



Assignment 2 - Vote Choice in Germany  
Statistical Inference and Modelling - SIM  
1st Semester 2022

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# 1 Explanatory Data Analysis - EDA

## 1.1 Loading Voting Data

In this part of the report, setting up the working environment and loading of the data into R are taking place. Additionally, a first look at the summary of the raw voting choice in Germany data set is taken.

```
load("gles.RData")
summary(gles)
```

```
##      vote      egoposition_immigration  ostwest  political_interest
## Length:1000      Min.   : 0.000      Min.   :0.000      Min.   :0.000
## Class :character  1st Qu.: 3.000      1st Qu.:1.000      1st Qu.:2.000
## Mode  :character  Median : 4.000      Median :1.000      Median :3.000
##                      Mean   : 4.361      Mean   :0.759      Mean   :2.874
##                      3rd Qu.: 6.000      3rd Qu.:1.000      3rd Qu.:4.000
##                      Max.   :10.000     Max.   :1.000      Max.   :4.000
##      income      gender
## Min.   :0.000      Min.   :0.000
## 1st Qu.:3.000      1st Qu.:0.000
## Median :3.000      Median :0.000
## Mean   :2.906      Mean   :0.462
## 3rd Qu.:3.000      3rd Qu.:1.000
## Max.   :4.000      Max.   :1.000
```

## 1.2 Data Types

To begin with, the types of the raw variables contained into the data set are being checked. It is clear, that the raw data set consists of 5 numerical variables and 1 categorical. On the one hand, based on the raw data types, the numeric variables are the following: *egoposition\_immigration*, *ostwest*, *political\_interest*, *income* and *gender*, while the categorical one is variable *vote*. On the other hand, if page 3 of the assignment statement (subsection *Variables*) is taken into account, all of the numerical variables correspond to qualitative concepts. In more detail, variables *egoposition\_immigration*, *political\_interest* and *income* (*income-satisfaction*) correspond to ordered factors, while *ostwest* and *gender* variables are binary ones. In the following sections, all the numerical variables will be transformed into labeled factors (ordered or not).

## 1.3 Checking for Missing Data

To continue with, a check for missing data is conducted on the raw data set. Considering the summary of the data set presented before, there are no NA values in the variables of the data set. The same conclusion is derived when a check is completed for each individual variable.

## 1.4 Checking for Duplicates

By checking if there are duplicate rows inside the raw data set, the result indicates that a total number of 359 occurrences of duplicates exist.

```
dupli <- duplicated(gles); dupli_ind <- which(dupli); length(dupli_ind)
```

```
## [1] 359
```

With the following command, a closer look can be taken into the values of the first 5 duplicate rows (for space saving reasons).

```
gles[dupli_ind,][1:5,]

## # A tibble: 5 x 6
##   vote    egoposition_immigration ostwest political_interest income gender
##   <chr>          <dbl>      <dbl>          <dbl>    <dbl>   <dbl>
## 1 Gruene          2          1              3         3       0
## 2 SPD             4          1              3         3       1
## 3 Gruene          4          1              3         3       1
## 4 LINKE           3          0              2         3       1
## 5 FDP             6          1              3         3       0
```

By taking a closer look at the duplicates, one can understand that, it is logical people with the same characteristics to vote for the same party during the elections. For that reason, the duplicates are not removed or treated, but a new factor will be created in the dataset indicating if a row is a duplicate or not.

## 1.5 Creating Factors for Qualitative Variables

In this subsection of EDA, all qualitative variables are transformed into labeled factors (nominal, ordinal and binary). All variables of the raw data set, as mentioned before, correspond to categorical ones. First of all, their unique values are presented below:

```
unique(gles$vote); unique(gles$egoposition_immigration); unique(gles$ostwest)

## [1] "FDP"      "SPD"      "CDU/CSU" "Gruene"  "AfD"      "LINKE"
## [1]  4  8  3  7  2  1  5  0  6 10  9
## [1] 1 0

unique(gles$political_interest); unique(gles$income); unique(gles$gender)

## [1] 3 2 1 4 0
## [1] 3 2 4 1 0
## [1] 0 1
```

The next step includes the creation of the labeled factors based on the unique values of the categorical variables. Following the practice below, in case a categorical variable includes NA values, they will be transformed into zeros, which is an incorrect approach. In this case, once missing values check indicated that there are no missing data, proceeding with this practice does not result in erroneous data.

