

Final Project - Replication of Fetzner (2019)

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1 Introduction

Political polarization has been a major issue in Western countries since the beginning of the 21st century. [Arzheimer \(2009\)](#) considered that: “research on the voters of the extreme right in Western Europe [had] become a minor industry”. This rise in popularity may be explained by different factors such as the backlash of globalization that made losers and winners ([Autor et al., 2016](#); [Colantone and Stanig, 2018](#)), but also the implementation of austerity measures led by governments in place ([Guriev and Papaioannou, 2022](#)).

The paper of [Fetzer \(2019\)](#) is the first one to show the causal effect between austerity measures led by the British government in the early 2010s on the Brexit vote in 2016. The author’s approach consists in estimating the rise in UK Independence Party (UKIP) votes - a populist pro-Brexit party created in 1993 - during the period 2000-2015 at the district level, controlling for socio-demographic characteristics of areas.

Our project is threefold. First, by using the original data and the pooled difference-in-differences strategy from [Fetzer \(2019\)](#), we try to replicate the result for the effect of austerity incidence at the district level measured by [Beatty and Fothergill \(2013\)](#) on UKIP vote share since 2010. Second, we do simulations with generated data mimicking the original data used by [Fetzer \(2019\)](#) to check the robustness of the difference-in-difference strategy. Third, we introduce a logit model and a probit model in our simulations by converting the outcome variable into a categorical ordered variable.

For the simulation part of our project, we build a data generating process with respect to the data from the replication package of [Fetzer \(2019\)](#). After inferring theoretical distributions of our variables of interests, we try to found similar estimates as in the original paper, in the case they have correct hypotheses. Then, in the logit part, we try to see if we still see a link between austerity incidence at the district level and the level of UKIP support.

2 Replication

More precisely, for the replication part we will estimates the following model with panel OLS regressions:

$$y_{i,r,t} = \alpha_i + \beta_{r,t} + \gamma \times \mathbb{1}(Year > 2010) \times Austerity_i + \epsilon_{i,r,t} \quad (1)$$

where:

- $y_{i,r,t}$ denotes UKIP vote share in council elections of district i , in region r , at time t
- α_i is a fixed effect that absorbs any time-invariant differences in political preferences or sentiment across districts

- $\beta_{r,t}$ are region-by-time fixed effects that capture nonlinear time trends specific to each of the 11 regions across the United Kingdom.
- γ measures the effect of the austerity incidence at the district level on the support for UKIP after 2010

The results found by [Fetzer \(2019\)](#) that we want to replicate are the following:

TABLE 1—THE IMPACT OF DIFFERENT AUSTERITY MEASURES ON SUPPORT FOR UKIP
ACROSS LOCAL, EUROPEAN, AND WESTMINSTER ELECTIONS

UKIP vote share in:	Overall (1)	TC (2)	CB (3)	CTB (4)	DLA (5)	BTX (6)
<i>Panel A. Local elections</i>						
$\mathbf{1}(\text{Year} > 2010) \times \text{Austerity}$	0.014 (0.003)	0.081 (0.013)	0.036 (0.044)	0.128 (0.036)	0.166 (0.031)	0.162 (0.086)
Average effect	6.460	7.116	2.587	0.9208	6.084	1.747
Standard deviation	1.747	1.903	0.3405	0.9960	2.028	0.9033
Mean of dependent variable	4.49	4.49	4.49	4.49	4.49	4.49
Local authority districts	345	346	346	346	346	346
Observations	3,260	3,263	3,263	3,263	3,263	3,263

The replication we did:

Table 1: Fetzer replication results

Dependent Variable:	pct_votes_UKIP
Model:	(1)
<i>Variables</i>	
Austerity * Post(2010)	0.0144*** (0.0027)
<i>Fixed-effects</i>	
District	Yes
Region-Year	Yes
<i>Fit statistics</i>	
Observations	3,260
R ²	0.82551
Within R ²	0.04136
<i>Clustered (District) standard-errors in parentheses</i>	
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>	

3 Simulation

For the simulation part, we generate an Austerity incidence variable at a district level, and a UKIP vote share variable at a district-region-year level.

