Replication of ‘Sexism and the Far-Right Vote: The Individual Dynamics of Gender Backlash’ (Anduiza & Rico, 2022)

Reeka Estacio and Belynda Herrera

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Introduction

The study “Sexism and the Far-Right Vote: The Individual Dynamics of Gender Backlash” by Eva Anduiza and Guillem Rico (2022), published in the American Journal of Political Science (AJPS), examines the relationship between sexist attitudes and support for far-right political parties. The authors argue that gender backlash—a reactionary response to perceived advances in gender equality—plays a crucial role in shaping voting behavior.

Using survey data collected between 2017 and 2020, the original study investigates whether changes in sexism over time are associated with increased support for Vox, a far-right party in Spain. The authors hypothesize that individuals who express greater sexist attitudes over time are more likely to support the far-right, reflecting a broader trend of gendered political polarization.

Original Study

The unit of analysis in the dataset used in the original study is individual survey respondents. Each row in the dataset represents an individual who participated in the survey, providing responses on their political preferences, sexist attitudes, and demographic characteristics over multiple time periods. The data was collected before and after key political events (e.g., elections, feminist protests) to capture potential shifts in attitudes and voting behavior. The cleaned dataset that the authors ultimately used in their analysis (which we also use in our analysis) consists of 123 observations.

Observational independence concerns exist because the longitudinal dataset (2017-2020) introduces within-subject correlation as the same individuals were tracked over time. Respondents may modify their self-reported sexism and political preferences based on social norms, creating measurement bias. Additionally, major events like #MeToo and Women’s Day protests likely influenced responses across the sample simultaneously, creating time-based dependencies.

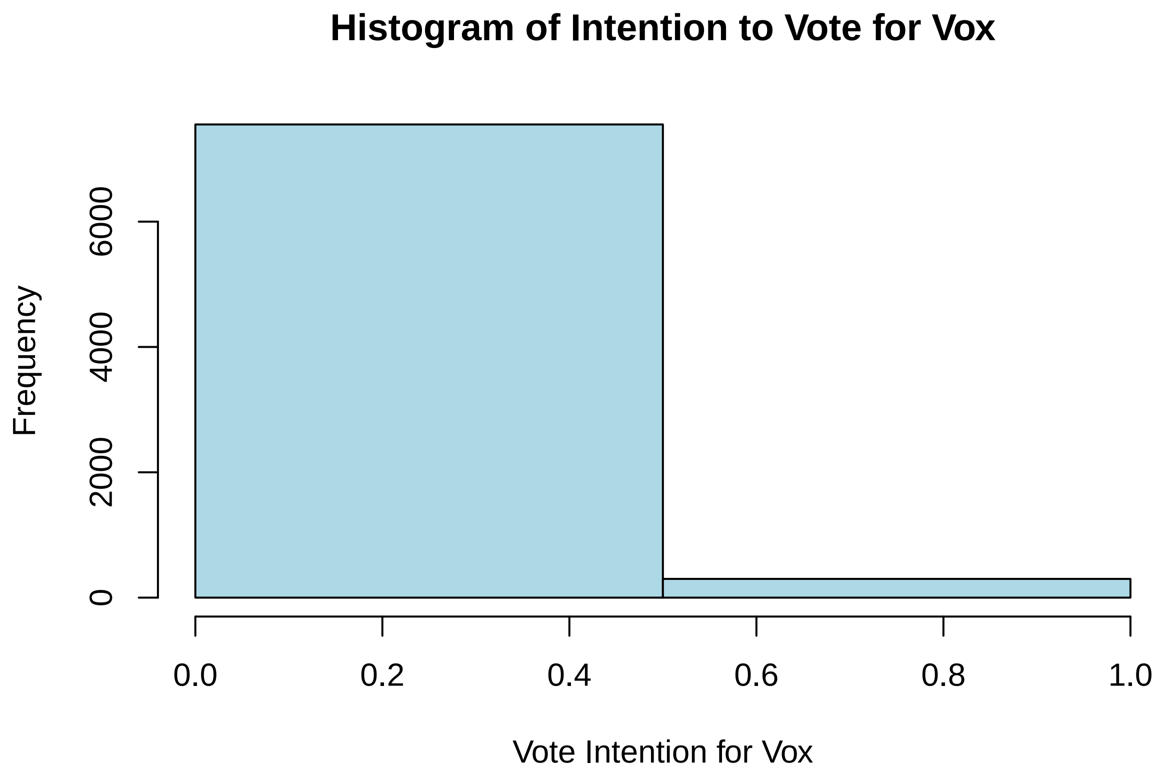
Original Model

The original authors fit two logistic regression (logit) models predicting intention to vote for the Vox party for 2019 and 2020 (Table 1: Predictors of Intention to Vote for Vox in 2019 and 2020).In the study, they describe the linear predictor as:

$$vox_{it} = sexism_{it} + otherattitudes_{it} + controls_{it}$$

where i refers to individuals and t refers to wave (2019 or 2020). For the purposes of the current analysis, we will only consider the $t = 2019$ wave.

