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 acccepting 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.

```r
df_long_all <-
  bind_rows(dplyr::filter(df_long) |> mutate(group = "All"),
    dplyr::filter(df_long, vaccinated == 0) |> mutate(group =
        "Unvaccinated"),
    dplyr::filter(df_long, vaccinated == 1) |> mutate(group =
        "Vaccinated"))
custom.coef.map = list(
  "severity" = "Pandemic severity",
  "stringency" = "Policy stringency",
  "universality" = "Policy universality",
  "severity:stringency" = "Severity * Stringency",
  "severity:universality" = "Severity * Universality",
  "universality:stringency" = "Stringency * Universality",
  "severity:stringency:universality" = "Triple interaction")
```

Code - Fit the Model

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

```r
lapply(function(g)
  list(rating = lm_robust(rating ~ severity * universality * stringency,
         fixed_effects = ~ ID,
           data = df_long_all, subset = group == g, se_type = "stata"),
         choice = lm_robust(choice ~ severity * universality * stringency,
             fixed_effects = ~ ID,
           data = df_long_all, subset = group == g, se_type = "stata"),
         trust = lm_robust(trust ~ severity * universality * stringency,
             fixed_effects = ~ ID,
           data = df_long_all, subset = group == g, se_type = "stata")))
```

Code - Fit the Model

Also, the author calculate the probability of acccepting vaccinated.

```
fig_1_models$Unvaccinated$vaccination <-
  lm_robust(vaccine_probability ~ severity * universality *stringency ,
      fixed_effects = ~ ID,
          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:

```
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 = Rating Regression

	Estimate	Std. Error	$\Pr(>\lvert t\rvert)$
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:

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

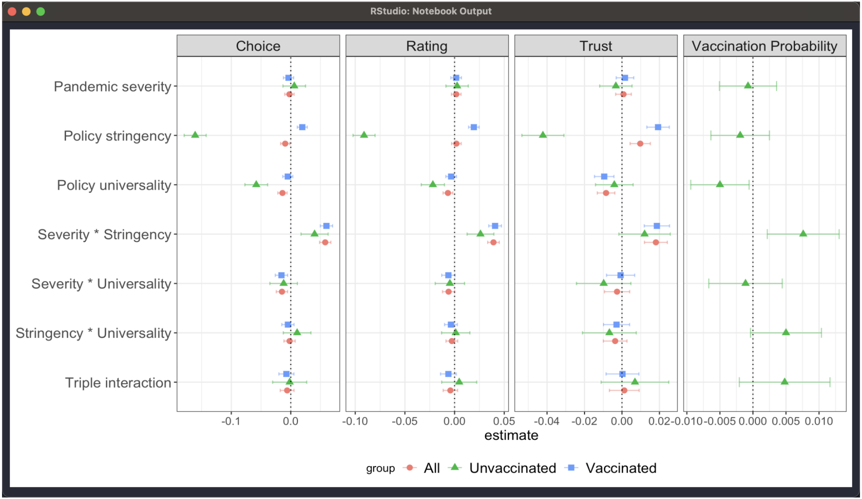
Where Z_1 represents severity, Z_2 represents stringency, and Z_3 represents universality.

Coefficient Visualisation

```
fig_main <- fig_1_data %>%
  ggplot(aes(x = estimate, y = term, color = group, shape=group)) +
  geom_point(size = 2.5, position =position_dodge(width=0.5)) +
  geom_errorbarh(aes(y = term, xmin =conf.low, xmax = conf.high),
                 size =0.5, alpha = 0.5, height = 0.2,
                      position =position_dodge(width=0.5)) +
  facet_grid(~ outcome, scales = "free") + theme_bw() +
  scale_y_discrete(limits =rev)+
  theme(axis.title.y=element_blank()) +
  theme(axis.title.x=element_text(size = 14)) +
  theme(axis.text.y =element_text(size = 14)) +
  theme(axis.text.x = element_text(size = 11)) +
  theme(strip.text.x = element_text(size = 14))+
  theme(legend.text=element_text(size=14))+
  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:

```
choice = lm_robust(choice ~ severity * universality * stringency ,
    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:

```
contri_model_1 <- glm(choice ~ severity* universality *stringency ,
      family="binomial", data=df_long_all )
summary(contri_model_1)
```

where we can get AIC value is 114676.

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

```
contri_model_2 <- glm(choice ~ severity+ universality +stringency,
      family="binomial", data=df_long_all )
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 '
```

```
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 :)