3.1 Exploration of the Fetzer data

Exploring the Fetzer data, we elicit the following theoretical distributions for the outcome variable, the region-time fixed-effect, and the explanatory variable:

$$vote_pct_{i,r,t} \sim \Gamma(0.3, 8)$$

$$BD_{r,t} \sim \mathcal{N}(0, 0.97^2)$$

$$Austerity \sim \Gamma(2.7, 85)$$

3.2 Data Generating Process according to the exploration of the Fetzer data

We fix the distributions of region-year fixed effects and Austerity depending on the distributions we elicit from plotting the distributions of the Fetzer's variables.

Then, we generate the vote percentages from region-year fixed effects and from Austerity.

We also integrate an overall mean and an error term in the generation formula for vote percentages. The overall mean and the error term are allowed to varies until the distribution of generated vote percentages matches the distribution of vote percentages from the Fetzer data. Thus we generate our variables the following way:

$$BD_{r,t} \sim \mathcal{N}(0, 0.97^2)$$

$$Austerity \sim \Gamma(2.7, 85)$$

$$vote_pct_{i,r,t} = \beta_0 + \beta_1 \times \mathbb{1}(Year > 2010) \times Austerity_i + BD_{r,t} + \epsilon_{i,r,t}$$

Where we allow β_0 and $\epsilon_{i,r,t}$ to varies until the distribution of our $vote_pct_{i,r,t}$ matches the distribution from the Fetzer data.

We settle on :

$$\beta_0 = -4$$

$$\epsilon_{i,r,t} \sim \Gamma(0.3, 1.7)$$

3.3 Checking the distributions of our generated variables

To check whether our DGP is valid, we plot the distributions of the variables we generated against the distributions of the variables from Fetzer. The results are convincing for the region-time fixed-effects and for Austerity.

Figure 1: Generated region-time fixed-effects against Fetzer fixed-effects

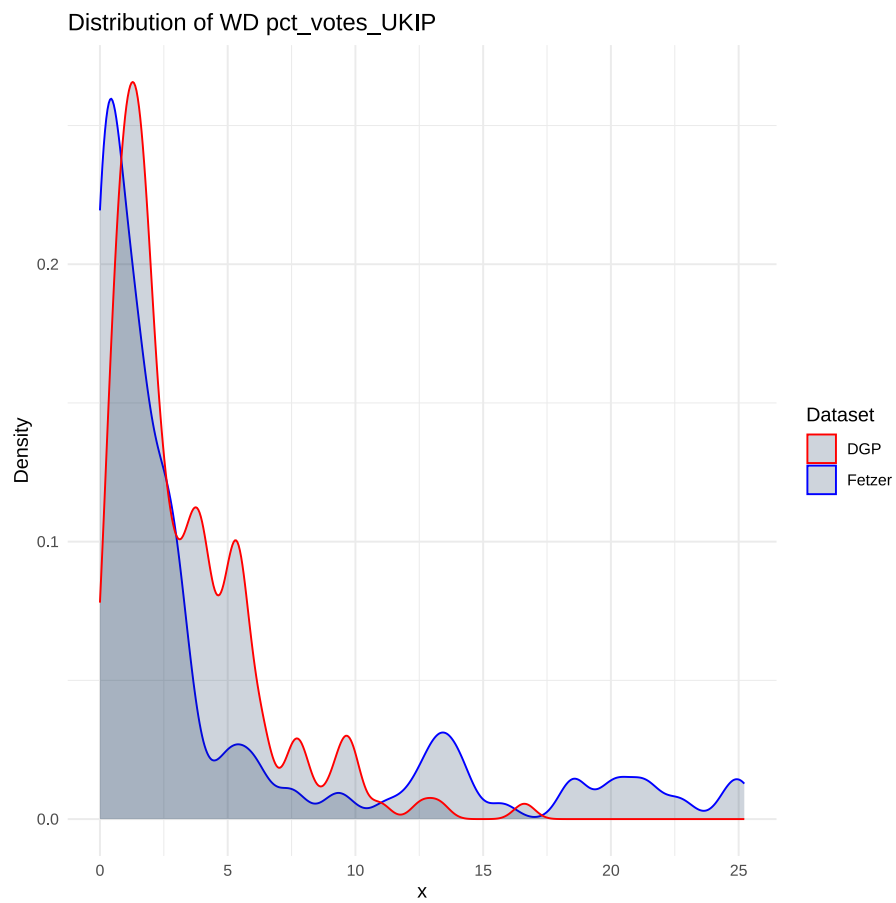
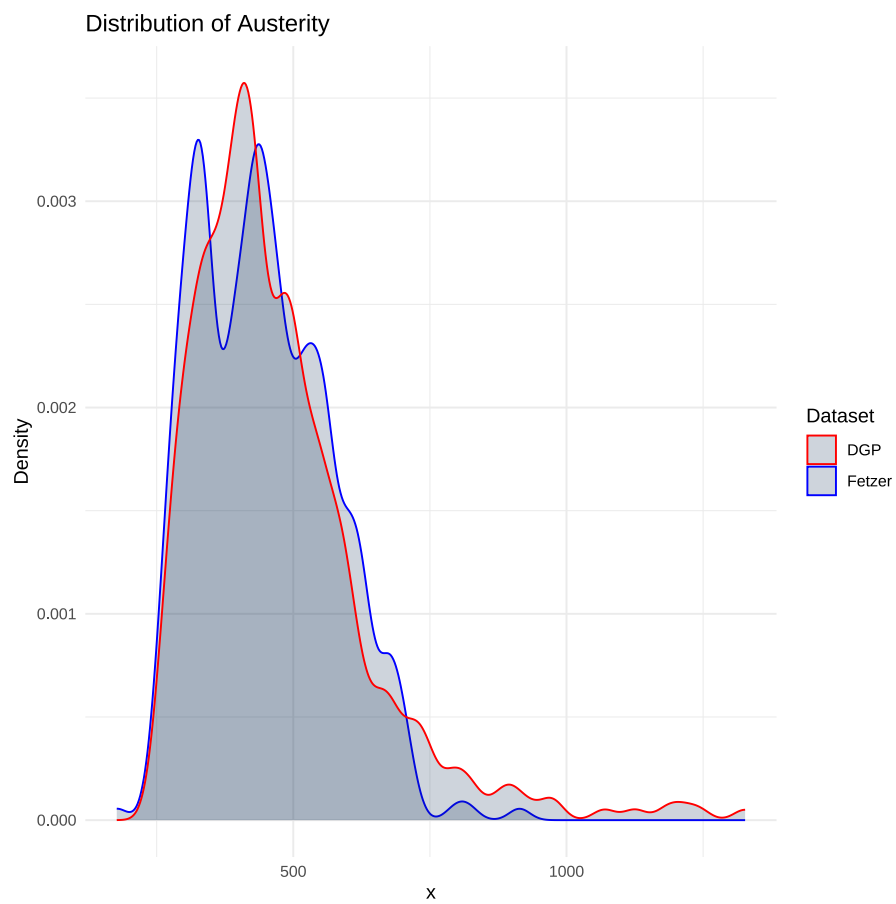


