Reproduction of 'Sexism and the far-right vote: The Individual dynamics of gender backlash by Eva Anduiza & Guillem Rico

Jenna Brooks

```
Loading required package: ggplot2


Please cite as:

 Hlavac, Marek (2022). stargazer: Well-Formatted Regression and Summary Statistics Tables.

 R package version 5.2.3. https://CRAN.R-project.org/package=stargazer

Loading required package: grid

Loading required package: Matrix

Loading required package: survival


Attaching package: 'survey'

The following object is masked from 'package:graphics':

    dotchart


Attaching package: 'dplyr'
```

```
The following objects are masked from 'package:stats':

    filter, lag


The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union

corrplot 0.95 loaded
```

Reproduction of "Sexism and the far-right vote: The individual dynamics of gender backlash"

Authors: Eva Anduiza & Guillem Rico

This paper examines how sexism has played a role the electoral rise of the far-right party, Vox, in Spain. Anduiza and Rico () argue that having sexist beliefs is one of the most influential attitudinal predictors of voting for the far-right party Vox.

Original Study

Data

Using panel data from Spain, collected before, during and after prominent feminist protests in 2018 and 2019, the authors assess individual changes in measures of sexism occurring in various contexts of feminist movement and the surge of far right support.

The data utilized in this study is drawn from the Spanish Political Attitudes dataset (Hernández Pérez et al., 2021), a longitudinal online panel survey conducted annually. The survey uses a quota sampling method to ensure a representative sample of the Spanish adult population aged 18 to 56, with quotas based on gender, age, educational background, geographic region, and municipality size. The unit of analysis is individual voters in Spain.

Observational independence could be questioned in this data set due to the longitudinal design (repeated observations) and the geographic clustering of like-minded voters in specific regions, as well as demographic factors such as age, gender, and education.

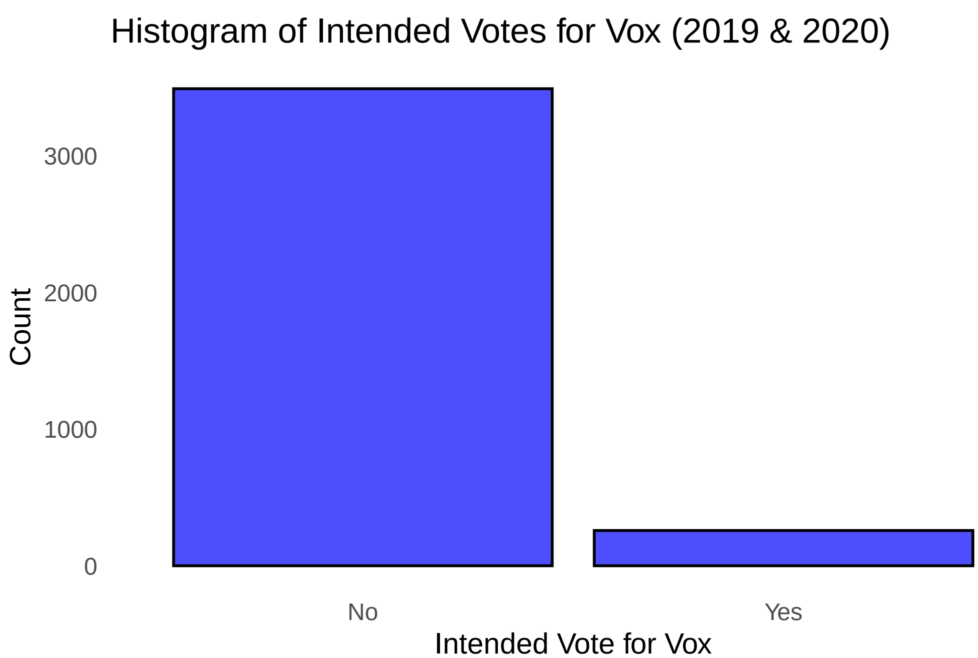
This study specifically examines the four survey waves conducted between 2017 and 2020, as these waves include the modern sexism battery, which is central to the analysis. Key to the analysis was the collection of the first wave of data before the first massive feminist movement and the second wave before the rise of the far-right party Vox.

