In this study, I examined how the hegemony that has shaped the opposition to labour unions in Turkey, which has been shaped by neoliberal policies since the 1980s and the AKP's religious discourse ,can be identified through a specific data set.

Logit, RFE and PCA

The data I used as a basis comes from cross-sectional panel data covering World Value Survey's 7th Wave conducted in 2018 and 6th Wave conducted in 2011 in Turkey. As the questions differed between the two waves, I first detect the common questions in both waves and then sorted the questions related to the subject I was trying to examine and control variables. Since the regions of the participants were at the NUTS 2 level in the 7th wave and at the NUTS 1 level in the 6th wave, I arranged the location variable according to the NUTS 1 level and allocated a dummy variable for each respondent for the year from which the data came.

For most questions, the scale responses had to be reverse coded, so I started by coding the responses first. While the scoring criteria were the same for most questions, there was a difference between the two waves for the question covering the highest level of education. In Wave 7, the scale ended at 9, while in Wave 6, the highest value was 8. For this reason, I normalised the education level variable separately for these two waves and then combined them. I also followed standardisation steps for the other variables to ensure consistency. As I wanted to examine the effect of religiosity, economic insecurity and the interaction between them on syndicalism, I determined variables that would enable the construction of both religiosity and economic insecurity indices. Because I decided that taking either the harmonic or arithmetic mean of the selected variables might not fully capture the variance, I developed two separate PCA scores for both religiosity and economic insecurity. Since the data structure gives negative values to questions that are left unanswered or undecided and does not specifically indicate NaN, I changed the values -1, -2, and -3, which indicate no answer, to NaN. I decided to set a threshold for my outcome value, which includes the union perception and turned it into a binary form.

During the model building stage, I made a bold decision to drop missing values, which is perhaps one of the most important issues. The fact that there were not many missing values in the data was influential in my decision, and I concluded the loss of these values would not make a difference.

I determined which of my standardised indexes to use in the model using the Recursive Feature Elimination method. The result of the iteration, performed with a maximum of 2000 Ridge regulators, produced the variables to be included in the model: the PCA indexes, age, income statement, education level, perceived social class, and a dummy variable indicating whether the person was a member of the AKP. In addition to this variables, I also assigned the gender dummy variable as compulsory, and since I wanted to examine Fixed Effects, I added the region and time dummy variables, which I converted into categorical variables to run my Logistic Regression like this.