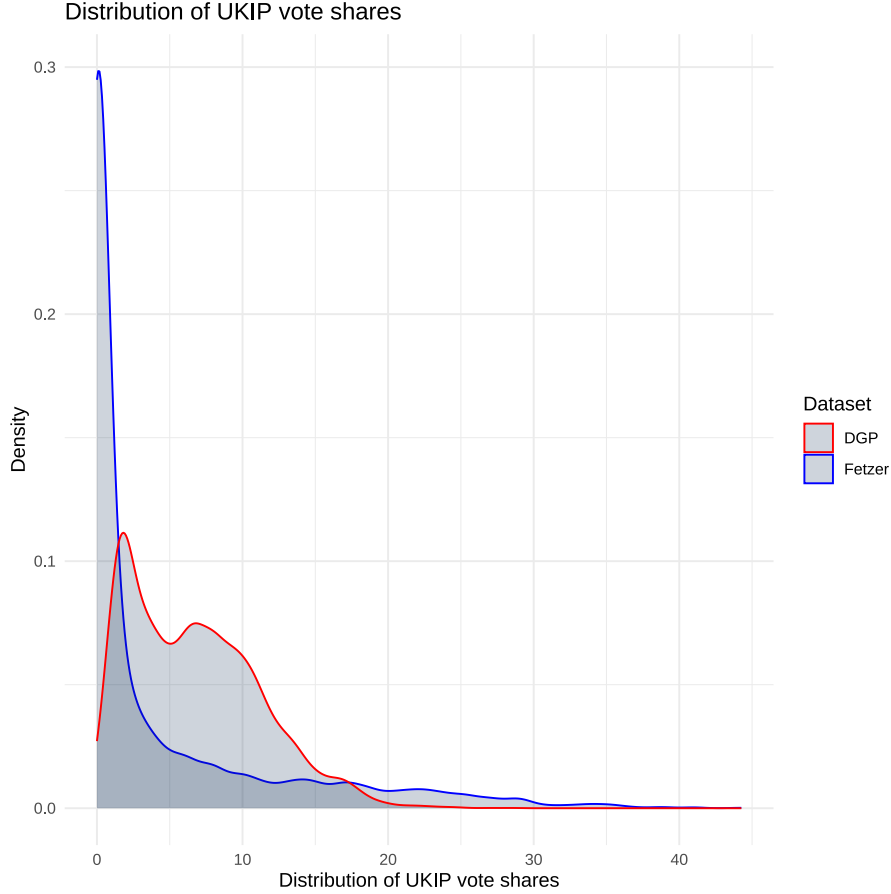
Figure 2: Generated Austerity against Fetzer Austerity



