

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

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## **Summary:**

This reproduction of the paper **‘Sexism and the far-right vote: The Individual dynamics of gender backlash by Eva Anduiza & Guillem Rico’** examines how sexism has played a role the electoral rise of the far-right party, Vox, in Spain. Anduiza and Rico (2024) argue that having sexist beliefs is one of the most influential attitudinal predictors of voting for the far-right party Vox in 2019 and 2020.

This paper replicates the authors’ original findings of the logistic regression model displayed in Table 1 (Anduiza and Rico 2024, 478). Then, it expands on the analysis to fit two other similar models (a probit and a cloglog) to compare their performance against the authors’ original model, using both in-sample and out of sample cross validation to assess their performance. Lastly, it expands on the authors’ original findings by presenting a scenario in which the relationship between sexism, gender, and voting behavior can be further explored.

## **Background**

The main intention of this paper is to examine the role of sexist beliefs in the intention to vote for Vox, a far-right political party in Spain. Based on the previous literature, the authors hypothesized that voters that identify more with sexist attitudes are more likely to vote for far right parties, such as Vox (Anduiza and Rico 2024).

## **Data**

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 data comprises of 7,850 observations and the unit of analysis is individual voters in Spain. 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, which reduces the number of observations to 3,491.

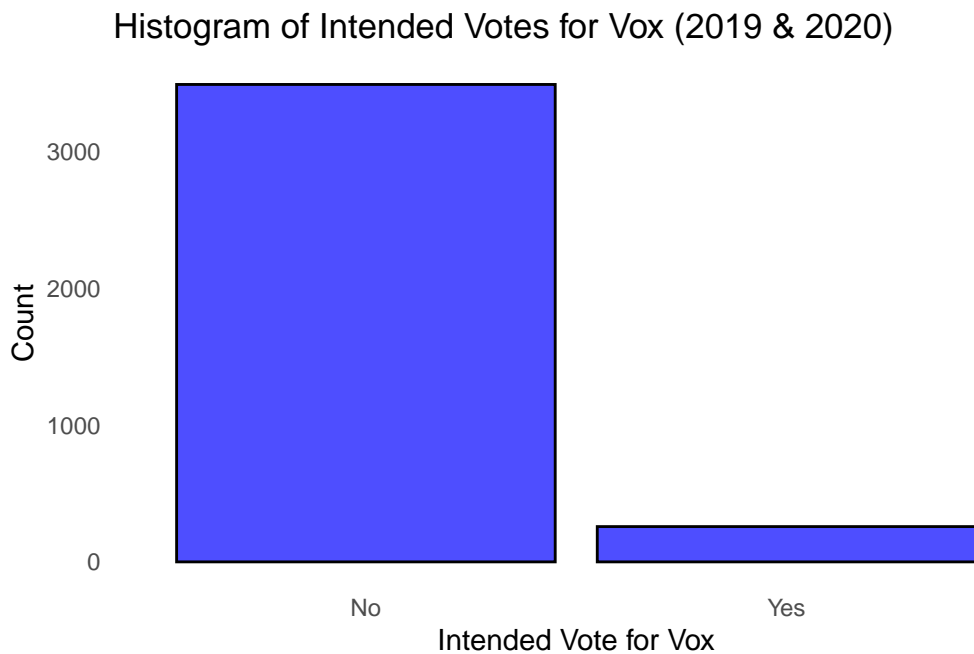
Observational independence could be questioned in this data set due to the longitudinal design (repeated observations) and the geographic clustering of like-minded voters in specific regions, as well as demographic factors such as age, gender, and education.

## **Dependent Variable: Votes 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.

The distribution of the dependent variable is binary, with 258 observations (approximately 7%) corresponding to votes for Vox, the dependent variable of interest, while the remaining 3,491 observations (approximately 93%) represent votes for other political parties in Spain. While not necessarily a rare event, the low number of 1’s indicating a intention to vote for Vox (258 total) is something to consider when assessing model performance.



### **Missing Data:**

The authors do not explicitly remove rows with missing values (NA) entirely from the dataset. Instead, they handle missing data on a variable-by-variable basis, often using imputation or recoding strategies to retain as much data as possible.

## Replication of Table 1: Cross-Sectional Logit

My analysis will be replicating Table 1 “Predictors of Intention to Vote for Vox in 2019 and 2020” (Anduiza and Rico 2024, 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.

Based on the logistic regression results presented in Table 1, 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. This reiterates the authors’ argument that sexism plays a prominent role in an intention to vote for the far-right party, Vox.

Table 1: Logistic Regression results match those of the original authors. This table shows support for Vox positively associated with sexist beliefs.

