Estimating Perceptions of Social Cohesion During Covid-19 Pandemic in German Federal States Using Multilevel Regression with Poststratification

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Abstract

This paper aims to estimate perceptions of social cohesion in German Federal States during the first wave of the covid-19 pandemic. The estimation is carried out by multilevel regression with poststratification (MRP) technique. According to model output, Bayern, Saarland, Baden-Württemberg, Nordrhein-Westfalen and Hamburg are the top five federal states in which inhabitants are estimated to perceive more social cohesion during the pandemic. In Sachsen, Mecklenburg-Vorpommern, Schleswig-Holstein, Niedersachsen and Hessen inhabitants are estimated to perceive less social cohesion.

***Keywords*:**
Perceptions of Social Cohesion, *Germany*, *MRP*, *Bayesian Analysis*

1 Introduction

Covid-19 pandemic is one of the most challenging global threats since the end of World War 2. It has impacted the daily lives of billions of people in different ways. Besides causing an ever increasing number of deaths and high number of infected people, the organisational structures of the societies are also impacted by the covid-19. The economic production is forced to be limited only to core sectors while the majority of the services are suspended. Similarly, different preventive measures taking place in different countries are restricting the social life into a very narrow scheme. When these pandemic related changes are viewed all together, one can safely conclude that the fabric of the society is being strained and pressured. It is important to this social fabric of the society especially during such difficult times. However, this is a task which requires special analytical tools dedicated to it. The concept of social cohesion is a well suited analytical tool for making account on examining social fabric during the times of pandemic. Yet, as the concept itself has different definitions and theoretical implications, a special care must be taken on restricting the analytical boundaries of the concept beforehand it is put into practice on examining social fabric.

2 Theoretical Frame

Before adopting an already existing definition of social cohesion or specially tailoring one for the purpose of this study, a fundamental point must be addressed. For any given concept, a theoretical definition and ways of measuring it are intrinsically embedded on each other. For instance, the term unemployment might have varying definitions but for most of the definitions of it, the measurements can be made quite easily. This is due to the less abstract nature of the concept. However, as for social cohesion, a brief survey of literature regarding the definition of social cohesion, shows that the definition of the concept is more abstract. In most of the cases, it makes use of other sets of abstract concepts within its definition. It is even called as a quasi-concept(Bernard, 1999). To make this point more intuitive, take Chan, To and Chan's definition as an example. They define social cohesion as "... a state of affairs concerning both the vertical and the horizontal interactions among members of society as characterized by a set of attitudes and norms that includes trust, a sense of belonging and the willingness to participate and help, as well as their behavioral manifestations'" (Chan, To, & Chan, 2006). Similarly, The Council of Europe has adopted its own definition which characterizes social cohesion as "society's capacity to ensure the well-being of all its members by minimizing disparities and avoiding marginalization; to manage differences and divisions and to ensure the means of achieving welfare for all. Social cohesion is a dynamic process and is essential for achieving social justice, democratic security and sustainable development. Divided and unequal societies are not only unjust, they also cannot guarantee stability in the long term" (*A new strategy for Social Cohesion Revised strategy for Social Cohesion approved by the Committee of Ministers of the Council of Europe on 31 March 2004*, n.d.).

Both definitions are clearly calling for other abstractions such as social justice, democratic security, horizontal and vertical interactions, sense of belonging etc. Making these sorts of definitions work in the practical realm is another bold task. For instance Dragalov et al reported that they used 57 indicators in making a social cohesion index within their social cohesion radar. Given the limited nature of this study, it's not feasible to make an effort on predicting, estimating or measuring social cohesion. Rather, in this study I tend to focus on perceptions of social cohesion. Estimating perceptions of social cohesion does not necessarily imply social cohesiveness in a society. Perceptions are purely subjective measures of how people perceive their environment which might be way off from the actual situation in their living environment. Keeping the distinction between so-called objective measures of social cohesion and perceptions of it to defer causal misinterpretations, it should also be noted that there might be a correlation between the two. Langer and colleagues also observe this. We argue that social cohesion is essentially a matter of how individuals perceive others and the state and not of more ‘objective’ measures of interactions, although these perceptions are likely to be the outcome of actual interactions and we would expect considerable correlation between the two (Langer, Stewart, Smedts, & Demarest, 2017)

This study estimates the perceptions of social cohesion in German federal states. However, to achive this task, this study utilises a recent but less conventional method. Unlike raw aggregations of survey responses, in order to ensure less sampling bias and regional and demographic representativeness, I use multilevel regression and poststratification method proposed by Andrew Gelman (Gelman, Lax, Phillips, Gabry, & Trangucci, 2016; Ghitza & Gelman, 2013; Trangucci, Ali, Gelman, & Rivers, 2018; Wang, Rothschild, Goel, & Gelman, 2015). The strategy is to model social cohesion as a function of sets of local demographic covariates (age, gender, education, state) and state level covariates (covid incidence rate and subnational human development index). The Subnational Human Development Index consists of 3 dimensions, education, health and income indices per federal state.

3 Methods

3.1 Data Sources

Trust in State and Society during the Corona Crisis (April 2020)(Presse-und Informationsamt der Bundesregierung, 2020) survey, conducted by Presse- und Informationsamt der Bundesregierung, Berlin is taken as the primary data source of this study. The data was collected between 22.04.2020 - 29.04.2020 by CATI(computer assisted telephone interview) method. Within the wide array of topics that the survey addresses, six of the items are being utilised in the current study.

Item Name	Question	Coding
V0A	In welchem Bundesland wohnen Sie? (in which state are you living?)	Categorical with 16 unique values
VA	Geschlecht des Befragten. (gender of the respondent)	Categorical with 2 unique values
VB	Wie alt sind Sie? (How old are you?)	Irregular Interval with 11 levels
VF	Welchen Schulabschluss haben Sie selbst? (What school-leaving qualifications do you yourself have?)	Categorical with 5 unique values
VG	Haben Sie ein abgeschlossenes Studium an einer Universitat, Hochschule oder Fachhochschule? (Do you have a degree from a university, college or university of applied sciences?	Categorical with 2 unique values
V19A	Zum Zusammenhalt in der Gesellschaft: Was meinen Sie, gibt es im Rahmen der Corona-Krise jetzt ... (On cohesion in society: what do you think, in the context of the Corona crisis, are there now) - eher mehr Zusammenhalt in der Gesellschaft, (more cohesion in the society) - eher weniger, oder (less cohesion in the society) - ist da kein großer Unterschied zu vorher? (not big change)	Categorical with 3 unique values

Table 1: Survey Items

Within the MRP framework, multilevel regression is fitted on the sample data. Concerning the poststratification part of the MRP, the same model should be provided with population level data to make predictions on. To comply with this necessity, census data of Germany that reports the number of people for every distinct combination of state, gender, age, and education variables is used as population level data.

