

Models

Project: Dominant Party Regimes in Sub-Saharan Africa

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This file reports the modelling process and the associated analytic decisions. It also includes the results of sensitivity tests.

Read in the data compiled in the *data_building.qmd* file.

```
data <- read_rds(here("data", "data_built", "data.built.rds"))
```

The main and only model in my original work was a multinomial logistic model. The main disadvantage of using this class of models in this context is that logistic models typically require more observations than linear models. Nevertheless, I start with a multinomial model to i) establish a baseline, ii) provide ground to validate the analytical coding of the dominant party regimes and iii) because there are not many alternative methods to analyze the data.

I first use a preferred specification, with party system institutionalization and education variables imputed with the mean of 2013-2018 values for the country with missing data, ELF imputed with previous values for the country and oil rents variable presented as a dummy.

```
m1a <- multinom(party_reg ~ v2xps_party_mean + elf_fill + col_type
+ housesys + v2x_polyarchy + oil_rent_dummy + e_peaveduc_mean,
data = data)

m1b <- multinom(relevel(party_reg, ref = "Autocratic Dominant")
~ v2xps_party_mean + elf_fill + col_type
+ housesys + v2x_polyarchy + oil_rent_dummy + e_peaveduc_mean,
data = data)
```

```
modelsummary(list("Ref: Non-dominant" = m1a,
"Ref: Autocratic Dominant" = m1b), stars = T,
shape = term ~ response, coef_rename = T,
output = "kableExtra") |>
kable_styling(latex_options = c("scale_down"))
```

Table 1: Multinomial logistic model, preferred specification

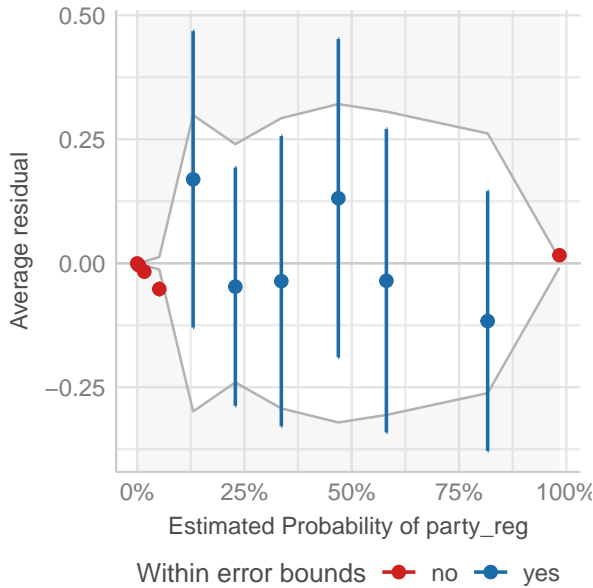
	Ref: Non-dominant		Ref: Autocratic Dominant	
	Democratic Dominant	Autocratic Dominant	Democratic Dominant	Not Dominant
(Intercept)	2.131 (4.319)	8.219 (5.973)	-6.090 (4.960)	-8.239 (5.977)
PSI (Mean)	11.261+ (5.836)	8.545 (7.040)	2.708 (5.826)	-8.556 (7.041)
ELF (Imputed)	3.852 (3.218)	3.559 (3.872)	0.305 (3.228)	-3.544 (3.871)
Colonial Legacy [France]	0.477 (1.585)	-1.215 (1.967)	1.693 (1.680)	1.220 (1.968)
Colonial Legacy [Mixed]	-7.858 (123.274)	-3.529 (113.129)	-3.489 (129.126)	6.267 (166.662)
Colonial Legacy [None]	-5.960 (135.665)	2.763 (16.287)	-7.018 (57.399)	-2.748 (16.298)
Colonial Legacy [Other]	-3.770 (3.034)	-4.459 (4.202)	0.696 (3.202)	4.475 (4.205)
Electoral Rules [Plural]	-4.987* (2.525)	-3.997 (3.831)	-0.988 (3.121)	4.005 (3.830)
Democracy	-15.564* (6.615)	-26.599** (9.945)	11.022 (8.265)	26.608** (9.945)
Oil Dummy [Not equal to zero]	-0.961 (1.494)	0.111 (2.049)	-1.078 (1.746)	-0.118 (2.050)
Education (Mean Imputed)	0.164 (0.264)	-0.082 (0.392)	0.246 (0.361)	0.082 (0.392)
Num.Obs.	38		38	
R2	0.511		0.511	
R2 Adj.	0.488		0.488	
AIC	86.5		86.5	
BIC	122.5		122.5	
RMSE	0.34		0.34	

