

COVID-19 Policy-Compliance in Europe

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Contents

Introduction	1
Variation in Policy-Compliance	2
Modelling	4
Linear Non-Hierarchical Model	4
Linear Multi-Level Model	4
Model comparison	6
Conclusion	6
References	6

Introduction

The COVID-19-Pandemic is an ongoing challenge for policymakers. Especially, because overcoming it is so dependent on the policy-compliance of each and every individual. However, how is the state of this policy-compliance in Europe? Does it differ across different countries and how does it evolve over time?

To find an answer to these questions, the following analysis will assess the following hypotheses.

H_0 : There **is no** difference in compliance with mobility-reducing policies across European countries and this policy-compliance **does not** express a trend.

H_a : There **is** a difference in compliance with mobility-reducing policies across European countries and this policy-compliance **does** express a trend.

This analysis combines data from the Google COVID-19 Community Mobility Reports (“COVID-19 Community Mobility Report” 2020) and data from the Oxford Policy Tracker (Hale et al. 2020). The Google Mobility Report charts “movement trends over time by geography, across different categories.” (“COVID-19 Community Mobility Report” 2020) For the sake of this analysis the movement trends of the categories retail and recreation, supermarkets and pharmacies, public transport and workplaces were included and averaged without weighting. The Stringency Index was obtained from the Oxford Policy Tracker and records information on “the strictness of ‘lockdown style’ policies that primarily restrict people’s behaviour.” (Hale et al. 2020)

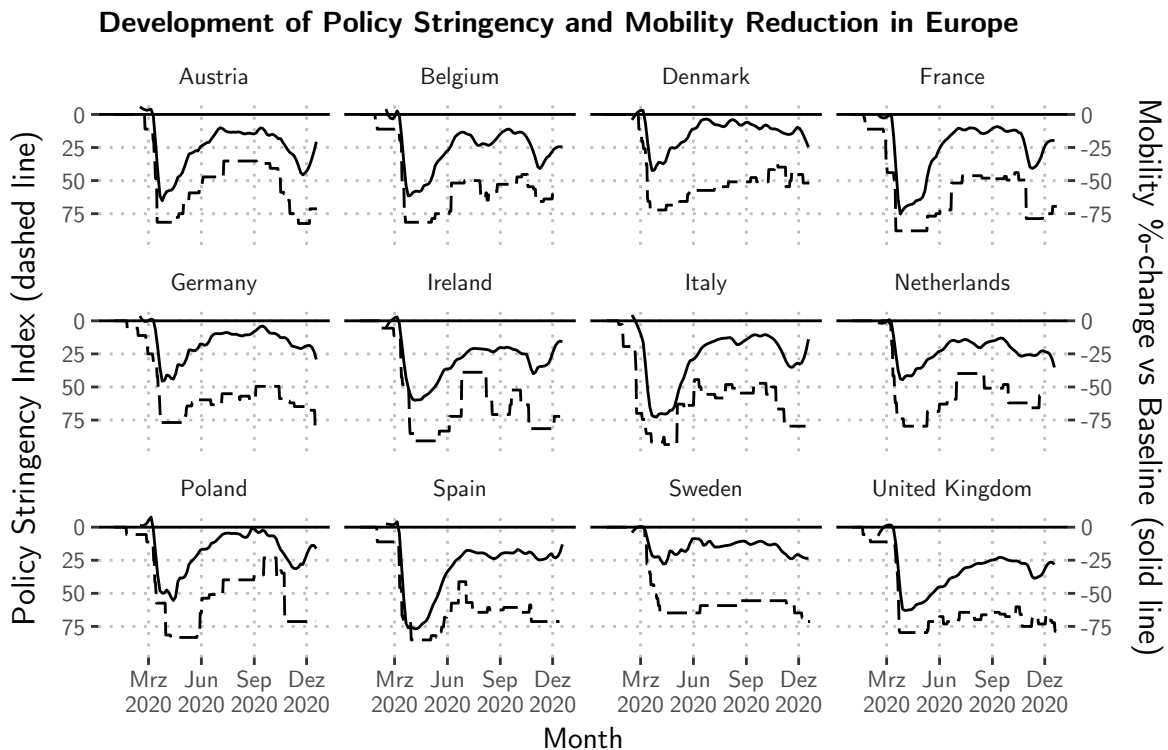
For this analysis, policy-compliance is approximated as the difference between the level of policy-stringency and the observed reduction in mobility.

$$\text{Compliance} = 100 - (\text{Policy Stringency Index} - \%\text{-change in Mobility})$$

To assess our hypothesis more thoroughly, policy-compliance is additionally corrected for COVID-19-cases (“Data on 14-Day Notification Rate of New Covid-19 Cases and Deaths” 2020) and public attention on the topic, as approximated by Google search queries with the terms “covid” and “corona” (“Google Trends” n.d.).