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

	Dependent variable:	
	-----	
	vim	
	2019	2020
	(1)	(2)
-----		
female	0.118 (0.277)	-0.145 (0.220)
age	0.004 (0.016)	-0.009 (0.010)
factor(edu3)2	-0.716 (0.442)	0.198 (0.286)
factor(edu3)3	-0.075 (0.300)	0.080 (0.256)
dhincome_all	-0.529 (0.575)	-0.061 (0.446)
livingpartner	0.192 (0.301)	0.018 (0.231)
intpol	0.634 (0.478)	0.915** (0.364)
authoritarian	-0.499 (0.540)	0.136 (0.408)
ideol	5.497*** (0.729)	4.965*** (0.587)
nativism	2.646*** (0.655)	2.280*** (0.564)
orgterr	-1.314** (0.528)	-1.905*** (0.398)
pop6amz	0.894 (0.741)	1.418** (0.525)
msexism	4.159*** (0.749)	2.983*** (0.583)
Constant	-9.712*** (1.189)	-8.419*** (0.829)

## **Additional Models**

### **Reduced Logit, Probit and ClogLog**

I extended the original logit model by fitting two additional models: a probit model and a cloglog model, both using the same dependent variable, vote for Vox. Beyond changing the link function (to probit and cloglog), I narrowed the analysis to the 2020 data from Table 1 to simplify the comparison across models by focusing on a single year. Additionally, I encountered issues when running ROC and cross-validation analyses due to missing values (NAs) in the `dhincome_all` variable, which was included in the original model. To address this, I removed the variable from the analysis.

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 analyze 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.

### **In Sample Performance**

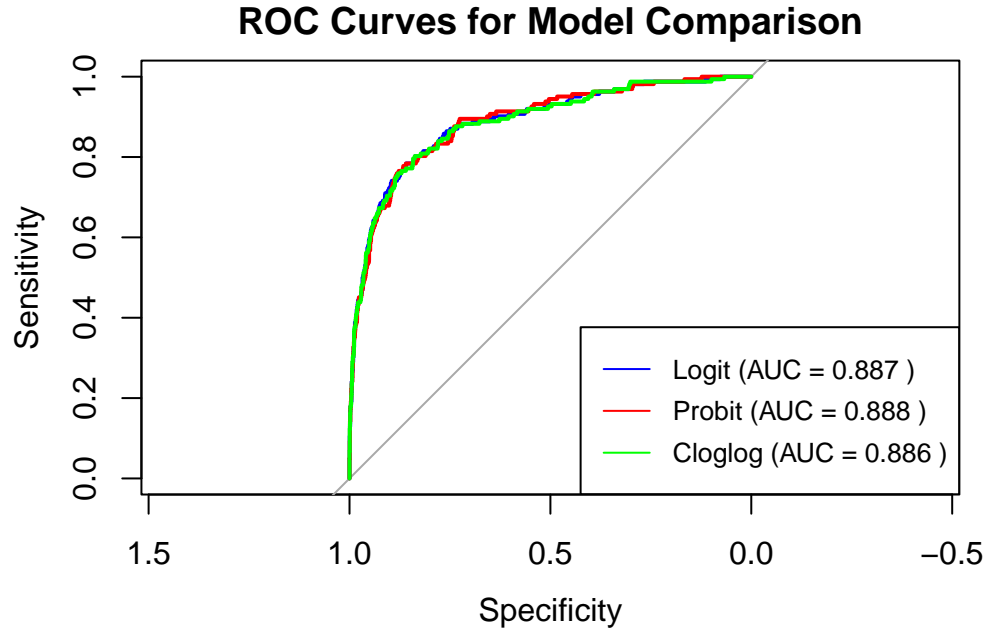
As shown in Table 2, the logit model outperforms both the probit and cloglog models. The logit model has the lowest AIC value, which suggests better in-sample performance. The cloglog model ranks second in terms of AIC, while the probit model ranks third for in-sample performance, however the relative difference in performance is negligible, as seen in the ROC

Table 2: Logit vs. Probit vs. ClogLog Model. Varying the link function does little to change the performance of the model