Additionally, it is crucial to mention here that the following variables were transformed into ordered factors: *income*, *political\_interest* and *egoposition\_immigration*. Moreover *gender*, *vote* and *ostwest* variables were transformed to nominal factors and finally a new nominal factor was generated, named *political\_orientation*. This new variable discretize the 6 German parties into three political wings with labels *Left\_Wing*, *Center\_Wing* and *Right\_Wing* respectively. In order to accomplish this discretization, page 3 of the assignment statement (subsection *Variables* - indicating the character of each political party: left, center, right) was taken into account one more time.

## 1.6 Factor Conversion Check

After checking both manually and by executing commands on the terminal, the conversion of the categorical and numerical variables to factors has been completed correctly. In addition, while the categorical variables *vote*, *ostwest* and *gender* have been transformed into labeled factors, their old versions are discarded from the data frame (in those cases it is sure that their numerical representation does not provide any extra information). The remaining variables were not discarded in order to check if better results could be obtained by using their numerical representation in higher powers (poly function). Below the new structure of the data frame is presented.

```
summary(gles)
```

```
## egoposition_immigration political_interest income f.duplicate
## Min. : 0.000 Min. :0.000 Min. :0.000 No.Duplicate :641
## 1st Qu.: 3.000 1st Qu.:2.000 1st Qu.:3.000 Yes.Duplicate:359
## Median : 4.000 Median :3.000 Median :3.000
## Mean : 4.361 Mean :2.874 Mean :2.906
## 3rd Qu.: 6.000 3rd Qu.:4.000 3rd Qu.:3.000
## Max. :10.000 Max. :4.000 Max. :4.000
##
## f.eastGermany f.gender f.income
## No.EastGermany :241 M:538 Low.Sat : 13
## Yes.EastGermany:759 F:462 Low_to_Medium.Sat : 28
## Medium.Sat :188
## Medium_to_High.Sat:582
## High.Sat :189
##
## f.political_interest f.egoposition_immigration f.vote
## Low.Inter : 3 4_Level.Imm :179 AfD : 69
## Low_to_Medium.Inter : 34 5_Neutral_Level.Imm:155 CDU/CSU:289
## Medium.Inter :308 3_Level.Imm :134 FDP :121
## Medium_to_High.Inter:396 2_Level.Imm :130 Gruene :143
## High.Inter :259 6_Level.Imm : 95 LINKE :123
## 7_Level.Imm : 78 SPD :255
## (Other) :229
## f.political_orientation
## Center_Wing:665
## Left_Wing :266
## Right_Wing : 69
##
##
##
##
```

## 1.7 Univariate Descriptive Analysis - UDA

As it is stated in the assignment's statement, but as it was concluded in the previous subsection, data set is unbalanced and it contains individuals who mostly vote for parties belonging in the center wing of politics, followed by left wing and finally left wing respectively. The differences

between the numbers of each wing are significant. More details are presented below.

### 1.7.1 Descriptive Analysis for Numerical Variables

In this subsection, summary statistics, the standard deviation and histograms are presented for the numerical representation of the variables *egoposition\_immigration*, *political\_interest* and *income*.

