# Area-level excess mortality in times of COVID-19 in Switzerland

## geographical, socioeconomic and political determinants

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# Background

- Excess all-cause mortality is central to assessing the impact of the COVID-19 pandemic
- Spatial granularity: country, region, canton, municipality? (Staub et al. 2022, Konstantinoudis et al. 2022, Riou et al. 2023)
- Association with local characteristics (Bertoli et al. 2020, Brandily et al. 2021)

# Study aims

1. Estimate excess all-cause mortality at the municipality level
2. Explore correlations with local characteristics:
   - urbanisation
   - language region
   - vicinity of international borders
   - socioeconomic position
   - voting behavior for COVID-19 referendums

# Data

- All-cause deaths by week, municipality, age, sex for 2011-2020 from BFS (through Swiss National Cohort)
- Temperature from ERA5

# Step 1: excess by municipality

The usual approach:

- fit a regression model on 2011-2019
- predict expected deaths for 2020 by week, municipality, age, sex
- excess = observed - expected
- **problem**: difficult to work with so many strata (2,141 municipalities, 4 age groups, 2 sex groups → 17,128 strata)

# Step 1: excess by municipality

The chosen solution was to use downscaling:

- estimate expected at a higher level (canton) for the full year 2020
- distribute the expected deaths from the cantonal to the municipality level according to the observed distribution of deaths
- random draws from a multinomial distribution repeated 100 times
- take the median

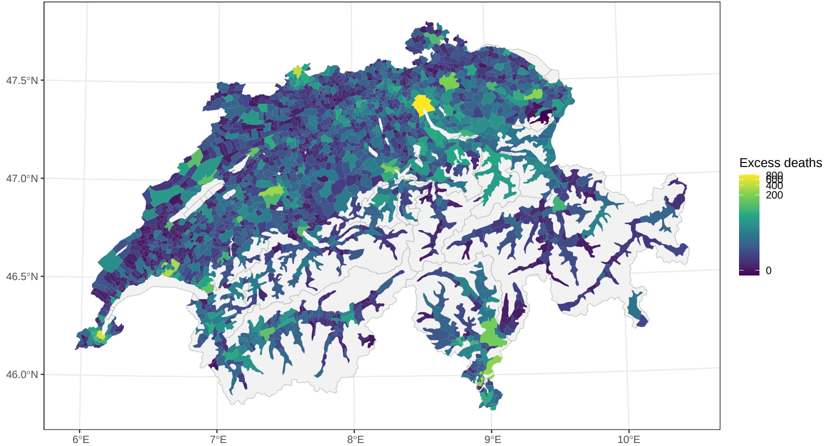
# Step 1: excess by municipality

| Age group | Sex | Observed | Expected (median) | Expected (lower bound) | Expected (upper bound) | Relative excess (median) | Relative excess (lower bound) | Relative excess (upper bound) |
|---|---|---|---|---|---|---|---|---|
| 40-59 | Female | 1,713 | 1,769 | 1,642 | 1,895 | 0.97 | 0.90 | 1.04 |
| 40-59 | Male | 2,966 | 2,230 | 2,074 | 2,396 | 1.33 | 1.24 | 1.43 |
| 60-69 | Female | 2,611 | 2,592 | 2,421 | 2,753 | 1.01 | 0.95 | 1.08 |
| 60-69 | Male | 4,478 | 3,201 | 3,013 | 3,449 | 1.40 | 1.30 | 1.49 |
| 70-79 | Female | 6,203 | 5,028 | 4,708 | 5,376 | 1.23 | 1.15 | 1.32 |
| 70-79 | Male | 8,972 | 5,953 | 5,615 | 6,310 | 1.51 | 1.42 | 1.60 |
| 80+ | Female | 27,541 | 17,205 | 16,453 | 18,284 | 1.60 | 1.51 | 1.67 |
| 80+ | Male | 20,292 | 17,677 | 16,791 | 18,900 | 1.15 | 1.07 | 1.21 |
| Total | Total | 74,776 | 55,676 | 53,865 | 57,821 | 1.34 | 1.29 | 1.39 |

# Step 1: excess by municipality

Mapping raw excess deaths by municipality:

