Homework Challenge: Regularization

Microeconometrics and Application: Report 4

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1 Statistical Background

When the number of covariates is large relative to the number of observations, we speak of high-dimensional data (cf. Athey et al, 2019). In the presence of high-dimensional data there are a lot of statistical methods to do predicition. A large drawback is that a lot of these methods can result in making incorrect conclusions when the aim is to do inference about model parameters. To be able to conclude something relevant and meaningful while analysing high-dimensional data, we need to conduct regularization. With regularization, we mean constraining estimates in a way, so that there occurs no overfitting and the model can be used to do out-of-sample prediciton. (cf. Mullainathan et al., 2017)

1.1 Ridge Regression

Regularization with Ridge requires the use of the L2 penalty, where we are estimating the values of $\widehat{\beta}^R$ by minimizing the following equation:

$$\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda\sum_{j=1}^{p}\beta_j^2 = RSS + \lambda\sum_{j=1}^{p}\beta_j^2 \tag{1}$$

The penalty level which is also called tunning parameter λ, determines the magnitude of the penalty. The higher the λ, the more we penalize the coefficients, and the lower the λ, the closer the coefficients are to the coefficents estimated by OLS. Ridge has the aim to shrink the coefficients close to zero, but unlike LASSO, the coefficients do not shrink to exactly zero. Thus we see that it is crucial to determine a good value for λ which can be done by cross-validation. (cf. Gareth, et al., 2013, p. 215 f.)

1.2 Least Absolute Shrinkage and Selection Operator (LASSO)

While Ridge concentrates on the L2 penalty, LASSO has the specialty of using the L1 penalty, which uses the idea of approximate sparsity of a high-dimensional linear model. This is when only s ($s < n$) out of all x variables are important for prediciton, and thus non-zero, while the rest of the $x - s$ variables are set to zero. (cf. Mullainathan et al., 2017) Since LASSO has the specialty of also performing variable selection, it overcomes the disadvantage of Ridge, which would at the end inlcude all x variables in the model only shrinking them towards zero. To determine our coefficients, LASSO minimizes the following quantity:

$$\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda\sum_{j=1}^{p}|\beta_j| = RSS + \lambda\sum_{j=1}^{p}|\beta_j| \tag{2}$$

LASSO has the advantage of not only shrinking the coefficients but also setting some coefficients to zero, when the penalty level is large enough. Just as for Ridge, determining a good value for λ is crucial. This can be done by cross-validation. (cf. Gareth, et al., 2013, p. 219 ff.) The penalty term λ is proportional to the sum of the absolute values of the parameters (cf. Athey et al, 2019). Another advantage of LASSO is that due to it being a convex optimization problem, the solution can be found by highly efficient computational algorithms. Moreover, the estimators of LASSO have properties that allow under some assumptions for approximation errors, heteroskedasticity, clutering, fixed effects and non-normality. A drawback of LASSO is that the remaining s non-zero variables are substantially biased towards zero. (cf. Mullainathan et al., 2017) The LASSO performs better than subset selection methods in cases where the ratio of signal to noise is small (cf. Athey et al, 2019). In the $n > p$ case, with high correlation between our explanatory variables, LASSO has proven to have a better prediction performance than Ridge. Due to its property of doing variable selection and its sparse representation, Lasso has become much more appealing than other regularization methods. Despite all its advantages, the LASSO is connected with the following drawbacks:

- When the number of variables is larger than the number of observation, LASSO selects at most n variables. Furthermore, when the bound on the L1-norm of the coefficients is larger than a certain value, the lasso is not well defined.
- If we have multicolinearity among our variables, LASSO selects only one variable, without caring which one to select.

Because of those above mentioned limitations and because our aim still is to do a variable selection, another regularization approach will be introduced in the next section, which is a combination of Ridge and LASSO. (cf. Zou et al., 2005)

1.3 Elastic Net

The aim of elastic net is to shrink together the coefficients of correlated explanatory variables like Ridge, while still doing some variable selection to encourage a sparse representation as with LASSO. To do so, another parameter, α, is introduced which determines the magnitude of shrinkage. To estimate the coefficients, we now aim to minimize the following equation:

$$RSS + \lambda(\alpha \sum_{j=1}^{p} |\beta_j| + \frac{(1-\alpha)}{2} \sum_{j=1}^{p} \beta_j^2) \tag{3}$$

(cf. Friedman et al., 2010)

The elastic net penalty is a weighted combination of the L1 and L2 penalty. If $\alpha = 0$ the elastic net becomes a Ridge regularization, and a LASSO regularization when $\alpha = 1$. Zou et al. (2005) found out that elastic net, as defined in equation 3, does only perform well if α is either very close to 1 or 0, thus very close to LASSO or Ridge.

As our aim is to interpret the results and not to do prediction, we are going to use the elastic net procedure with a small α in the empirical implementation. (cf. Zou et al., 2005)

2 Empirical Implementation

We decided to choose data from the European Social Survey (ESS), a cross-national survey conducted across Europe since 2001, for our empirical analysis. The ESS takes place every two years, and measures the attitudes, beliefs and behavioural patterns of the population in more than thirty nations in Europe, including EU and non-EU countries. The data we are analyzing is from the ninth ESS wave conducted in 2018, which means that we are dealing with cross-sectional data. (cf. European Social Survey, 2018)

2.1 Dependent Variable

```r
getwd()
```

```
## [1] "/Users/Simuuu/Desktop/Data"
```

```r
library(foreign)
ess <- read.dta("ESS9e01_1.dta")
```

Our dependent variable is *vteurmmb* which investigates if a person would vote for his or her country to remain in the EU or leave the EU. Since there are multiple answers to this question, we are conducting a multinomial logistic regression using a weighted L1 and L2 regularizer. Before conducting the elastic net we need to delete all categories that have 0 observations, which are "Refusal", "Don't know" and "No answer". We delete all observations that have a missing value for *vteurmmb*. Missing values exits because countries could chose whether to ask this question or not. The countries that did not ask the question about remaining in the EU were Switzerland, Estonia, United Kingdom, Norway and Serbia. Switzerland, Norway and Serbia are not part of the EU which is why they could not ask the question. Great Britain has a special position with the upcoming Brexit which is why the country probably decided not to ask the question. Estonia did not ask the question either.

```r
library(glmnet)
summary(ess$vteurmmb)
```

```
## Remain member of the European Union           Leave the European Union
##                               19826                               3201
##   Would submit a blank ballot paper        Would spoil the ballot paper
##                                 374                                 102
##                      Would not vote                Not eligible to vote
##                                1159                                 375
##                             Refusal                          Don't know
##                                   0                                   0
##                           No answer                                NA's
##                                   0                               10978
```

```r
ess$vteurmmb <- droplevels(ess$vteurmmb, exclude =c("Refusal", "Don't know", "No answer"))
levels(ess$vteurmmb)
```

```
## [1] "Remain member of the European Union"
## [2] "Leave the European Union"
## [3] "Would submit a blank ballot paper"
## [4] "Would spoil the ballot paper"
## [5] "Would not vote"
## [6] "Not eligible to vote"
## [7] NA
```

2.2 Explanatory Variables

Next we will describe all variables that we chose to explain our dependent variable and explain why it is important to include them into the analysis.

2.2.1 Selection of Explanatory Variables

cntry (Country): Different countries have different view points on the EU. We need to make this variable a factor variable.

```
ess$cntry <- as.factor(ess$cntry)
```

nwspol (News about politics and current affairs, watching, reading or listening, in min): The amount of time a person informs himself about politics and especially the EU influences his understanding about the EU and the advatanges and disadvantages connected to it.

netusoft (Internet use, how often): Using the internet can influence your political opinion, because of websites like Twitter and Facebook.

ppltrst (Most people can be trusted or you can't be too careful): Being cautious about other people might mean you are also cautious about other countries.

pplhlp (Most of the time people helpful or mostly looking out for themselves): If a person thinks that people mostly try to be helpful he or she might also think that countries want to help each other, which means they tend to work together in the EU.

polintr (How interested in politics): Being interested in politics obviously effects whether you will vote in the referendum at all, but does not determine the answer of the vote.

psppsgva (Political system allows people to have a say in what government does): If a person thinks that he or she cannot influence what her countries government does, might make her hope that she can influence the European government which could make her vote in favor of the EU. On the other hand, this could also decrease her trust in any government including the European one. Then she would not care about the EU and it's institutions.

psppipla (Political system allows people to have influence íin politics): Indicates how open a country is towards its citizens being politically engaged, and thus lead a person to believe they have a voice in political decisions, not only country wise but maybe also EU wise.

cptppola (Confident in own ability to participate in politics): If a person is confident that he or she is able to participate in politics and might also change something, that person might also believe that he or she can be part of a EU wide change.

trstprl (Trust in country's parliament): Trusting in one's country's parliament can lead to a person trusting also the EU's parliament, leading to a vote in favor of the EU, but also if one does not have any trust in his or her country's parliament, they might also not trust the EU's parliament, which would lead to a vote against staying in the EU.

trstlgl (Trust in the legal system): As this is very much connected to politics, people who trust in the legal system of their country, might also trust the EU legal system (for example European Court of Justice), or if they do not trust in their legal system, they might try to find justice on the EU level. They might also be in favor of the EU if the do not trust their own country's legal system but hope that the EU will sanction their country for not having a good legal system as was the case with Poland at the end of 2017 (cf. dpa, 2017).

trstplc (Trust in the police): If a person believes the police is fair, they might also believe the legal system is fair as the two are working together. This might also make them believe that the EU legal system is fair and make them be in favor of stying in the EU.

trstprt (Trust in political parties): If a person has trust in political parties, he or she also thinks that whatever a certain party stands for is also going to be discussed on a EU level basis, meaning that being in the EU, could be beneficial for a persons political view which is supported by a political party. This also goes in the other direction, meaning no trust, can lead to a person thinking that also on the EU level they can not trust, or maybe then they might trust what happens in the higher positions (EU) more than on country level.

trstep (Trust in the European Parliament): If there is no trust in the European Parliament, a person obviously rather wants his/her country to leave the EU, while on the other hand, if there is trust then they want the country to stay in the EU.

trstun (Trust in the United Nations): As the members of the EU have voting rights in the UN, trusting the UN would maybe also lead a person to trust in the EU. The contrary holds too.

contplt (Contacted politician or government official last 12 months): This variable could be an indicator for someone being interested and/or concerned about politics, and thus wants his/her opinion to be heard. Might also be important for that person to have a vote in the referendum.

wrkprty (Worked in political party or action group last 12 months): Is an indicator for a person being interested in politics in general, so he or she wants to participate in politics, thus it is more probable that this person will also be voting in the referendum.

wrkorg (Worked in another organisation or association last 12 months): A person being part of other organisations or associations, is important as this indicates general interest in working together with other people for a certain cause. Often this can be also politicaly related, or maybe also not at all. Which could lead to a person take vote in the referendum.

badge (Worn or displayed campaign badge/sticker last 12 months): This indicates major interest in politics and especially for a certain party. So this person would either want his or her party in favor to have a voice in the EU, or on the other hand is not in the favor of the EU, and thus wont vote for staying in the EU.

sgnptit (Signed petition last 12 months): This variable also indicates interest in politics, or maybe generally saying in a certain cause, which is why this person wants his/her voice to be heard. So participating in the referendum would be another way, to be heard.

pbldmn (Taken part in lawful public demonstration last 12 months): Can be interepreted like sgnptit, just that this is something even less people do, so it would be a stronger indication for a person wanting his/her voice to be heard. This can influence a persons vote in the referendum.

bctprd (Boycotted certain products last 12 months): Strong indicator for a person standing for a cause, and thus also more likely to be taking part in the referendum, to be heard.

pstplonl (Posted or shared anything about politics online last 12 months): As this is not something everybody does or even would do, this means that a person is very much interested in politics and either is in total support for the politics in his/her country or totally against it. This could influence his vote in the referendum.

clsprty (Feel closer to a particular party than all other parties): The closer a person feels to a certain party, the more he she is in support of it and thus might also wants the party to be represented in the EU, which could lead to a vote in favor of the EU.

lrscale (Placement on left right scale): This is how people see themselves politicaly, so this als conincides with them feeling close to a particular party and thus has an effect of them voting in the referendum. But it might also mean that if they are totally on the right scale or left scale and maybe no party in their country or EU is on the same scale, they might not want their country to stay in the EU.

