Exploring the effects of socioeconomic factors on voter preferences: A case-study of France 2022

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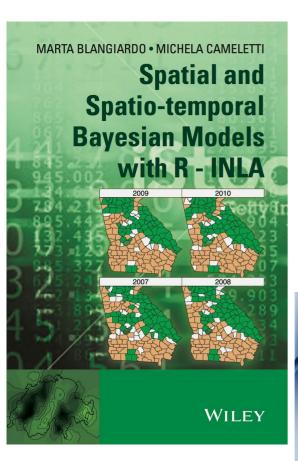


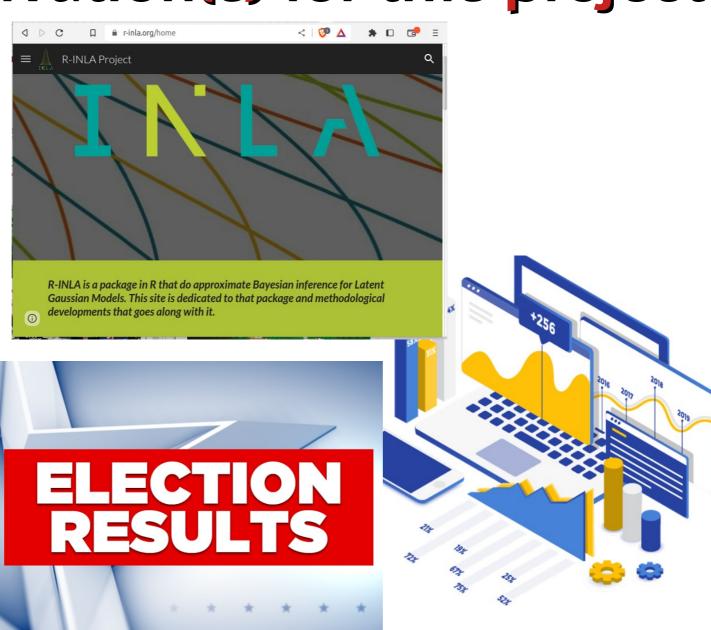






Our motivation(s) for this project







What is the relationship between different socioeconomic factors and voters' preferences?

Are there any significant effects that have not been considered?

Data and source code - reproducibility







Raw census data files for departments, raw 2022 first-round French election result data and the French departments' boundaries data are extracted from INSEE(2), Open Data France(3) and Berkeley library(4) websites



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2https://www.insee.fr/fr/accueil
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³https://www.data.gouv.fr/

⁴https://geodata.lib.berkeley.edu/

Model data preparation

Election results

1st-round voting

12 candidates

2nd-round voting

2 candidates

Census data (6)

- Immigration rate
- Poverty rate
- Higher education rate
- Average life expectancy
- Unemployment rate
- White-collar rate

Boundaries Census data dataset 34,938 rows 96 objects

French metropolitan boundaries

Regions

• 13 regions

Departments

• 96 departments

Cantons

• 1,995 cantons

Communes

• 3,4826 communes

Flection results dataset 1,284 rows Merge By 'department code' Complete merged dataset 96 rows

Model formulation

The Poisson log-linear model used here is defined as follows:

$$y_{ij} \sim Poisson(\lambda_{ij})$$
$$\log(\lambda_{ij}) = \phi_i + X_i B_j + s_{ij}$$

where y_{ij} is the number of votes for candidate j in the department i, ϕ_i is the intercept for department i, X_i is the vector of covariates for department i, B_j is the vector of coefficients for candidate j, and s_{ij} is the spatial random effect for candidate j in department i.