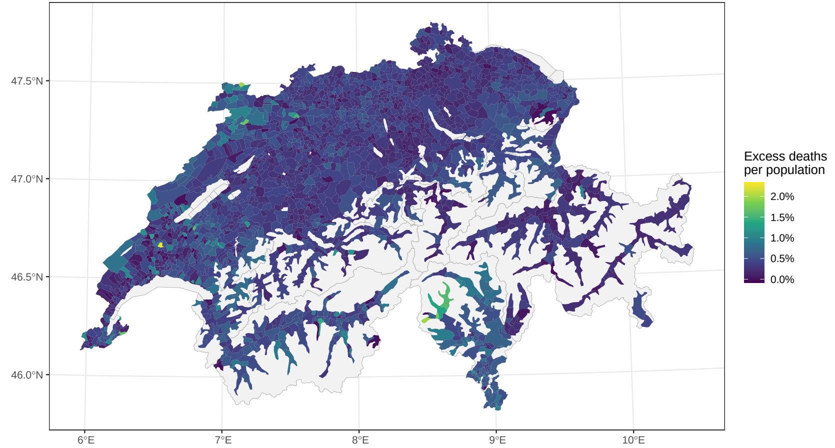
- does not account for population size



# Step 1: excess by municipality

Scale by population:

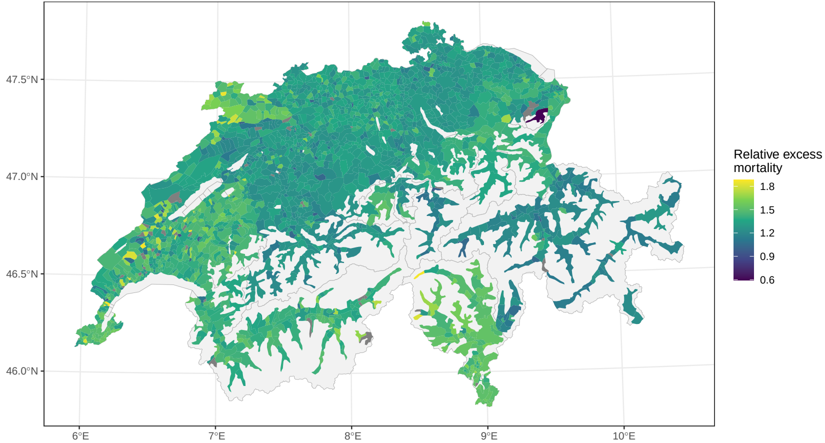
- does not account for population structure (age, sex...)



# Step 1: excess by municipality

Scale by expected mortality ($\rightarrow$ relative excess mortality):

- problems with zero denominators and small area estimation



# Step 2: local correlates of excess mortality

Explore correlations with local covariates:

- yet another Poisson regression model
- let $O_{t,i,j,k}$ be the number of observed deaths during week $t$ in municipality $i$, age group $j$ and sex group $k$
- depends on the number of expected deaths $E_{t,i,j,k}$
- and a log-linear predictor $\log \lambda = \alpha + \beta X$

$$O_i \sim \text{Poisson}(\lambda E_i)$$

# Step 2: local correlates of excess mortality

Other advantage:

- stabilizes small area estimation using spatial models
- log link means that all effects are multiplicative

Iterative model development:

- start simple and add complexity progressively
- compare models with WAIC

# Model 1.0

We start with a baseline model without covariates (only $\alpha$):

- $\lambda = \exp(\alpha)$ can be interpreted as a relative excess mortality ($\lambda = O/E$)

Code:

```
m1.0 = inla( observed ~ 1 + offset( expected ), ...)
```

# Model 1.0

Results:

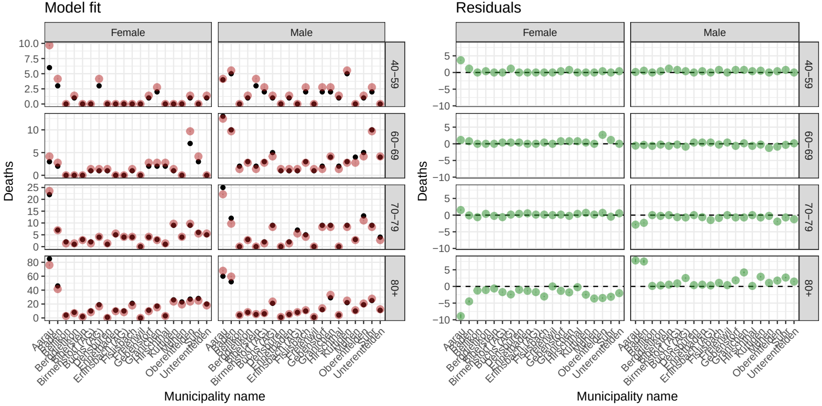
```
##               mean 0.025quant 0.975quant
## (Intercept) 1.38       1.37       1.39
```