Since census data doesn't contain the vast majority of the questions that are usually asked in surveys, MRP method brings a serious limitation to the number of individual level independent variables that can be added to the model. However, as MRP, as the name suggests, being a multilevel modelling strategy, this limitation can be relaxed by adding group level independent variables to the model. In order to compensate for this limitation, the group level predictors listed in table 2 were added to the model

Data Source	Variable	Coding
Human Development Index	Subnational Human Development Index	Index variable take values between 0-1
2019 Novel Coronavirus Visual Dashboard operated by the Johns Hopkins University Center for Systems Science and Engineering	Incidence Rate	Numeric

Table 2: Group Level Predictors

3.2 Operationalisation

In order for MRP to function as intendedly, the sample data and population level data should be standardized in the same format. For these purposes, along with standardising the variable names, variable levels should also be coded in the same format. However, in the survey, the age variable was coded irregularly whereas in the census data it was following 5 years of intervals. In order to avoid this irregularity, the age variable in both survey and census data are coded in 10 years intervals which yielded 8 age categories in the end. Another, but this time much deeper irregularity occurs in the education variable. While on the population level data the education variable is coded in ISCED format, in the survey data the same variable is coded in a completely different format. This is mainly because of the particularity of German education system. Besides this format difference, in the survey, people who have an educational attainment level of Abitur/Hochschulreife/Fachhochschulreife were asked another question to indicate whether they have a university or similar level degree. These two questions were merged. Following that, the education level in the survey was translated into ISCED levels as Schneider (Schneider, 2008) explains.
The statistical model building was carried out by an R package called BRMS (Bayesian Regression Models using Stan). As it's expressed in the name, this R package is a higher level interface for fitting statistical models in Stan language.(Bürkner, 2017, 2018)

3.3 Statistical Model

As the dependent variable is a nominal variable that consists of three levels, the best suited approach for modelling is using multinomial regression. Statistical model becomes this:

$$\text{Cohesion}_i \sim \text{Multinomial}(n_i, p_i)$$

$$\text{p}_i = \text{Softmax}(0, \mu_i^{\text{less}}, \mu_i^{\text{more}})$$

$$\mu_i^{\text{less}} = \alpha_{\text{state}_{[i]}} + \beta_{\text{state}_{[i]}}\text{gender}_i + \beta_{\text{state}_{[i]}}\text{age}_i + \beta_{\text{state}_{[i]}}\text{education}_i + \beta_{\text{state}_{[i]}}\text{hdi}_i + \beta_{\text{state}_{[i]}}\text{incidence}_i$$

$$\mu_i^{\text{more}} = \alpha_{\text{state}_{[i]}} + \beta_{\text{state}_{[i]}}\text{gender}_i + \beta_{\text{state}_{[i]}}\text{age}_i + \beta_{\text{state}_{[i]}}\text{education}_i + \beta_{\text{state}_{[i]}}\text{hdi}_i + \beta_{\text{state}_{[i]}}\text{incidence}_i$$

$$\begin{bmatrix} \alpha_{\text{state}} \\ \beta_{\text{state}} \end{bmatrix} \sim \text{MVNORMAL}\left(\begin{bmatrix} \alpha \\ \beta \end{bmatrix}, \mathbf{\Sigma} \right)$$

$$\mathbf{\Sigma}^{\text{less}} = \begin{bmatrix} \sigma_\alpha^{\text{less}} & 0 \\ 0 & \sigma_\beta^{\text{less}} \end{bmatrix} \text{R} \begin{bmatrix} \sigma_\alpha^{\text{less}} & 0 \\ 0 & \sigma_\beta^{\text{less}} \end{bmatrix}$$

$$\mathbf{\Sigma}^{\text{more}} = \begin{bmatrix} \sigma_\alpha^{\text{more}} & 0 \\ 0 & \sigma_\beta^{\text{more}} \end{bmatrix} \text{R} \begin{bmatrix} \sigma_\alpha^{\text{more}} & 0 \\ 0 & \sigma_\beta^{\text{more}} \end{bmatrix}$$

$$\alpha^{\text{less}} \sim \text{Normal}(0, 1.5)$$
$$\alpha^{\text{more}} \sim \text{Normal}(0, 1.5)$$
$$\beta^{\text{less}} \sim \text{Normal}(0, 1.5)$$
$$\beta^{\text{more}} \sim \text{Normal}(0, 1.5)$$
$$\sigma^{\text{less}} \sim \text{Truncated Normal}(0, 1)$$
$$\sigma^{\text{more}} \sim \text{Truncated Normal}(0, 1)$$
$$\text{R} \sim \text{LKJcorr}(2)$$

Prior distributions are useful tools for both incorporating prior information into a model as well as relaxing the computational difficulties that arise during the model fitting. The priors I outlined in the model equation are weakly informative priors that are not incorporating strong beliefs about how the effects of explanatory variables are distributed relative to the reference category; rather, they are only bringing information about the plausible boundaries of the distribution which might be considered as technical limits.

Metrics	Data set	
	Training	Test
Mean Squared Error	0.5284799520979059	3.2324659384827372
Median Absolute Error	0.39411046074582323	0.8716680832404675
Mean Squared Log Error	0.0022940548754641784	0.011976161317056177
R^2	0.988196578894564	0.916430619829086

Table 3: Model Criticism

3.4 Model Diagnostics

In order to evaluate the model fit, I use posterior predictive checks. The following plot represents how well the model can reproduce the distribution of the dependent variable for each level of it. It basically compares the distribution of the observed data and 500 draws from the posterior distribution.