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However, whichever overall mean and error term we choose to generate vote percentages, we had not been able to mimic perfectly the vote percentages from Fetzer.

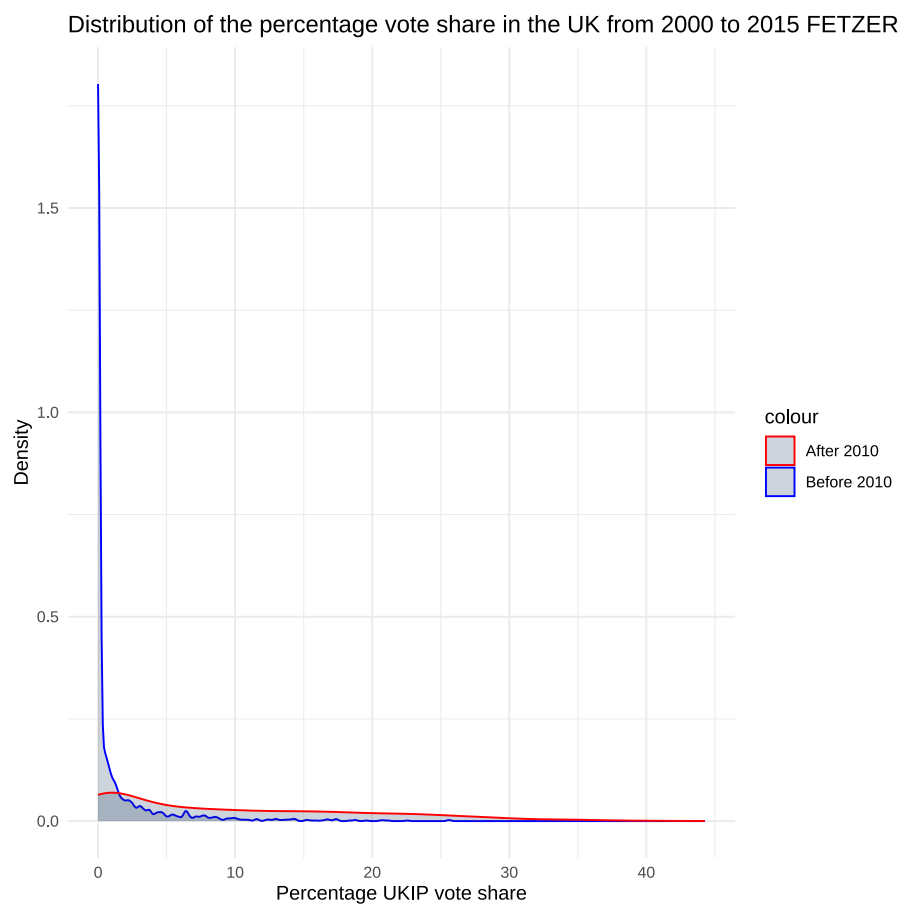
Figure 3: Generated vote percentages against Fetzer vote percentages