- this corresponds to the overall average relative excess

# Model 1.0

Check model fit and residuals:

```
## WAIC = 49278.96
```



# Model 1.1

We expect that excess mortality differs by age and sex:

- added as a covariate (as everything multiplies)

Code:

```
m1.1 = inla( observed ~ -1 +
                        sex:age_group +
                        offset( expected ),
             ...)
```

# Model 1.1

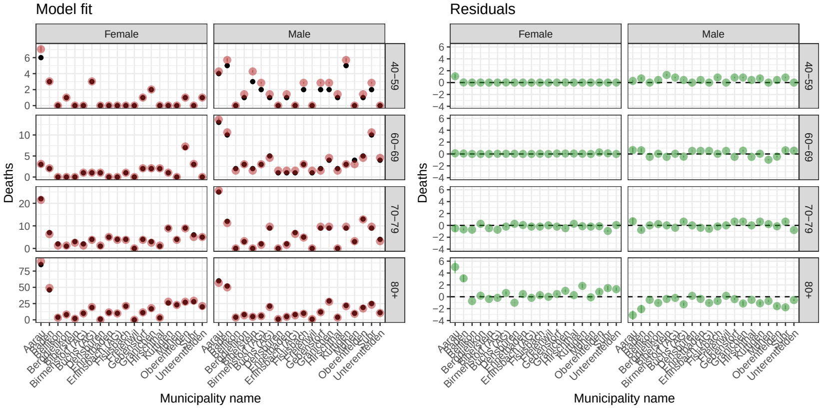
As expected, the relative excess mortality varies a lot across age and sex groups:

```
##                              mean 0.025quant 0.975quant
## sexFemale:age_group40-59 1.01       0.96       1.06
## sexMale:age_group40-59   1.42       1.37       1.48
## sexFemale:age_group60-69 1.04       1.00       1.08
## sexMale:age_group60-69   1.52       1.47       1.56
## sexFemale:age_group70-79 1.26       1.23       1.30
## sexMale:age_group70-79   1.61       1.57       1.64
## sexFemale:age_group80+   1.64       1.62       1.66
## sexMale:age_group80+     1.16       1.15       1.18
```

# Model 1.1

Big improvement of model fit:

```
## deltaWAIC = -2088.29
```



# Model 1.2

Allow for spatial variability:

- i.i.d. random effect by municipality
- all effects are pulled towards a global average
- excess by municipality can vary independently from the others around this global average
- "municipality effect" applies the same to all age and sex groups.

Code:

```
m1.2 = inla( observed ~ -1 +
                        sex:age_group +
                        f(id_space, model = "iid") +
                        offset( expected ),
             ...)
```

# Model 1.2

The age and sex effect remains similar:

```
##                            mean 0.025quant 0.975quant
## sexFemale:age_group40-59 1.01       0.96       1.06
## sexMale:age_group40-59   1.43       1.38       1.48
## sexFemale:age_group60-69 1.04       1.00       1.08
## sexMale:age_group60-69   1.52       1.48       1.57
## sexFemale:age_group70-79 1.27       1.24       1.30
## sexMale:age_group70-79   1.61       1.58       1.64
## sexFemale:age_group80+   1.64       1.62       1.66
## sexMale:age_group80+     1.17       1.15       1.18
```

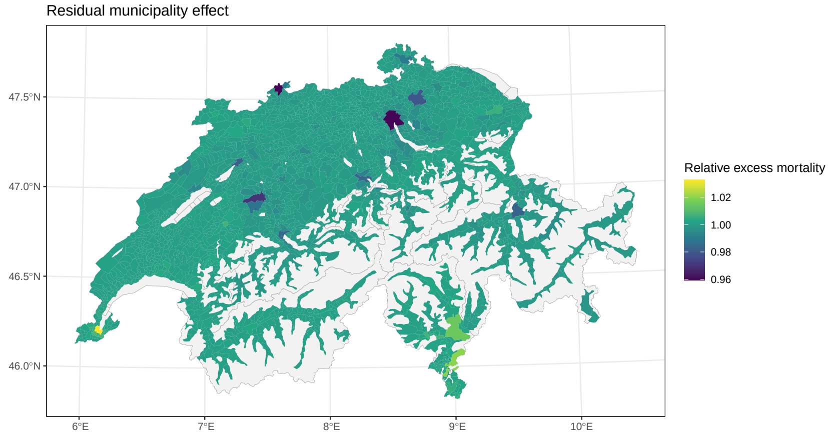
# Model 1.2

Again, improvement of model fit:

```
## deltaWAIC = -31.47579
```

# Model 1.2

Now we can look at the spatial variation:



# Model 1.3

Structured spatial variability:

- municipalities are no longer independent
- correlation between neighboring municipalities with a BYM model

Code:

```
m1.2 = inla( observed ~ -1 +
                        sex:age_group +
                        f(id_space, model = "bym", ...) +
                        offset( expected ),
             ...)
```

# Model 1.3

Improvement of model fit:

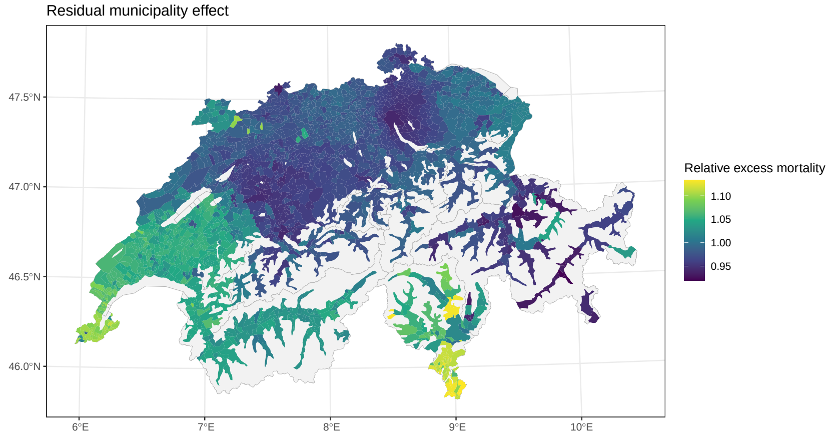
```
## deltaWAIC = -178.0986
```

The proportion of "structured variability" (as opposed to i.i.d) is high:

```
##                   mean 0.025quant 0.975quant
## Phi for id_space 0.98       0.88          1
```

# Model 1.3

## Actual spatial variation:



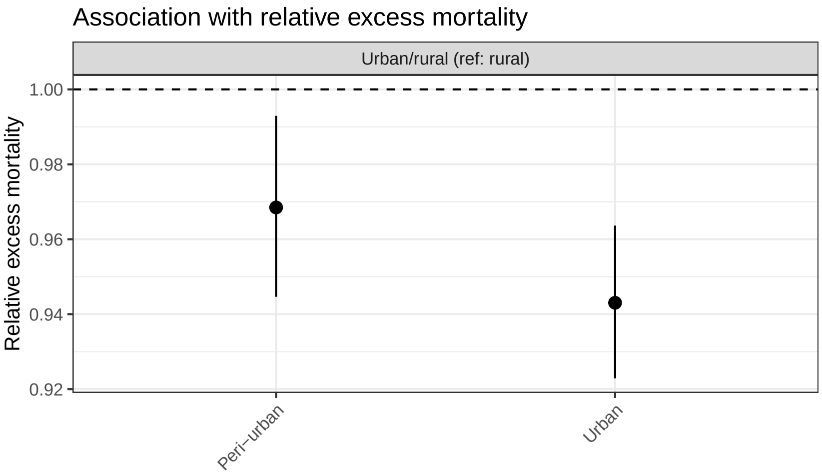
# Model 1.4

We now have a good model of excess mortality by municipality, we can add local covariates:

- urbanisation
- socioeconomic position
- international links
- language region
- voting behavior for COVID-19 referendums (June and Nov 2020)