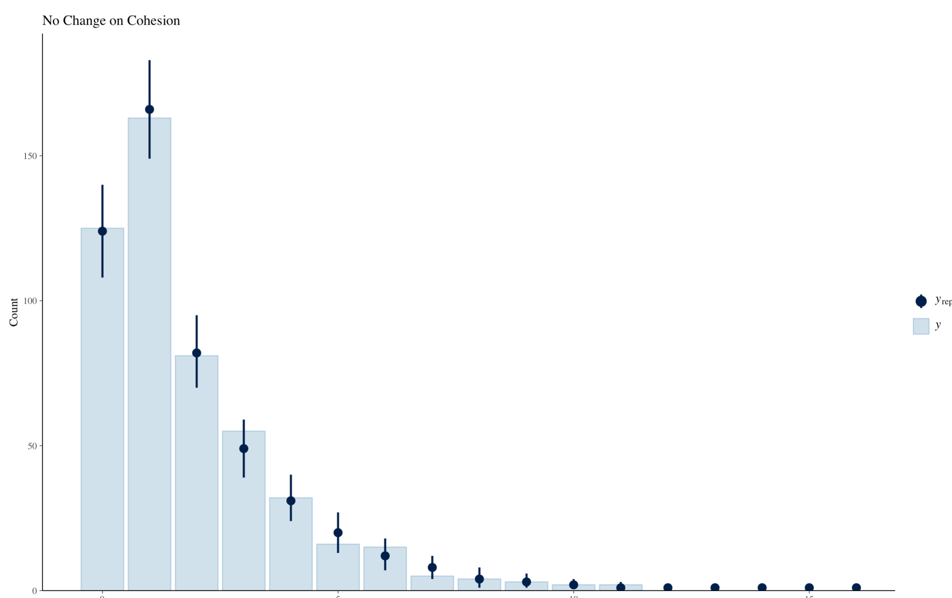

Figure 1: Distribution of Replicated vs Observed Values for No Change on Cohesion.

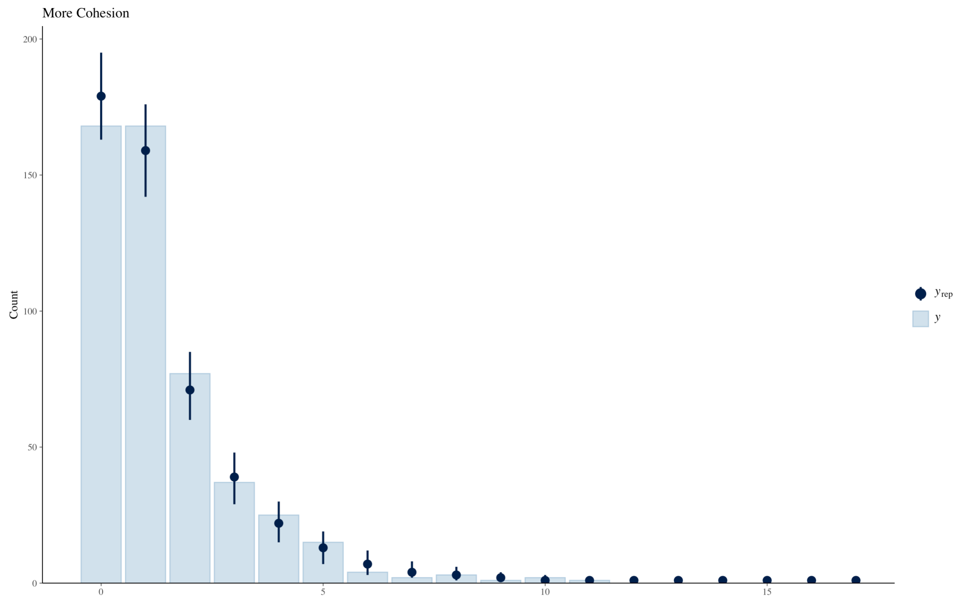

Figure 2: Distribution of Replicated vs Observed Values for More Cohesion.

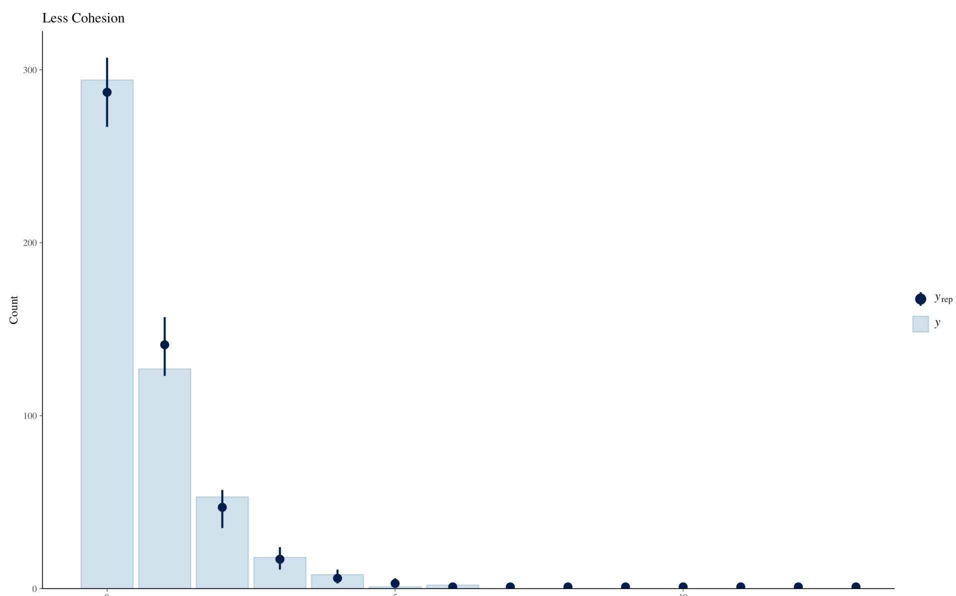

Figure 3: Distribution of Replicated vs Observed Values for Less Cohesion.

As it can be seen from the plots above the model is able to reproduce the underlying data quite well. However, as the model is a multilevel one, it is important to evaluate the model fit not only globally but also on the local levels, in this case, it is German federal states level. The following plot relies on the same idea above but this time it gives a state level overview of the comparison of the observed distribution against 500 draws from the posterior distribution.