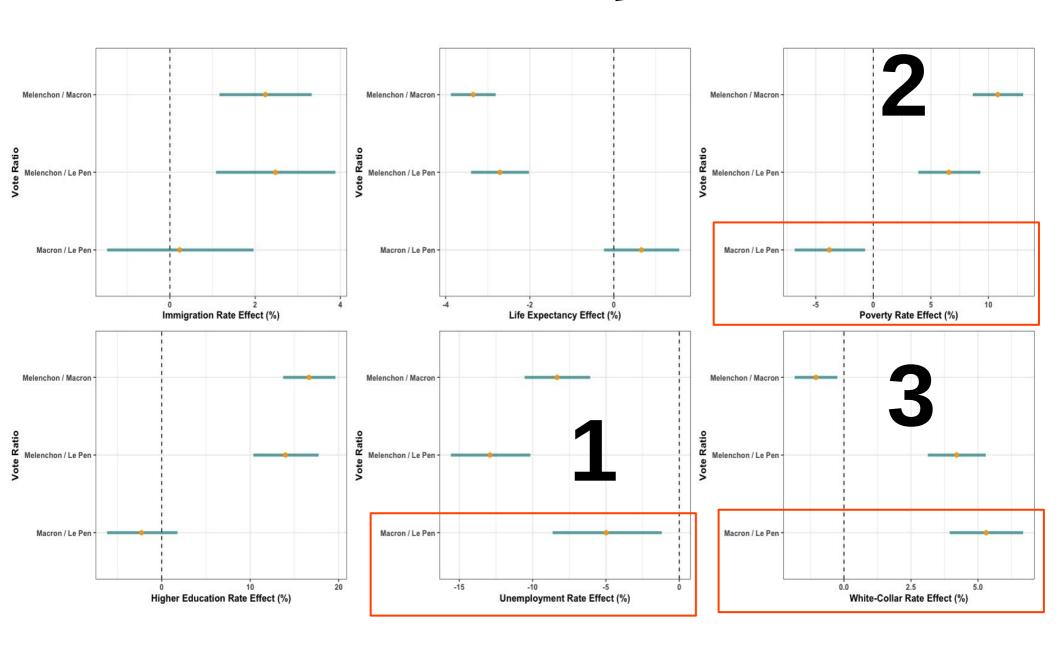
$$s_i \mid s_{k \neq i} \sim N\left(\frac{1}{n_i} \sum_{k \sim i} s_i, \frac{\sigma_s^2}{n_i} \right)$$
 We've dropped the j subscript for simplicity

where $k \sim i$ refers to all neighbors of the department i, with n_i representing the total number of neighbors and σ_s^2 is the variance of the spatial random effect.

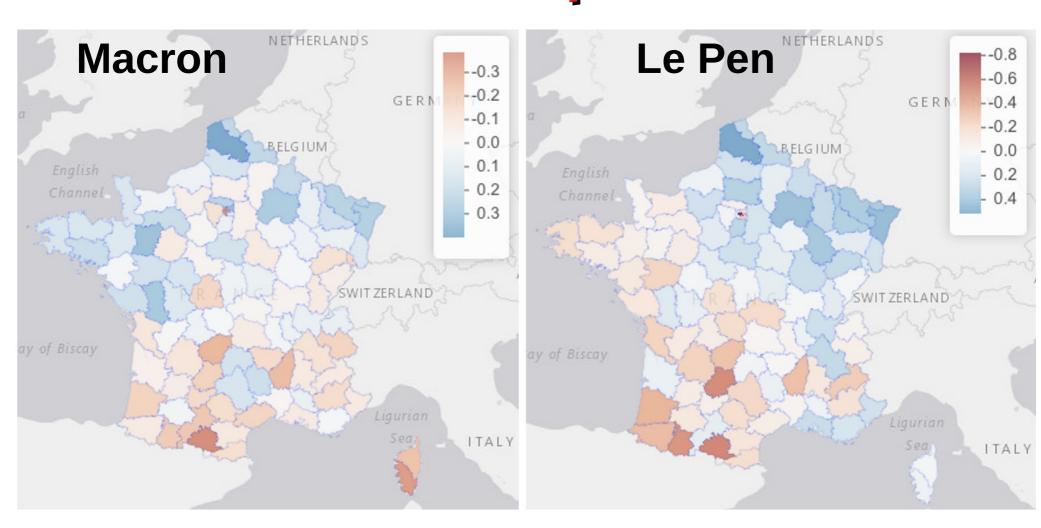
Efforts to make this approach less computationally expensive this shoudint be candidates' votes in each

- Candidate votes each in a department follow a multinomial distribution (expensive)
- Convert this distribution to a less expensive Poisson distribution
- Poisson Log-linear faciliated by INLA in R.
- However: coefficients of covariates are no longer identifiable (but we have the ratio of covariates for each pair of candidates)