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

```
check_model(m1a)
```

Binned Residuals

Points should be within error bounds



Collinearity

High collinearity (VIF) may inflate parameter uncertainty

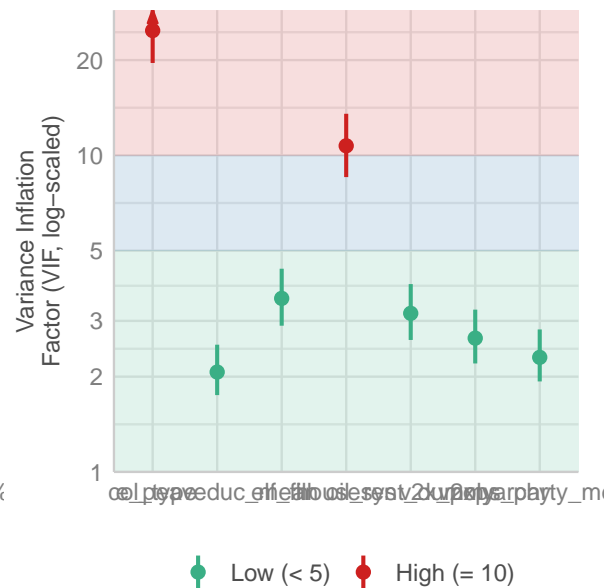


Figure 1

Table 1 reveals that there are not many valid inferences to be drawn from this way of modelling the data. While democracy scores are correlated with whether the dominant regime will be autocratic or democratic dominant, this is really not a significant contribution and is indeed to be expected. Other variables that reach conventional significance levels do so when I compare both dominant regime types with non-dominant regimes. This suggests that the model is too underpowered to capture differences between autocratic and democratic dominant regimes.

With this in mind, I try and confirm this with a continuous measure of party dominance: ENPP.

```
m2 <- lm(enpp ~ v2xps_party_mean + elf_fill + col_type
+ housesys + v2x_polyarchy + oil_rent_dummy + e_peaveduc_mean,
data = data)

m2a <- lm(enpp ~ v2xps_party_next + elf_fill + col_type
+ housesys + v2x_polyarchy + oil_rent_dummy + e_peaveduc_mean,
data = data)

m2b <- lm(enpp ~ v2xps_party_mean + elf_fill + col_type_collapsed
+ housesys + v2x_polyarchy + oil_rent_dummy + e_peaveduc_mean,
data = data)

m2c <- lm(enpp ~ v2xps_party_mean + elf_fill + col_type
```

```

+ housesys + v2x_polyarchy + oil_rent_perc_gdp + e_peaveduc_mean,
data = data)

modelssummary(list("Preferred" = m2, "PSI next year imputed" = m2a,
  "Oil rent in % of GDP" = m2b, "Colonial Legacy Collapsed" = m2c),
stars = T, coef_rename = T,
coef_map = c("(Intercept)", "PSI (Mean)",
  "PSI (Next Year Imputed)", "ELF (Imputed)",
  "Colonial Legacy [France]",
  "Colonial Legacy [Mixed]",
  "Colonial Legacy [None]",
  "Colonial Legacy [Other]",
  "Colonial Legacy (Collapsed) [France]",
  "Colonial Legacy (Collapsed) [Other]",
  "Electoral Rules [Plural]", "Democracy",
  "Oil Dummy [Not equal to zero]",
  "Oil Rents (%)",
  "Education (Mean Imputed)"),
  output = "kableExtra") |>
kable_styling(latex_options = c("scale_down")) |>
column_spec(column = 2:5, width = "2.5cm")