Reproduction of Predictors of Intention to Vote for Vox in 2020

	Dependent variable:		
	-----		
	vox		
	logistic	probit	glm: binomial link = cloglog
	2020 Logit	2020 Probit	2020 Cloglog
	(1)	(2)	(3)
-----			
female	-0.150 (0.216)	-0.054 (0.109)	-0.154 (0.183)
age	-0.010 (0.010)	-0.008 (0.005)	-0.010 (0.009)
factor(edu3)2	0.169 (0.283)	0.104 (0.142)	0.031 (0.246)
factor(edu3)3	0.068 (0.235)	0.003 (0.119)	0.126 (0.199)
livingpartner	0.049 (0.224)	0.017 (0.113)	-0.023 (0.192)
intpol	0.893** (0.362)	0.523*** (0.187)	0.814*** (0.300)
authoritarian	0.110 (0.406)	0.141 (0.205)	0.057 (0.348)
ideol	5.080*** (0.584)	2.421*** (0.302)	4.238*** (0.467)
nativism	2.303*** (0.564)	1.373*** (0.292)	1.868*** (0.465)
orgterr	-1.903*** (0.396)	-0.879*** (0.193)	-1.709*** (0.351)
pop6amz	1.364** (0.622)	0.758** (0.320)	1.257** (0.524)
msexism	2.925*** (0.580)	1.559*** (0.303)	2.160*** (0.478)
Constant	-8.401*** (0.813)	-4.470*** (0.408)	-7.242*** (0.672)

Table 3: The ROC plot compares in-sample performance of logit, probit and cloglog. All three seem to have similar performance and a high rate of true positives, indicating good performance.



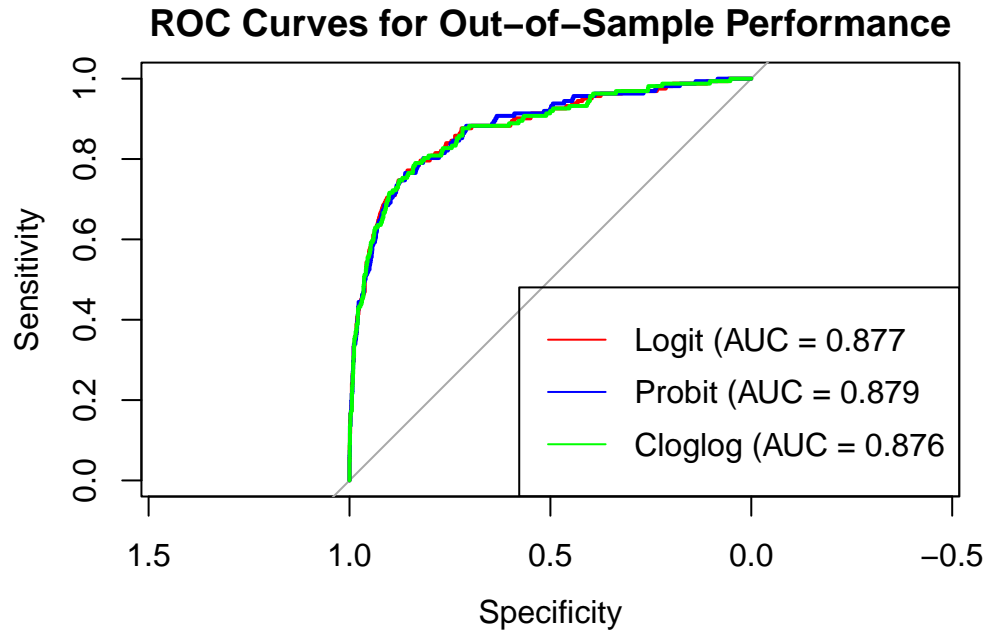
plot (Table 3). The AUC values in Table 3 are the same, indicating similar performance. Furthermore, the logit model achieves the highest log-likelihood value, further confirming its better performance. These results indicate that the original logit model is the most effective among the three for this dataset.

## Out of Sample Performance

Table 4 shows the outcome of 10-fold cross validation: the logit, probit and cloglog are nearly identical and closely match their in sample performance. The values of the AUC remain constant both in sample and out of sample, indicating that that models are not over fitting and perform similarly on unseen data. As seen in the in sample performance, changing the link function doesn't change the performance.



Table 4: The ROC plot compares out-of-sample performance of logit, probit and cloglog. All three seem to have similar performance and a high rate of true positives, indicating good performance and no evidence of overfitting.



	Model	AUC
1	Logit	0.88236 (0.01903)
2	Probit	0.88188
3	Cloglog	0.88101

## The Best Model

The best model for both in sample and out of sample performance is the authors' original logit model. This makes me more confident in their analysis and conclusions they made showing increased sexism makes a person more likely to vote for far-right party Vox.