Results – our 6 predictors



Maps of the spatial random effect in latent space

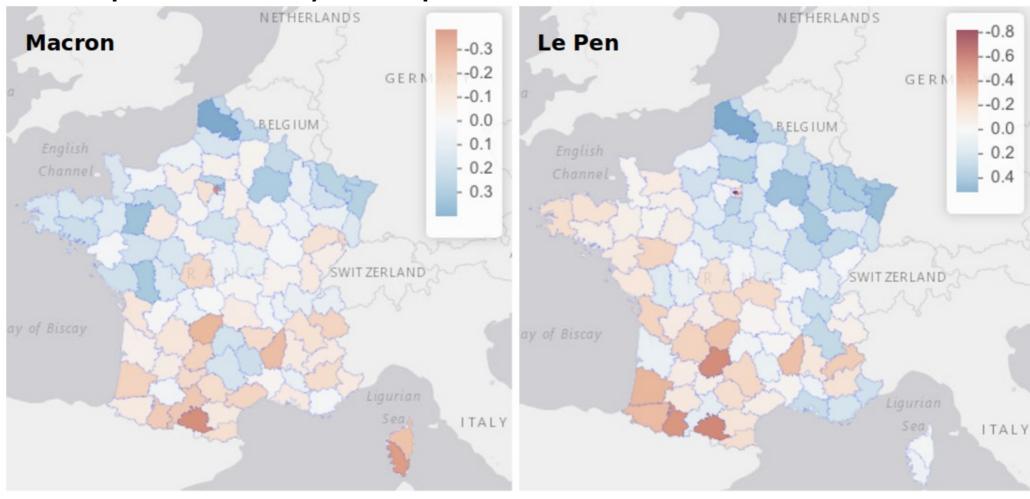


What is the relationship between different socioeconomic factors and voters' preferences?

Candidates	Higher Education Rate	Unemployment Rate	White-collar Rate	Poverty Rate	Immigration Rate	Average Life Expectancy
Melenchon / Macron		\	\			_
Melenchon / Le Pen						
Macron / Le Pen	Not Significant		/		Not Significant	Not Significant

Are there any significant effects that have not been considered?

 Spatial effect accounted for the variance not explained by the predictors of our dataset.



Conclusions from our work

- The socioeconomic factors significantly shape voters' preferences towards candidates for the French presidential election and their impact varies spatially.
- It is crucial to consider the spatial random effects in order to effectively capture the tendencies of over and underestimation in our model.
- Openly available data and strong software support makes this work possible.

Future and further work

- Consider analysis of 2012 and 2017 French presidential elections (for comparisions)
- Test the effectiveness of the model in other countries and compare to observations from the French presidential election(s)
- Look at other problems outside of voting and elections for application of this approach

An investigation of the effects of lockdowns and COVID-19 vaccinations in Ireland

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cine or pharmaceutical treatment, efforts to contain the spread of COVID-19 focused on isolation measures for confirmed cases and self-quarantine for those who had been exposed. However, due to the high transmissibility of the virus, including spread from asymptomatic cases, these measures were not sufficient alone to fully contain the spread (Kissler et al., 2020b). Pandemic response measures, such as closing schools, public spaces, and non-essential businesses, were also implemented in an effort to reduce social interaction and opportunities for person-to-person transmission. The intended impact was to reduce the risk of overwhelming health systems and allow-

Abstract. The COVID-19 pandemic resulted in many deaths and much upheaval worldwide. Public health responses to the pandemic differed greatly between countries. In 2023, as we emerge from the aftermath of the pandemic, it is now timely to assess the impact of specific public health response measures such as lockdowns and vaccinations. This assessment can help inform the development of evidence-based strategies for future public health responses in pandemic scenarios. We describe the implementation of a Bayesian Hierarchical Poisson Regression (BHPR) model to estimate the impact of pandemic response measures and vaccination on all-cause deaths, in-

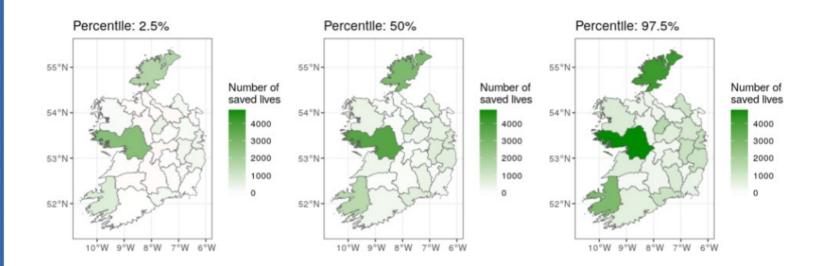
cluding COVID-19, in Irelan mentation of lockdown measu cination timeline were effecti of deaths in Ireland by, most li 19 mortality rate. We believe to to assess the impact of pander vaccination in other countries a available.

Keywords. COVID-19 pande gency index, vaccination rate modelling

1 Introduction and motivat

The COVID-19 pandemic, whome of the most globally impaory. No continent, country, or by the effects of the pandemi 2022, over 8, 250 people in Irel 19 infection (Dong et al., 20 ing, COVID-19 is still circular fatalities in many countries.) the emergence of new variant 2020). In the early days of the

1https://covid19.who.int



AGILE Association of Geographic Information Laboratories in Europe

Figure 3. The number of lives saved because of lockdowns and vaccination in each county is depicted. From left to right, the maps are associated with 2.5%, 50% and 97.5% cumulative probability for the estimated numbers, respectively. The numbers in the 2.5% and the 97.5% maps indicate the 95% credible interval for saved lives in each county.

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Acknowledgements etc