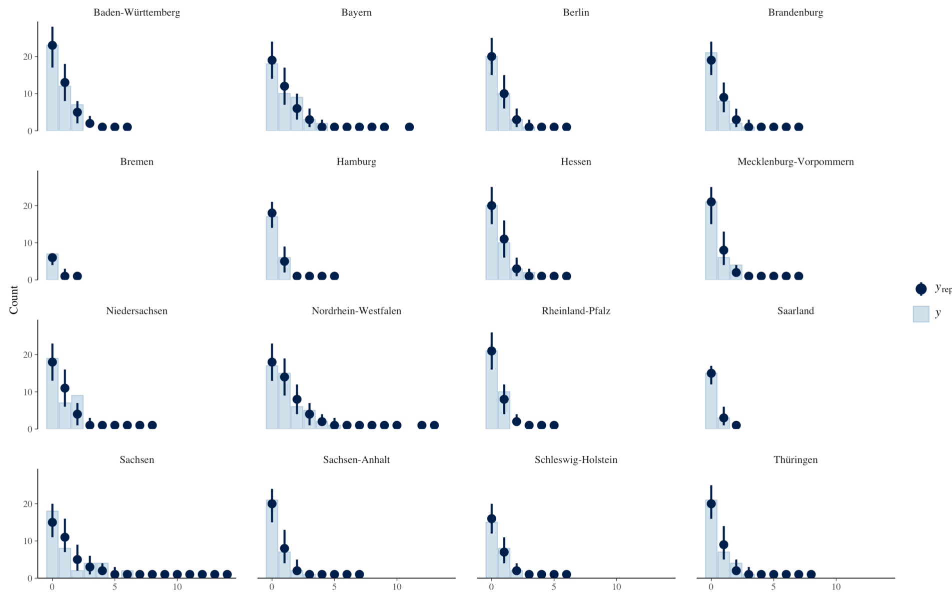

Figure 4: Distribution of Replicated vs Observed Values for Less Cohesion per each State

Again, we see that the model is able to reproduce the underlying data on the local level with slight deviations. Another important visualisation for the model fit is to check whether the model is able to capture standard deviations and means correctly.

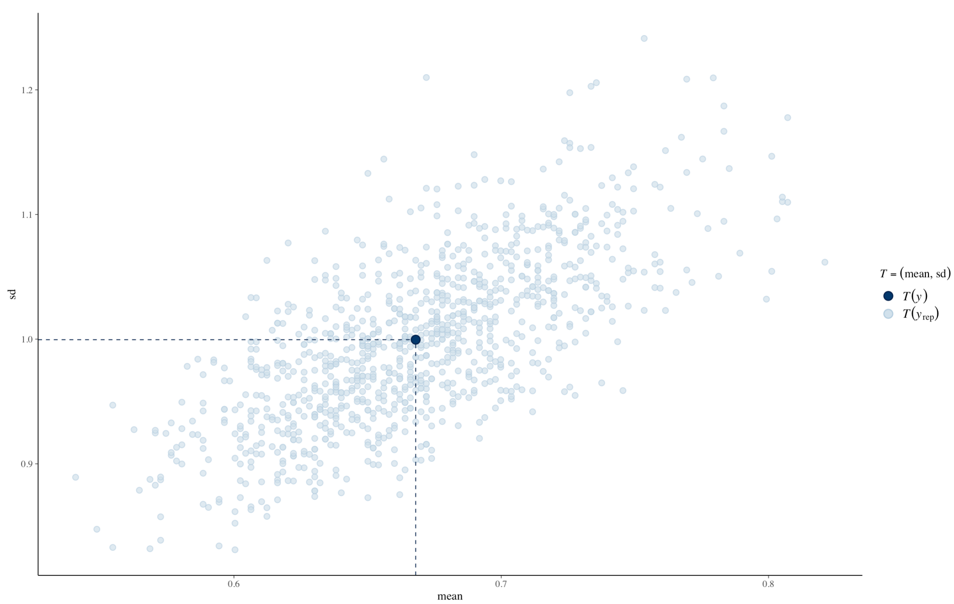

Figure 5: Replicated means and Standard Deviations vs Observed

Here, the important factor is that the observed mean and standard deviation stays in the center of the hypothetical ellipse made of the scatters of posterior draws. It is visible that this is the case. Lastly, I want to check whether the residuals are normally distributed for the majority of the posterior draws. The following plot indicates that this assumption holds true for posterior draws.

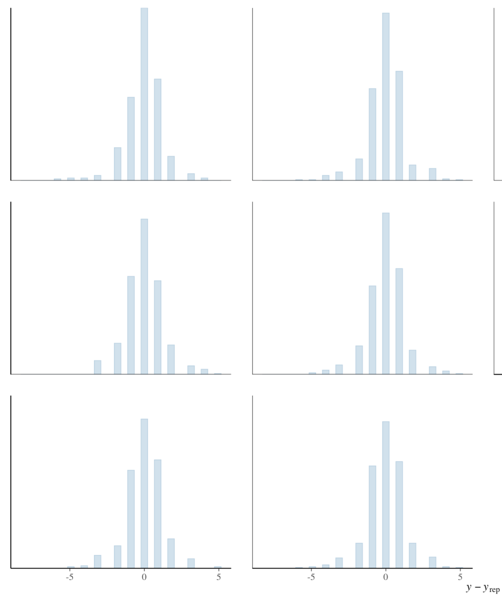

Figure 6: Distribution of Residuals.

Model diagnostics can be plotted further in many different ways however I suggest that there is enough evidence to indicate that the model fits the data well enough.

4 Results

Due to it's random effects components, regression output contains a long list of covariance parameters that are not intuitively interpretable. Additionally, as this study is utilising a regression model from the predictive perspective rather than a causal inference perspective, it is not so vital here to interpret the parameters directly. Here, I will interpret the parameters with the help of visualisation in order to convey the information much efficiently.

4.1 Fixed Effects

In the following plots I will be visualizing the fixed effects. The y axis of the plot indicates the number of counts for each level of the dependent variable within the number of fixed trials. I explicitly set the number of trials to 1 so that interpretation can be equivalent to probability. X axis of the plot is the observed levels of each independent variable. So the overall interpretation is that the lines indicate the mean of the effect, shaded areas are the 95% credible intervals of the parameter. It's important to note that these plots are produced for each respective variable of interest while holding all other variables fixed.