stflife (How satisfied with life as a whole): This can have a big influence in participating in something like the referendum. If a person's country who is in the EU, is satisfied with his life the way it is, he or she might also want nothing to change, so they would vote for staying in the EU. But on the other hand, if a person is not satisfied with his life as a whole, he might think it is caused by the current political situation, so leaving the EU, could sound like a possible change for this person.

stfeco (How satisfied with present state of economy in country): If a person is all satisfied with the present state of economy in their country while being part of the EU, he or she might want the country to stay in the EU, to keep the state of the economy the way it is or even imporve it. On the other hand, if a person is not satisfied with the present state, leaving th EU could cause a change.

stfgov (How satisfied with the national government): This could be equally interepreted as stfeco. The more satisfied a person is with the present national government, the more trust they have in their government representing their country in the EU. This can lead a person to be more in favor of staying in the EU. On the contrary, there are also people that are very satsified with their own nationalist government and do not trust the EU because their government is sceptical about the EU as it is the case in Hungary.

gincdif (Government should reduce differences in income levels): If a person strongly agrees in the government reducing differences in income levels, he or she might think that this would rather be possible when they are seperated from the EU, so when the only focus of the country lies on it's own citizens. Especially if they feel like their own country has to give a lot of money to other EU countries whcih they then cannot use to get rid of inequalities in income.

freehms (Gays and lesbians free to live life as they wish)/ hmsacld (Gay and lesbian couples right to adopt children): As this has been something recently enforced in some countries in the EU, this can have a strong influence on people wanting to stay in the EU, as they want their rights and opinions to be heard and also other countries in the EU to enforce the right of adoption for gay and lesbian couples. On the other hand, someone who is against these liberties for lesbians and gays might want his or her country to leave the EU so that the rights recently introduced in other countries will not be introduced in their own country.

euftf (European Union: European unification go further or gone too far): This obviously influences if a person wants to stay in the EU or not.

impcntr (Allow many/few immigrants from poorer countries outside Europe): As immigration plays an important role in the whole world, but also in the EU, a person who is in favor of the EU, might also welcome more immigratns to his/her country, as they support the unification role of the EU and thus might be more open for immigrants coming also from countries outside of Europe. Moreover, the recent wave of refugees in the EU could have for some people a negative view/opinion about staying in the EU, as in some parts in the EU, it lead to some problems.

imbgeco (Immigration bad or good for country's economy): Some people might think immigration is good for a country's economy as it boosts it, but on the other hand some people might think that immigrants only take their jobs away and thus don't want them to be in their country. As immigration especially from EU countries has been very easy due to the Freedom of Movement of People, people in favor of immigration might want to stay in the EU, but people who think immigration is bad for their country's economy find it better that the country leaves the EU.

imueclt (Country's cultural life undermined or enriched by immigrants): If a person feels that it's country's cultural life is enriched by immigrants, he or she might be more open toward immigration and thus as mentioned for *imbgeco* be in favor of staying in the EU. But if poeple feel their country's cultural life is undermined by immigrants, they don't want them to be in their country and thus might vote against staying in the EU.

sclmeet (How often socially meet with friends, relatives or colleagues): Being very much socially engaged can influence a person's view about politics and also make a person having more trust in social engagements, thus believing in unitity which could lead a person to vote in favor of staying in the EU, or if a person is very much socially engaged with people having a certain bad opinion about the EU, might lead him or her to vote against staying in the EU. An generally if a person is not very socially engaged, he or she might also not be interested in taking part in something like the referendum, as they might not even care about anyone or anything.

sclact (Take part in social activities compared to others of same age): It makes a differences if a person takes part in certain social activities which might be very popular in a certain age and if not, as this can influence if a person is interested in what is going on, or if a person stucks more to his/her view and does not want to be part of a big society.

crmvct (Respondent or household member victim of burglary/assault last 5 years): This could be important because of the recent wave of refugees and thus people believing that there is an increasing rate of burglary and assault. If a person knows one who has been a victim of such an event, he or she might connect it to new immigrants and then does not want to stay in the EU.

atchctr (How emotionally attached to [country]): This is obviously a huge indicator for people wanting to stay in EU or not. A person being very much attached to his/her country, might only care about their own country and have no interest in the EU, but on the other hand a person being very much attached to his/her country, and it being positvely influenced by the EU, might lead the to vote in favor of staying in the EU.

atcherp (How emotionally attached to Europe): People believing in unity and feeling like a part of the European Union, want to stay in the EU.

rlgblg (Belonging to particular religion or denomination): Belonging to a particular religion or denomination which is in favor of staying in the EU, as they support different religions and are open for people from other religions, could lead in a vote in favor of staying in the EU. The contrary holds too.

rlgatnd (How often attend religious services apart from special occasions): This can be an indicator of how much religion plays an importance for one person. If religion is very important for a person, thus attending religious services more often and thus being socially engaged in their religious community can also lead a person to adopt the views and opinions of the community. And as often religion is connected with politics, this can lead a person to take part in the referendum.

dscrgrp (Member of a group discriminated against in this country): If a person feels discriminated against because of his or her religion, sexuality or something else, he or she might hope that being part of the EU can have an effect on the discrimination if other European countries or the EU itself are doing something against discrimination. Then he or she would be in favor of staying in the EU.

ctzcntr (Citizen of country) - Being a citizen of the country plays an important role of a person being interested in that country's political situation. If a person is a citizen, he she might be more interested in his/her country staying or leaving the EU, then somebody who is not a citizen.

brncntr (Born in country) - This is quite like being a citizen but has an additional meaning. Being also born in the country, might make you feel closer to it and be more interested in that country's political situation and future and thus taking part in the referendum is more probable.

blgetmg (Belong to minority ethnic group in country): Belonging to a minority ethnic group will be in favor of the European Union if there are a lot of people from your ethnic minority living in other countries in the European Union and the European Union has programs against the discrimination of your ethnic group. But it would make you vote against remaining in the EU if you do not feel like your ethnic group is accepted by the EU institutions and other countries.

facntr (Father born in country) and mocntr (Mother born in country): The migrational background which can be seen in the variables stating whether the parents were born in the country defines how integrated into the society a person might be and how much a person feels like he or she belong to the country. This also influences how much a person feels to be part of the EU. Children of migrants from other EU countries profited from the EU because their parents could mirgate which makes them likely vote in favor of the EU.

evpdemp (Paid employment or apprenticeship at least 3 months 20 hours weekly): Paid employmentship influences the way a person sees the economic situation in it's own country which they might link to the economic situation of the EU as the different countries in the EU are economically connected together through payment programs for weak member states.

nbthcld (Number of children ever given birth to/ fathered): The number of children influences your way of life which might also influence political opinions, for exmaple about the EU.

age_birth (Age of a person at the birth of their first child): We create a variable for the age of a person at the brith of their first child, only taking into account parents that were at least 14 at the birth of the first child, the rest we assume to be measurement errors. The age when a person had their first child influences the way he or she developed their life, like what kind of job they chose and how much education they had. These things influence political opinions.

```
ess$age_birth <- ifelse((ess$fcldbrn-ess$yrbrn)>13, ess$fcldbrn-ess$yrbrn, NA)
summary(ess$age_birth)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   14.00   23.00   26.00   26.52   30.00   70.00   11547
```

plnftr (Plan for future or take each day as it comes): Planning for the future might make a person spend time thinking about the future of the European Union which could influence the vote.

gndr (Gender): At the last election for the European parliament, women generally voted less for nationalist parties and more for environmentally friendly parties. This could mean that they vote less for nationalist parties making their country leave the EU.

agea (Age of respondent, calculated): A person's age influences their view on the European Union. At the Brexit referendum most young people voted against the Brexit while older people voted in favor of it.

eduyrs (Years of full-time education completed): The amount of education a person had is correlated with amount of political education he or she had. As political education plays an important role in many of the EU countries, people at an young age start to be aware of the political system in their country and are also motivated to go and take part in votes. This could be a good indicator of a person wanting to take part in the referendum.

uempla (Doing last 7 days: unemployed, actively looking for job): If a person is unemployed but actively looking for a job, he or she might be in favor of staying in the European Union as this could increase their chances of finding a job because he or she could be looking for a job in another country as well. On the other hand, a person that has been unemployed for a long time could also blame the European Union and migrants from other EU countries for taking away possible jobs. Then he or she would vote to leave the EU.

tporgwk (What type of organisation work/worked for): Working for the central or local government will make people more likely to be in favor of the own government. If the own governemnt support the EU, the person might also do that.

eiscedf (Father's highest level of education, ES - ISCED) / eiscedm (Mother's highest level of education, ES - ISCED): The education of people around us influences our opinions as we share thoughts with them and are influenced by their thoughts, especially our parents thoughts. These opinions can also be related to the EU which influnces how someone would vote in a referendum.

frprtpl (Political system in country ensures everyone fair chance to participate in poli): If someone does not believe that his own country enables him to participate in politics he or she might hope to be able to participate in the European Union and thus vote to remain in the EU. On the other hand it could also mean they do not believe in being able to participate in any political institutions and thus might not care about staying in the EU.

gvintcz (Government in country takes into account the interests of all citizens): If a person believes that the government in his or her country does not take everyones interest into account, they might not believe that it is any differnt at the European level. Then they would not care about the vote.

poltran (Decisions in country politics are transparent): If a person thinks that politcal decisions in his or her country are not transparent, they might not take part in the referendum if they do not believe the final decision will be transparent. Then they might even spoil the ballot paper.

evfredu (Everyone in country fair chance achieve level of education they seek) / evfrjob (Everyone in country fair chance get job they seek): If a person thinks chances to get a job or an education in the own country are not fair, they might consider moving to a different EU country, like for example German students wishing to study medicine often move to different European countries. This would make a person be in favor of staying in the EU.

sofrdst (Society fair when income and wealth is equally distributed) / sofrwrk (Society fair when hard-working people earn more than others) / sofrpr (Society fair when takes care of poor and in need, regardless of what give back) / sofrprv (Society fair when people from families with high social status enjoy privileges): These questions reflect whether a person thinks the society she lives in and the European society are fair and influences how the person sees the European Union.

2.2.2 Correlation between explanatory variables

Since the Lasso selects only one of several mutlicollinear variables without caring which one to select, we next make sure that we do not include multicollinear variables for our analysis. The following output was generated in Stata and shows the correlation coefficients between all variables. We highlighted all the correlation coefficients that are larger than 0.5 in red. It shows that only few of the used variables are highly correlated. This might be because we already tried to include only variables that are not highly correlated. It can be seen that the variables psppipla and psppsgva, trstlgl and trstprl, trstplc and trstlgl, trstprt and trstprl, trstep and trstprt, imueclt and imbgeco, gvintcz and frprtpl, poltran and gvintcz, ecfrjob and evfredu have a correlation coefficient which is higher than 0.6. The variables facntr and brncntr, mocntr and brncntr, mocntr and facntr have a correlation coefficient which is higher than 0.7. These variables are dummy variables for whether the person was born in the countr (brncntr) and if the mother (mocntr) and father (facntr) of the person were born in the country. It makes a lot of sense that these variables are highly correlated because if a family moved to the country after the child was born, all three variables equal 0. Two other variables that have a correlation coefficient that is higher than 0.7 are trstun and trstep, whether a person trusts in the European Parliament and in the United Nations. Since a correlation coefficient that is higher than 0.7 indicates a high correlation, we discard the highly collinear variables. We decide to discard mocntr and facntr as brncntr is the most important one of the three variables. We also discard trustun as trustep is more important for an analysis of who wants to remain in the European Union. All other variables can be used.