```

Table 2: Linear model with ENPP as the dependent, all specifications

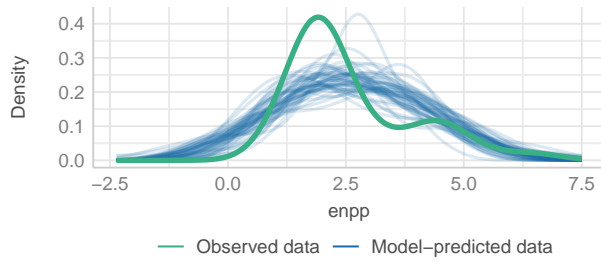
	Preferred	PSI next year imputed	Oil rent in % of GDP	Colonial Legacy Collapsed
(Intercept)	3.261** (1.142)	3.242** (1.077)	3.995*** (1.031)	3.286** (1.170)
PSI (Mean)	-3.526* (1.481)		-3.988** (1.333)	-3.594* (1.514)
PSI (Next Year Imputed)		-4.344** (1.532)		
ELF (Imputed)	-0.393 (0.823)	-0.120 (0.798)	-0.415 (0.803)	-0.692 (0.796)
Colonial Legacy [France]	0.121 (0.485)	-0.028 (0.479)		0.053 (0.498)
Colonial Legacy [Mixed]	-1.805+ (0.892)	-1.760+ (0.861)		-1.651+ (0.905)
Colonial Legacy [None]	-0.201 (0.983)	-0.510 (0.974)		-0.066 (0.998)
Colonial Legacy [Other]	-0.130 (0.701)	-0.113 (0.676)		-0.107 (0.716)
Colonial Legacy (Collapsed) [France]			-0.003 (0.483)	
Colonial Legacy (Collapsed) [Other]			-0.635 (0.498)	
Electoral Rules [Plural]	0.807 (0.526)	0.757 (0.504)	0.514 (0.448)	0.920+ (0.527)
Democracy	4.227** (1.258)	4.502** (1.228)	3.626** (1.175)	4.140** (1.408)
Oil Dummy [Not equal to zero]	-0.489 (0.451)	-0.459 (0.435)	-0.446 (0.452)	
Oil Rents (%)				-0.007 (0.033)
Education (Mean Imputed)	-0.166+ (0.091)	-0.129 (0.091)	-0.152+ (0.089)	-0.159 (0.095)
Num.Obs.	37	37	37	37
R2	0.494	0.529	0.445	0.472
R2 Adj.	0.299	0.348	0.287	0.268
AIC	123.0	120.3	122.3	124.5
BIC	142.3	139.6	138.4	143.9
Log.Lik.	-49.480	-48.145	-51.168	-50.266
RMSE	0.92	0.89	0.96	0.94

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

```
check_model(m2)
```

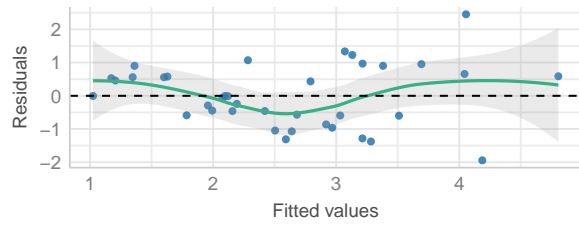
Posterior Predictive Check

Model-predicted lines should resemble observed data line



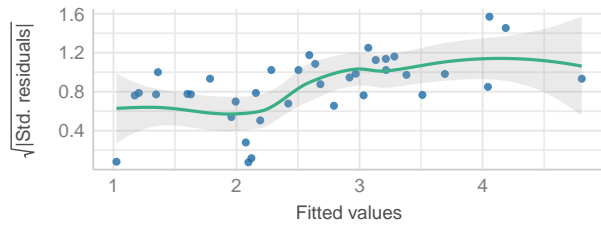
Linearity

Reference line should be flat and horizontal



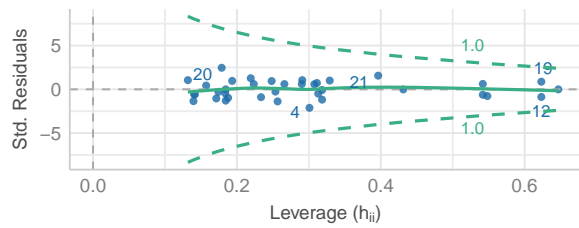
Homogeneity of Variance

Reference line should be flat and horizontal



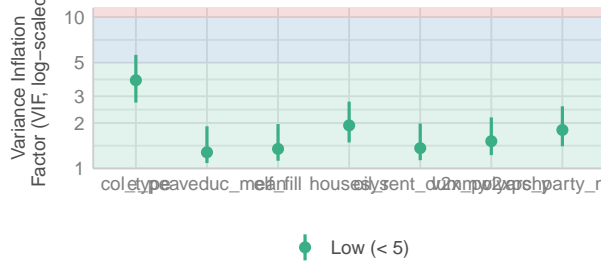
Influential Observations

Points should be inside the contour lines



Collinearity

High collinearity (VIF) may inflate parameter uncertainty



Normality of Residuals

Points should fall along the line

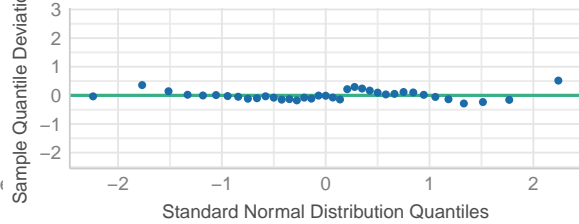


Figure 2