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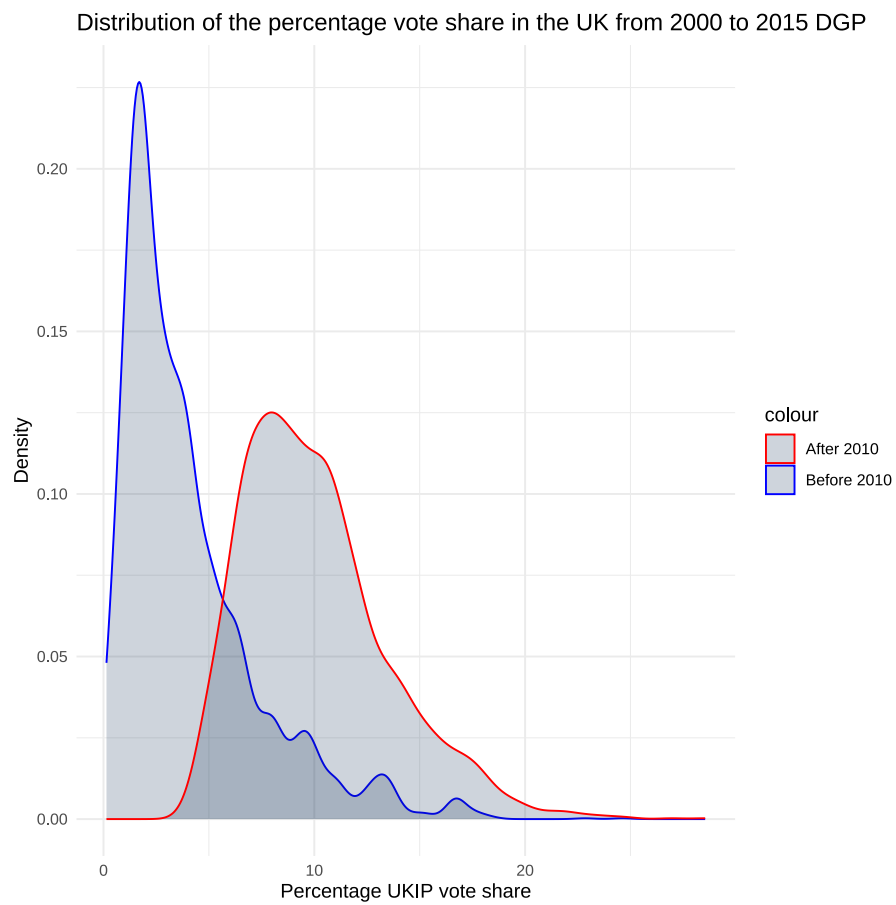
To better explain this, we dive into the temporal composition of vote percentages. We split vote percentages before and after 2010 - the date from which austerity is supposed to have an effect on the distribution of votes. We then compare the before and after distributions of votes from Fetzer (figure 4) to the before and after distributions of votes from our generated data (figure 5). We observe that before 2010, most districts from the Fetzer data had a vote percentage for UKIP equal to zero or very low. After 2010, the distribution of vote shares for UKIP in the Fetzer data is flattened so that some districts begin to have higher vote shares for UKIP and the variance has increased. There is still some districts with very low vote share for UKIP. This phenomenon is not grasped in our data. Our before 2010 vote shares distribution doesn't quite match the distribution from Fetzer data, but the main issue comes from the distribution of our after 2010 vote shares: every district have increased their vote share for UKIP and there is no more district with zero or low vote share. We assume that this can be explained by the fact that our DGP does not include district-time fixed-effects, which could have forced some districts to keep a low vote share for UKIP even if the trend across the year is for the region to become more conservative.

Figure 4: Generated vote percentages against Fetzer vote percentages



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Figure 5: Generated vote percentages against Fetzer vote percentages



3.4 Estimations

With our simulated data, we found the same results for β_1 as Fetzer when estimating his model. Here explain why we don't have the same number of observations.

