

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
References	6

Introduction

The COVID-19-Pandemic is an ongoing challenge for policy-makers. 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 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)

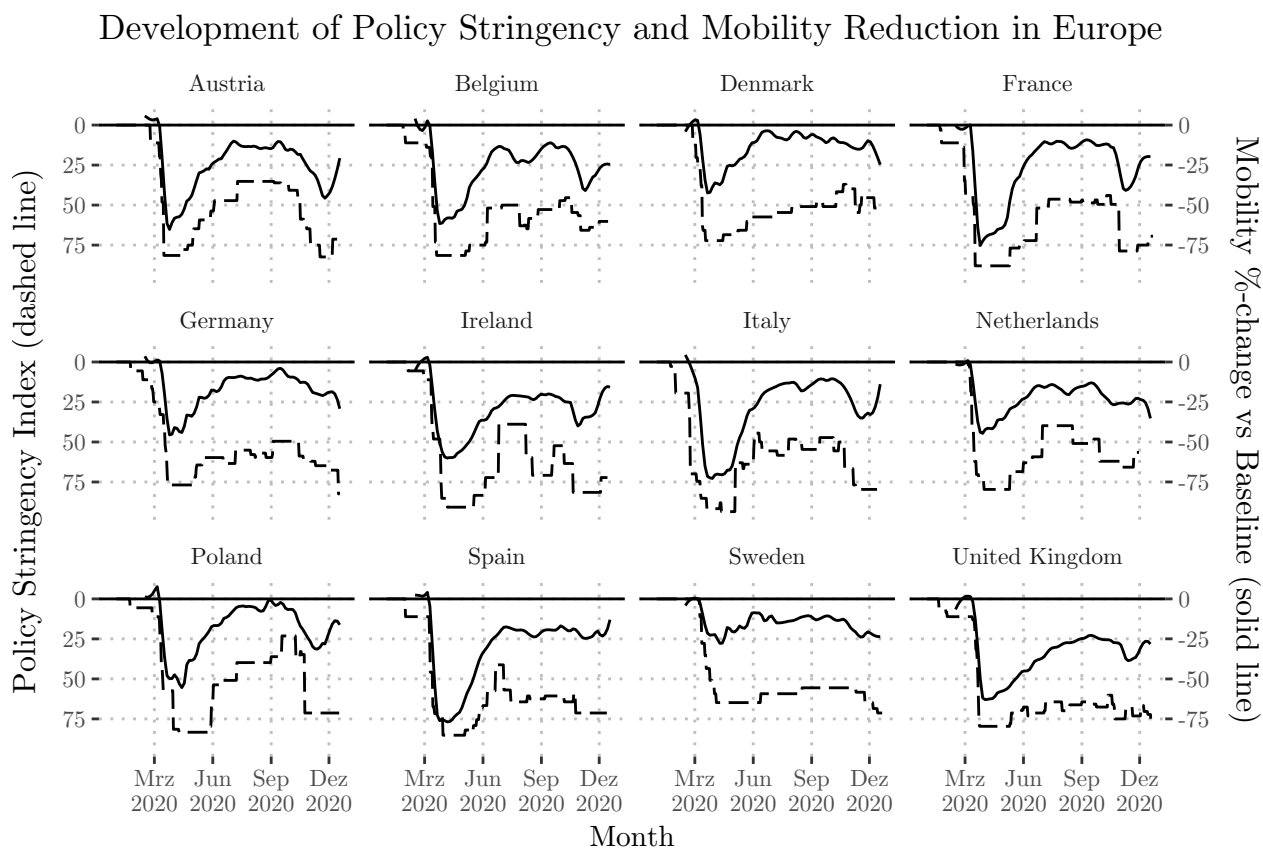
For this analysis, policy-compliance is approximated as the difference between the level of policy-stringency and the observed reduction in mobility.

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

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” & “coronavirus” (“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.

