

Trading Liberties: Estimating COVID-19 Policy Preferences from Conjoint Data

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Research Question

The research questions of this paper are:

- In which conditions citizens support restricting freedoms?
- How such restrictions affect trust in political institutions?

Research Review

What we already known are:

- citizens are willing to trade individual liberties for security in light of an external threat (?)
- Regarding COVID-19, citizens with higher health related insecurity are more willing to sacrifice civil liberties (?)

Research Conclusions

And what we can conclude are:

- There is a greater acceptance of more strict policies when severity increases.
- Vaccinated citizens will strongly support stringent policies in extreme conditions.
- Also, Vaccinated citizens will differentiate between vaccinated and unvaccinated fellow citizens and are most likely to support restrictions for unvaccinated people only.

Dependent Variable

In this paper, we have 4 different regression models, which refers to 4 different dependent variables Y .

- Y_{choice} : A binary or ordered variable measuring which policy the interviewers prefer. And in this case, the author points out 2 policies to choose (0/1).
- Y_{rating} : The rating to these two proposals (0-10).
- Y_{trust} : Their trust to the federal government (0-10).
- $Y_{probability}$: The probability of accepting vaccinated for non-vaccinated interviewers.

Independent Variables

1. Pandemic Severity

- Moderate worsening (7-day-incidence 150, intensive care bed occupancy 80%)
- Sharp worsening (... 300, ... 90%)
- Dramatic worsening (... 800, ... 100%)

2. Policy Stringency

- Least restrictions (masks)
- Moderate restrictions (plus limitations on social events)
- Most restrictions (plus broader limitations on movements)

3. Policy Universality

- Most exemptions (restrictions do not apply to vaccinated, recovered, or tested citizens)
- Some exemptions (... vaccinated or recovered citizens)
- Fewest exemptions (... all citizens)

Regression Formula

So we can get our regression formula:

$$\begin{aligned} Y_{it} = & \beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3 \\ & + \beta_3 Z_1 Z_2 + \beta_4 Z_1 Z_3 + \beta_5 Z_2 Z_3 \\ & + \beta_6 Z_1 Z_2 Z_3 + u_i + \varepsilon_{it} \end{aligned}$$

Here, the author made a mistake which wrote β_3 twice.
Where Z_1 represents severity, Z_2 represents stringency, and Z_3 represents universality (?).

Code - Prepare the Variables

Let's see the code in R. These code is used to prepare for the independent variable including interactions.

```
1 df_long_all <-  
2   bind_rows(dplyr::filter(df_long) |> mutate(group = "All"),  
3             dplyr::filter(df_long, vaccinated == 0) |> mutate(group =  
4               "Unvaccinated"),  
5             dplyr::filter(df_long, vaccinated == 1) |> mutate(group =  
6               "Vaccinated"))  
7 custom.coef.map = list(  
8   "severity" = "Pandemic severity",  
9   "stringency" = "Policy stringency",  
10  "universality" = "Policy universality",  
11  "severity : stringency" = "Severity * Stringency",  
12  "severity : universality" = "Severity * Universality",  
13  "universality : stringency" = "Stringency * Universality",  
14  "severity : stringency : universality" = "Triple interaction")
```


Code - Fit the Model

Let's see the code in R. This code is used to fit the regression model, and we can see details through this block:

```
1  lapply(function(g)
2    list(rating = lm_robust(rating ~ severity * universality * stringency ,
3                           fixed_effects = ~ ID,
4                           data = df_long_all , subset = group == g, se_type = "stata"),
5         choice = lm_robust(choice ~ severity * universality * stringency ,
6                             fixed_effects = ~ ID,
7                             data = df_long_all , subset = group == g, se_type = "stata"),
6         trust = lm_robust(trust ~ severity * universality * stringency ,
7                             fixed_effects = ~ ID,
8                             data = df_long_all , subset = group == g, se_type = "stata"))))
```

Code - Fit the Model

Also, the author calculate the probability of accepting vaccinated.

```
1 fig_1_models$Unvaccinated$vaccination <-  
2   lm_robust(vaccine_probability ~ severity * universality * stringency ,  
              fixed_effects = ~ ID,  
3             data = df_long_all , subset = group == "Unvaccinated",  
               se_type = "stata")
```

Code - Check the Model

Now, let's check one of the model. For example, if we want to check when Y is rating in unvaccinated group, then we can write:

```
1 summary(fig_1_models[["Unvaccinated"]][["rating"]])
```

And then we will see the outputs from R:

Code - Check the Model

Table 1: Coefficient and Significant of $Y = \text{Rating}$ Regression

	Estimate	Std. Error	$\text{Pr}(> t)$
severity	0.002545	0.005734	6.572e-01
universality	-0.021862	0.005951	2.417e-04
stringency	-0.091130	0.005649	4.293e-57
severity:universality	-0.004736	0.007526	5.292e-01
severity:stringency	0.026078	0.006853	1.435e-04
universality:stringency	0.001157	0.007251	8.733e-01
severity:universality:stringency	0.004653	0.008978	6.043e-01