### 1.7.2 Standard Deviation

```
lapply(quantData, sd)
```

```
## $egoposition_immigration
## [1] 2.490157
##
## $political_interest
## [1] 0.8454814
##
## $income
## [1] 0.7731505
```

```
summary(gles$egoposition_immigration)
```

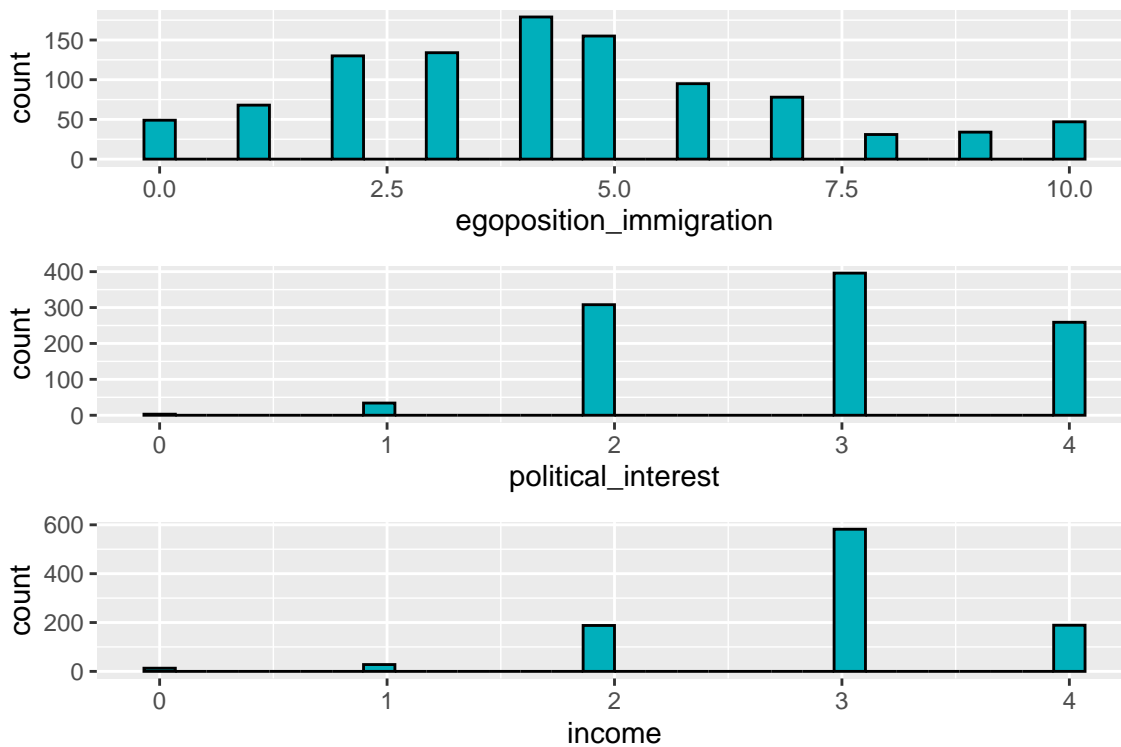
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.000   3.000   4.000   4.361   6.000   10.000
```

```
summary(gles$political_interest)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.000   2.000   3.000   2.874   4.000   4.000
```