Table 2: Simulation results

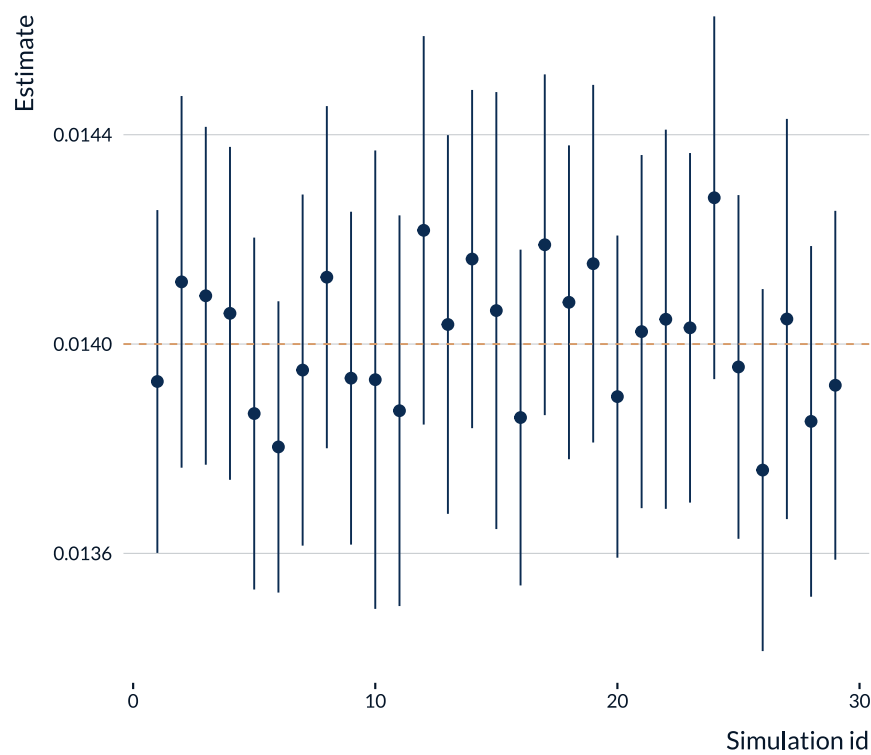
Dependent Variable:	pct_votes_UKIP
Model:	(1)
<i>Variables</i>	
Austerity * Post(2010)	0.0140*** (0.0001)
<i>Fixed-effects</i>	
Region-Year	Yes
<i>Fit statistics</i>	
Observations	6,160
R ²	0.95125
Within R ²	0.69485
<i>Clustered (Region-Year) standard-errors in parentheses</i>	
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>	

3.5 Multiply the simulations and the estimations

We then repeat the process a hundred times and here are plotted the 30 firsts estimates we found for β_1 . They are all significantly closed to to estimate's value found by Fetzer, 0.014:

Figure 6: Generated vote percentages against Fetzer vote percentages

Estimates
Computed on 30 different data sets



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The following figure displays the distrubution of our 100 estimates:

Figure 7: Generated vote percentages against Fetzer vote percentages

Distribution of estimates
Computed on 100 different data sets

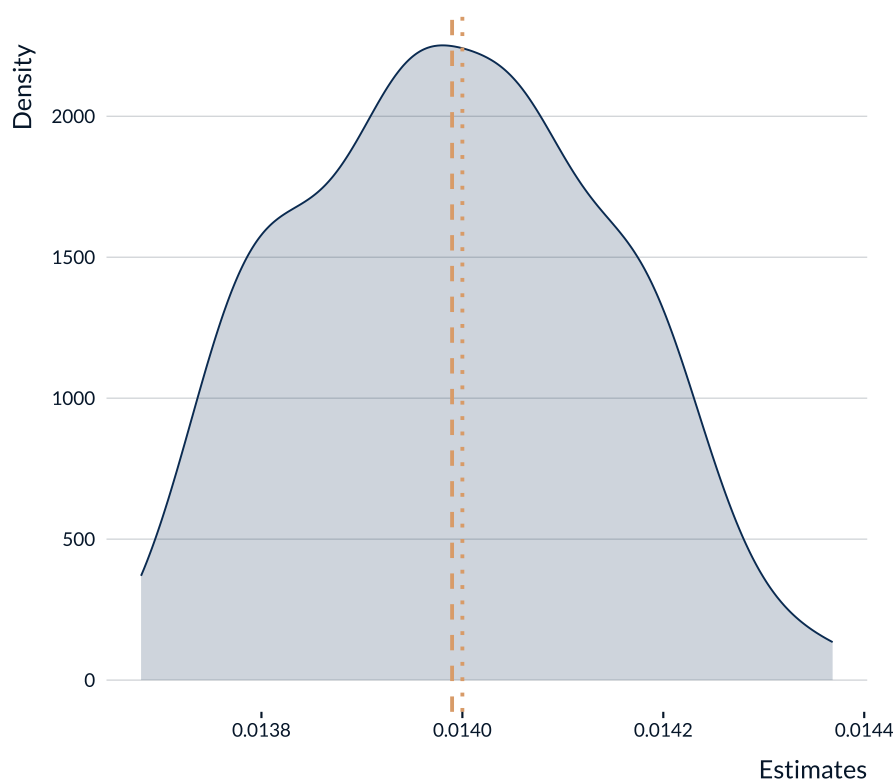


Table 3: Simulation results

Dependent Variable:	pct_votes_UKIP
Model:	(1)
<i>Variables</i>	
Austerity * Post(2010)	0.0140*** (0.0001)
<i>Fixed-effects</i>	
Region-Year	Yes
<i>Fit statistics</i>	
Observations	6,160
R ²	0.95125
Within R ²	0.69485