Countries included in the analysis were chosen based on their membership to the EU (including the United Kingdom) and their GDP.

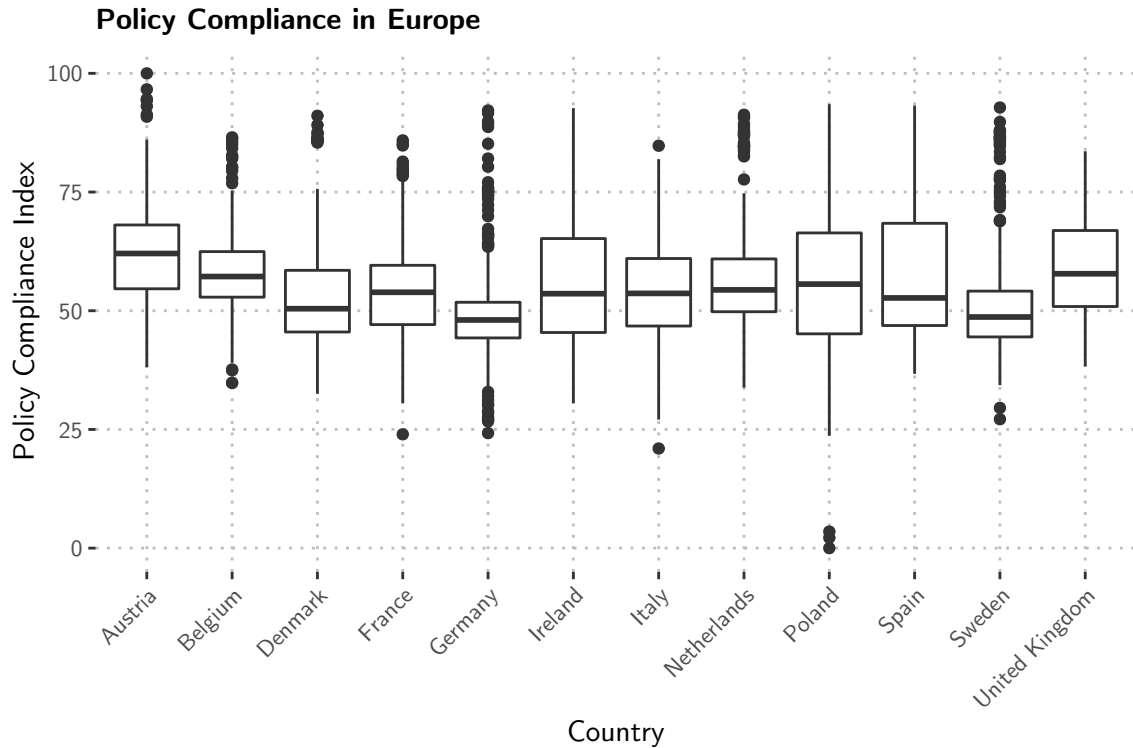
The following diagram shows how in March, April and May lockdown-style policies were introduced and how mobility was reduced in concordance in almost all the countries assessed. However, beginning immediately from there on, mobility started to increase again, with the gap between policy stringency and observed mobility-reduction widening - signaling reduced levels of policy-compliance.