Dependent Variable: Vote for Vox

The dependent variable in this study is binary – the intention to vote for Vox, coded as 1, with all other responses, including non-responses and nonvoters, coded as 0. This measure is based on respondents' answers to the question, "Which party would you vote for if the general elections were tomorrow?" The authors chose to analyze voting intention rather than past voting behavior to capture respondents' support for Vox at the exact moment of their interview. Given that Vox did not gain significant traction until late 2018, the analysis of voter intention is restricted to the 2019 and 2020 waves of the survey.

The dataset initially comprised 7,850 observations for vote intentions. However, after filtering the data to include only the years 2019 and 2020, the total number of observations was reduced to 3,491. Within this subset, 258 observations (approximately 7.39%) correspond to votes for Vox, the dependent variable of interest, while the remaining 3,233 observations (approximately 92.61%) represent votes for other political parties in Spain.

```
{r} # table(data_2020$vim_vox) #
```




```
   0    1
3491  258
```

The histogram above, which depicts intended votes for Vox (coded as 1 for "Yes" and 0 for "No"), continues to show a binary distribution, with a significantly higher frequency of 0s (non-Vox voters) compared to 1s (Vox voters). This refined approach provides a more precise assessment of Vox's appeal during its period of rising popularity.

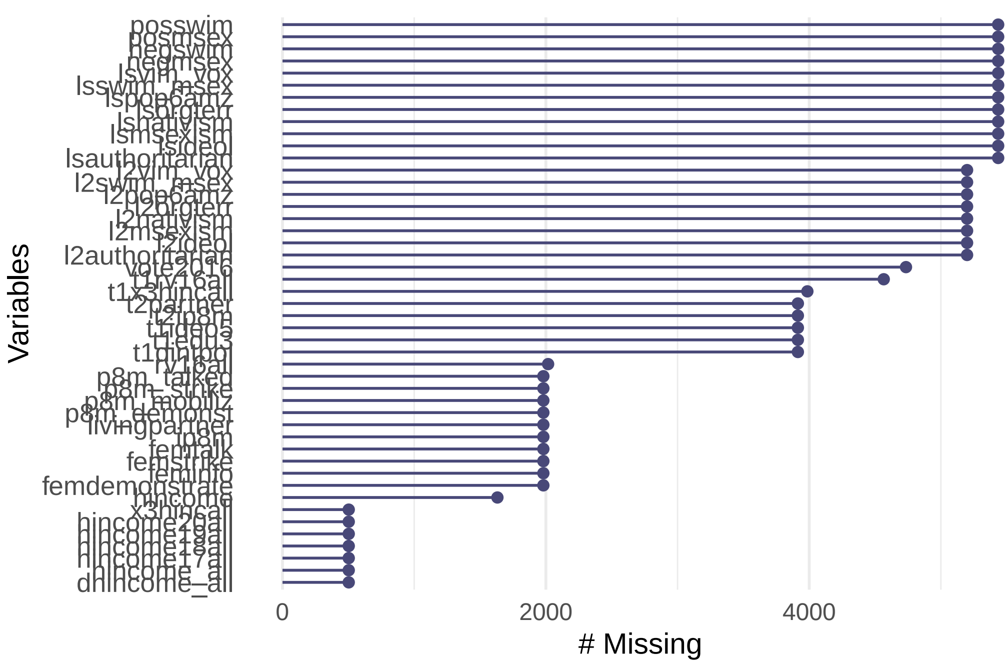
Plot and Distribution:

The dataset comprises a total of 7,850 observations for vote intentions, of which 299 instances (approximately 3.81%) correspond to votes for Vox, the dependent variable of interest, while the remaining 7,551 observations (approximately 96.19%) represent votes for other political parties in Spain. The histogram above, which represents the intended vote for Vox (coded 1 for Yes, 0 for No), shows a binary distribution, with a higher frequency of 0s (non-Vox voters) compared to 1s (Vox voters).

Data Cleaning and Missing Data

- Income (missing values imputed from other waves)
- na.rm = True a lot for NAs
- The (.=.) part ensures that missing values (.) in the original variables are preserved in the new variables. (under modern sexism scale)

```
[1] TRUE
```



Other Attitudinal Factors

Anduiza and Rico include a set of control variables to account for potential confounding factors leading to a vote for the far right. These factors included **General ideological identification**, measured on an 11-point left–right scale; **Authoritarianism**, assessed using a 4-item battery based on childrearing values (Feldman and Stenner 1997); **Nativism**, which evaluates attitudes toward the economic and cultural impacts of migration; **Populist attitudes**, operationalized using the framework developed by Akkerman, Mudde, and Zaslove (2014); and **Territorial preferences**, where higher values indicate stronger support for decentralization. Additionally, the model controlled for sex, age, education (middle school or less, high school/vocational training, college), whether the respondent lives with a partner, household income (a scale with 12 intervals), and a 4-point measure of interest in politics. With the exception of age (in years), all variables were recoded to run from zero to one.