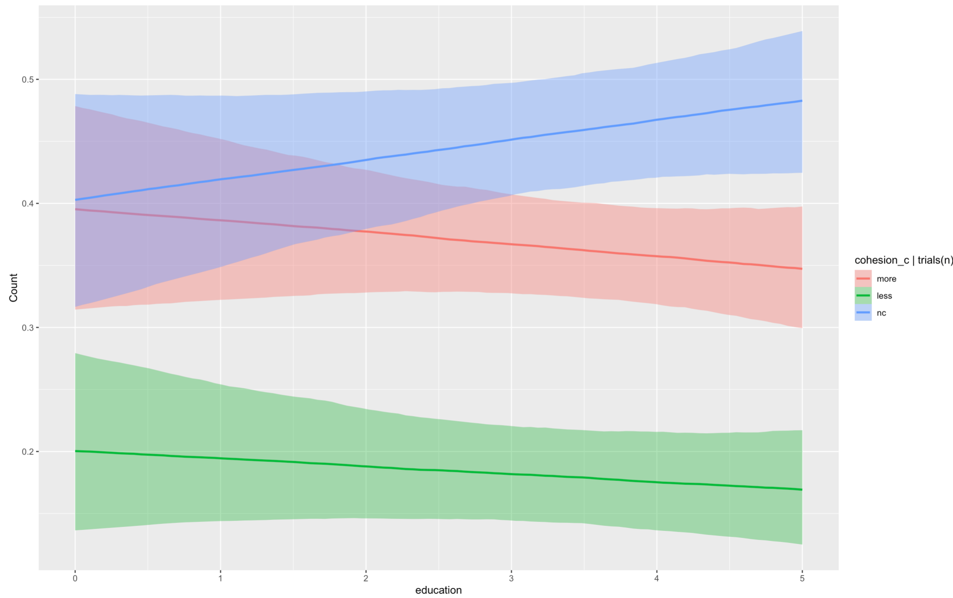

Figure 7: Fixed Effect of Education

The plot above shows the fixed effect of education. As I assumed a linear effect of education on perceptions of social cohesion during covid-19 pandemic. Even though the uncertainty is wide, the mean of the effect indicates that the tendency to perceive no big changes in social cohesion increases in line with the levels of education. The other two categories, less and more, are observed to decline slightly in reaction to the surge in no big difference.

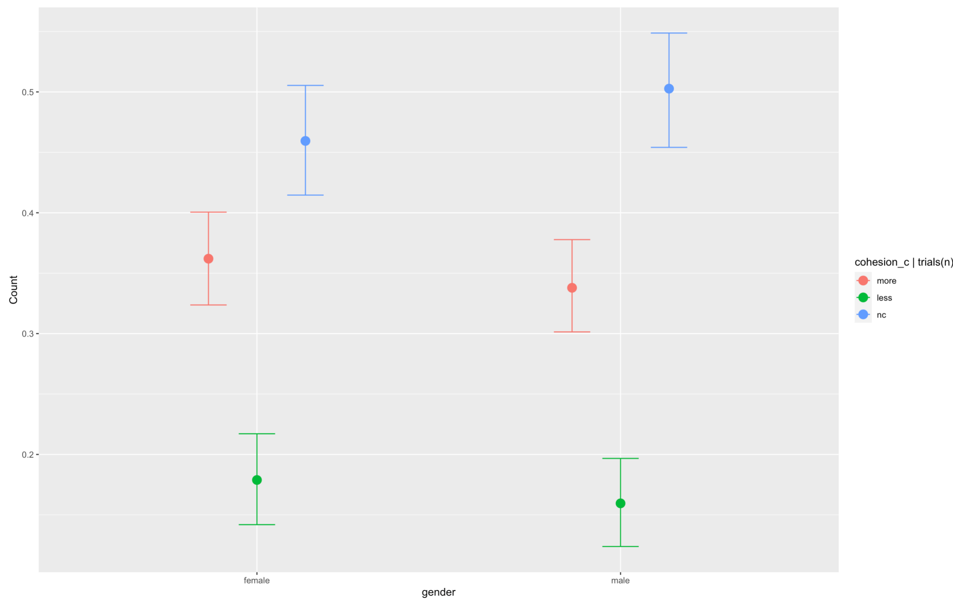

Figure 8: Fixed Effect of Gender

For the gender, we only see marginal differences between male and female only for the no big change category. Overall this plot indicates that gender itself alone doesn't give sufficient explanatory capacity. However, it still stays in the model because even if there is no significant effect, it still increases the predictive performance of the model which is the primary goal of this study.

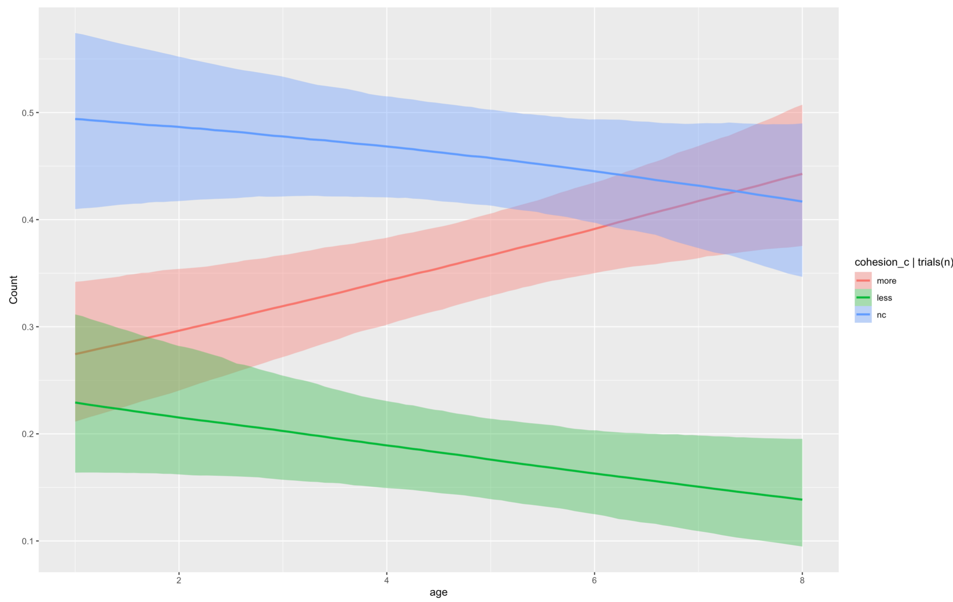

Figure 9: Fixed Effect of Age

As for the age, once again I assumed a linear relationship in the model building part. Theoretically there is no justified mechanism to expect a linear relationship due to cohort effects, however for the sake of the simplicity it is considered a linear relationship. Reflecting this research assumption, the effects show linear trends. It is observed that as people in the sample get older, they tend to perceive more social cohesion in the society during the pandemic. Reaction to this, as the levels of no big change and less are observed to have negative linear relationship with age.