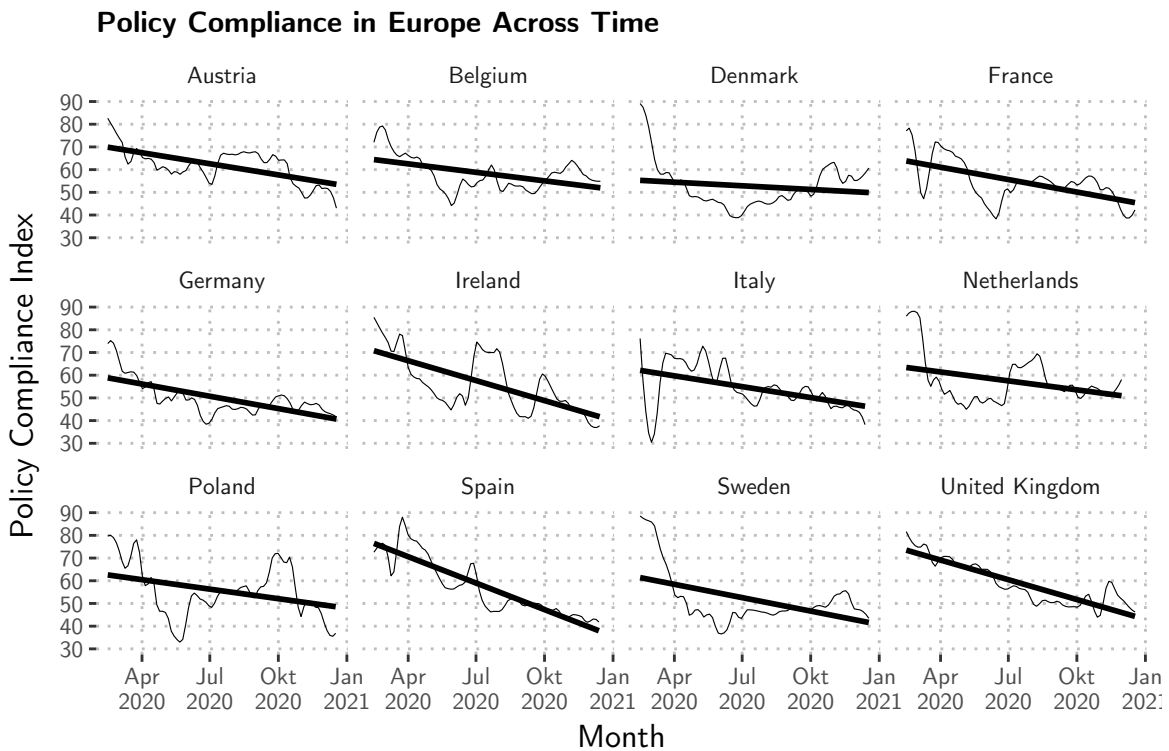
Variation in Policy-Compliance

In order to build our model, we can make a preliminary, bivariate analysis that shows the variance of policy compliance across different European countries.

The boxplot shows us that, indeed, the levels of policy compliance across European countries differ while the intra-group variance is roughly the same.



Additionally, as we want to assess the change of policy compliance across time in Europe, we can fit a linear regression line to the compliance data. This shows us that in all of the European countries analyzed, compliance with mobility-reducing-policies has reduced.



Modelling

Linear Non-Hierarchical Model

The following non-hierarchical model predicts the Mobility Index as the dependent variable, with the Stringency Index, Date and Country as the independent variables.

$$ComplianceIndex = \beta_0 + \beta_1 * Date + \beta_2 * Country + \beta_3 * Publicity + \beta_4 * Cases/100.000/14days + \epsilon \quad (1)$$

It yields the following result. Except for Date, none of the continuous variables Publicity and Cases/100.000/14 Days are statistically significant. Date is statistically significant at the 0.05 level. Its coefficient shows that when holding Publicity, Cases and Country constant, Compliance decreases on average by 0.07 points each day.

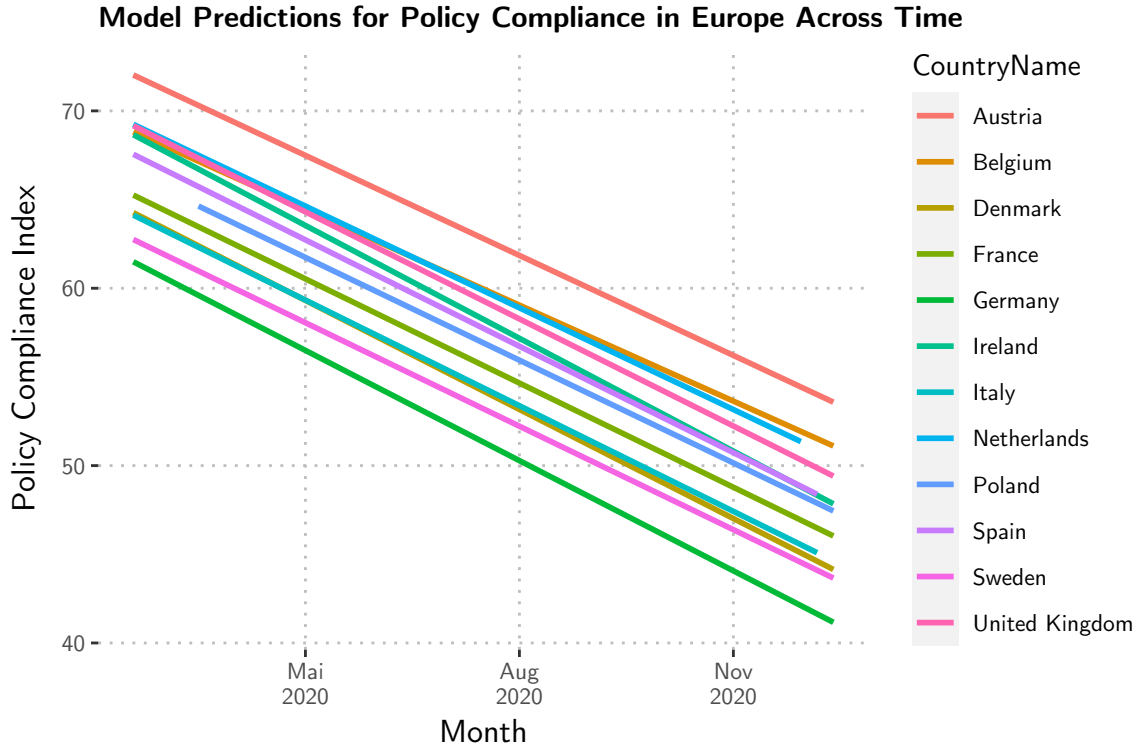
Variable	Coefficient	Std. Error	P-Value
Date	−0.07	0.01	***
Publicity	−0.01	0.02	
Cases/100,000/14 Days	0.00	0.00	
Belgium	−3.21	2.12	
Denmark	−8.29	2.12	***
France	−7.15	2.11	***
Germany	−11.06	2.12	***
Ireland	−4.07	2.13	
Italy	−8.12	2.17	***
Netherlands	−2.97	2.14	
Poland	−5.67	2.17	**
Spain	−4.79	2.24	*
Sweden	−9.53	2.11	***
United Kingdom	−3.25	2.13	