	nwspol	netusoft	ppltrst	pplhlp	polintr	psppsgva	psppipla	cptppola	trstprl	trstlgl
nwspol	1.0000									
netusoft	-0.0828	1.0000								
ppltrst	-0.0126	0.1676	1.0000							
pplhlp	-0.0226	0.1024	0.5264	1.0000						
polintr	-0.1007	-0.1126	-0.1735	-0.1526	1.0000					
psppsgva	-0.0274	0.1146	0.2191	0.1964	-0.2853	1.0000				
psppipla	-0.0344	0.1636	0.2544	0.2124	-0.3401	0.6140	1.0000			
cptppola	0.0456	0.1817	0.1285	0.0972	-0.4244	0.2500	0.3601	1.0000		
trstprl	-0.0179	0.1010	0.3586	0.3075	-0.2261	0.3984	0.4232	0.1796	1.0000	
trstlgl	-0.0529	0.1404	0.3552	0.3025	-0.1557	0.3074	0.3439	0.1402	0.6535	1.0000
trstplc	-0.0401	0.0755	0.2936	0.2812	-0.1148	0.2060	0.2494	0.0895	0.5159	0.6560
trstprt	-0.0007	0.0616	0.3618	0.3188	-0.2167	0.3942	0.4171	0.1388	0.6915	0.5630
trstep	0.0139	0.0630	0.2758	0.2430	-0.1118	0.2964	0.3082	0.0873	0.5364	0.4909
trstun	-0.0119	0.0893	0.2735	0.2319	-0.1092	0.2348	0.2621	0.0784	0.4762	0.4666
contplt	-0.0034	-0.1074	-0.0797	-0.0556	0.2304	-0.1198	-0.1861	-0.2402	-0.0897	-0.0539
wrkprty	-0.0192	-0.0344	-0.0558	-0.0311	0.2058	-0.1068	-0.1567	-0.2142	-0.0633	-0.0379
wrkorg	0.0143	-0.1521	-0.1828	-0.1384	0.2276	-0.1375	-0.2111	-0.2163	-0.1630	-0.1570
badge	-0.0257	-0.0879	-0.0780	-0.0583	0.1486	-0.0770	-0.1241	-0.1451	-0.0554	-0.0382
sgnptit	0.0154	-0.2139	-0.1247	-0.0931	0.2162	-0.0879	-0.1472	-0.2135	-0.0681	-0.0856
pbldmn	-0.0465	-0.0717	-0.0198	-0.0228	0.1368	-0.0486	-0.0722	-0.1296	-0.0008	0.0057
bctprd	0.0155	-0.1676	-0.1034	-0.0724	0.2215	-0.0685	-0.1398	-0.2154	-0.0682	-0.0729
pstplonl	-0.0028	-0.2340	-0.0548	-0.0087	0.1874	-0.0449	-0.0973	-0.1928	-0.0060	-0.0188
clsprty	-0.0681	0.0304	-0.0937	-0.0419	0.3052	-0.1643	-0.1878	-0.1590	-0.1672	-0.1013
lrscale	0.0068	0.0086	-0.0139	-0.0196	0.0173	0.0682	0.0548	-0.0045	0.0958	0.0491
stflife	-0.0373	0.1484	0.2695	0.2359	-0.1328	0.1745	0.2068	0.1389	0.2827	0.2821

stfeco	−0.0776	0.1089	0.3004	0.2729	−0.1753	0.3229	0.3226	0.1491	0.4758	0.4224
stfgov	−0.0277	−0.0007	0.2042	0.1905	−0.0661	0.3325	0.2941	0.0525	0.5407	0.3974
gincdif	−0.0533	0.1159	0.0622	0.0336	−0.0302	0.1409	0.1234	0.0691	0.1022	0.0866
freehms	0.0030	−0.2695	−0.1679	−0.1375	0.1485	−0.0878	−0.1298	−0.1244	−0.1013	−0.1378
hmsacld	0.0275	−0.2387	−0.2039	−0.1907	0.1180	−0.1169	−0.1444	−0.0885	−0.1416	−0.1734
euftf	0.0474	0.0729	0.1705	0.1412	−0.1449	0.1799	0.1724	0.1178	0.2014	0.1682
impcntr	−0.0098	−0.1872	−0.2057	−0.1686	0.2048	−0.1463	−0.1686	−0.1903	−0.1473	−0.1480
imbgeco	0.0160	0.1580	0.2837	0.2430	−0.2543	0.2152	0.2546	0.2126	0.3008	0.2850
imueclt	0.0135	0.1989	0.3117	0.2432	−0.2131	0.1863	0.2472	0.1747	0.2917	0.2805
sclmeet	0.0003	0.1559	0.1381	0.1351	−0.1230	0.0763	0.0932	0.0904	0.0767	0.0699
sclact	0.0146	0.0912	0.1254	0.1063	−0.1483	0.1090	0.1390	0.1471	0.0840	0.0747
crmvct	−0.0239	−0.0969	−0.0074	0.0134	0.0627	−0.0046	−0.0177	−0.0603	0.0198	0.0201
atchctr	0.0115	−0.0659	0.0599	0.0829	−0.1091	0.0451	0.0585	0.0239	0.1320	0.1436
atcherp	−0.0020	0.0475	0.1710	0.1489	−0.1446	0.1895	0.1833	0.0749	0.2568	0.2472
rlgblg	−0.0615	0.1482	0.0386	0.0298	0.0453	0.0187	0.0157	−0.0259	−0.0241	−0.0077
rlgatnd	−0.0423	0.1854	0.0274	0.0053	0.0148	−0.0125	−0.0027	−0.0308	−0.0357	0.0167
dscrgrp	0.0075	−0.0322	0.0614	0.0721	0.0183	0.0451	0.0419	−0.0448	0.0760	0.0768
ctzcntr	0.0028	0.0452	−0.0077	−0.0065	0.0264	0.0072	−0.0130	0.0109	0.0413	0.0373
brncntr	0.0009	0.0367	−0.0246	0.0016	−0.0005	0.0200	−0.0131	0.0178	0.0258	0.0306
blgetmg	0.0007	−0.0021	0.0380	0.0441	−0.0326	−0.0080	0.0089	−0.0028	0.0096	0.0102
facntr	−0.0049	0.0368	−0.0268	−0.0101	0.0150	0.0088	−0.0193	0.0152	0.0170	0.0209
mocntr	−0.0012	0.0368	−0.0323	−0.0142	0.0042	0.0064	−0.0234	0.0069	0.0127	0.0221
vteurmmb	−0.0008	−0.0662	−0.0573	−0.0462	0.1068	−0.0638	−0.0812	−0.0681	−0.0702	−0.0565
evpdemp	0.0651	−0.0726	−0.0264	−0.0171	0.0467	−0.0351	−0.0474	−0.0212	−0.0321	−0.0395
nbthcld	0.0061	−0.1156	0.0334	0.0518	−0.0565	−0.0056	0.0119	0.0101	0.0256	0.0065
plnftr	0.0171	−0.1516	−0.0125	0.0100	0.0677	−0.0685	−0.0905	−0.1136	−0.0661	−0.0720
gndr	−0.0397	−0.0024	−0.0170	0.0257	0.1842	−0.0505	−0.0710	−0.1618	−0.0556	−0.0508
agea	0.1176	−0.5037	−0.0063	0.0331	−0.1635	−0.0467	−0.0681	−0.0649	0.0081	−0.0411
eduyrs	−0.0433	0.3757	0.1690	0.1102	−0.2135	0.1891	0.2141	0.2352	0.1389	0.1354
uempla	0.0077	0.0290	−0.0195	−0.0189	0.0202	−0.0332	−0.0398	−0.0058	−0.0325	−0.0409
tporgwk	−0.0076	−0.0295	−0.0267	−0.0328	0.0709	−0.0500	−0.0462	−0.0259	−0.0297	−0.0232
eiscedf	−0.0561	0.1472	0.0778	0.0497	−0.0751	0.0994	0.0980	0.0848	0.0609	0.0539
eiscedm	−0.0668	0.1768	0.0769	0.0583	−0.0498	0.0920	0.1005	0.0883	0.0579	0.0574
frprtpl	−0.0444	0.1469	0.2647	0.2276	−0.2686	0.4194	0.4546	0.2181	0.4175	0.3565
gvintcz	−0.0379	0.1009	0.2523	0.2176	−0.2144	0.4420	0.4340	0.1603	0.4832	0.3882
poltran	−0.0340	0.0405	0.2163	0.1913	−0.1555	0.3849	0.3770	0.1215	0.4269	0.3422
evfredu	−0.0656	0.0343	0.1361	0.1575	−0.0421	0.1720	0.1547	0.0217	0.1995	0.1950
evfrjob	−0.0739	0.0770	0.2022	0.2236	−0.0430	0.2310	0.2147	0.0491	0.2665	0.2624
sofrdst	−0.0714	0.1556	0.1118	0.0584	−0.1089	0.1282	0.1506	0.0742	0.1162	0.1155
sofrwrk	−0.0146	0.0266	0.0445	0.0441	0.0100	0.0294	0.0277	−0.0370	0.0279	0.0122
sofrprv	0.0447	0.0448	0.0422	−0.0079	−0.0709	−0.0333	0.0042	0.0100	−0.0032	−0.0074
cntry	0.0434	0.0115	−0.0027	−0.0093	0.0093	−0.0371	−0.0257	−0.0304	−0.0293	−0.0751
age_birth	0.0060	0.1902	0.1104	0.0534	−0.1513	0.1154	0.1403	0.1757	0.1400	0.1318