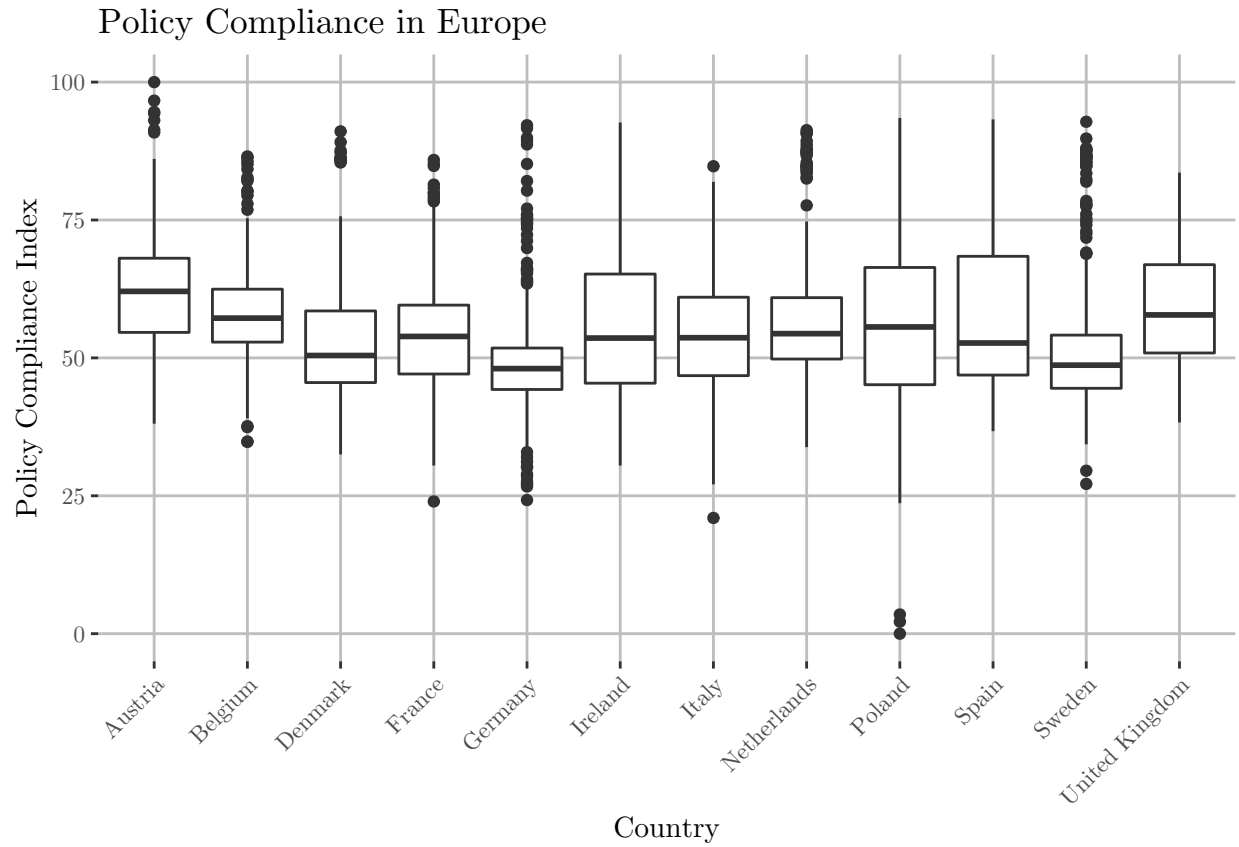
The following diagram shows how in March, April and May lockdown-style policies were introduced and how mobility was reduced in concordance in almost all of the countries assessed. However, beginning immediately from there on, mobility started to increase again, with the gap between policy stringency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