Model: Table 1

My analysis will be replicating Table 1 "Predictors of Intention to Vote for Vox in 2019 and 2020" (pg.487). The authors hope to achieve a descriptive analysis in this paper, assessing how sexist attitudes, alongside other factors typically associated with voting for the far-right, are associated with support for Vox.

Table 1 displays the the estimates of **two cross-sectional logit models** of intended vote for the 2019 and 2020 waves, respectively:

$$vox_{it} = sexism_{it} + other\_attitudes_{it} + controls_{it}$$

where i indexes individuals and t as time (wave); $other\_attitudes_{it}$ encompasses measures of ideology, authoritarianism, nativism, territorial preferences, and populism; and the controls include sex, age, education, income, living with a partner, and interest in politics.

Reproduction of Predictors of Intention to Vote for Vox in 2019 and 2020

	Dependent variable:	
	vim	
	2019	2020
	(1)	(2)
female	0.118	-0.145
	(0.277)	(0.220)

age	0.004	-0.009
	(0.016)	(0.010)
factor(edu3)2	-0.716	0.198
	(0.442)	(0.286)
factor(edu3)3	-0.075	0.080
	(0.300)	(0.256)
dhincome_all	-0.529	-0.061
	(0.575)	(0.446)
livingpartner	0.192	0.018
	(0.301)	(0.231)
intpol	0.634	0.915**
	(0.478)	(0.364)
authoritarian	-0.499	0.136
	(0.540)	(0.408)
ideol	5.497***	4.965***
	(0.729)	(0.587)
nativism	2.646***	2.280***
	(0.655)	(0.564)
orgterr	-1.314**	-1.905***
	(0.528)	(0.398)
pop6amz	0.894	1.418**
	(0.741)	(0.625)
msexism	4.159***	2.983***
	(0.749)	(0.583)
Constant	-9.712***	-8.419***
	(1.189)	(0.829)
Observations	1,651	1,972
Log Likelihood	-230.096	-360.017
Akaike Inf. Crit.	488.192	748.034

```
=============================================
Note:              *p<0.1; **p<0.05; ***p<0.01

Reproduction of Predictors of Intention to Vote for Vox in 2019 and 2020
=
n
-
```

![**Author's Table 1 reflects the same results as my table above.**]

The models indicate that the effects of the attitudinal variables align with the authors' expectations: support for Vox was positively associated with right-wing ideology, sexism, nativism, and populist attitudes (with the latter reaching statistical significance only in 2020), while it is negatively associated with attitudes favoring decentralization. Among these factors, modern sexism has the second-largest impact, surpassed only by ideological orientation. When holding all other variables constant at their observed values, individuals in the 95th percentile of the sexism scale are 8.6 percentage points (in 2019) and 9.9 percentage points (in 2020) more likely to express an intention to vote for Vox compared to those in the 5th percentile. This reiterates the authors' argument that sexism plays a prominent role in an intention to vote for the far-right party, Vox.

Additional Models

Different Link Functions

In my analysis, I chose to focus specifically on the 2020 data from Table 1 to simplify the comparison of the models. I fit two additional models to the original – a probit and a cloglog model on the same dependent variable and covariates.

My primary aim was to investigate whether altering the link function from logit to probit or cloglog resulted in any measurable differences in performance. This exploration was driven by an interest in understanding the comparative behavior of probit, logit, and cloglog models when applied to binary data, particularly in terms of their predictive accuracy and suitability for the dataset.

Specifically, I was interested in the cloglog to anlayze instances of rare events in binary data. Given the low frequency of "1"s in the dependent variable (a vote for Vox), I hypothesized that rare events might be a significant feature of my dataset. By incorporating the cloglog, I aimed to ensure that the analysis could effectively capture and model the infrequent occurrences of the event of interest, providing a more robust evaluation of the data. #### Probit and ClogLog:

Reproduction of Predictors of Intention to Vote for Vox in 2020

	Dependent variable:		
	vim		
	logistic	probit	glm: binomial link = cloglog
	2020 Logit	2020 Probit	2020 Cloglog
	(1)	(2)	(3)
female	-0.145	-0.051	-0.149
	(0.220)	(0.111)	(0.186)
age	-0.009	-0.007	-0.009
	(0.010)	(0.005)	(0.009)
factor(edu3)2	0.198	0.119	0.065
	(0.286)	(0.144)	(0.250)
factor(edu3)3	0.080	0.005	0.149
	(0.256)	(0.130)	(0.216)
dhincome_all	-0.061	-0.013	-0.115
	(0.446)	(0.228)	(0.374)
livingpartner	0.018	0.0004	-0.041
	(0.231)	(0.116)	(0.198)
intpol	0.915**	0.534***	0.839***
	(0.364)	(0.188)	(0.302)
authoritarian	0.136	0.151	0.073
	(0.408)	(0.206)	(0.349)
ideol	4.965***	2.363***	4.142***
	(0.587)	(0.303)	(0.470)
nativism	2.280***	1.363***	1.843***
	(0.564)	(0.292)	(0.466)
orgterr	-1.905***	-0.879***	-1.712***
	(0.398)	(0.194)	(0.353)

```
pop6amz             1.418**     0.783**      1.297**
                    (0.625)     (0.321)      (0.527)

msexism             2.983***   1.588***      2.219***
                    (0.583)     (0.305)      (0.482)

Constant           -8.419***  -4.483***     -7.240***
                    (0.829)     (0.416)      (0.684)

-------------------------------------------------------
Observations         1,972       1,972        1,972
Log Likelihood     -360.017   -363.769      -361.747
Akaike Inf. Crit.  748.034     755.537      751.494
=======================================================
Note:                        *p<0.1; **p<0.05; ***p<0.01
```

In Sample Comparison of Models

As shown in the table above, the original logit model outperforms both the probit and cloglog models. The logit model has the lowest AIC value, which suggests better in-sample performance. The cloglog model ranks second in terms of AIC, while the probit model ranks third for in- sample performance, however the relative difference in performance is negligible. Furthermore, the logit model achieves the highest log-likelihood value, further confirming its better performance. These results indicate that the original logit model is the most effective among the three for this dataset.

When testing out these models in out of sample performance in cross validation, I frequently received NA values for the MSEs. I believe this is due to the low number of 1's in my data set compared to 0's (with 1846 0's and 162 1's in the year 2020) leading to perfect separation in my sample. To remediate this issue, I decided to combine the years 2019 and 2020 in my models to allow them to train on more data.

Simpler Model

```
Loading required package: lattice
```

```
Attaching package: 'caret'
```

```
The following object is masked from 'package:survival':

    cluster
```

```
Mean MSE for t1simp: 0.05146221 (SE: 0.006039902 )
```

```
Mean MSE for t1m2: NA (SE: NA )
```

Cross Validation on simple model

I tried CV with both 2019 and 2020 data

```
    Model MSE
1   Logit  NA
2  Probit  NA
3 Cloglog  NA
```

Out of Sample Performance: 10-Fold Cross Validation

There is evidence of perfect separation in my dataset.

I tried CV with just 2020 data and stratifying the folds.

```
    Model MSE
1   Logit  NA
2  Probit  NA
3 Cloglog  NA
```

2. Multiplicative relationship

I decided to look at the multiplicative relationship between nativism and modern sexism because these beliefs tend to coincide as predictors of rightwing support. If someone is nativist but not high in msexism, they might support another party, however with both they are likely to support far right.

include another predictor variable that author didn't use.

try gender * msexism - I think men are more likely to be sexist lol

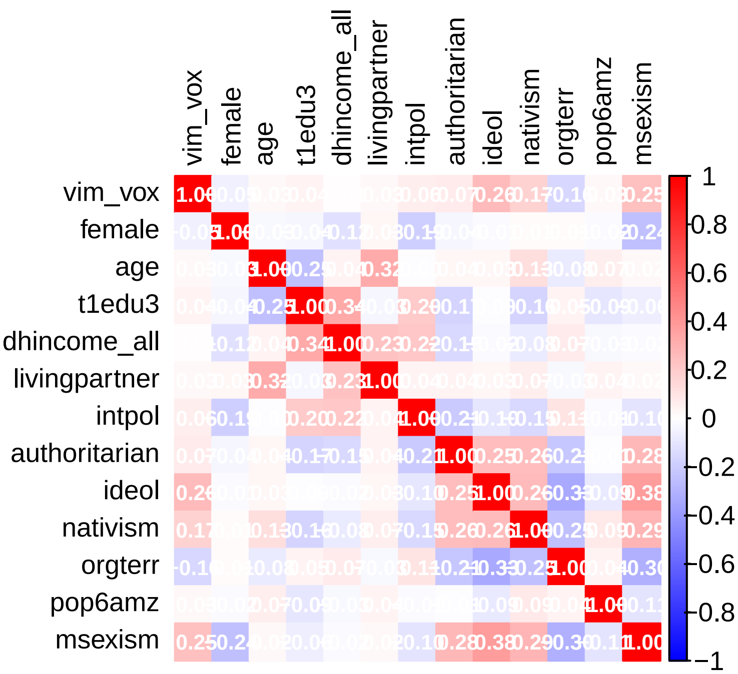
Reproduction of Predictors of Intention to Vote for Vox in 2019 and 2020