The group level predictor sub national human development index brings no explicit explanatory power to the model. However, I still keep it in the model because together with the incidence rate they will inform the model about the characteristics of the federal states and in turn the shrinkage will be applied

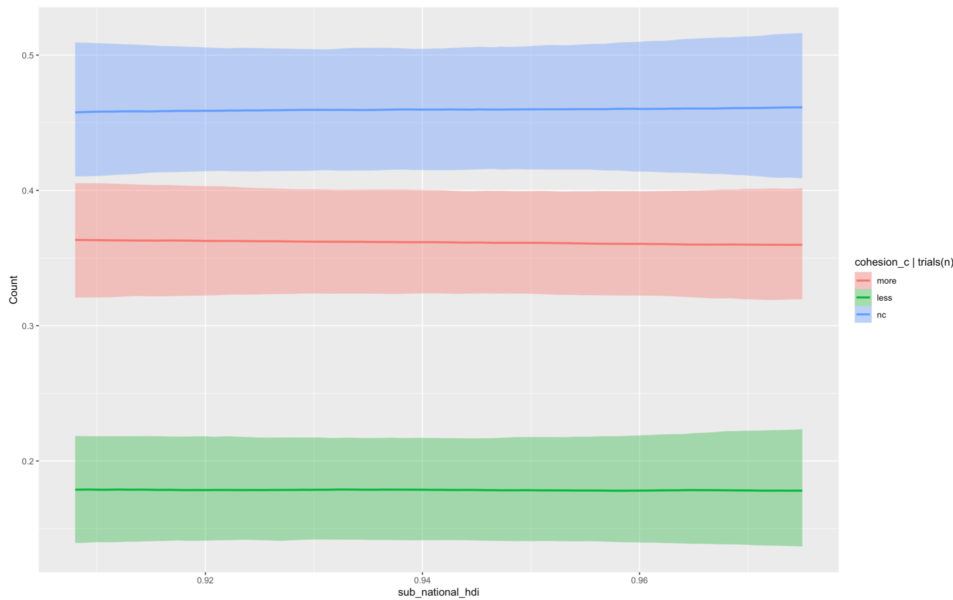

Figure 10: Fixed Effects of Subnational Human Development Index

And, lastly, the plot below is showing the differentiations of the effect of incidence rate per each category. In the federal states where the incidence rate is observed higher, people perceived more social cohesion in the society.

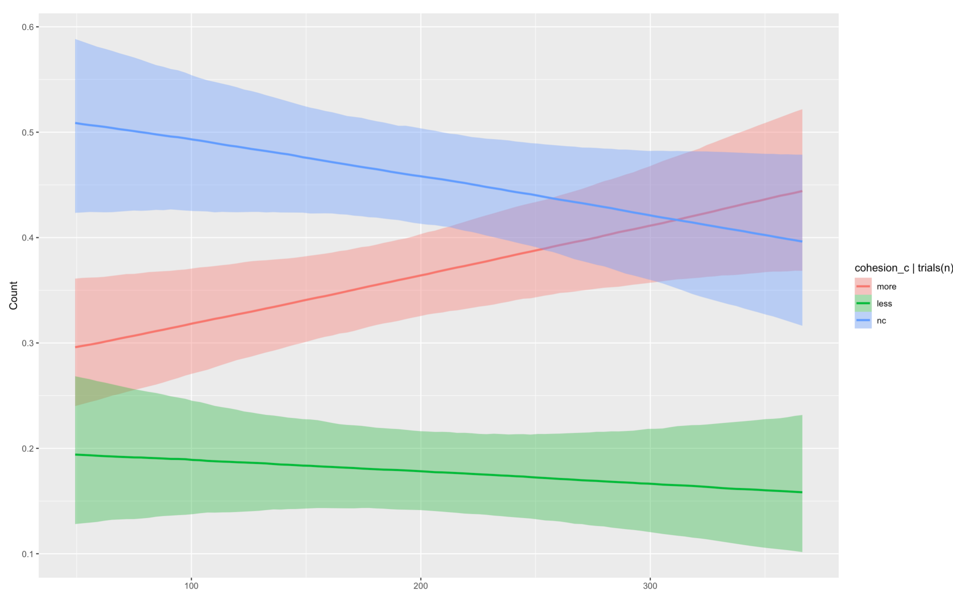

Figure 11: Fixed Effects of Covid Incidence Rate

4.2 Poststratified Estimation

For the poststratification part, the trained model on survey dataset is fitted to the census dataset. By this way, the relationship between predictors and the target variable is mapped onto population level to estimate the total number of people who perceive more or less cohesion per each demographic cluster. Following this estimation, the results are aggregated on state level to estimate state level perceptions of social cohesion.