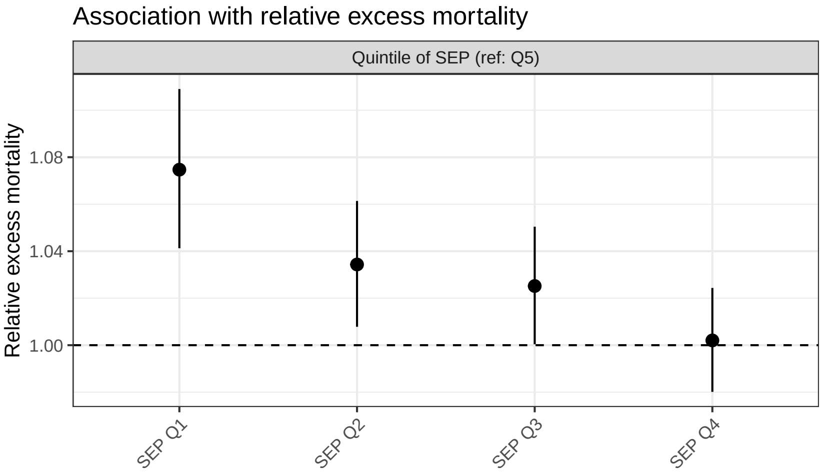
# Model 1.4a

For urbanisation, FSO classifies Swiss municipalities in 3 classes (urban, peri-urban or rural):



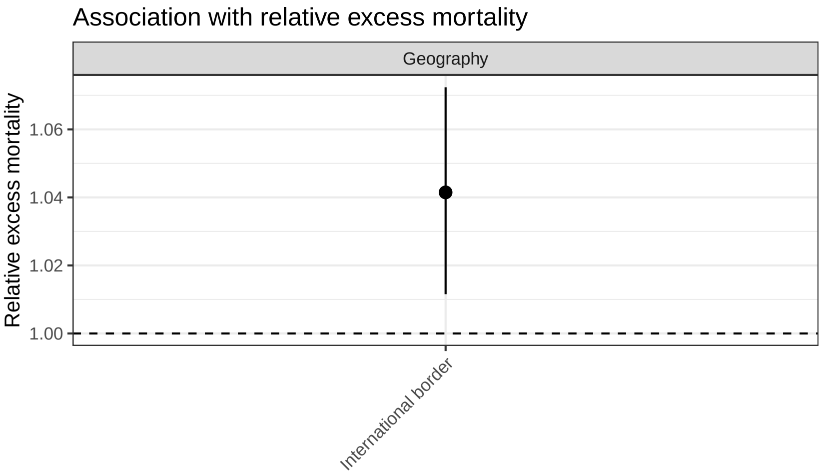
# Model 1.4b

For socioeconomic position, we take the median of the Swiss neighbourhood index of SEP, then transform into quintiles:



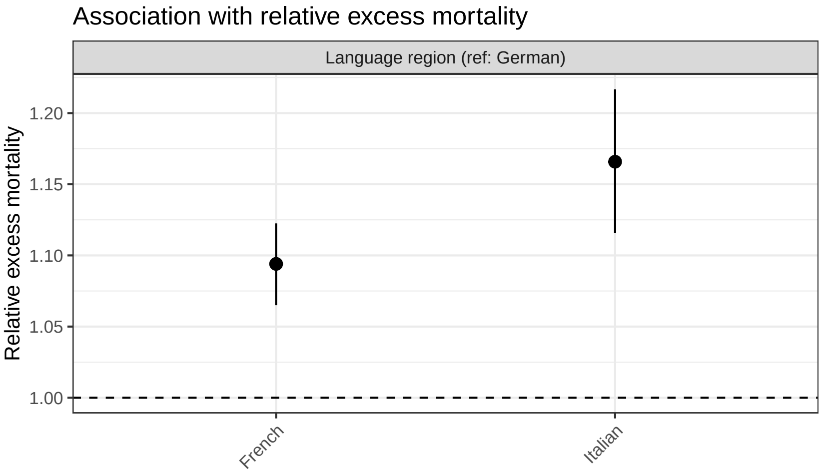
# Model 1.4c

For international links, we assess whether municipality belongs to a *cross-border labor region* (FSO):