	trstplc	trstprt	trstep	trstun	contplt	wrkprty	wrkorg	badge	sgnptit	pbldmn
trstplc	1.0000									
trstprt	0.4588	1.0000								
trstep	0.3793	0.6063	1.0000							
trstun	0.4065	0.5007	0.7194	1.0000						
contplt	-0.0339	-0.0797	-0.0353	-0.0344	1.0000					
wrkprty	-0.0187	-0.0849	-0.0408	-0.0240	0.2988	1.0000				
wrkorg	-0.1270	-0.1416	-0.0765	-0.0968	0.2960	0.2365	1.0000			
badge	-0.0255	-0.0644	-0.0508	-0.0566	0.2010	0.2869	0.2501	1.0000		
sgnptit	-0.0583	-0.0305	-0.0212	-0.0657	0.2230	0.1507	0.2541	0.2590	1.0000	
pbldmn	0.0676	0.0140	0.0005	-0.0010	0.1387	0.1598	0.1301	0.2425	0.2616	1.0000
bctprd	-0.0388	-0.0068	-0.0050	-0.0431	0.1749	0.0919	0.2097	0.1899	0.3400	0.1775
pstplonl	0.0010	0.0125	-0.0051	-0.0137	0.1842	0.1784	0.1370	0.2090	0.3145	0.2134
clsprty	-0.0955	-0.1823	-0.0819	-0.0828	0.1253	0.1424	0.1177	0.1015	0.1021	0.0728
lrscale	0.0932	0.0848	0.0120	0.0249	0.0182	0.0229	0.0032	0.0203	0.0849	0.0957
stflife	0.3036	0.2331	0.1704	0.1858	-0.0838	-0.0417	-0.1535	-0.0461	-0.0933	0.0044
stfeco	0.3677	0.4430	0.2809	0.2629	-0.0785	-0.0345	-0.1538	-0.0021	-0.0472	0.0545
stfgov	0.3617	0.5150	0.3296	0.2725	-0.0127	0.0069	-0.0576	0.0274	0.0881	0.1063
gincdif	0.0459	0.0849	0.0648	0.0572	-0.0482	-0.0007	-0.0366	0.0237	0.0019	0.0355
freehms	-0.1233	-0.0603	-0.0860	-0.1398	0.0878	0.0125	0.1318	0.0707	0.1981	0.0874
hmsacld	-0.1124	-0.1420	-0.1416	-0.1726	0.0769	0.0178	0.1351	0.0761	0.1886	0.0703
euftf	0.1049	0.1865	0.3497	0.2666	-0.0616	-0.0422	-0.0852	-0.0481	-0.0549	-0.0613
impcntr	-0.0842	-0.1113	-0.1795	-0.1738	0.1135	0.0591	0.1562	0.0980	0.1989	0.1186
imbgeco	0.1893	0.2493	0.2987	0.2782	-0.1013	-0.0709	-0.1684	-0.1030	-0.1617	-0.0876
imueclt	0.1919	0.2441	0.3186	0.3264	-0.0966	-0.0549	-0.1760	-0.1342	-0.1906	-0.0801
sclmeet	0.0604	0.0584	0.0191	0.0374	-0.1098	-0.0695	-0.1693	-0.0919	-0.1412	-0.0791
sclact	0.0491	0.0824	0.0668	0.0610	-0.1059	-0.0901	-0.1927	-0.0969	-0.0875	-0.0707
crmvct	0.0176	0.0333	0.0192	-0.0046	0.0720	0.0264	0.0636	0.0668	0.1045	0.0510
atchctr	0.1837	0.0858	0.0836	0.1052	-0.0340	-0.0228	-0.0235	-0.0325	-0.0095	0.0077
atcherp	0.1886	0.2374	0.3561	0.3038	-0.0410	-0.0359	-0.0745	-0.0206	-0.0389	-0.0163
rlgblg	-0.0480	-0.0092	-0.0328	-0.0012	0.0061	0.0126	0.0176	-0.0121	-0.0442	-0.0329
rlgatnd	-0.0224	-0.0479	-0.0694	-0.0255	0.0283	0.0357	0.0184	0.0149	-0.0486	-0.0222
dscrgrp	0.0978	0.0727	0.0560	0.0632	0.0540	0.0408	0.0215	0.0501	0.0647	0.0606
ctzcntr	0.0279	0.0263	0.0362	0.0115	0.0173	0.0123	0.0265	0.0198	0.0275	-0.0025
brncntr	0.0151	0.0074	0.0233	-0.0158	0.0259	0.0268	0.0386	0.0206	0.0123	-0.0052
blgetmg	0.0369	0.0065	-0.0222	0.0192	-0.0224	0.0021	-0.0196	0.0109	-0.0259	0.0043
facntr	0.0061	-0.0014	0.0142	-0.0247	0.0336	0.0173	0.0565	0.0124	0.0025	-0.0210
mocntr	0.0070	-0.0092	0.0105	-0.0335	0.0233	0.0228	0.0411	0.0059	-0.0012	-0.0187
vteurmmb	-0.0562	-0.0653	-0.0966	-0.0917	0.0321	0.0176	0.0444	0.0202	0.0506	0.0003
evpdemp	-0.0214	-0.0198	0.0150	0.0071	0.0182	-0.0006	0.0589	0.0056	0.0414	-0.0036
nbthcld	0.0297	0.0249	-0.0002	0.0119	-0.0518	-0.0386	-0.0501	-0.0211	0.0069	0.0035
plnftr	-0.0501	-0.0408	-0.0509	-0.0398	0.0441	0.0026	0.0538	-0.0057	0.0283	0.0127
gndr	-0.0197	-0.0071	0.0337	0.0141	0.0660	0.0552	0.0676	-0.0287	-0.0448	0.0184
agea	0.0033	0.0242	-0.0268	-0.0406	0.0164	-0.0343	-0.0113	0.0400	0.1046	0.0285
eduyrs	0.0301	0.0950	0.1139	0.1154	-0.1485	-0.0763	-0.1649	-0.1016	-0.2066	-0.1031
uempla	-0.0202	-0.0388	-0.0365	-0.0221	-0.0032	0.0150	0.0182	-0.0070	-0.0192	-0.0074
tporgwk	-0.0042	-0.0368	-0.0320	-0.0294	0.0577	0.0493	0.0535	0.0580	0.0511	0.0513
eiscedf	0.0207	0.0456	0.0471	0.0406	-0.0388	-0.0291	-0.0761	-0.0385	-0.0708	-0.0351
eiscedm	0.0113	0.0444	0.0611	0.0651	-0.0443	-0.0396	-0.0756	-0.0477	-0.0923	-0.0441
frprtpl	0.2891	0.3887	0.2486	0.2355	-0.1305	-0.0921	-0.1921	-0.0785	-0.1110	0.0033
gvintcz	0.3031	0.4534	0.3110	0.2652	-0.0959	-0.0610	-0.1456	-0.0342	-0.0392	0.0286
poltran	0.2687	0.4355	0.2999	0.2456	-0.0626	-0.0484	-0.1066	-0.0331	0.0028	0.0354
evfredu	0.1814	0.2250	0.1400	0.1125	-0.0015	-0.0011	-0.0590	0.0289	0.0350	0.0709
evfrjob	0.2100	0.3022	0.1919	0.1652	-0.0204	-0.0013	-0.0601	0.0233	0.0260	0.0767
sofrdst	0.0717	0.0984	0.0547	0.0672	-0.0796	-0.0178	-0.0966	0.0025	-0.0567	0.0391
sofrwrk	-0.0346	0.0455	0.0369	0.0373	0.0001	-0.0141	-0.0233	-0.0399	-0.0330	-0.0242
sofrprv	-0.0139	-0.0502	-0.0555	-0.0080	-0.0386	-0.0058	-0.0369	-0.0535	-0.0689	-0.0514
cntry	-0.0206	-0.0294	0.0338	0.0905	0.0122	0.0406	0.0432	-0.0189	0.0527	-0.0022
age_birth	0.0786	0.0843	0.0964	0.0953	-0.0652	-0.0181	-0.0764	-0.0221	-0.1014	-0.0544

	bctprd	pstplonl	clsprty	lrscale	stflife	stfeco	stfgov	gincdif	freehms	hmsacld
bctprd	**1.0000**									
pstplonl	**0.2467**	**1.0000**								
clsprty	**0.1073**	**0.0892**	**1.0000**							
lrscale	**0.1001**	**0.0543**	**-0.0439**	**1.0000**						
stflife	**-0.0677**	**-0.0034**	**-0.0828**	**0.0953**	**1.0000**					
stfeco	**-0.0303**	**0.0270**	**-0.1158**	**0.1227**	**0.4450**	**1.0000**				
stfgov	**0.0926**	**0.0919**	**-0.1168**	**0.2675**	**0.2726**	**0.5432**	**1.0000**			
gincdif	**-0.0022**	**-0.0152**	**-0.0033**	**0.1870**	**0.1121**	**0.1886**	**0.1502**	**1.0000**		
freehms	**0.1772**	**0.1406**	**0.0229**	**0.1270**	**-0.1620**	**-0.0919**	**0.0337**	**0.0285**	**1.0000**	
hmsacld	**0.1599**	**0.1263**	**0.0153**	**0.1680**	**-0.1339**	**-0.1193**	**0.0061**	**0.0213**	**0.5892**	**1.0000**
euftf	**-0.0748**	**-0.0088**	**-0.0625**	**-0.0615**	**0.1307**	**0.1745**	**0.0907**	**0.0303**	**-0.1519**	**-0.1758**
impcntr	**0.1971**	**0.1188**	**0.0460**	**0.2044**	**-0.1552**	**-0.0926**	**0.0137**	**0.0143**	**0.3342**	**0.3494**
imbgeco	**-0.1703**	**-0.0808**	**-0.0859**	**-0.1179**	**0.2080**	**0.2858**	**0.1422**	**0.0686**	**-0.2578**	**-0.2757**
imueclt	**-0.1979**	**-0.0962**	**-0.0632**	**-0.1549**	**0.2020**	**0.2142**	**0.1041**	**0.0305**	**-0.2990**	**-0.3312**
sclmeet	**-0.0965**	**-0.0939**	**-0.0637**	**-0.0030**	**0.2012**	**0.0793**	**0.0261**	**0.0245**	**-0.1991**	**-0.1648**
sclact	**-0.0556**	**-0.0519**	**-0.0738**	**0.0211**	**0.1759**	**0.0732**	**0.0584**	**0.0390**	**-0.0744**	**-0.0545**
crmvct	**0.1177**	**0.1137**	**0.0332**	**-0.0040**	**0.0049**	**0.0506**	**0.0438**	**-0.0239**	**0.0797**	**0.0574**
atchctr	**0.0113**	**0.0288**	**-0.1333**	**0.0803**	**0.1809**	**0.1033**	**0.1213**	**-0.0278**	**0.0260**	**0.1061**
atcherp	**-0.0428**	**0.0006**	**-0.0868**	**0.0036**	**0.1939**	**0.2405**	**0.1602**	**0.0339**	**-0.0723**	**-0.0848**
rlgblg	**-0.0614**	**-0.0663**	**0.0801**	**-0.1021**	**-0.0207**	**0.0320**	**-0.0466**	**0.0457**	**-0.1394**	**-0.1927**
rlgatnd	**-0.0855**	**-0.0817**	**0.0544**	**-0.1351**	**-0.0313**	**0.0042**	**-0.0943**	**0.0184**	**-0.2164**	**-0.2499**
dscrgrp	**0.0975**	**0.1175**	**-0.0134**	**0.0236**	**0.1183**	**0.0937**	**0.0979**	**0.0277**	**-0.0069**	**-0.0007**
ctzcntr	**-0.0004**	**-0.0145**	**0.0768**	**-0.0365**	**-0.0012**	**0.0306**	**0.0364**	**0.0275**	**0.0266**	**0.0133**
brncntr	**-0.0034**	**-0.0296**	**0.0510**	**-0.0612**	**-0.0142**	**0.0345**	**0.0389**	**0.0262**	**0.0170**	**0.0134**
blgetmg	**0.0014**	**0.0122**	**-0.0119**	**0.0365**	**0.0619**	**0.0037**	**-0.0120**	**-0.0131**	**-0.0762**	**-0.0386**
facntr	**-0.0036**	**-0.0248**	**0.0464**	**-0.0906**	**-0.0138**	**0.0234**	**0.0203**	**0.0151**	**0.0098**	**0.0066**
mocntr	**-0.0192**	**-0.0337**	**0.0463**	**-0.0787**	**-0.0266**	**0.0185**	**0.0076**	**0.0164**	**0.0062**	**0.0057**
vteurmmb	**0.0330**	**0.0228**	**0.0566**	**-0.0141**	**-0.0701**	**-0.0449**	**-0.0276**	**-0.0134**	**0.0762**	**0.0738**
evpdemp	**0.0386**	**0.0033**	**0.0260**	**0.0182**	**-0.0503**	**-0.0535**	**0.0130**	**0.0027**	**0.0604**	**0.0235**
nbthcld	**0.0030**	**0.0336**	**-0.0524**	**0.0504**	**0.0371**	**0.0133**	**0.0235**	**0.0039**	**0.0260**	**0.0274**
plnftr	**0.0175**	**0.0482**	**0.0235**	**-0.0084**	**-0.0635**	**-0.0537**	**-0.0523**	**-0.0467**	**-0.0227**	**-0.0151**
gndr	**-0.0339**	**-0.0014**	**0.0720**	**-0.0493**	**-0.0320**	**-0.0847**	**-0.0433**	**-0.0635**	**-0.0701**	**-0.1166**
agea	**0.0507**	**0.1743**	**-0.1583**	**0.0040**	**-0.0334**	**-0.0180**	**0.0258**	**-0.0846**	**0.1543**	**0.1616**
eduyrs	**-0.2069**	**-0.1631**	**-0.0283**	**-0.0442**	**0.1313**	**0.1205**	**0.0148**	**0.1349**	**-0.1978**	**-0.1995**
uempla	**-0.0196**	**-0.0366**	**0.0282**	**-0.0193**	**-0.0508**	**-0.0595**	**-0.0292**	**-0.0141**	**0.0053**	**0.0131**
tporgwk	**0.0589**	**0.0273**	**0.0248**	**0.0686**	**-0.0162**	**-0.0020**	**0.0181**	**0.0408**	**0.0324**	**0.0436**
eiscedf	**-0.0956**	**-0.0669**	**-0.0113**	**-0.0136**	**0.0488**	**0.0767**	**0.0134**	**0.0721**	**-0.0666**	**-0.0706**
eiscedm	**-0.0862**	**-0.0775**	**-0.0026**	**-0.0026**	**0.0525**	**0.0832**	**0.0102**	**0.0817**	**-0.0613**	**-0.0779**
frprtpl	**-0.1258**	**-0.0374**	**-0.1737**	**0.0620**	**0.2490**	**0.4011**	**0.3207**	**0.1571**	**-0.1660**	**-0.1757**
gvintcz	**-0.0420**	**0.0170**	**-0.1571**	**0.1251**	**0.2364**	**0.4403**	**0.4928**	**0.1805**	**-0.0679**	**-0.1171**
poltran	**0.0056**	**0.0298**	**-0.1232**	**0.1165**	**0.1860**	**0.3601**	**0.4429**	**0.1206**	**-0.0028**	**-0.0567**
evfredu	**0.0692**	**0.0545**	**-0.0329**	**0.1204**	**0.1803**	**0.2962**	**0.2512**	**0.1513**	**0.0091**	**0.0217**
evfrjob	**0.0456**	**0.0343**	**-0.0327**	**0.1295**	**0.1968**	**0.3776**	**0.3132**	**0.1843**	**-0.0106**	**-0.0640**
sofrdst	**-0.0679**	**-0.0374**	**-0.0401**	**0.1348**	**0.1276**	**0.2143**	**0.1064**	**0.3936**	**-0.0525**	**-0.0313**
sofrwrk	**-0.0264**	**-0.0024**	**0.0341**	**-0.0406**	**-0.0180**	**0.0043**	**0.0158**	**0.0452**	**0.0297**	**-0.0645**
sofrprv	**-0.1019**	**-0.0337**	**-0.0935**	**-0.0538**	**0.0023**	**-0.0679**	**-0.0868**	**-0.0956**	**-0.0875**	**-0.0486**
cntry	**0.0542**	**-0.0025**	**0.0217**	**0.0177**	**-0.0228**	**-0.1005**	**-0.0183**	**-0.0154**	**0.0127**	**0.0551**
age_birth	**-0.1117**	**-0.0754**	**-0.0416**	**-0.0066**	**0.0892**	**0.0924**	**0.0533**	**0.0912**	**-0.1394**	**-0.1267**