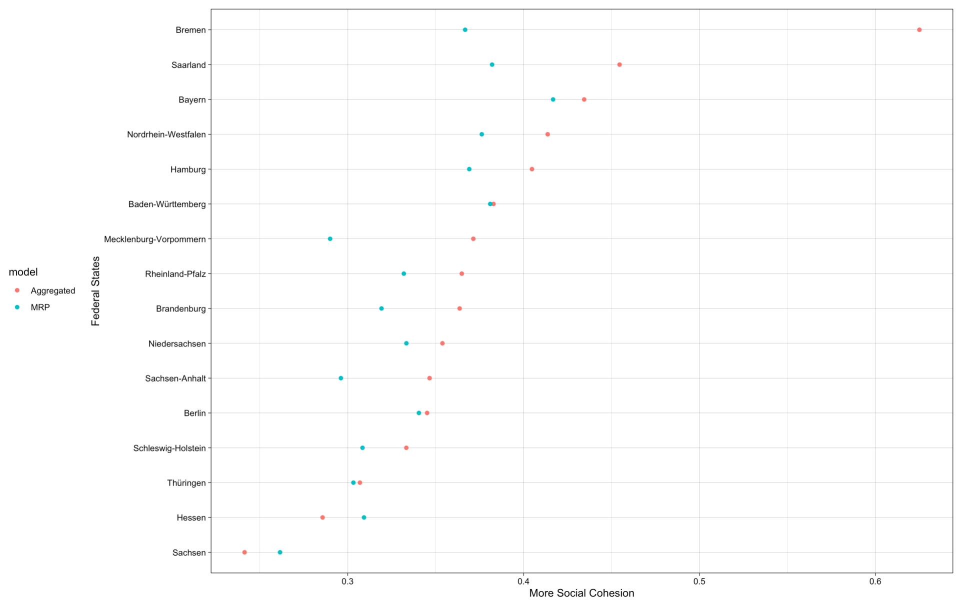

Figure 12: MRP based vs Aggregation based Estimations of More Social Cohesion

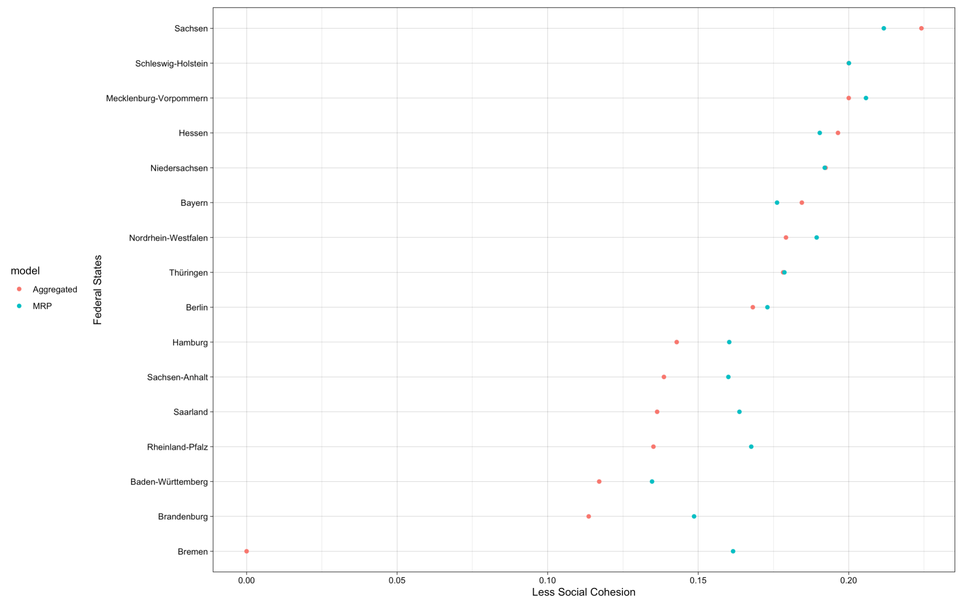

Figure 13: MRP based vs Aggregation based Estimations of Less Social Cohesion

The plots above show the differences between MRP based estimations and raw survey aggregation technique. As expected, the biggest difference occurs in Bremen. The main reason for this is the sample size of Bremen. In the raw survey, there are seven complete observations. The strength of multilevel modelling strategy helped overcoming this problem. Inside the model, due to information exchange between clusters, the parameters for Bremen(or for any state) was estimated by borrowing information from the estimated mean of that particular parameter. And, in the poststratification part, when these learned parameters were fitted to census level dataset to make predictions, the state level estimates dropped back to a more realistic level.

The shrinkage is not happening proportional to the sample size. When large sample sized states are considered (Baden-Württemberg, Bayern and Nordrhein-Westfalen) this becomes more salient. Nordrhein-Westfalen and Baden-Württemberg both have big sample sizes, 46 and 42 respectively. The difference between MRP based estimates and raw aggregations for both are 3.7 % and 0.0001 %

5 Discussion

The plots below are alternative visualisations for the same numbers above. The motivation behind is, by locating the states on Germany map the geographical interpretation becomes more easy.

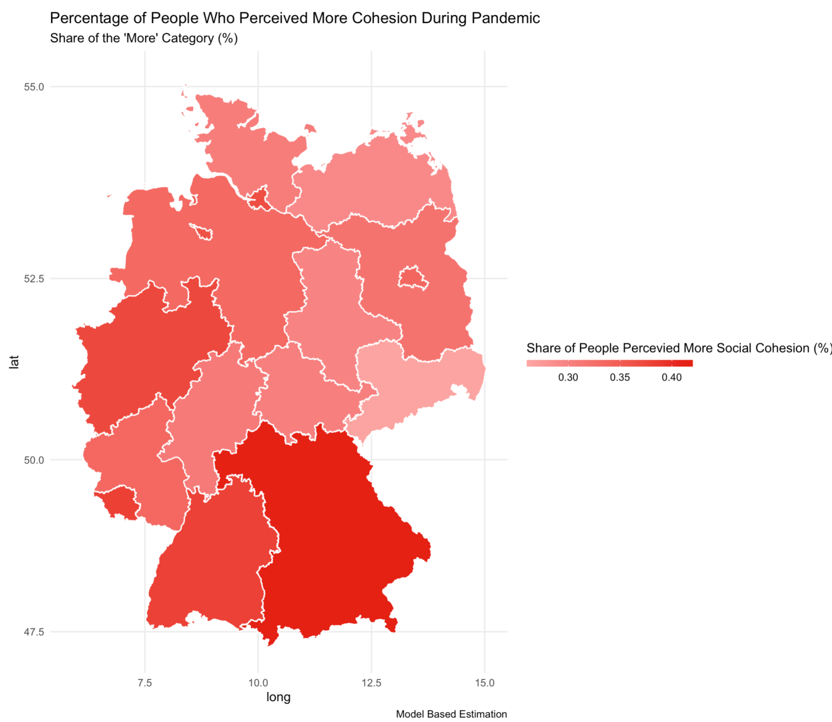

Figure 14: Map of More Social Cohesion Perceived per State

With closer examination, one can see that the southern and south-western states of Bayern, Baden-Württemberg, Nordrhein-Westfalen and Saarland are colored with darker tones of red, indicating that the estimated percentage of people perceive more social cohesion is higher. These four states are among the top five states with the highest coronavirus incidence rate. As it was plotted above in the regression results section, the coronavirus incidence rate has a strong effect on perceptions of social cohesion.