Despite the weak explanatory power of the model I developed, the pseudo R-square value of 0.0 5, which is considered acceptable in this type of opinion-based study, shows that it is at least som ewhat significant. The most important point that the model can explain the interaction variable I created with a p-value of 0.06. This variable, which indicates situations where religiosity and eco nomic insecurity tend to move in the same direction, suggests that both an increase in religiosity and an increase in economic insecurity reduce trust in trade unions. Even though it is not statistic ally significant, the negative coefficient of the religiosity variable and the positive coefficient of economic insecurity bring me closer to my hypotheses.

```
FINAL MODEL FORMULA

pro_union ~
R_pca1_z + E_pca1_z + RE_pca + age_z + inc_z + edu_z + class_z + dum_akp
+ female
+ C(reg_nuts1)
+ C(dum_year)

FINAL LOGIT REGRESSION OUTPUT
                    Logit Regression Results
================================================================================
Dep. Variable:              pro_union   No. Observations:                 2498
Model:                          Logit   Df Residuals:                     2476
Method:                           MLE   Df Model:                           21
Date:                Thu, 22 Jan 2026   Pseudo R-squ.:                  0.05115
Time:                        19:56:06   Log-Likelihood:                 -797.68
converged:                       True   LL-Null:                        -840.68
Covariance Type:            nonrobust   LLR p-value:                  7.827e-10
================================================================================
                       coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept             1.7378      0.193      9.017      0.000       1.360       2.115
C(reg_nuts1)[T.2]     0.9874      0.414      2.383      0.017       0.175       1.800
C(reg_nuts1)[T.3]     1.0296      0.271      3.801      0.000       0.499       1.561
C(reg_nuts1)[T.4]     0.9327      0.304      3.069      0.002       0.337       1.528
C(reg_nuts1)[T.5]     0.2642      0.228      1.161      0.246      -0.182       0.710
C(reg_nuts1)[T.6]     0.6584      0.256      2.572      0.010       0.157       1.160
C(reg_nuts1)[T.7]    -0.3146      0.254     -1.240      0.215      -0.812       0.183
C(reg_nuts1)[T.8]     1.0362      0.369      2.805      0.005       0.312       1.760
C(reg_nuts1)[T.9]    -0.5751      0.301     -1.910      0.056      -1.165       0.015
C(reg_nuts1)[T.10]    1.5572      0.606      2.571      0.010       0.370       2.744
C(reg_nuts1)[T.11]    0.8363      0.450      1.858      0.063      -0.046       1.719
C(reg_nuts1)[T.12]   -0.4204      0.251     -1.673      0.094      -0.913       0.072
C(dum_year)[T.1]      0.1774      0.198      0.894      0.371      -0.211       0.566
R_pca1_z             -0.0329      0.080     -0.411      0.681      -0.190       0.124
E_pca1_z              0.1044      0.073      1.428      0.153      -0.039       0.248
RE_pca               -0.1318      0.071     -1.851      0.064      -0.271       0.008
age_z                -0.0773      0.076     -1.018      0.309      -0.226       0.072
inc_z                 0.0482      0.081      0.599      0.549      -0.110       0.206
edu_z                -0.0122      0.098     -0.125      0.901      -0.204       0.179
class_z              -0.0857      0.081     -1.063      0.288      -0.244       0.072
dum_akp               0.1585      0.144      1.105      0.269      -0.123       0.440
female               -0.3507      0.139     -2.518      0.012      -0.624      -0.078
================================================================================
```
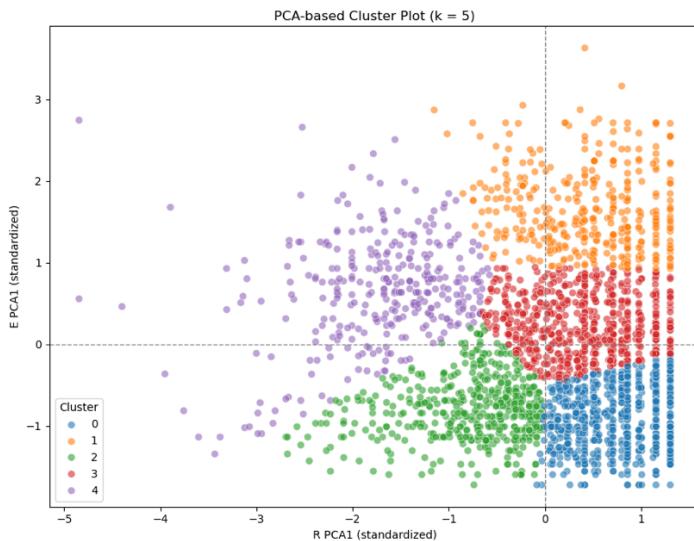
Later, as I was curious about what caused the differentiation among individuals in the PCA, I looked at both religiousness and economic insecuritys' PCA loadings. I found that while all values

similarly influenced differentiation in religiousness, in economic insecurity, the ability or inability to satisfy basic human needs caused differentiation.

	PC1		PC1
x_r_imp_relg	0.465659	x_e_fin_sat	0.372402
x_r_imp_god	0.454877	x_e_job_worry	0.235289
x_r_att_srv	0.420994	x_e_no_food	0.513100
x_r_freq_pray	0.476515	x_e_no_med	0.542885
x_r_self_rel	0.414664	x_e_no_cash	0.497956

When I cluster individuals and examine their positions, I can say that we have a population that is generally religious and economically insecure, distributed similarly around the centre, with no particularly outlying groups in terms of differentiation.