Variation in Policy-Compliance

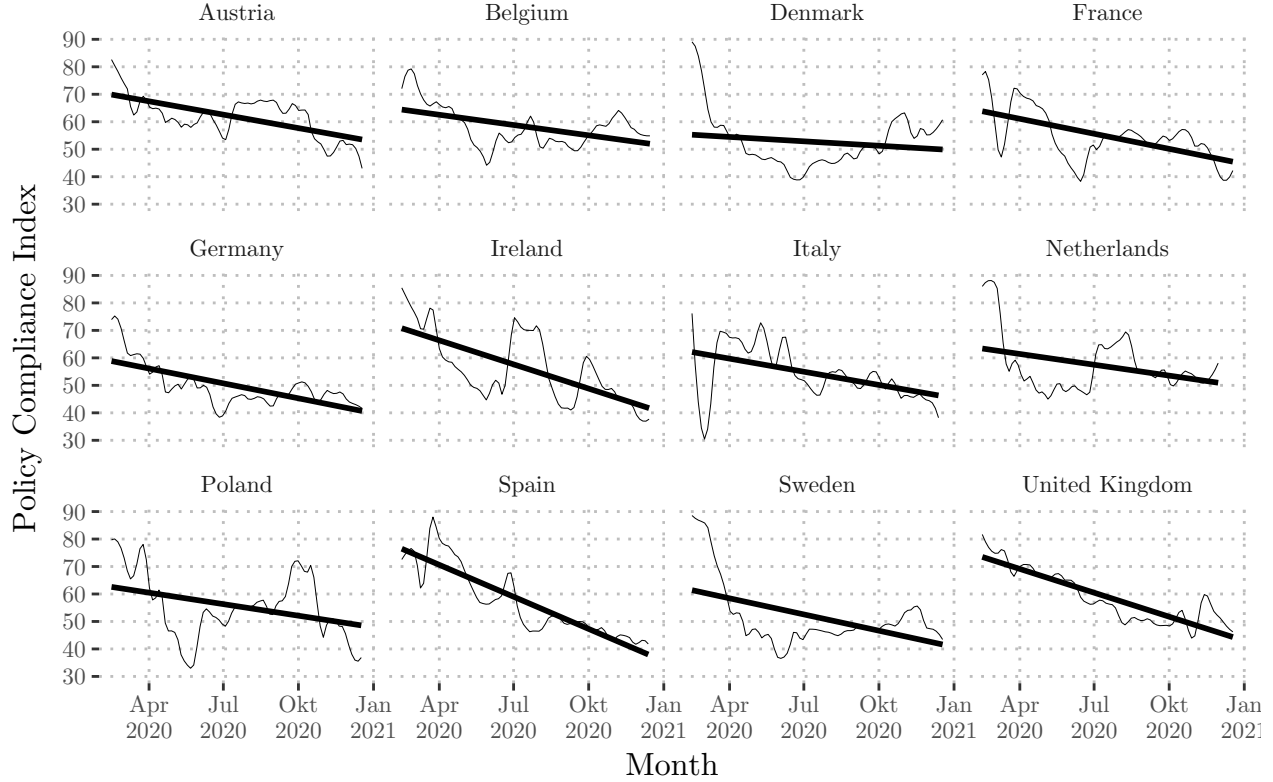
In order to build our model, we can make a preliminary, bivariate analysis that shows the variance of policy compliance across different European countries.

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.

Policy Compliance in Europe Across Time



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, non of the continuous variables Publicity and Cases/100.000/14 Days are statistically significant. Date is statistically significant at the 0.05 level. It's coefficient shows that when holding Publicity, Cases and Country constant, Compliance decreases by 0.07 points each day.

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.