This can be explained by the extraordinary status of coronavirus pandemic.Taking into account that the data was collected in the midst of the first wave, the pandemic was, perhaps still is, considered as “one of the most serious threats that the Germany is facing since the second world war” as German Chancellor Angela Merkel put it in her address to the nation. The presence of a common threat or an acute social stress can be considered as factors leading to prosocial behaviour (Von Dawans, Fischbacher, Kirschbaum, Fehr, & Heinrichs, 2012)..

Observing more prosocial behaviour taking place in one's common environment could result in perceiving more social cohesion.

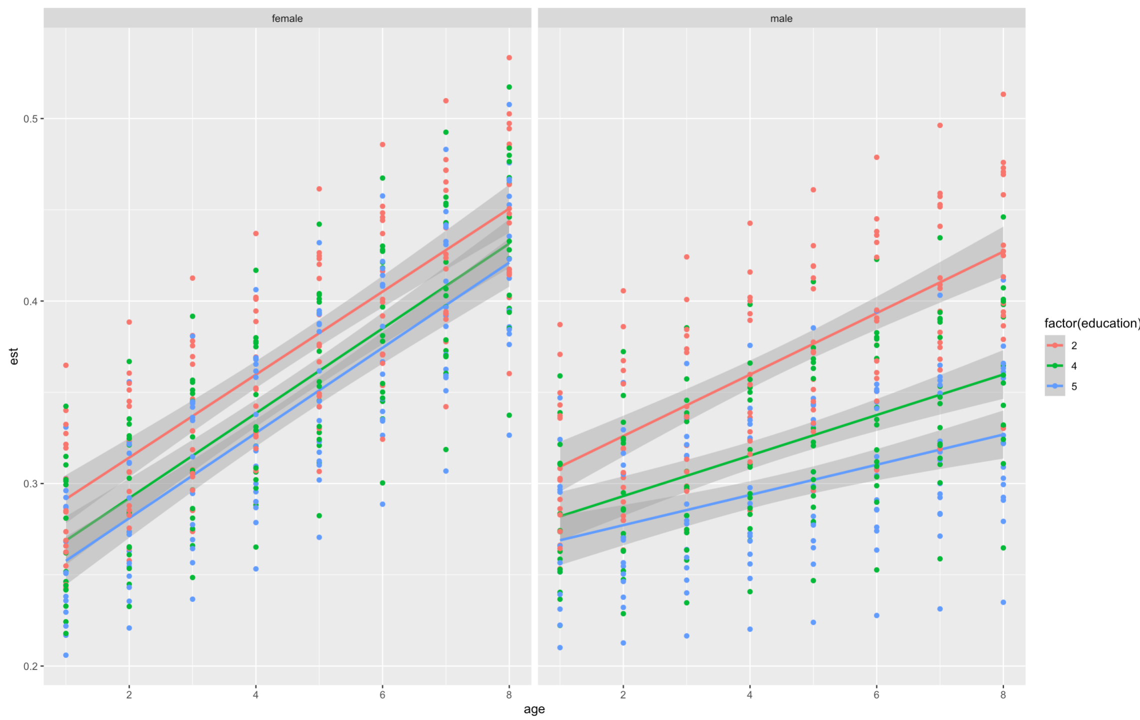

Figure 15: Three Way Interaction Between Age, Gender and Education Effects

The three-way interaction plot between age, gender and education indicates that older females with lowest educational attainment levels tend to perceive more social cohesion. As for the male the interaction effect of education and age becomes more divergent for the people with lowest educational attainment. Making a satisfactory explanation on the effect of education is a broader task and can't be made by relying on the analysis at hand. However, speculatively, it might be reasonable to assume that the people with more education are having more long term perspective to make any judgement on cohesion levels, rather than reaching swift conclusions.

Considering the age effects, the risk and prevention discourse targeting the older people might be one of the reasons why particularly older people perceive more social cohesion compared to younger. It should also be noted that Germany is having a 45.5 median age and MRP estimates might be pushed up by the demographic structure of the individual states.

References

Bernard, P. (1999). *Social cohesion: A critique.*

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*(1), 1–28. doi: 10.18637/jss.v080.i01

Bürkner, P.-C. (2018). Advanced Bayesian multilevel modeling with the R package brms. *The R Journal*, *10*(1), 395–411. doi: 10.32614/RJ-2018-017

Chan, J., To, H.-P., & Chan, E. (2006). Reconsidering social cohesion: Developing a definition and analytical framework for empirical research. *Social indicators research*, *75*(2), 273–302.

Gelman, A., Lax, J., Phillips, J., Gabry, J., & Trangucci, R. (2016). Using multilevel regression and poststratification to estimate dynamic public opinion. *Unpublished manuscript, Columbia University*, *2*.

Ghitza, Y., & Gelman, A. (2013). Deep interactions with mrp: Election turnout and voting patterns among small electoral subgroups. *American Journal of Political Science*, *57*(3), 762–776.

Langer, A., Stewart, F., Smedts, K., & Demarest, L. (2017). Conceptualising and measuring social cohesion in africa: Towards a perceptions-based index. *Social Indicators Research*, *131*(1), 321–343.

A new strategy for social cohesion revised strategy for social cohesion approved by the committee of ministers of the council of europe on 31 march 2004. (n.d.). Retrieved from `14.04.2021,12:23`

Presse-und Informationsamt der Bundesregierung, B. (2020). *Trust in state and society during the corona crisis (april 2020).* GESIS Data Archive, Cologne. ZA7672 Data file Version 1.0.0, https://doi.org/10.4232/1.13620. doi: 10.4232/1.13620

Schneider, S. L. (2008). Applying the isced-97 to the german educational qualifications. *The International Standard Classification of Education (ISCED-97). An evaluation of content and criterion validity for*, *15*, 76–102.

Trangucci, R., Ali, I., Gelman, A., & Rivers, D. (2018). Voting patterns in 2016: Exploration using multilevel regression and poststratification (mrp) on pre-election polls. *arXiv preprint arXiv:1802.00842*.

Von Dawans, B., Fischbacher, U., Kirschbaum, C., Fehr, E., & Heinrichs, M. (2012). The social dimension of stress reactivity: acute stress increases prosocial behavior in humans. *Psychological science*, *23*(6), 651–660.

Wang, W., Rothschild, D., Goel, S., & Gelman, A. (2015). Forecasting elections with non-representative polls. *International Journal of Forecasting*, *31*(3), 980–991.