# Model 1.4d

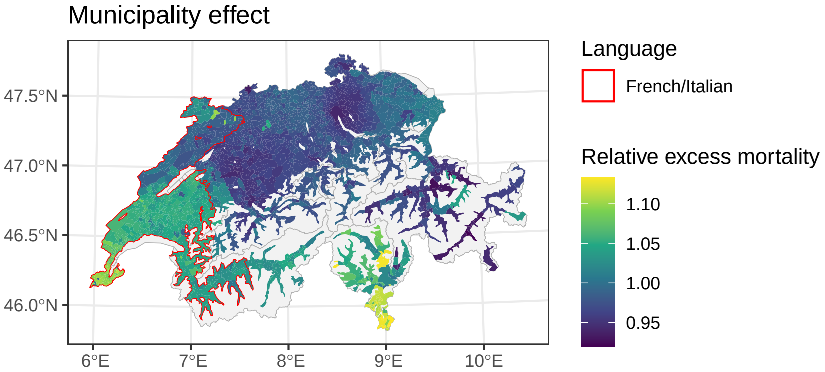
For language regions, we take the official language of each municipality:



# Model 1.4d

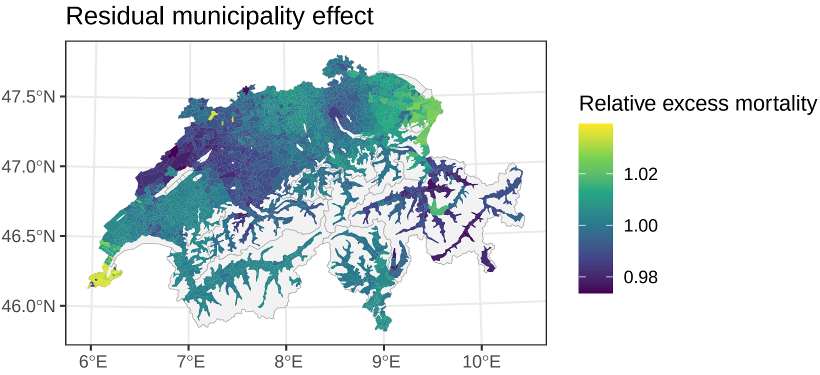
This one is not so easy:

- the association is likely confounded by the way the first wave started (in Ticino and the South-West)



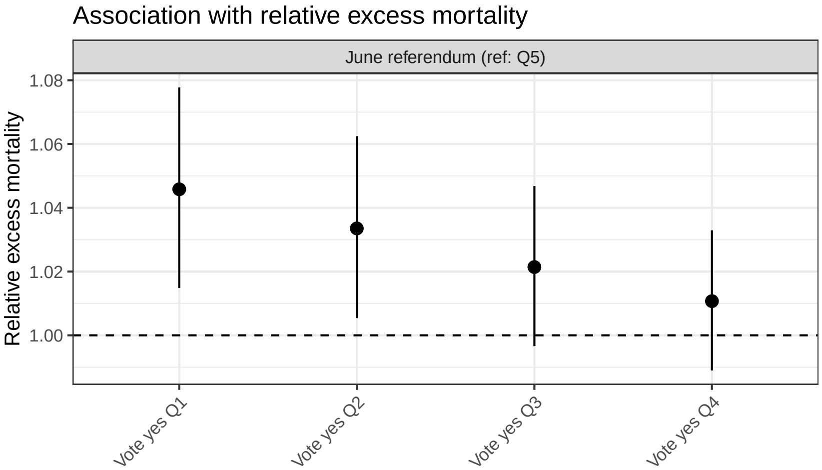
# Model 1.4d

Adding language region disrupts the geographical variation observed before:



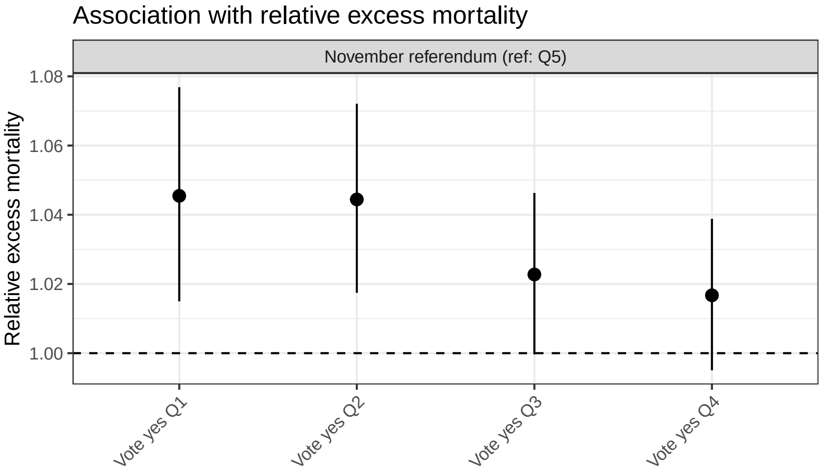
# Model 1.4e

For voting behavior, we take the proportion of Yes at the June 2020 referendum (November is very similar):