Regression Model

So in the upon case, we can write our regression formula:

$$\begin{aligned} Y_{rating} = & 0.00Z_1 - 0.02Z_2 - 0.09Z_3 \\ & + 0.00Z_1Z_2 + 0.02Z_1Z_3 + 0.00Z_2Z_3 \\ & + 0.00Z_1Z_2Z_3 \end{aligned}$$

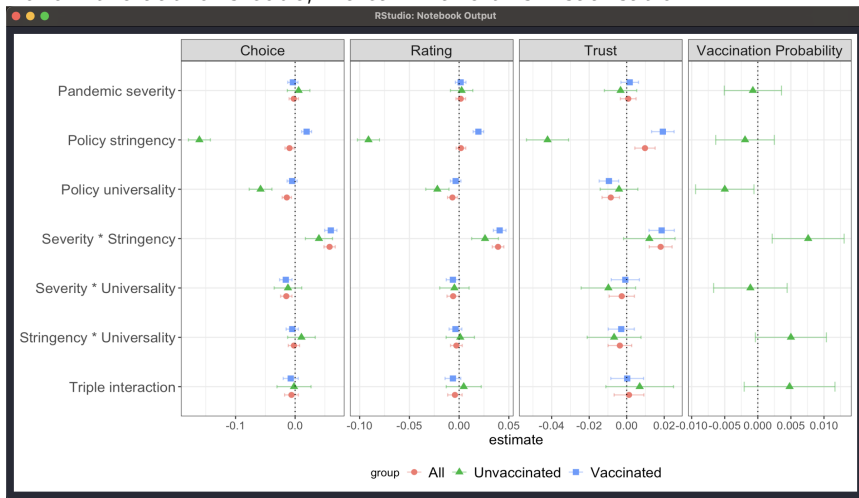
Where Z_1 represents severity, Z_2 represents stringency, and Z_3 represents universality.

Coefficient Visualisation

```
1 fig_main <- fig_1_data %>%
2   ggplot(aes(x = estimate, y = term, color = group, shape=group)) +
3   geom_point(size = 2.5, position=position_dodge(width=0.5)) +
4   geom_errorbarh(aes(y = term, xmin =conf.low, xmax = conf.high),
5                   size=0.5, alpha = 0.5, height = 0.2,
6                   position=position_dodge(width=0.5)) +
7   facet_grid(~ outcome , scales = "free") + theme_bw() +
8   scale_y_discrete ( limits =rev)+
9   theme(axis.title.y=element_blank()) +
10  theme(axis.title.x=element_text(size = 14)) +
11  theme(axis.text.y =element_text(size = 14)) +
12  theme(axis.text.x = element_text(size = 11)) +
13  theme(strip.text.x = element_text(size = 14))+
14  theme(legend.text=element_text(size=14))+
15  geom_vline(xintercept = 0, linetype="dotted", color = "black") +
    theme(legend.position="bottom")
pdf("fig_1.pdf", width = 12, height = 5)
```

Coefficient Visualisation

Follow the author's code, we can make this visualisation:



Key Conclusions

- Severity*Stringency: Citizens strongly prefer more severe policies when conditions are bad. Also we can say, there is a clear evidence that citizens are more supportive of more stringent policies as conditions worsen.
- Greater stringency is associated with greater willingness to vaccinate.
- Severity*Universality: Citizens are still less supportive of universal restrictions (with fewest exemptions) when conditions are bad.
- There is no evidence for interactions between the stringency and universality of conditions or for three-way interactions.

Logistic Regression

In this paper, the author used a robust linear regression:

```
1      choice = lm_robust(choice ~ severity * universality * stringency ,  
2      fixed_effects = ~ ID,  
      data = df_long_all , subset = group == g, se_type = "stata"),
```

And the R^2 of this model is poorly 0.01.

Logistic Regression

But we should notice that the variable choice can be seen as a binary as well, so the logistic regression model should can be used in this case:

```
1 contri_model_1 <- glm(choice ~ severity* universality *stringency ,  
    family="binomial", data=df.long_all )  
2 summary(contri_model_1)
```

where we can get AIC value is 114676.

Also, we want to try the logistic model without interactions:

```
1 contri_model_2 <- glm(choice ~ severity+ universality +stringency ,  
    family="binomial", data=df.long_all )  
2 summary(contri_model_2)
```

where we can get AIC value is 114982.

Logistic Regression

And the ANOVA for these two models shows that:

Model 1: choice ~ severity * universality * stringency

Model 2: choice ~ severity + universality + stringency

	Resid. Df	Resid. Dev	Df	Deviance	Pr(>Chi)
1	82952	114660			
2	82956	114974	-4	-313.99	< 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
1 anova(contri_model_1, contri_model_2, test = "Chisq")
```

We can conclude that, the model 1, which with an interaction, is significantly better than model 2.

Thank you for your listening and wish you all the best :)