Clustered (Region-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4 Adding categorical variables in the simulation

For this part, we transform the continuous explained variable by dividing the UKIP vote share in 4 ordered categories (0%-5%, 5%-10%, 10%-15%, and >15%). We use the same model as in the previous parts, without district and region-time fixed-effects, for logit regressions. We use ordered logit regressions to adapt to this new categorical ordered variable representing a gradation in the vote shares.

4.1 Ordered logit and probit on Fetzer data

Applying an ordered logit on Fetzer data produces estimates which are coherent with the effect originally measured by Fetzer with a continuous variable. The estimate for the coefficient for the interaction between post 2010 and the exposure to austerity is positive, meaning that an increase in the overall exposure to austerity increases the likelihood of moving from a category to the next higher one. The estimate equals 0.005794, meaning that each 1-unit increase in austerity exposure results in an increase of 0.005794 in the log-odds of moving to a higher category of UKIP vote percentages. This increase is relatively small, but statistically significant, as indicated by the very high t-value of 29.09.

For those data, an ordered probit seems to perform better, with a smaller AIC equal to 4575.116 compared to the AIC associated to the logit model, which is slightly bigger and equal to 4608.307.

The magnitude of the effect of Austerity measured with ordered probit is reduced compared to the ordered logit.

4.2 Ordered logit and probit on simulation data

When applying an ordered logit on our first set of generated data, we found an estimate positive equal to 0.008081 which is also coherent with the effect originally measured by Fetzer with a continuous variable. Each 1-unit increase in austerity exposure results in an increase of 0.008081 in the log-odds of moving to a higher category of UKIP vote percentages. This increase is relatively small, but statistically significant, as indicated by the very high t-value of 52.65.

Contrary to what happens with Fetzer data, for our simulated data, ordered logit seems more suited than ordered probit, regarding the AIC. However, on both case, probit and logit, the AIC for estimations on simulated data are much more bigger than on real data. It may be explained by the fact that our generated data do not perfectly mimic Fetzer data and are then less suited for ordered logit/probit models because some assumptions, regarding the distribution of the error term for example, do not hold.

Table 4: Fetzer logit and probit

	<i>Dependent variable:</i>	
	UKIP	
	<i>ordered logistic</i>	<i>ordered probit</i>
	(1)	(2)
Effect	0.006*** (0.0002)	0.003*** (0.0001)
Observations	3,287	3,287
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01	

Table 5: Simulated logit and probit

	<i>Dependent variable:</i>	
	UKIP	
	<i>ordered logistic</i> (1)	<i>ordered probit</i> (2)
Effect	0.008*** (0.0002)	0.004*** (0.0001)
Observations	6,160	6,160
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01	

References

- Arzheimer, Kai**, “Contextual Factors and the Extreme Right Vote in Western Europe, 1980-2002,” *American Journal of Political Science*, 2009, *53* (2), 259–275. Publisher: [Midwest Political Science Association, Wiley].
- Autor, David, David Dorn, and Gordon Hanson**, *The China Shock: Learning from Labor Market Adjustment to Large Changes in Trade* January 2016.
- Beatty, Christina and Steve Fothergill**, “Hitting the Poorest Places Hardest: The Local and Regional Impact of Welfare Reform,” *Unpublished*, 2013.
- Colantone, Italo and Piero Stanig**, “The Trade Origins of Economic Nationalism: Import Competition and Voting Behavior in Western Europe,” *American Journal of Political Science*, April 2018, *62* (4), 936–953.
- Fetzer, Thiemo**, “Did Austerity Cause Brexit?,” *American Economic Review*, November 2019, *109* (11), 3849–3886.
- Guriev, Sergei and Elias Papaioannou**, “The Political Economy of Populism,” *Journal of Economic Literature*, September 2022, *60* (3), 753–832.