	euftf	impcntr	imbgeco	imueclt	sclmeet	sclact	crmvct	atchctr	atcherp	rlgblg
euftf	**1.0000**									
impcntr	**-0.3041**	**1.0000**								
imbgeco	**0.3862**	**-0.5213**	**1.0000**							
imueclt	**0.3887**	**-0.5280**	**0.6848**	**1.0000**						
sclmeet	**0.0414**	**-0.1493**	**0.1071**	**0.1127**	**1.0000**					
sclact	**0.0622**	**-0.0805**	**0.0990**	**0.0833**	**0.3897**	**1.0000**				
crmvct	**0.0015**	**0.0607**	**-0.0137**	**-0.0428**	**-0.0406**	**-0.0189**	**1.0000**			
atchctr	**0.0150**	**0.0541**	**0.0254**	**-0.0123**	**0.0364**	**0.0706**	**0.0160**	**1.0000**		
atcherp	**0.3121**	**-0.1281**	**0.2546**	**0.2314**	**0.0391**	**0.0861**	**0.0344**	**0.3823**	**1.0000**	
rlgblg	**0.0140**	**-0.0193**	**0.0015**	**0.0270**	**0.0308**	**-0.0286**	**-0.0246**	**-0.1815**	**-0.0418**	**1.0000**
rlgatnd	**-0.0134**	**-0.0208**	**-0.0086**	**0.0314**	**0.0316**	**-0.0561**	**-0.0317**	**-0.1174**	**-0.0263**	**0.5465**
dscrgrp	**0.0214**	**0.0423**	**-0.0061**	**-0.0277**	**-0.0170**	**0.0323**	**0.0722**	**0.0620**	**0.0741**	**-0.0007**
ctzcntr	**0.0416**	**-0.0715**	**0.0676**	**0.0780**	**0.0088**	**-0.0324**	**-0.0059**	**-0.0770**	**0.0152**	**-0.0189**
brncntr	**0.0402**	**-0.0970**	**0.0826**	**0.0940**	**0.0045**	**-0.0294**	**-0.0215**	**-0.0603**	**0.0140**	**-0.0198**
blgetmg	**-0.0209**	**0.0378**	**-0.0372**	**-0.0382**	**-0.0123**	**0.0099**	**0.0202**	**0.0586**	**0.0054**	**0.0376**
facntr	**0.0383**	**-0.0994**	**0.0755**	**0.0879**	**0.0191**	**-0.0283**	**-0.0147**	**-0.0730**	**0.0129**	**-0.0028**
mocntr	**0.0359**	**-0.0958**	**0.0748**	**0.0850**	**0.0151**	**-0.0188**	**-0.0237**	**-0.0615**	**0.0171**	**-0.0138**
vteurmmb	**-0.0969**	**0.0644**	**-0.0815**	**-0.0907**	**-0.0028**	**-0.0143**	**0.0133**	**-0.0410**	**-0.0984**	**0.0225**
evpdemp	**-0.0199**	**0.0262**	**-0.0346**	**-0.0302**	**-0.0647**	**-0.0373**	**0.0083**	**-0.0201**	**-0.0383**	**-0.0318**
nbthcld	**-0.0002**	**-0.0385**	**0.0413**	**0.0397**	**0.0296**	**0.0006**	**-0.0182**	**0.0627**	**-0.0143**	**-0.1301**
plnftr	**0.0078**	**0.0177**	**-0.0377**	**-0.0094**	**-0.0128**	**-0.0794**	**0.0032**	**-0.0324**	**-0.0593**	**0.0524**
gndr	**-0.0235**	**0.0015**	**-0.0622**	**0.0045**	**0.0155**	**-0.0081**	**0.0115**	**0.0082**	**0.0399**	**-0.0349**
agea	**0.0053**	**0.1027**	**-0.0062**	**-0.0649**	**-0.0563**	**0.0336**	**0.0649**	**0.1542**	**0.0591**	**-0.1548**
eduyrs	**0.1579**	**-0.2567**	**0.2412**	**0.2613**	**0.0851**	**0.0803**	**-0.0840**	**-0.0382**	**0.1101**	**0.0825**
uempla	**-0.0254**	**-0.0022**	**-0.0301**	**-0.0145**	**-0.0073**	**-0.0149**	**-0.0428**	**-0.0137**	**-0.0175**	**0.0085**
tporgwk	**-0.0432**	**0.0415**	**-0.0131**	**-0.0407**	**-0.0285**	**-0.0382**	**-0.0092**	**-0.0365**	**-0.0551**	**-0.0151**
eiscedf	**0.0496**	**-0.0919**	**0.0809**	**0.0793**	**0.0407**	**0.0286**	**-0.0484**	**-0.0395**	**0.0555**	**0.0823**
eiscedm	**0.0464**	**-0.0738**	**0.0833**	**0.0897**	**0.0379**	**0.0343**	**-0.0334**	**-0.0474**	**0.0564**	**0.1065**
frprtpl	**0.1719**	**-0.1659**	**0.2568**	**0.2632**	**0.1148**	**0.0868**	**-0.0108**	**0.0880**	**0.1982**	**0.0268**
gvintcz	**0.1645**	**-0.1204**	**0.2419**	**0.2292**	**0.0721**	**0.0750**	**0.0108**	**0.0910**	**0.2071**	**0.0100**
poltran	**0.1214**	**-0.0487**	**0.1801**	**0.1663**	**0.0361**	**0.0633**	**0.0332**	**0.0943**	**0.1756**	**-0.0193**
evfredu	**0.0461**	**0.0351**	**0.0755**	**0.0297**	**0.0345**	**0.0397**	**0.0374**	**0.1103**	**0.1231**	**-0.0125**
evfrjob	**0.0860**	**0.0094**	**0.1282**	**0.0820**	**0.0608**	**0.0547**	**0.0503**	**0.0491**	**0.1489**	**0.0623**
sofrdst	**0.0508**	**-0.0087**	**0.0873**	**0.0756**	**0.0299**	**0.0217**	**-0.0286**	**0.0018**	**0.0634**	**0.0615**
sofrwrk	**0.0391**	**-0.0314**	**0.0300**	**0.0755**	**-0.0096**	**-0.0127**	**0.0074**	**-0.0963**	**-0.0071**	**0.0905**
sofrprv	**0.0260**	**-0.0692**	**0.0235**	**0.0658**	**0.0816**	**0.0151**	**-0.0443**	**0.0525**	**0.0186**	**0.0311**
cntry	**0.0706**	**-0.0593**	**0.0131**	**0.0797**	**-0.1028**	**-0.0257**	**-0.0052**	**0.0239**	**-0.0179**	**0.0092**
age_birth	**0.0851**	**-0.1819**	**0.1668**	**0.1776**	**0.0352**	**0.0112**	**-0.0145**	**-0.0496**	**0.0333**	**0.0348**

	rlgatnd	dscrgrp	ctzcntr	brncntr	blgetmg	facntr	mocntr	vteurmmb	evpdemp	nbthcld
rlgatnd	1.0000									
dscrgrp	0.0094	1.0000								
ctzcntr	-0.0388	-0.0896	1.0000							
brncntr	-0.0471	-0.1279	0.5747	1.0000						
blgetmg	0.0390	0.2523	-0.2000	-0.3153	1.0000					
facntr	-0.0249	-0.1377	0.5222	0.7170	-0.2982	1.0000				
mocntr	-0.0280	-0.1331	0.5239	0.7290	-0.3052	0.7414	1.0000			
vteurmmb	0.0048	-0.0445	0.1261	0.0746	-0.0623	0.0644	0.0741	1.0000		
evpdemp	-0.0584	0.0041	0.0367	0.0123	-0.0155	0.0064	0.0097	0.0086	1.0000	
nbthcld	-0.1824	-0.0334	0.0206	0.0262	-0.0200	0.0148	0.0201	0.0017	0.0307	1.0000
plnftr	0.0104	-0.0531	-0.0000	0.0050	-0.0339	0.0078	0.0127	0.0257	0.0397	0.0905
gndr	-0.0494	-0.0181	-0.0186	-0.0032	-0.0187	0.0035	0.0042	0.0168	0.0036	-0.0232
agea	-0.1491	0.0669	-0.0995	-0.0804	0.0770	-0.1037	-0.0868	-0.0021	0.0394	0.1954
eduyrs	0.1044	-0.0271	0.0018	0.0131	0.0348	0.0069	0.0085	-0.0830	-0.0447	-0.0798
uempla	0.0119	-0.0423	0.0610	0.0522	-0.0167	0.0505	0.0422	0.0116	0.0030	0.0075
tporgwk	-0.0129	0.0052	0.0497	0.0323	-0.0180	0.0277	0.0255	0.0208	0.0188	0.0011
eiscedf	0.0868	-0.0115	0.0320	0.0497	-0.0052	0.0449	0.0342	-0.0229	-0.0352	-0.0490
eiscedm	0.1027	-0.0127	0.0266	0.0322	-0.0110	0.0250	0.0133	-0.0025	-0.0336	-0.0896
frprtpl	0.0326	0.0564	-0.0026	0.0103	0.0133	0.0037	0.0086	-0.0774	-0.0823	0.0183
gvintcz	-0.0147	0.0787	0.0301	0.0431	-0.0135	0.0280	0.0268	-0.0537	-0.0498	0.0209
poltran	-0.0454	0.0781	0.0292	0.0278	-0.0057	0.0137	0.0114	-0.0434	-0.0383	0.0105
evfredu	-0.0335	0.0797	0.0147	0.0221	-0.0027	0.0014	0.0171	-0.0381	-0.0396	0.0031
evfrjob	0.0182	0.0804	0.0314	0.0270	0.0080	0.0085	0.0191	-0.0382	-0.0082	0.0042
sofrdst	0.0678	0.0298	-0.0222	-0.0171	0.0279	-0.0280	-0.0249	-0.0383	-0.0471	-0.0040
sofrwrk	0.0267	-0.0059	0.0001	-0.0129	-0.0000	-0.0140	-0.0167	0.0083	0.0479	-0.0040
cntry	-0.1126	0.0398	-0.0575	-0.0145	0.0456	-0.0489	-0.0486	-0.0470	0.0327	0.0404
age_birth	0.0320	-0.0060	0.0263	0.0386	0.0233	0.0132	0.0100	-0.0567	0.0016	-0.2338

	plnftr	gndr	agea	eduyrs	uempla	tporgwk	eiscedf	eiscedm	frprtpl	gvintcz
plnftr	1.0000									
gndr	0.0284	1.0000								
agea	0.1644	-0.0552	1.0000							
eduyrs	-0.1787	-0.0057	-0.2440	1.0000						
uempla	0.0122	0.0038	-0.0833	-0.0218	1.0000					
tporgwk	-0.0081	-0.1289	-0.0710	-0.1449	0.0452	1.0000				
eiscedf	-0.0603	0.0175	-0.1410	0.2494	-0.0168	-0.0422	1.0000			
eiscedm	-0.0771	0.0401	-0.2218	0.2455	0.0042	-0.0271	0.3434	1.0000		
frprtpl	-0.0508	-0.0616	0.0045	0.2027	-0.0398	-0.0407	0.1084	0.0920	1.0000	
gvintcz	-0.0680	-0.0772	-0.0018	0.1647	-0.0403	-0.0241	0.0937	0.0679	0.6169	1.0000
poltran	-0.0597	-0.0487	0.0084	0.0859	-0.0387	-0.0111	0.0515	0.0558	0.4970	0.6073
evfredu	-0.0226	-0.0333	0.0139	0.0291	-0.0434	0.0241	0.0350	0.0614	0.2774	0.2817
evfrjob	-0.0074	-0.0595	-0.0406	0.0687	-0.0448	0.0394	0.0564	0.0799	0.3070	0.3408
sofrdst	-0.0697	-0.0409	-0.0637	0.1988	-0.0290	0.0189	0.1034	0.1106	0.2258	0.1931
sofrwrk	0.0624	0.0481	-0.0130	0.0105	0.0009	-0.0456	0.0153	0.0286	0.0105	0.0259
sofrprv	-0.0023	-0.0189	0.0382	0.0480	0.0133	-0.0385	-0.0246	-0.0202	0.0222	-0.0275
cntry	0.0369	-0.0084	-0.0216	0.0213	0.0181	-0.0030	-0.0814	-0.0717	-0.0498	-0.0288
age_birth	-0.1010	-0.2292	-0.1294	0.3011	-0.0060	-0.0021	0.1034	0.0920	0.1315	0.1370

	poltran	evfredu	evfrjob	sofrdst	sofrwrk	sofrprv	cntry	age_bi~h
poltran	1.0000							
evfredu	0.2704	1.0000						
evfrjob	0.3112	0.6429	1.0000					
sofrdst	0.1169	0.1283	0.1516	1.0000				
sofrwrk	0.0313	-0.0501	-0.0067	0.0921	1.0000			
sofrprv	-0.0944	-0.0996	-0.1175	0.0230	0.0009	1.0000		
cntry	-0.0167	-0.0482	-0.1169	-0.0203	0.0606	0.1206	1.0000	
age_birth	0.0670	-0.0022	0.0247	0.0901	0.0067	0.0474	0.0686	1.0000