```
summary(gles$income)
```

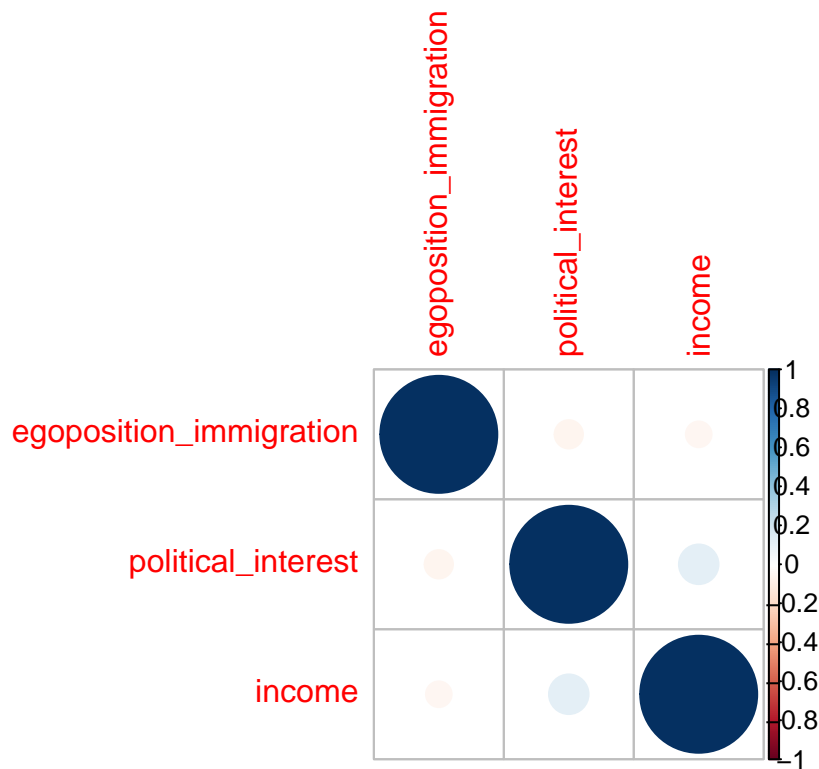
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.000   3.000   3.000   2.906   3.000   4.000
```



From the histograms, it is clear that those 1000 German citizens show interest in the political elections since most of the observations belong to categories *Medium* to *High*. The same is true for variable *income* which depicts the satisfaction of the citizens with their income. Concerning variable *egoposition\_immigration* it can be seen that the plot is close to follow a normal distribution with a slight right skewness. This means that most of the citizens in the data set are *Neutral* concerning immigration while the rest of them are scattered through the rest of the variable levels, with a small trend to follow more open ideas for immigration issues.

In addition, the calculation of Spearman correlation is presented for the numerical variables. In the following graph, it is clear that there is not strong correlation between the numerical representation of the variables *egoposition\_immigration*, *political\_interest* and *income*. By checking the correlation matrix the values are extremely low.

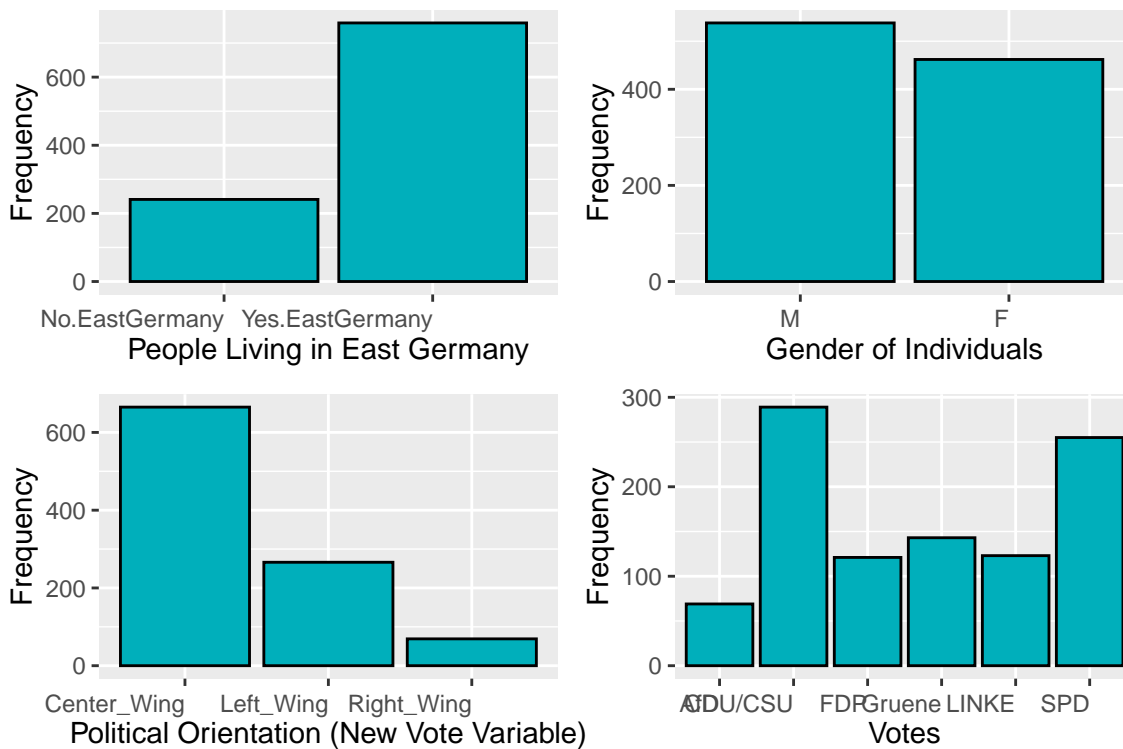
```
##               egoposition_immigration political_interest      income
## egoposition_immigration      1.00000000      -0.05861542 -0.04823165
## political_interest          -0.05861542       1.00000000  0.11449194
## income                     -0.04823165       0.11449194  1.00000000
```