PCA-based Cluster Plot (k = 5)

DML
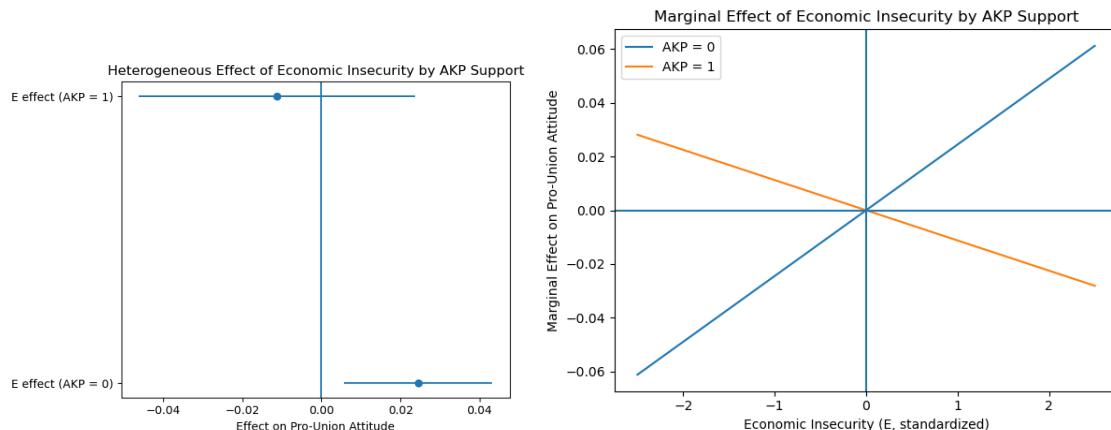
In the second part of the study, I integrated a double/debiased machine learning model into this dataset . The main purpose of this algorithm is to eliminate the effect of covariates from both the Y value, which in this study is attitude towards labour unions and the D treatment value, which in this study is religiosity, economic insecurity, and their interaction with each other. So, first, by using a machine learning model (ElasticNet, GradientBoost, or Random Forest), we try to predict outcome variables based on control variables. Then, we subtract the original values from the model's predictions and obtain residuals. In the second step, we perform the same process on the treatment variables and obtain residuals from there as well. Once the double part of the process is

complete, we use the OLS model to regress the residuals obtained from the y and the treatment variables. This model helps us predict the part of Y that is explained only by the treatment variables.

In the training part of these ML models, I set k to 5 and performed cross-validation and I used a hybrid model called Stacking Regressor. In addition, I decided to take the work one step further in this two-stage model and develop two separate models. I used two different structures, one with and one without my dummy variable indicating whether individuals were AKP members. To further develop this DML method I explained, I used the Partial Out method to rerun the model. This method first predicts the Y and D values using FE dummies, subtracts them from the actual values to obtain residuals, and then runs the initial DML model using these residuals as the main values, as if they were the actual values.