2.3 Preparation of Dataset

Now, we need to define our dataset for which we not only remove all observations with missing values in the dependent variable but also in the explanatory variables. This reduces the sample size from originally 36015 to 10236 observations. This is a large decrease but we wanted to include all variables to not have an omitted variable bias.

```
attach(ess)
dataset <- data.frame(vteurmmb,cntry,nwspol, netusoft,  ppltrst, pplhlp, polintr,
                      psppsgva, psppipla, cptppola, trstprl, trstlgl, trstplc, trstprt,
                      trstep, contplt, wrkprty, wrkorg, badge, sgnptit, pbldmn, bctprd,
                      pstplonl, clsprty, lrscale, stflife, stfeco, stfgov, gincdif,
                      freehms, hmsacld, euftf, impcntr, imbgeco, imueclt, sclmeet, sclact,
                      crmvct, atchctr, atcherp, rlgblg, rlgatnd, dscrgrp, ctzcntr, brncntr,
                      blgetmg,evpdemp, plnftr, gndr, agea, eduyrs, uempla,  eiscedm,
                      eiscedf,frprtpl,gvintcz, poltran, evfredu, evfrjob, sofrdst, sofrwrk,
                      sofrprv, age_birth, nbthcld, tporgwk)
dataset$vteurmmb <- droplevels(dataset$vteurmmb, exclude = NA)
dataset <- na.omit(dataset)
dataset[] <- lapply(dataset, function(x) if(is.factor(x)) factor(x) else x)
detach(ess)
```

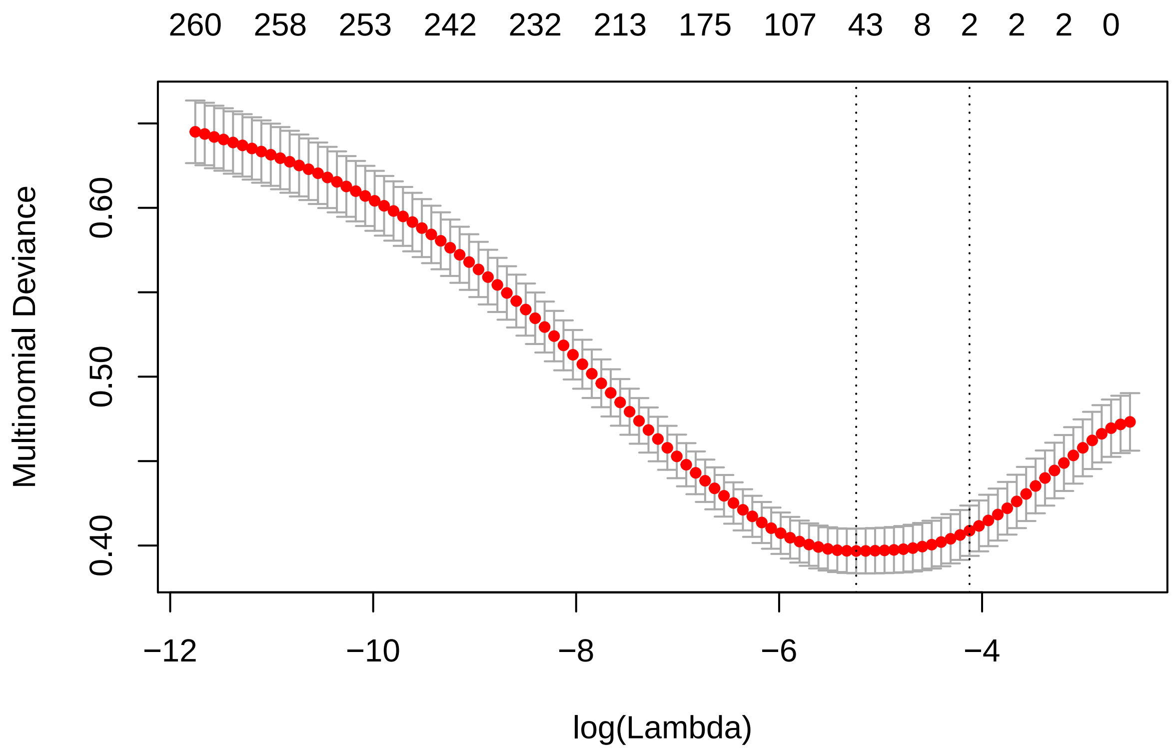
2.4 Multinomial Logistic Regression Using Elastic Net

First, we decided to do an Elastic net regularization by using the R function `cv.glmnet()`. For this we have to create a matrix X containing all the explanatory variables using `model.matrix`. We do not need to standardize our explanatory variables as the command `glmnet` does this by default. We chose alpha to be 0.3 as we want to do some variable selection but also want to interpret our results and thus not want all coefficients shrunk to 0. Since alpha is closer to 0 than to 1, the elastic net uses more of a ridge penelization than of a lasso. As we want to use the lambda which minimizes the mean-squared error, we will use cross-validation to find this value, which is 0.0053. This means, that we penalize our estimates very little. We can see in table 1 to 6 that the number of variables, including dummies for each category of a factor variable, is much smaller than the original number of variables. This means that a number of variables are set to zero. Moreover, we can visualize the mean-squared error with different log lambdas as done in Figure 1, which shows that the log lambda that minimizes the MSE lies between -5 and -6. Furthermore, we visualize the values of the coefficients for different log lambdas in the other plot, giving us 5 different plots for the 5 different outcomes of our dependent variable, leaving out the category “Leave the EU” as it is our reference category. Here, we can see that the higher lambda gets, the more it shrinks the coefficients towards zero and also to exactly zero.

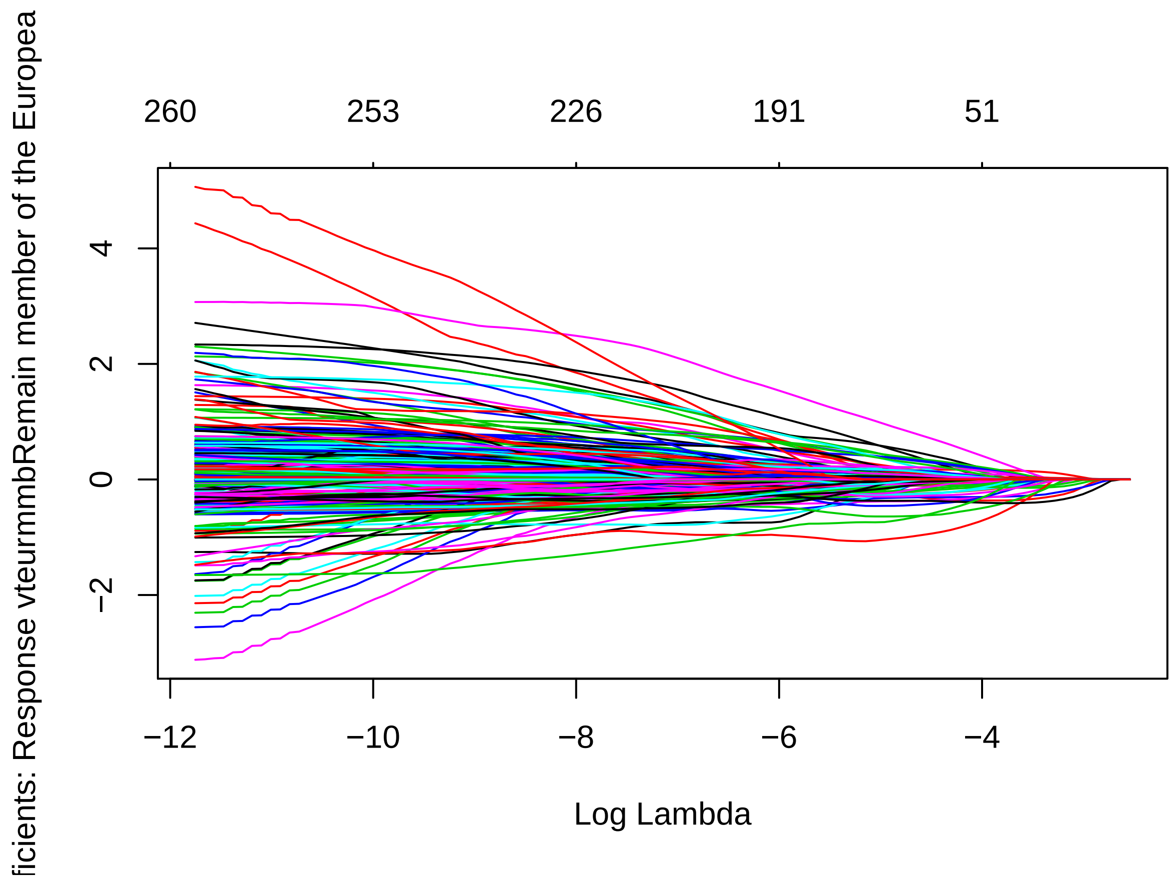
```
set.seed(1234)
library(glmnet)
library(stats)
x <- model.matrix(vteurmmb~.,dataset)[,-1] # no intercept
dataset$vteurmmb <- relevel(dataset$vteurmmb, "Leave the European Union")
ydummy <- model.matrix(~vteurmmb, dataset)
y <- ydummy[,2:6]

enetfit <- cv.glmnet(x,y, alpha=0.3, family = "multinomial")
enetfit$lambda.min
```