### 1.7.3 Descriptive Analysis for Categorical Variables

Moreover, bar plots are generated illustrating the content of the variables *ostwest*, *gender* and target variables *vote* and *political\_orientation* (new derived factor containing *left*, *center* and *right* wings).

### 1.7.4 Bar Plots



From the barplots, it is illustrated that most of the observations are from citizens of the Eastern



Germany, while the gender of them are balanced. In addition, there is a huge difference in the numbers of citizens voting for parties in the *center political wing* while a smaller number of them vote for the *left wing* and finally the *right* one. Finally, party wise, the one with the most votes is party *CDU/CSU*, followed by *SPD* with a small difference. At the same time Gruene, LINKE and FDP are pretty close with each other, but with approximately half of the votes of *CDU/CSU* and *SPD*.

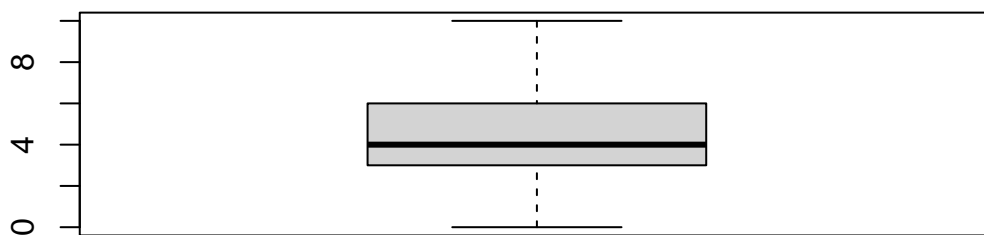
## 1.8 Outliers Detection

In the following subsections both uni-variate and multivariate outliers will be detected and treated.

### 1.8.1 Uni-variate Outliers

To start with, in the following subsection the uni-variate outliers will be detected for the numerical variables: *egoposition\_immigration*, *political\_interest* and *income* with the respective order. It is crucial to mention here, that only severe outliers were taken into account and not mild ones. Now, concerning variable *egoposition\_immigration*, as it is depicted in the boxplot of the variable, outliers do not exist. The same result is derived after trying to detect outliers using the IQR method, which is implemented by function `calcQ`.

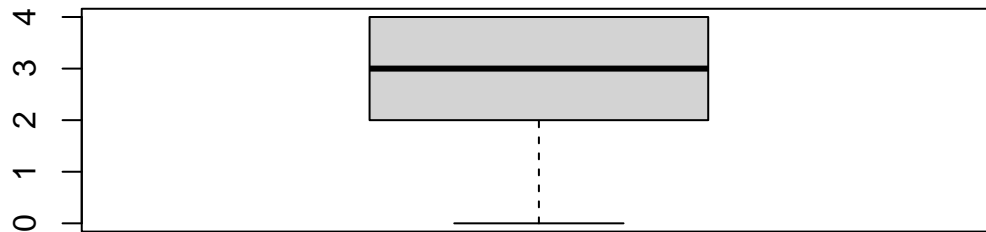
**Boxplot of Variable Egoposition Immigration**



```
## [1] 0
```

Following by, the same approach is used for variable *political\_interest*.