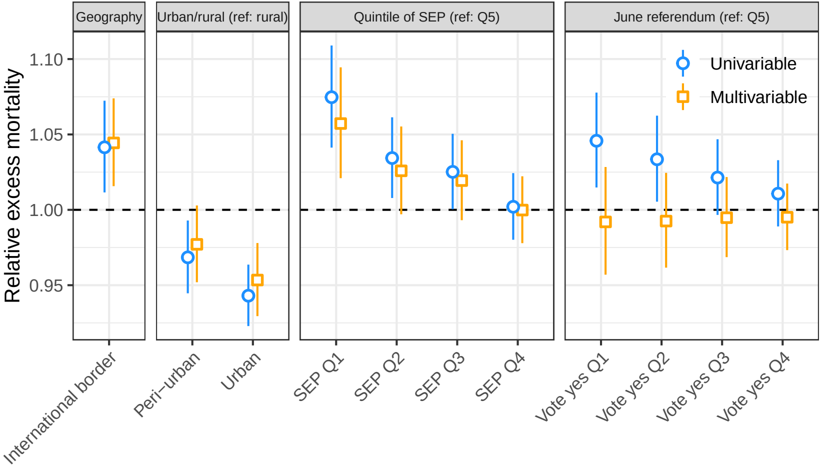
# Model 1.4e

November is very similar:



# Model 1.5

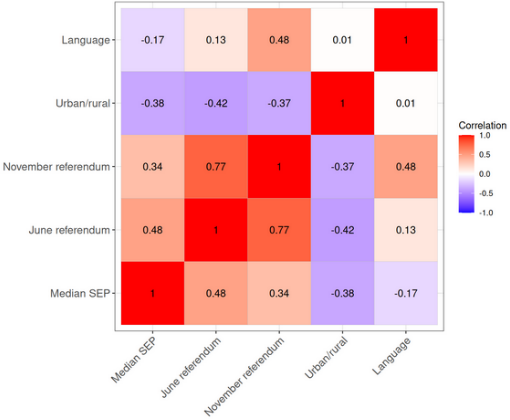
## Multivariable analysis:



# Model 1.5

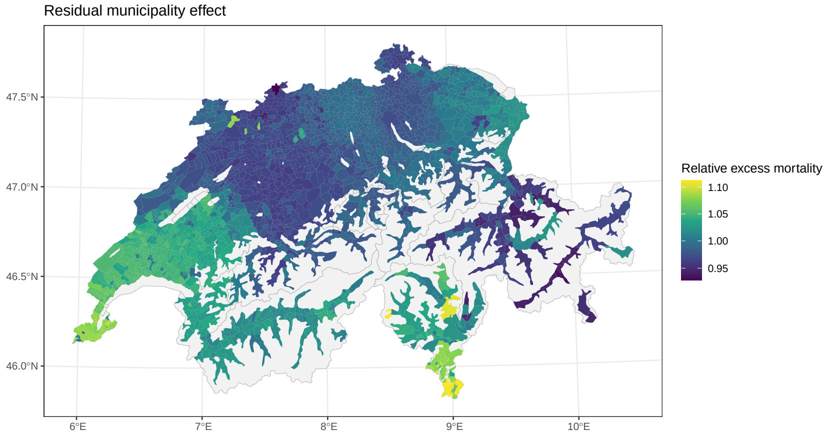
Intercorrelation between SEP and voting behaviour:

- impossible to disentengle between the two



# Model 1.5

Residual municipality effect (after removing the effects of covariates):



# Model 1.5

- Expected higher excesses in Ticino and Southwestern Switzerland
- A visible barrier between French-speaking and German-speaking regions
- Lower excess in the large cities of the German-speaking part (Zurich, Basel, Bern)
- Lower excess in relatively isolated valleys of Graubunden

# Conclusions

- Small-area excess mortality varied substantially in Switzerland in 2020, depending on the geographical location and type of municipality.
- Areas most affected included Ticino, the Lake of Geneva region, the Jura and the Northeast of the country.
- Rural municipalities, municipalities of lower socioeconomic position and showing lower support for COVID-19 control measures experienced higher excess mortality.