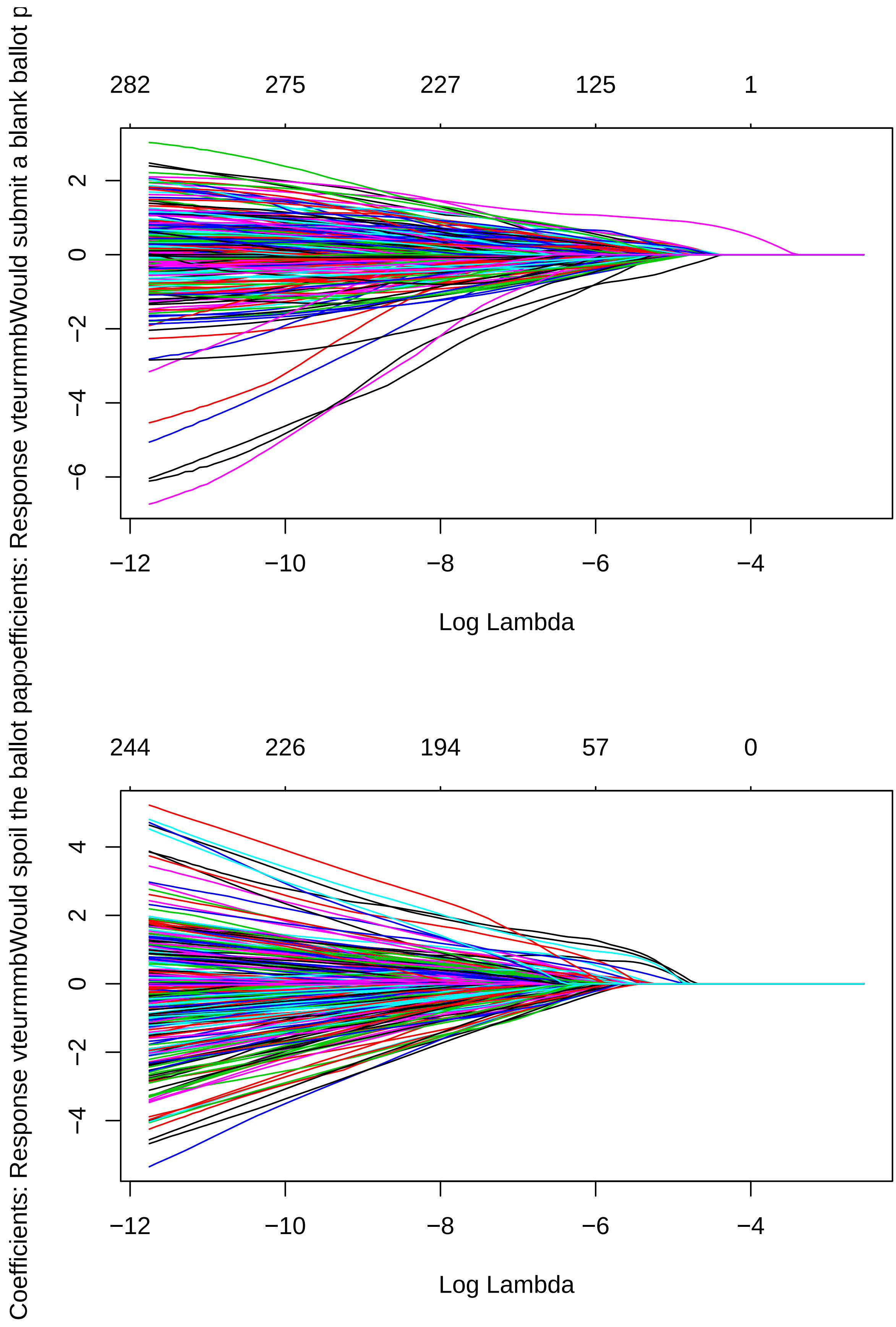
```
## [1] 0.005297368
```

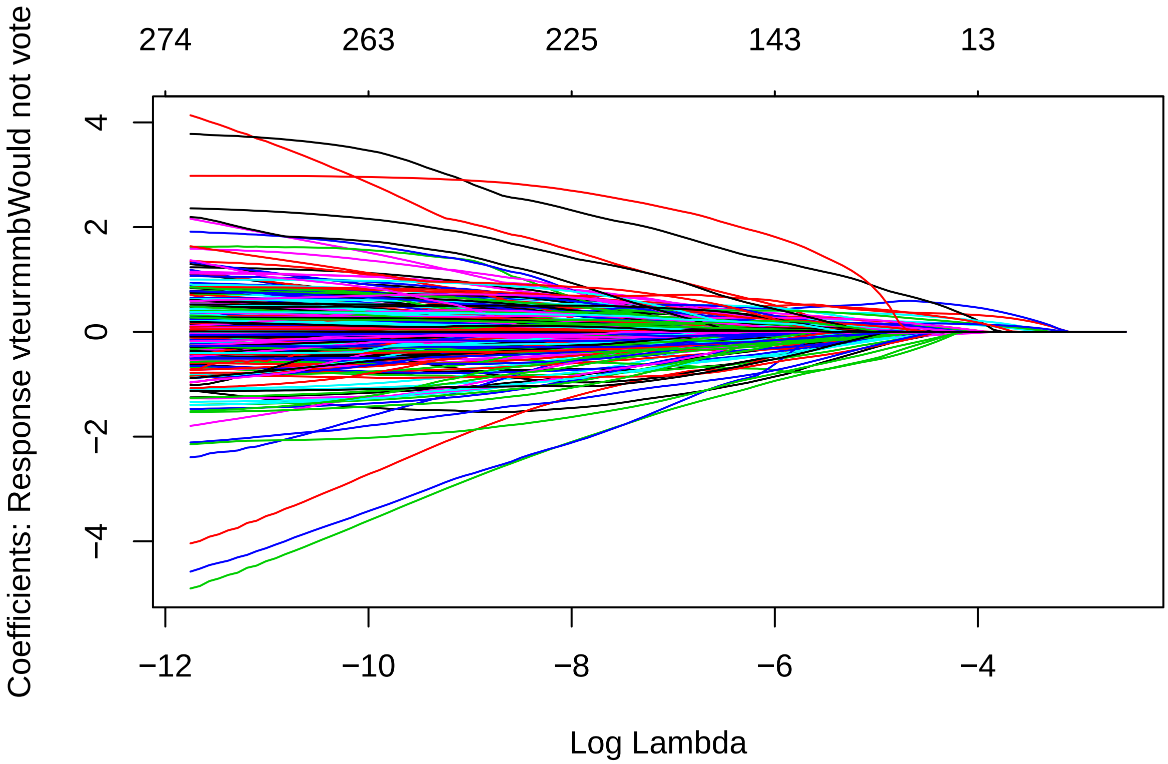
```
output <- coef(enetfit, s= "lambda.min")
plot(enetfit, xvar = "lambda")
```

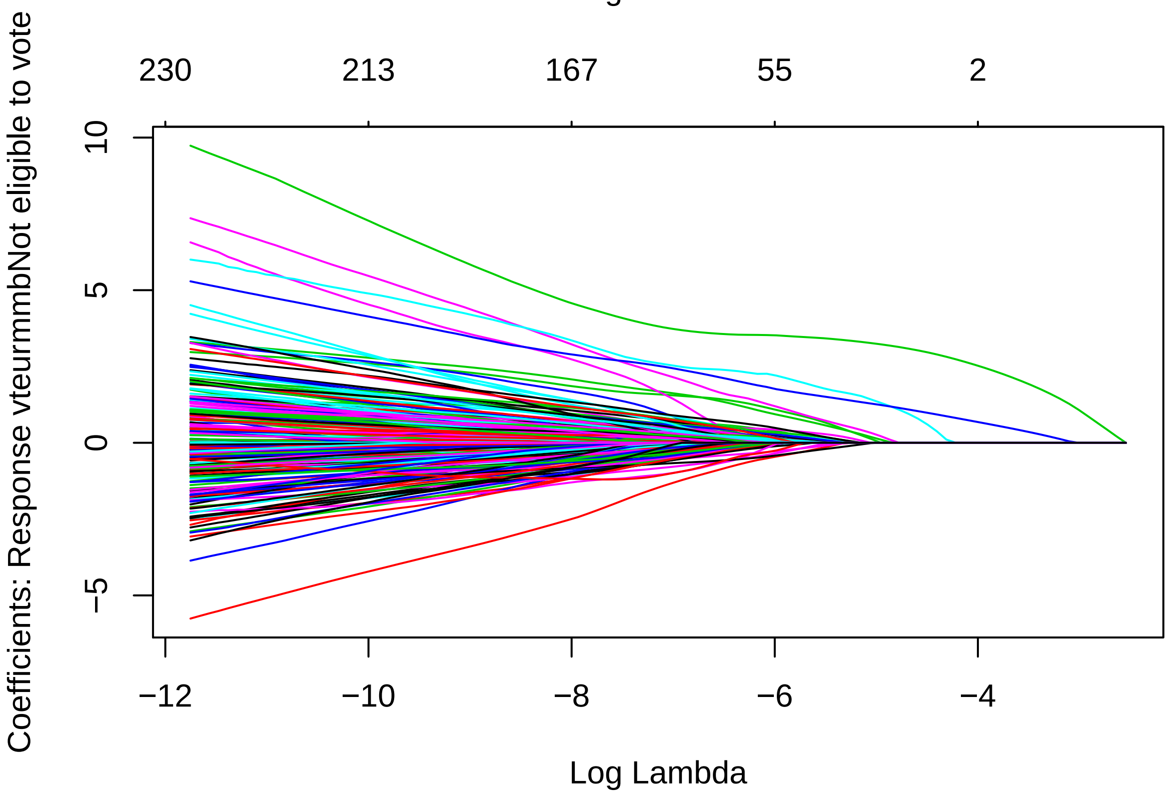



```
plot(enetfit$glmnet.fit, xvar = "lambda")
```




Coefficients: Response vteurmmbWould spoil the ballot papoefficients: Response vteurmmbWould submit a blank ballot p
282
275
227
125
1
2
0
−2
−4
−6
−12
−10
−8
−6
−4
Log Lambda
244
226
194
57
0
4
2
0
−2
−4
−12
−10
−8
−6
−4
Log Lambda






```
RemainEU_EN<- data.frame("Variable"= rownames(output[[1]])[output[[1]] [,1]!= 0],
                         "Value"=output[[1]] [which(output[[1]] [,1]!=0)])
BlankBallot_EN<- data.frame("Variable"= rownames(output[[2]])[output[[2]] [,1]!= 0],
                            "Value"=output[[2]] [which(output[[2]] [,1]!=0)])
SpoilBallot_EN<- data.frame("Variable"= rownames(output[[3]])[output[[3]] [,1]!= 0],
```

```
                            "Value"=output[[3]] [which(output[[3]] [,1]!=0)])
NotVote_EN<- data.frame("Variable"= rownames(output[[4]])[output[[4]] [,1]!= 0],
                        "Value"=output[[4]] [which(output[[4]] [,1]!=0)])
NotEligible_EN<- data.frame("Variable"= rownames(output[[5]])[output[[5]] [,1]!= 0],
                            "Value"=output[[5]] [which(output[[5]] [,1]!=0)])
```

Table 1: Remain in the EU

Variable	Value
(Intercept)	3.0738449
cntryBE	0.6485114
cntryBG	-0.1146618
cntryCY	0.3013225
cntryDE	0.1480852
cntryHU	0.2276978
cntryIE	0.5294029
cntryPL	0.2288632
cntrySI	0.7073924
netusoftMost days	0.0879984
netusoftEvery day	0.0978983
ppltrst3	-0.0231712
pplhlp3	-0.0714524
pplhlp4	0.0126199
pplhlp5	0.0425206
pplhlp6	0.1333490
pplhlp8	-0.1005158
pplhlp9	-0.0749217
pplhlpPeople mostly try to be helpful	-0.2362653
polintrQuite interested	0.1337038
polintrHardly interested	-0.2879540
polintrNot at all interested	-0.3358661
psppsgvaVery little	0.0587472
psppsgvaSome	0.0605125
psppiplaVery little	0.0103694
cptppolaA little confident	0.1536568
cptppolaQuite confident	0.0854295
cptppolaVery confident	0.3134812
cptppolaCompletely confident	-0.2336115
trstprl4	0.1279346
trstprl7	0.1163927
trstlgl2	0.0300107
trstlgl3	0.0833078
trstlgl7	0.0525197
trstlgl9	0.2441039
trstplc2	-0.0334431
trstplc3	0.1158121
trstprt1	0.0221230
trstprt4	0.1090711
trstprt6	-0.0988360
trstprt7	0.0209682
trstprt8	0.1216859
trstprt9	-0.3959428
trstep1	-0.3907081
trstep3	-0.2650420
trstep6	0.4566540
trstep7	0.1539447

trstep8	0.0440594
trstep9	0.1631723
trstepComplete trust	0.3193288
pbldmnNo	0.1851098
clsprtyNo	-0.1223800
lrscale2	-0.0433081
lrscale3	0.0856964
lrscale5	-0.0167871
lrscale7	-0.0194868
lrscale8	0.2166428
lrscaleRight	0.1019914
stflife2	-0.0935554
stflife4	-0.0978042
stflife5	-0.1757568
stflife7	-0.0371259
stflife8	0.0649248
stfeco2	0.0230913
stfeco5	-0.0171227
stfeco9	-0.2460203
stfgov1	0.0418598
stfgov4	0.0004292
stfgov7	0.0069994
stfgov8	-0.1468093
stfgovExtremely satisfied	-0.3601095
gincdifNeither agree nor disagree	0.0368487
gincdifDisagree strongly	-0.2431774
hmsacldAgree	0.0231838
hmsacldDisagree strongly	-0.0248320
euftf2	-0.0825016
euftf3	-0.2372956
euftf4	-0.1457967
euftf6	0.0399364
euftf7	0.5036108
euftf8	0.4239513
euftf9	0.4817594
euftfUnification go further	1.1149483
impcntrAllow none	-0.0545554
imbgeco3	-0.0151698
imbgeco4	0.0688004
imbgeco5	-0.1144446
imbgeco6	0.0538952
imbgeco7	0.1072406
imbgeco8	0.0662003
imbgecoGood for the economy	0.3239781
imueclt2	-0.2252766
imueclt3	-0.0123880
imueclt7	0.1873112
imuecltCultural life enriched	0.0671540
sclmeetLess than once a month	0.2578655
sclmeetEvery day	-0.0491131