|	DML-A_FE-in-X				DML-B_FE-in-X				DML-A_PartialOut				DML-B_PartialOut			
	coef	se	ci_low	ci_high	coef	se	ci_low	ci_high	coef	se	ci_low	ci_high	coef	se	ci_low	ci_high
R_pca1_z	-0.001249	0.006936	-0.014844	0.012346	-0.003054	0.007052	-0.016875	0.010768	0.000895	0.006785	-0.012404	0.014195	-0.001248	0.006896	-0.014765	0.012268
E_pca1_z	0.006266	0.007150	-0.007748	0.020279	0.006464	0.007184	-0.007616	0.020545	0.008603	0.007060	-0.005235	0.022441	0.008392	0.007120	-0.005563	0.022348
RE_pca	-0.007735	0.006097	-0.019685	0.004215	-0.007560	0.006128	-0.019571	0.004451	-0.010170	0.006010	-0.021950	0.001611	-0.010222	0.006035	-0.022051	0.001607
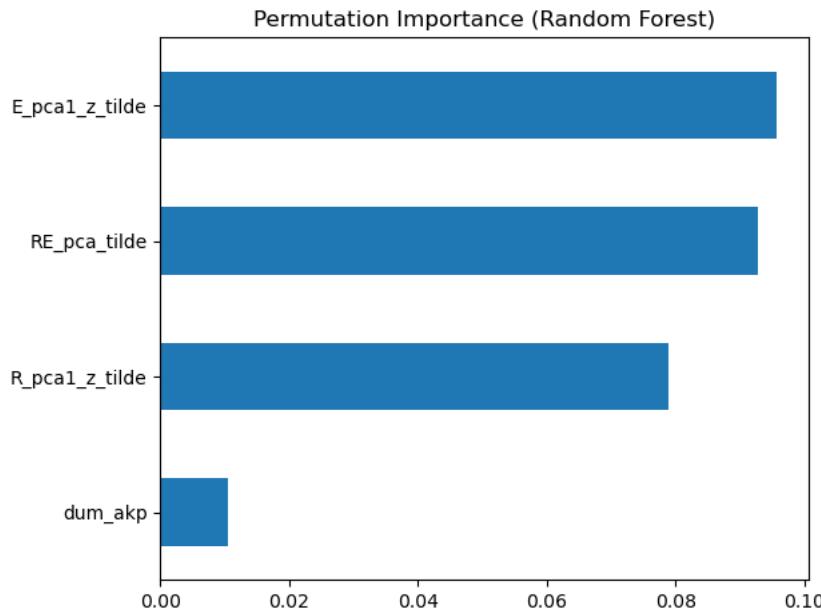
Although it is difficult to say that the results are meaningful since the confidence interval of the coefficients contains 0, the fact that the interaction coefficient is negative in every model leads us to interpret that the economic insecurity increases union sympathy and the religiosity reduces it. Also by examining the results obtained, we can study the impact of being an AKP voter on economic insecurity. As the confidence interval renders the results insignificant, but we can see that AKP voters do not support unions in situations of economic insecurity, while non-AKP voter do.

.
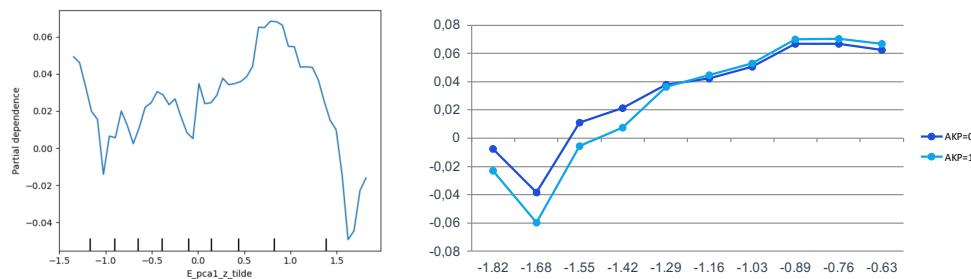
Random Forest

In the final step of the research, I set sail on an exploratory journey using the outputs I obtained from the DML model we built. In order to see what sort of information was being used by this model and to discover the relationship between features, I used the random forest method. I tried to identify the prounion output, cleaned up from FE, with treatment features and AKP dummies. More precisely, I tried to determine which channel the model obtained the most information from within these features and what caused the divergence. The output of the model, for which I set the

minimum sample leaf to 20, showed me that economic insecurity caused the most divergence.

Permutation Importance (Random Forest)

When we examine how the model's prediction changes as E changes in partial dependence, we see that the relationship is not linear. And when we look at the change in E according to whether the person is a member of the AKP or not, we see that E's effect in the model differs depending on whether the person is a AKP supporter or not.

PDP,ExAKP