The dependent variable of the model is `vim_vox`. This is a binary variable indicating a person’s intention to vote for the Vox party. The histogram below depicts the distribution of this variable.



The study examines several predictors to explain support for far-right parties, with a focus on sexist attitudes as the central explanatory variable. Specifically, "other attitudes" in the linear predictor refers to ideology, authoritarianism, nativism, territorial preferences, and populism variables. "Controls" refers to the variables of sex, age, education, income, living with a partner, and interest in politics.

Replication of Original Model

As in the original model, we fit a logistic regression predicting `vim_vox` for the 2019 wave,indicating the intention to vote for the Vox party, with all the original predictors.

The results are reported in Table 1. The coefficients match the ones reported in the original study.

Table 1: Replicated Original Model: Predictors of Intention to Vote for Vox in 2019

	(1)
Female	0.118
	(0.277)
Age	0.004
	(0.016)
High school / Vocational	-0.716
	(0.442)
College	-0.075
	(0.300)
Income	-0.529
	(0.575)
Lives with partner	0.192
	(0.301)
Interest in politics	0.634
	(0.478)
Authoritarianism	-0.499
	(0.540)
Ideological identification	5.497
	(0.729)
Nativism	2.646
	(0.655)
Territorial preference	-1.314
	(0.528)
Populism	0.894
	(0.741)
Sexism	4.159
	(0.749)
Num.Obs.	1651
AIC	488.2
BIC	563.9
Log.Lik.	-230.096
F	11.857
RMSE	0.20

Additional Model

For the new model, we attempted to fit a simpler model to test whether it performs just as well as the original model. We retained the control variables `female` and `age`, which we believe have a strong relationship with `vim_vox` (older, non-female individuals are more likely to support Vox).

From the original model, we also kept attitude predictors that likely have strong effects on voting behaviors. People with strong nationalist views were more likely to vote Vox (`nativism`). People against regional autonomy were less likely to vote for Vox (`orgterr`). People with more reported sexist attitudes (`msexism`) are more likely to vote for Vox. Table 2 shows the regression table for the new model.

Table 2: New Model: Predictors of Intention to Vote for Vox in 2019

	(1)
Female	0.257
	(0.257)
Age	0.003
	(0.014)
Nativism	2.832
	(0.609)
Sexism	5.243
	(0.689)
Territorial preference	-1.782
	(0.483)
Num.Obs.	1651
AIC	542.7
BIC	575.2
Log.Lik.	-265.357
F	26.785
RMSE	0.21

Comparing Models

In-Sample Prediction

To assess the performance of these models, we first compared the AIC and log likelihood reported in the regression tables.

```
## Original model AIC: 488.19
```

```
## New model AIC: 542.71
```

```
## Original model log likelihood: -230.1
```

```
## New model log likelihood: -265.36
```

The original model shows lower AIC, indicating that it performs better than the new model on in-sample prediction. The original model also has a greater log likelihood than the new model, suggesting that it explains more of the variance than the new model.

We then performed a likelihood ratio test between the original and new model. The test shows a significant difference between the models ($p < 0.001$), reinforcing the conclusion that the original model results in better fit.

Out-of-Sample Prediction

To assess out-of-sample prediction, we used a 10-fold cross-validation method and compared accuracy.

```
## Original model CV accuracy: 0.9473
```