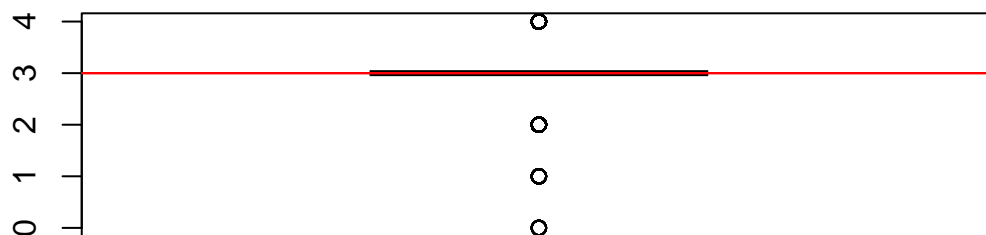
### Boxplot of Variable Political Interest



```
## [1] 0
```

The results are the same, there are no severe outliers for variable *political\_interest* as well. Finally, the outlier detection for the income is taking place.

### Boxplot of Variable Income



```
## [1] 418
```

In this case, there are extreme outliers for the income variable, which are presented below (only first 10 rows out of 418 in total).

```
gles[llout_income,][1:10,]
```

```
## # A tibble: 10 x 11
```

	egopo~1	polit~2	income	f.dup~3	f.eas~4	f.gen~5	f.inc~6	f.pol~7	f.ego~8	f.vote
	<dbl>	<dbl>	<dbl>	<fct>	<fct>	<fct>	<ord>	<ord>	<ord>	<fct>
## 1	8	2	2	No.Dup~	No.Eas~	F	Medium~	Medium~	8_Leve~	SPD
## 2	1	2	4	No.Dup~	Yes.Ea~	F	High.S~	Medium~	1_Leve~	Gruene
## 3	2	4	4	No.Dup~	Yes.Ea~	F	High.S~	High.I~	2_Leve~	Gruene
## 4	3	3	2	No.Dup~	Yes.Ea~	M	Medium~	Medium~	3_Leve~	AfD
## 5	4	4	4	No.Dup~	Yes.Ea~	M	High.S~	High.I~	4_Leve~	CDU/C~
## 6	4	2	2	No.Dup~	No.Eas~	F	Medium~	Medium~	4_Leve~	SPD

```
## 7      3      3      2 No.Dup~ Yes.Ea~ M      Medium~ Medium~ 3_Leve~ CDU/C~
## 8      1      3      1 No.Dup~ Yes.Ea~ F      Low_to~ Medium~ 1_Leve~ SPD
## 9      5      4      1 No.Dup~ Yes.Ea~ M      Low_to~ High.I~ 5_Neut~ FDP
## 10     5      2      2 No.Dup~ Yes.Ea~ F      Medium~ Medium~ 5_Neut~ Gruene
## # ... with 1 more variable: f.political_orientation <fct>, and abbreviated
## #   variable names 1: egoposition_immigration, 2: political_interest,
## #   3: f.duplicate, 4: f.eastGermany, 5: f.gender, 6: f.income,
## #   7: f.political_interest, 8: f.egoposition_immigration

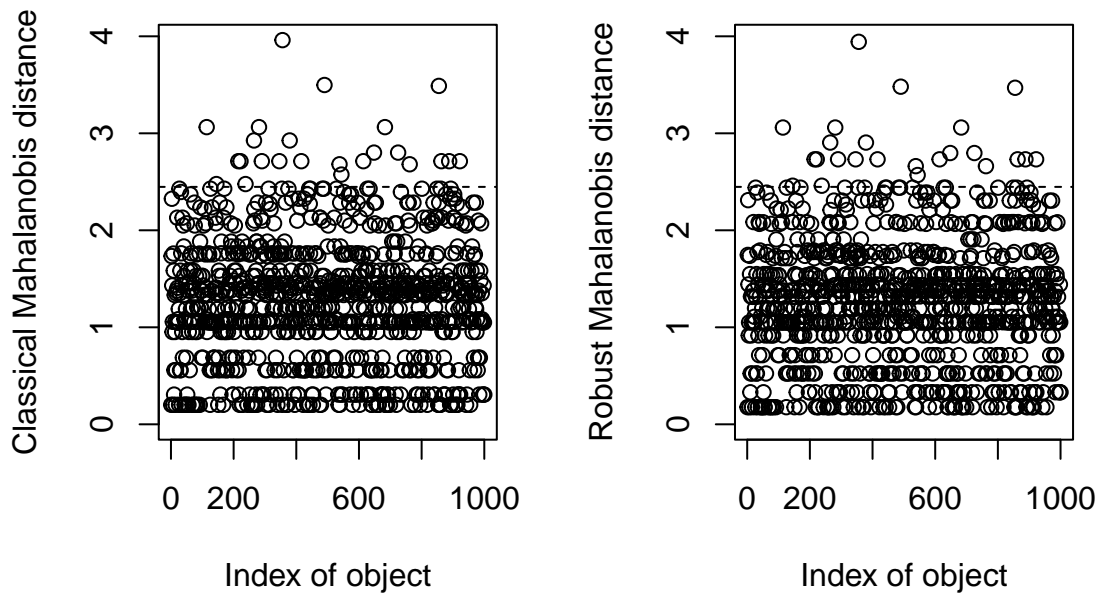
table(gles$income)

##
##  0   1   2   3   4
## 13  28 188 582 189
```