$R^2 = 0.31$; Adj. $R^2 = 0.29$; Num. obs. = 520; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

With Country as the categorical variable, all expressions are statistically significant at the 0.05 level, with the exception of Belgium, Ireland, the Netherlands, and the United Kingdom, when compared to Austria as the reference category. The adjusted R^2 indicates that the model explains 29% of the observed variance.

Linear Multi-Level Model

As we can see in the regression output of our non-hierarchical model, the fixed effects estimated for the different expressions of our country variable show substantial differences, with Germany showing more than 10 points less policy-compliance than our reference country Austria. Additionally, the following plot shows that the slopes for Compliance vs. Date by Country differ slightly.



Thus, to better assess the trends of policy-compliance in Europe over time, we can create a hierarchical model, allowing both random intercepts for the subgroups of Country as our grouping variable and random slopes along the Date variable.

$$ComplianceIndex_{ij} = \beta_0 + \beta_1 * Date_{ij} + \beta_2 * Publicity_{ij} + \beta_3 * Cases/100,000/14days_{ij} + \beta_{1j} * Date + Country_{0j} + \epsilon_{0ij} \quad (2)$$

Random effects			
	-	-	-
Groups	Name	Variance	Std. Dev.
Country	Intercept	96.44	9.82
	Date	0.00	0.00
Residual		96.43	9.82

Number of observations: 520, Number of groups: 12

Fixed effects				
	Estimate	Std. Error	t-value	p-value
Date	-0.07	0.01	-11.51	***
Publicity	-0.01	0.02	-0.44	
Cases/100,000/14 Days	0.00	0.00	1.87	

*** p < 0.001; ** p < 0.01; * p < 0.05

As we can see, the coefficients of the fixed effects at level one have not changed substantially. Still, the fixed

effect of Date is the only one that is statistically significant. The fact that the variance of the residual is almost as big as the variance of the random intercepts casts in doubt the explanatory value of our model.

Model comparison

Finally, to compare our hierarchical model-fit with the model-fit of our non-hierarchical model, we can compute a likelihood ratio test. This yields the following result.

Model 1: `ComplianceIndex ~ Date + Publicity + Date + notification_rate_per_100000_population_14.days`

Model 2: `ComplianceIndex ~ Date + Publicity + notification_rate_per_100000_population_14.days + (Date | CountryName)`

Model	Df	LogLik	Chisq	Pr(>Chisq)
1	5	-1947.3		
2	8	-1954.3	13.991	0.002917 **

*** p < 0.001; ** p < 0.01; * p < 0.05

As we can see, the improvement of our hierarchical model over our non-hierarchical model is statistically significant at the 0.05 level.

Conclusion

This analysis has shown that, interestingly, levels of compliance with mobility-reducing COVID-19-policies differ across selected European countries and that policy-compliance expresses an alarming, negative trend. We were able to show these findings using both a non-hierarchical and a hierarchical model. Nevertheless, this analysis has also shown that a large amount of variance in policy compliance remains unexplained by our models, which might be due to their linear character. Further attempts will have to be made in that regard.

References

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- Hale, Thomas, Noam Angrist, Emily Cameron-Blake, Laura Hallas, Beatriz Kira, Saptarshi Majumdar, Anna Petherick, Toby Phillips, Helen Tatlow, and Samuel Webster. 2020. “Oxford COVID-19 Government Response Tracker.” Blavatnik School of Government. <https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker>.