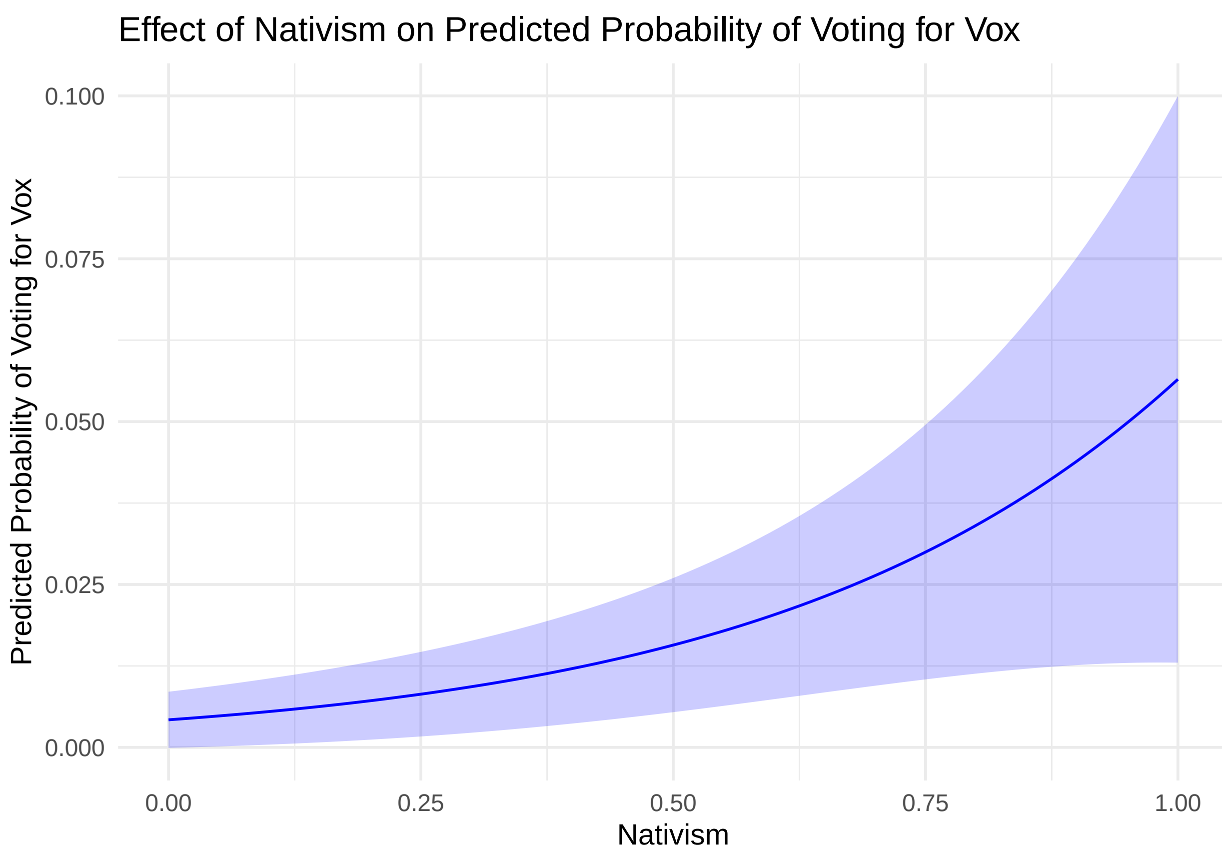
```
## New model CV accuracy: 0.9461
```

The original model shows a slightly higher accuracy than the new model on out-of-sample prediction. However, both models do relatively well.

Based on both the in-sample and out-of-sample prediction diagnostics we examined, we select the **original model** as the better of the two models. The original model shows lower AIC, greater log likelihood, and explains more of the variance within the data. It also performs slightly better than the new model in out-of-sample prediction.

Exploring the Effect of Nativism Predictor on Intention to Vote for Vox

Using the original model, we aim to explore the effect of `nativism` on intention to vote for Vox for the 2019 wave (`vim_vox`). We chose this variable because as the original study suggests, nativist attitudes seem to strongly align with the political beliefs associated with the Vox party.



Interpreting this plot, we see that nativism has an overall positive relationship on intention to vote for the Vox party. In other words, individuals with stronger nativist beliefs are more likely to vote for Vox based on the data. The 95% confidence interval, however, significantly widens at higher levels of nativism, indicating greater uncertainty around these predictions.

Summary

In summary, our current analysis supports the idea that the original model is so far the best model for predicting intention to vote for the Vox party for the 2019 wave. Simplifying the model does not seem to improve in-sample fit or out-of-sample prediction to the data. Our analysis also supports the original authors' conclusion that nativism is a key positive factor that increases the likelihood of a person voting for Vox. For further exploration, we could have included the 2020 wave and examined whether this model performs relatively better or poorer with the predictors of the simpler model. This could give insight into whether the issues associated with Vox have gotten more complex over time. Additionally, there are more variables in the dataset and possible interaction effects that could result in a more accurate model.

Appendix

We used ChatGPT to troubleshoot errors that came up when trying to run model evaluation diagnostics. When trying to perform the likelihood ratio test, for instance, it was resulting in an error about dataset size that we could not figure out. This was helpful because it helped us find a general solution that worked for this problem, as well as other problems down the road.

Link to conversation