## Expansion

### Scenario Construction

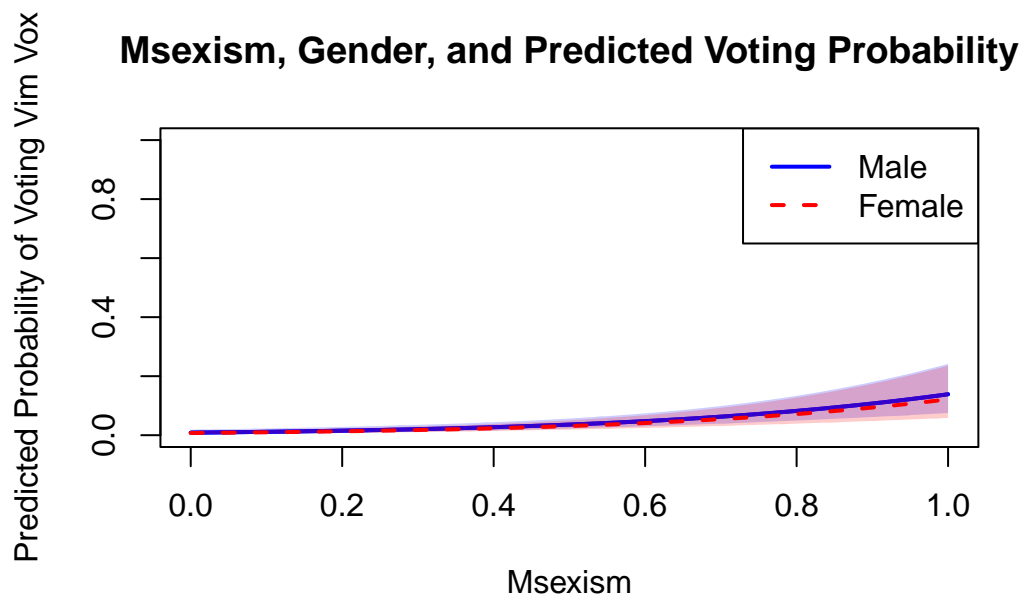
In the original study, the authors highlight the growing influence of sexist attitudes on election outcomes for far-right parties. While anti-feminism is not the central focus of Vox, the party has employed anti-feminist rhetoric, portraying feminists as “violent,” “radical,” and “communist,” while also denying the existence of discrimination against women (Anduiza and Rico 2024, 483). Based on this, the authors hypothesize that increasing levels of sexism among voters may contribute to the rise of Vox in Spain.

To explore this relationship further, I examined how sexist attitudes in `msexism` influence support for Vox between two genders, Male and Female. Using the best-performing model from the original study—the logistic regression model used in the original paper—I created two voter profiles: one male, one female while holding all other variables constant at their median values. These values allowed me to analyze how the likelihood of voting for Vox differs between genders based on how much they endorse sexist beliefs.

### Interpretation

Table 5 illustrates that as sexism increases, the predicted probability of voting for Vox rises slightly. This finding aligns with the authors’ original conclusions that sexism influences support for right-wing parties, though the effect appears less pronounced. The male (blue) and female (red) lines are nearly identical, indicating that modern sexism has a similar effect on voting behavior for both genders. This aligns with the authors’ original findings that gender did not play a significant role in a vote for Vox due to the low coefficient value. For low levels of `msexism` (close to 0), the predicted probability of voting Vox is very close to zero for both

Table 5: The plot shows the predicted probability of voting for Vim Vox based on msexism (modern sexism), with separate lines for males (blue, solid line) and females (red, dashed line) with 95% confidence intervals.



males and females. Therefore, we can interpret sexism as a predictor for voting for Vox, but gender does not significantly moderate this effect. Males and females with the same level of `msexism` have nearly the same probability of voting for Vox.

## Conclusion

Overall, the replication process strengthens confidence in the authors' conclusions. The original findings are robust to changes in model specification, and the additional analyses provide further insights into the relationship between sexism and far-right voting behavior. Future research may expand on these findings by considering longitudinal trends, interactions with other ideological factors, or examining the role of sexism in different political contexts. This study underscores the importance of attitudinal predictors in understanding far-right support and highlights the need for continued exploration of gendered political dynamics.

## Citations:

Anduiza, Eva, and Guillem Rico. 2024. "Sexism and the Far-Right Vote: The Individual Dynamics of Gender Backlash." *American Journal of Political Science* 68 (2): 478–493. <https://doi.org/10.1111/ajps.12759>.

Hernández Pérez, Enrique, Eva Anduiza Perea, Carol Galais González, Guillem Rico Camps, Jordi Muñoz Mendoza, María José Hierro Hernández, Roberto Pannico, Berta Barbet Porta, and Dani Marinova. 2021. "POLAT Project: Spanish Political Attitudes Panel Dataset (Waves 1–6)." Universitat Autònoma de Barcelona. <https://ddd.uab.cat/record/243399> (accessed September 13, 2021).

Hlavac, Marek. 2022. stargazer: Well-Formatted Regression and Summary Statistics Tables. Social Policy Institute, Bratislava, Slovakia.

## **AI Appendix**

- I used ChatGPT LLM/AI tool in this assignment.
- I used it to help troubleshoot errors in code, create plots and interpret results.
- I found it helpful in breaking down the results and providing clear understanding for how to evaluate models.

Link: <https://chatgpt.com/share/67d20de3-a52c-800d-be49-f64caef8f22f>