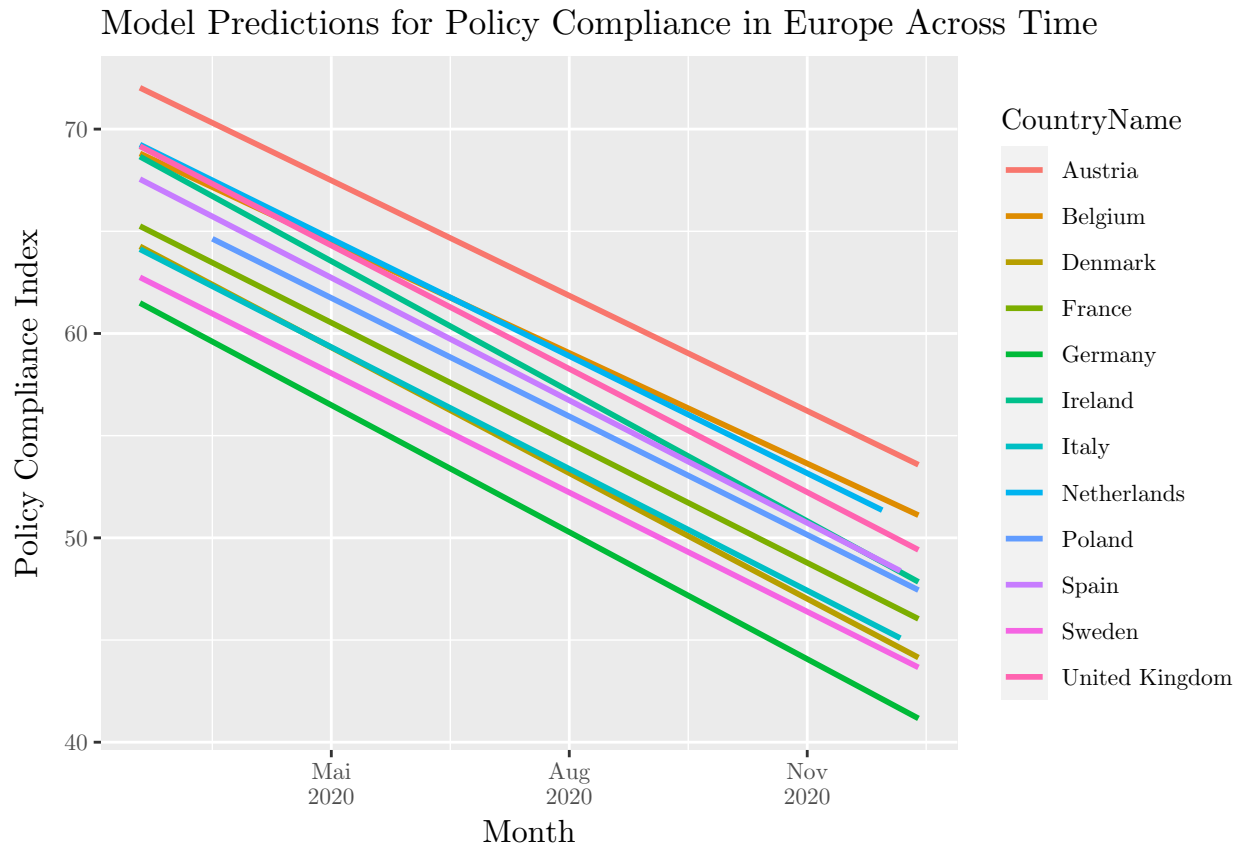
Linear Multi-Level Model

However, when plotting the fitted values from the non-hierarchical linear model by country, we can observe different discrete levels of compliance by date, e.g. with Austria showing much higher levels of compliance than Germany and Sweden.

Model 1	
Intercept	1380.70 (115.51)***
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

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

Table 1: Regression Table



This suggests creating a hierarchical model with a random intercept for country in order to improve model

	Model 1
Intercept	1387.55 (115.15) ^{***}
Date	-0.07 (0.01) ^{***}
Publicity	-0.01 (0.02)
Cases/100,000/14 Days	0.01 (0.00) [*]
AIC	3909.90
BIC	3935.42
Log Likelihood	-1948.95
Num. obs.	520
Num. groups: CountryName	12
Var: CountryName (Intercept)	8.13
Var: Residual	98.14

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

Table 2: Regression Table 2

fit. We can also see that the slopes do not differ substantially, so that for the sake of simplicity we can use only a random intercept in our model.

$$ComplianceIndex_{ij} = \beta_0 + \beta_1 * Date_{ij} + \beta_2 * Publicity_{ij} + \beta_3 * Cases/100,000/14days_{ij} + Country_j + \epsilon_{ij} \quad (2)$$

As we can see, the coefficients of the fixed effects at level one have not changed substantially, except for the fact that the predictor Cases/100,000/14Days has now become statistically significant. More interesting are the changes in the effects of our grouping variable.

References

- “COVID-19 Community Mobility Report.” 2020. Google LLC. <https://www.google.com/covid19/mobility?hl=en-GB>.
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- “Google Trends.” n.d. Google Trends. Accessed December 26, 2020. <https://trends.google.com/trends/?geo=UK>.
- 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>.