	Dependent variable:			
	vim			
	2019 Logit	2019 Multiplicative Nativism * Sexism	2020 Logit	2020 Nativism *
	(1)	(2)	(3)	(4)
female	0.118	0.121	-0.145	-0.137
	(0.277)	(0.277)	(0.220)	(0.219)
age	0.004	0.004	-0.009	-0.010
	(0.016)	(0.016)	(0.010)	(0.010)
factor(edu3)2	-0.716	-0.708	0.198	0.202
	(0.442)	(0.441)	(0.286)	(0.285)
factor(edu3)3	-0.075	-0.076	0.080	0.086
	(0.300)	(0.299)	(0.256)	(0.255)
dhincome_all	-0.529	-0.546	-0.061	-0.061
	(0.575)	(0.575)	(0.446)	(0.445)
livingpartner	0.192	0.195	0.018	0.025
	(0.301)	(0.300)	(0.231)	(0.230)
intpol	0.634	0.651	0.915**	0.930**
	(0.478)	(0.478)	(0.364)	(0.364)
authoritarian	-0.499	-0.513	0.136	0.149
	(0.540)	(0.540)	(0.408)	(0.408)
ideol	5.497***	5.485***	4.965***	4.911**
	(0.729)	(0.731)	(0.587)	(0.587)
nativism	2.646***	3.572*	2.280***	4.047**
	(0.655)	(1.933)	(0.564)	(1.541)
orgterr	-1.314**	-1.321**	-1.905***	-1.907**
	(0.528)	(0.528)	(0.398)	(0.397)
pop6amz	0.894	0.897	1.418**	1.410**

	(1)	(2)	(3)	(4)
	(0.741)	(0.741)	(0.625)	(0.622)
msexism	4.159***	5.388**	2.983***	5.178**
	(0.749)	(2.533)	(0.583)	(1.884)
nativism:msexism		-1.699		-3.214
		(3.328)		(2.595)
Constant	-9.712***	-10.359***	-8.419***	-9.571**
	(1.189)	(1.752)	(0.829)	(1.266)
Observations	1,651	1,651	1,972	1,972
Log Likelihood	-230.096	-229.966	-360.017	-359.248
Akaike Inf. Crit.	488.192	489.932	748.034	748.496

Note: *p<0.1; **p<0.05; **

A correlation matrix for the DV and IVs that the original authors included in the model you are replicating



Cross Validation

Interpretive Exercise (Scenarios) for the better model

- explain why you chose the values you did?
- Women - more likely to vote for vox? or less? M vs. F?
-

Limitations

The authors mention "We, thus, cannot rule out that Vox voters' opinions on women's discrimination are actually a consequence, rather than a cause, of their partisan preferences." (pg. 486)

Evaluate both models and come to a conclusion based on the

Use cross validation to get out of sample error for OG and your new model –> based on what I did, my new model doesn't really add anything to the outcome

not trying to overturn the author's original findings. or find a better model

Citations:

Swim et al (1995) Stargazer Library

AI Appendix Statement (update this):

- I used ChatGPT LLM/AI tool in this assignment.
- I used it to help write the code for the plots.
- I found it helpful in getting the results I was looking for and understanding the concept of a correlation matrix. Also helped with converting DTA to CSV
- Link: https://chatgpt.com/share/67af9007-561c-800f-9f0f-367b9f306c7e

Link2: https://chatgpt.com/share/67af908c-6de0-800f-aca5-1a1cdb82be69

Link3: https://chatgpt.com/c/67c76a1c-e874-800d-84f0-e5ddc106c044

Link4: