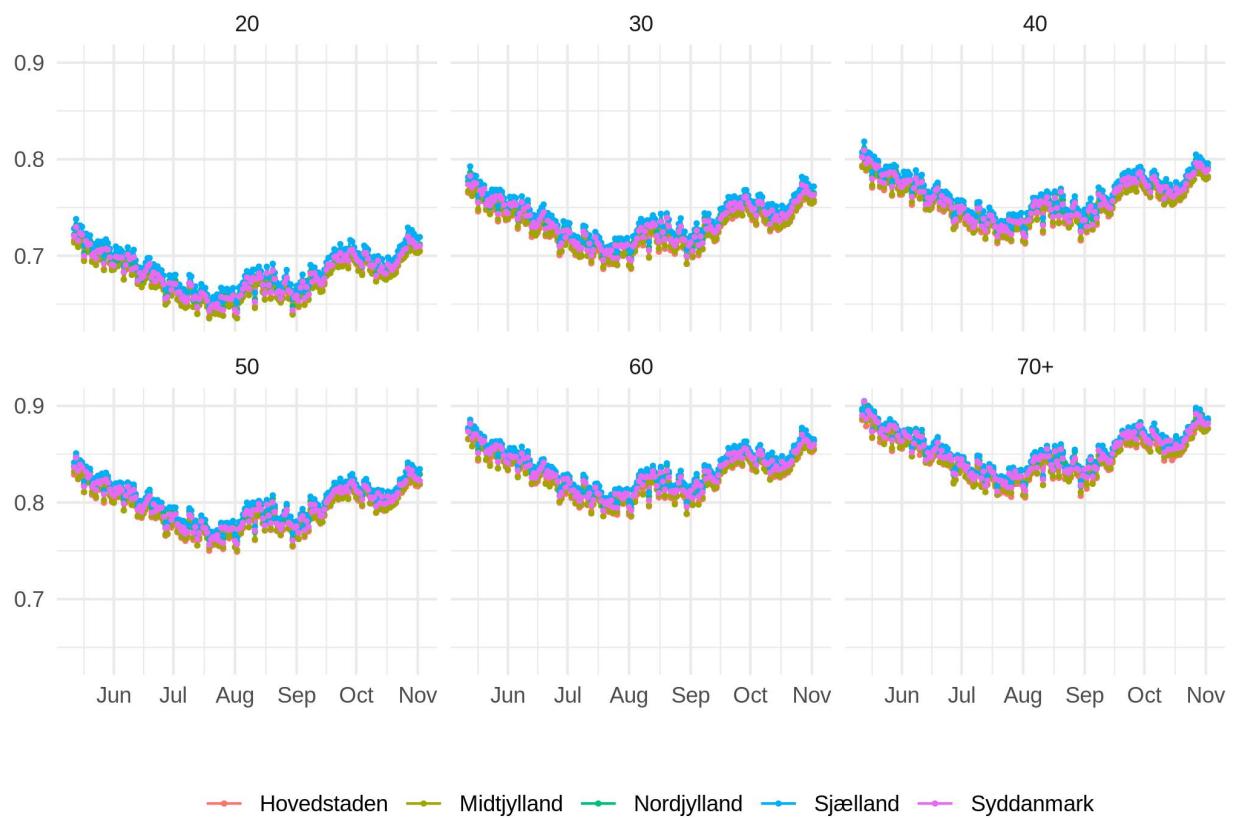
Contact with strangers within 1m



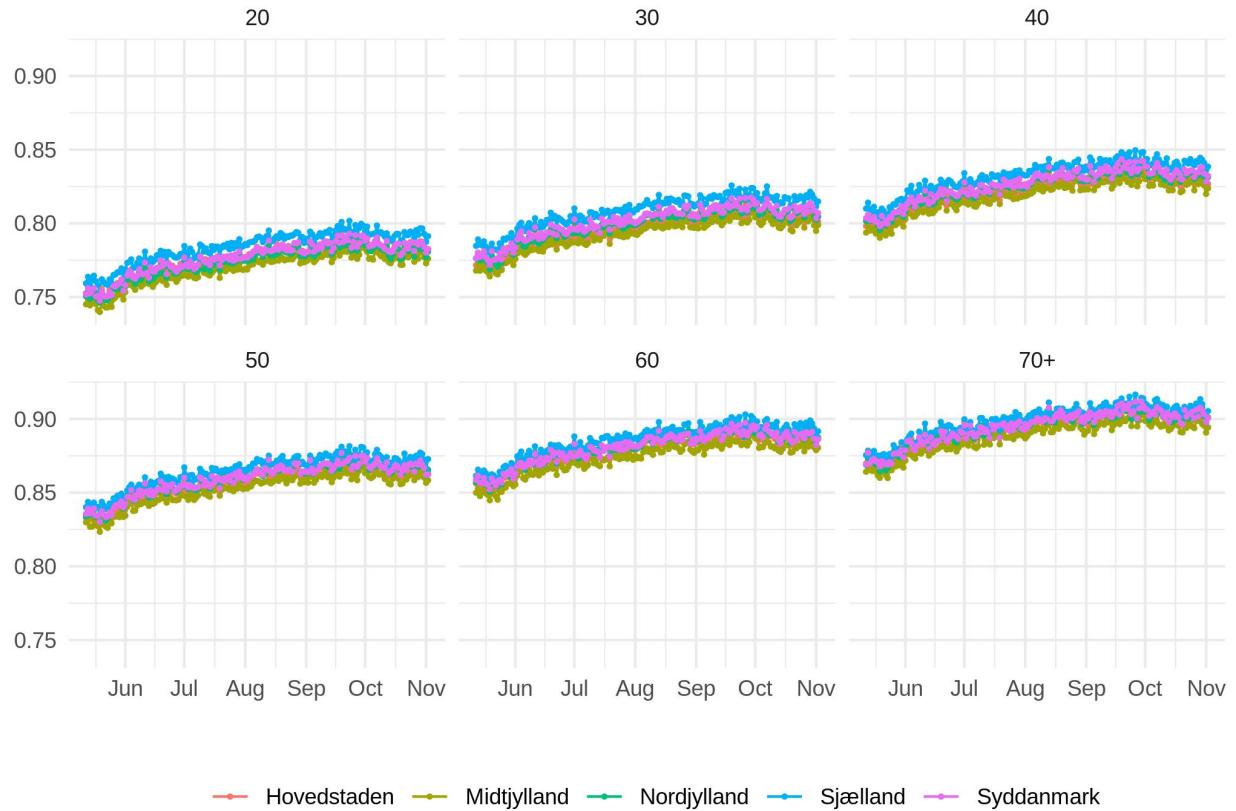
Sum of 1m contacts outside of household



Compliance with social distancing (Contact attention)



Compliance with hygiene measures (Hygiene attention)



Limitations

- As it turns out, regional differences in these variables are small. Consequently, including the region variable into our models offers little improvement in Stage 1. Preliminary evidence shows that respondent municipality carries more information. Including this into our model is our next step.
- For some models, the models exhibited divergent transitions after warm-up.

Contact

If you have any comments about these models, please contact Alexander Bor (<mailto:alexander.bor@ps.au.dk>).

Acknowledgements

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- Specifically, respondents are asked to remember “how many people they have been physically close to in the past 24 hours. Physically close is understood here as closer than 1 meters for at least 15 minutes.” ↵
- We take the date of the median respondent in each wave ↵
- The publicly available census info is limited to 5 year age categories between 15 and 69, we purchased the Census data for the elderly (70+). ↵