sclactMuch more than most	-0.0986105
atchctr3	-0.2615829
atchctr6	-0.1653062
atchctrVery emotionally attached	0.0257582
atcherp1	-1.0674006
atcherp2	-0.6213066
atcherp3	-0.4453444
atcherp4	-0.2583893
atcherp5	-0.2770204
atcherp6	0.0188451
atcherp7	0.0318357
atcherp8	0.1000515
atcherp9	0.1815570
atcherpVery emotionally attached	0.0364678
rlgblgNo	-0.0995759
rlgatndLess often	-0.0599971
dscrgrpNo	0.2248978
ctzcntrNo	-0.3654944
blgetmgNo	0.1308536
plnftr4	0.0022406
plnftr6	0.0442892
eduyrs	0.0324623
eiscedmES-ISCED V2, higher tertiary education, >= MA level	-0.1288548
eiscedfES-ISCED IIIb, lower tier upper secondary	-0.1505439
eiscedfES-ISCED IV, advanced vocational, sub-degree	0.0563388
frprtplA lot	0.0084088
gvintczVery little	-0.0183950
poltranVery little	0.0183484
evfredu3	-0.0265239
evfredu7	-0.2016648
evfredu9	0.4384180
evfrjob1	-0.1215599
evfrjob2	-0.1012209
evfrjob3	-0.0009596
evfrjob4	-0.0574071
evfrjob5	0.0363201
evfrjob6	0.0349885
evfrjob9	-0.1936220
evfrjobApplies completely	0.0205871
sofrdstNeither agree nor disagree	0.1139961
sofrdstDisagree	0.1811580
sofrwrkAgree	0.0600746
sofrwrkDisagree strongly	-0.7413987
sofrprvAgree	0.0035809
sofrprvDisagree	0.1191315
sofrprvDisagree strongly	-0.0412665
age_birth	0.0081084
tporgwkA state owned enterprise	-0.0871746
tporgwkSelf employed	-0.0507809

tporgwkOther	0.0075508

Table 2: Blank Ballot

Variable	Value
(Intercept)	0.0697559
cntryDE	-0.1580880
cntryFR	0.9570252
cntryHU	-0.5440508
cntryIE	-0.0360850
cntryIT	0.2632711
netusoftOnly occasionally	0.2740421
netusoftA few times a week	0.2938817
ppltrst1	0.0088407
ppltrst2	0.0376999
ppltrst4	0.0187704
pplhlp7	-0.0644154
trstprl2	0.0864067
trstplc1	0.3337675
trstprt2	-0.0610443
lrscale7	0.0597536
stflife1	-0.0365841
stflife2	0.3317520
stflife3	-0.0950579
stflife4	0.1018041
stflife6	-0.0378527
stfeco6	-0.0071231
stfgov2	0.1674146
stfgov4	-0.0971878
stfgov7	-0.0129274
stfgov8	0.1186158
stfgov9	0.0118778
freehmsDisagree	0.3927687
euftf3	0.0742375
euftf6	0.0199334
impcntrAllow some	0.0055853
imbgeco2	-0.0750380
imueclt4	0.1368209
imueclt5	-0.0323818
sclmeetSeveral times a month	0.0455257
sclmeetSeveral times a week	-0.0924011
atchctr3	0.2919754
atcherp2	0.2257257
atcherp6	-0.1773238
rlgatndAt least once a month	0.0421206
rlgatndOnly on special holy days	0.1256206
plnftr2	0.0595932
plnftr3	-0.1598857
plnftrI just take each day as it comes	-0.1051306

agea	-0.0020558
uemplaMarked	0.0871694
evfredu4	0.2750005
evfredu8	-0.1189927
evfrjob4	0.0536091
sofrdstNeither agree nor disagree	-0.1202264
tporgwkOther public sector (such as education and health)	0.0645625
tporgwkA state owned enterprise	0.0857741
tporgwkA private firm	-0.0085369

Table 3: Spoil Ballot

Variable	Value
(Intercept)	-1.3494953
cptppolaCompletely confident	0.6518418
trstlgl1	0.4900505
atchctr2	0.7042135
eiscedfES-ISCED IIIb, lower tier upper secondary	0.2310240
evfredu1	0.5915273

Table 4: Would not Vote

Variable	Value
(Intercept)	0.6316444
cntryBE	-0.4240985
cntryBG	0.4377834
cntryCY	-0.6058491
cntryCZ	0.5087284
cntryFI	0.0018996
cntryFR	-0.1910260
cntryHU	0.0297615
cntryIE	-0.2958801
netusoftEvery day	-0.1346042
pplhlp7	0.2638310
polintrNot at all interested	0.2245878
psppsgvaSome	-0.1375600
psppiplaSome	-0.1133593
cptppolaA little confident	-0.0222773
trstprl2	0.2383583
trstprl3	0.0824317
trstprl8	-0.0659410
trstprlComplete trust	-0.0481928
trstlgl1	-0.6193128
trstlgl5	0.0720261
trstlgl6	-0.1120953
trstplc8	-0.0144166
trstprt1	-0.0570705
trstprt2	0.0105813

trstep5	-0.0903799
trstep9	-0.1400398
sgnptitNo	0.1253255
pbldmnNo	-0.0382282
lrscale4	0.0717652
lrscale5	0.2428817
lrscale6	-0.1092903
lrscale8	-0.1839550
stflife1	1.0221769
stflife6	0.0914394
stfeco2	-0.0631460
stfgov1	-0.1264303
freehmsNeither agree nor disagree	0.1572157
freehmsDisagree strongly	0.3594100
hmsacldAgree	-0.0716143
hmsacldDisagree strongly	0.3467550
euftf1	0.1445826
euftf8	-0.0381668
impcntrAllow some	-0.0002418
impcntrAllow none	0.1545542
imbgeco3	0.0329568
imbgeco7	-0.1691697
imbgeco8	-0.2320451
imueclt1	0.4626147
imueclt3	0.0268720
imueclt4	-0.0730966
imueclt5	0.1050031
imueclt8	-0.0744375
sclmeetSeveral times a week	0.0221211
atchctr5	-0.3554636
atchctr6	0.0004630
atcherp3	0.1742619
atcherp5	0.1263744
atcherp8	-0.1103865
atcherp9	-0.3676048
atcherpVery emotionally attached	-0.2200867
rlgblgNo	0.2439739
rlgatndAt least once a month	-0.0288983
rlgatndOnly on special holy days	-0.0657670
rlgatndLess often	0.1187333
brncntrNo	-0.1404454
plnftr2	-0.0084693
plnftr6	-0.0033133
plnftr8	0.0410271
agea	0.0011482
eduyrs	-0.0170512
uemplaMarked	-0.1643144
eiscedmES-ISCED II, lower secondary	0.1455476
eiscedmES-ISCED V2, higher tertiary education, >= MA level	0.0699125
eiscedmOther	1.1667807

frprtplSome	-0.0016720
gvintczVery little	0.0124708
evfredu2	0.0302354
evfredu4	-0.0488247
evfreduApplies completely	-0.4828512
sofrdstDisagree	-0.0571541
sofrwrkDisagree strongly	0.0858424
sofrprvDisagree strongly	0.0210524

Table 5: Not eligble to Vote

Variable	Value
(Intercept)	-2.4257500
cntryCY	0.3556571
cntryIE	0.3592865
trstprlComplete trust	0.5011609
stfeco9	0.1420125
atchctr1	1.5999874
rlgatndNever	-0.0936233
ctzcntrNo	3.3397710
brncntrNo	1.3784529
plnftr3	0.0416061
evfrjob3	0.0465939

Due to the large amount of variables, we are only going to describe the ones with a large value. Our reference category of the outcome variable is *Leave the EU*.

It can be seen in Table 1 that being a citizen of some countries has a relative large effect on voting in favor of remaining in the EU. This can especially be seen for the countries Ireland, Belgium and Slovenia. Especially for Irealand, this makes a lot of sense, due to their closeness to United Kingdom which is affected by the upcoming Brexit. If a person is not at all interested in politics (polintr), the probability of voting to remain in the European Union decreases. Surprisingly, the probabilty of voting in favor of remaining in the EU decreases, if a person has a lot of trust in political parties (trstprt). However, as expected, the probability of voting in favor of the EU decreases if a person has no trust in the European Parliament and increases if he or she has complete trust (trstep). If a person states that he or she is extremly satisfied with the country's government (stfgov) the probability that this person wants the country to remain a member of the European Union decreases. This is what we mentioned above with nationalist governments like in Hungary. Additionally, the probability of wanting the country to remain a memeber of the EU increases a lot when a person believs that the unification of the EU should go further (euftf). If a person believes that immigration is good for the country's economy (imbgeco), he or she is more likely to vote in favor of the EU, as the EU and its regulations promote migration. Furthermore, if a person does not feel attached to Europe at all (atcherp), the person is very unlikely to want its country to remain a member of the European Union. A person not being a citizen of the country he or she lives in (ctzcntr), decreases the probability of voting to remain in contrast to leaving the EU. Morever, if a person thinks that everyone in his or her country has a fair chance to achieve the level of education he or she seeks, the probability of voting in favor of remaining in the EU increases (evfredu). If a person strongly disagrees with the statement "A society is fair when hard-working people earn more than others", the person's probability of voting to remain in the EU in contrast to leaving the EU decreases a lot.

The next category we are going to compare to our reference category is handing in a blank ballot (Table 2). It is important to mention that the number of observation falling into that specific category is very little.

Being a citizen of France, increases the probability of handing in a blank ballot a lot, while being a citizen of Hungary, decreases the probability (cntry). If a person does not trust in the police (trstplc), the probability of handing in a blank ballot increases, which is also true if a person is not very satisfied with his or her life (stflife). Moreover, if a person does not believes that gays and lesbians are free to live their lifes as they wish (freehms), this person is more likely to leave the ballot empty instead of voting to leave the EU.

Next, we are going to compare the reference category with handing in a spoilt ballot (Table 3). If a person is confident that he or she has the ability to participate in politics, he or she is more likely to spoil the ballot. This could be because the person believes that he or she would be a better politican than the one's in charge right now in the European Union (cptppola). This could also be the reason why a person does not trust the legal system, is more likely to spoil the ballot (trstlgl). Furthermore, feeling less attached to one's country and not believing that everyone in the own country has a fair chance to achieve the level of education they seek, increases the probability of handing in a spoilt ballot (evfredu).

The next category, is "Would not vote" and is compared to our reference category (Table 4). Living in Bulgaria or Czech Republic increases the probability that a person does not vote, while living in Belgium or Cyprus decreases it (cntry). If a person does not trust the legal system of his or her own country, he or she is more likely to vote, which could because the person hopes that the European Union can change the legal system in the country (trstlgl). Moreover, a person being not satisfied with his or her life as a whole, is more likely to not vote in the referendum. A person disagreeing with gays and lesbians being free to live their lifes as they wish (freehms) and thinking that gay and lesbian couples have the right to adopt children (hmsacld), would be more likely to vote in the referendum. If a person believes that his country's cultural life is undermined by immigrants, that person is less likely to vote (imuclt). Hoever, a person feeling very attached to Europe is more likely to vote in the referendum (atcherp). Furthermore, a person believing that everyone in the country has a fair chance to achieve the level of education they seek, decrease the probability of not voting (evfredu).

The last category we are comparing with the reference category is that a person is not eligble to vote (Table 5). Obviously, people that are not citizens of a country (ctzcntr) or born in that country (brncntr) are much more likely to not be eligble to vote. A person not being attached to his or her country at all, is more likely to be eligble to vote. This is probably because a person who is not eligble to vote could be a migrant, who does not feel very attached to his or her new country. It is interesting to see that people that are less likely to be eligble to vote, completly trust the parliament, although they are not eligble to vote themselves.

Concluding we can say that the analysis returned coefficients for most variables as expected, while some coefficients reflected very interesting and unexpected correlations between our explanatory variables and the dependent variable, for which we mostly found plausible explainations as well.

3 Literature

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