Additionally, by taking a look at the figure and the table of occurrences for factor variable *income*, it is clear that by using the IQR method in this case, all categories except *Medium\_to\_High.Sat* (*level 3*) are considered outliers ( $13+28+188+189 = 418$ ). For that reason, a new column is generated to indicate the uni-variate outliers for *income*. For now, those outliers are kept into the data set, and in the subsections below, it will be decided if it is necessary to be removed.

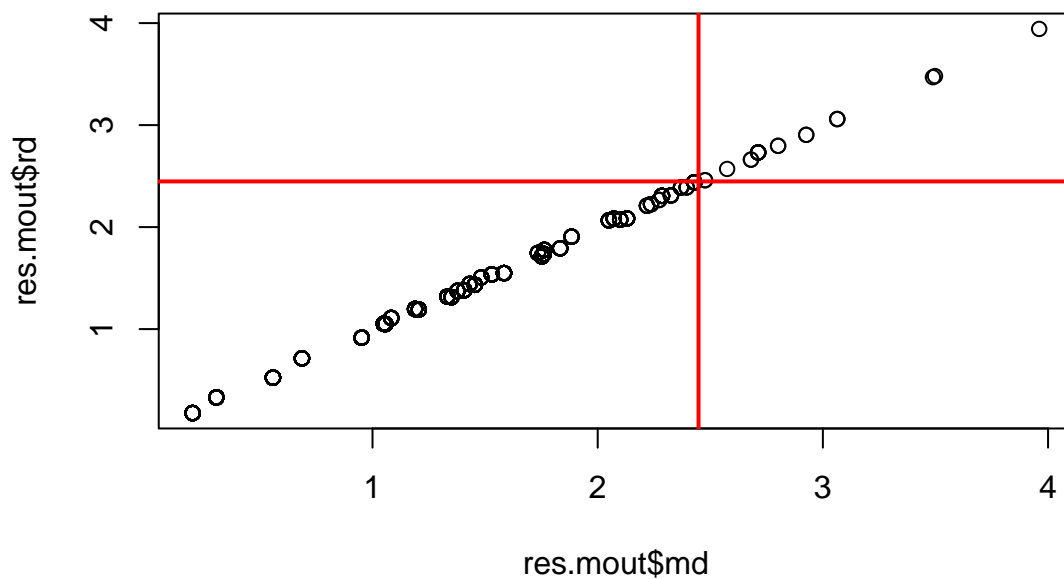
### 1.8.2 Multivariate Outliers

In this subsection, an attempt for the detection of multivariate outliers took place. To start with, the calculation of the Mahalanobis distance is possible only for numerical variables. At this point, at first, an attempt to calculate the Mahalanobis distance for the numerical representation of *egoposition\_immigration*, *political\_interest* and *income* with a confidence interval of 95% was followed. Due to the fact that those variables create a singular matrix for the calculation of the Mahalanobis distance, its inverse matrix cannot be calculated and in that way an error is thrown. Additionally, an attempt was completed to calculate the distance for all the variables in their raw format (all variables at numerical representation), but the same problem occurred again. The Classical and Robust Mahalanobis distances could be only calculated for the combination of *egoposition\_immigration* and *political\_interest* variables of the data set. The results are presented in the following figure:



After calculating Mahalanobis distance at a 95% confidence interval, the cut off given is 2.447747.

Then, all the observations which have a classical and a robust distance bigger than this cut off are marked as multivariate outliers (in this case the term *multivariate* refers only to *egoposition\_immigration* and *political\_interest* variables). After detecting them, a new factor (*f.mout*) is being created in the data set, indicating if an observation belongs to multivariate outliers or not. It can be seen in the final result that 24 observations are marked as multivariate outliers. Further analysis about them will be conducted in the following sections.



```
##      f.mout
```

```
## MvOut.No :976
## MvOut.Yes: 24
```

## 1.9 Profiling of Target Variable(s)

The goal of this chapter is to discover the relationships between the explanatory variables of the data set and the target variable(s). In order to do so the calculation and presentation of interactions between the target and explanatory variables by using the library FactoMineR and Boxplots is completed.

Moreover, with the usage of the library FactoMineR and specifically the function `catdes`, which calculate the dependencies of a categorical variable, it is able to check the dependencies of the target variable(s) with the explanatory variables of the data set. At first, the dependency between the target variable *f.vote* and the rest of the variables will take place, followed by the same analysis for the new derived target variable *f.political\_orientation*. Profiling is completed only by using the factor representation of the explanatory variables and the results are presented in the Appendix at the same subsection.

The main conclusions derived from profiling the target variables are presented here, starting from target variable *f.vote* following by the second target variable *f.political\_orientation*. For variable *f.vote* the main conclusions are:

- Party **AfD** (*right wing*) is strongly correlated with citizens who have high values for variable *egoposition\_imigration* (8-10) meaning they have more far-right beliefs, they are mainly *males* with *low\_political\_interest* and *low\_to\_medium* salary satisfaction.
- Party **CDU/CSU** (*center-right*) has strong relationship with people who achieve levels 5 to 7 of *egoposition\_imigration* meaning that they are mainly neutral with a slight orientation to *right beliefs* for immigration issues, while they present *medium political interest* and *medium salary satisfaction*.
- Party **FDP** (*center-right*) have strong connection levels 0, 2 and 6 of *egoposition\_imigration*, which is confusing. In this case, the conclusion is that maybe the data set does not contain data that will provide quality explanatory power for predicting the voting of this party.
- Party **Gruene** (*left*) shows strong relation with level 2 of variable *egoposition\_imigration*, which means that they are open for immigration issues. Additionally, most of the citizens voting this party are females with *medium\_to\_high political interest*.
- Party **LINKE** (*left*) is mainly described by observations containing values of *No.EastGermany* for variable *f.eastGermany*, level 0 (*Very Open*) for variable *egoposition\_imigration* and *medium income satisfaction*. Also, value *Yes.EastGermany* appear a lot for this party, so it can be concluded that variable *f.eastGermany* will not provide explanatory power for predicting this party.

For variable *f.political\_orientation* the main conclusions are:

- **Center Political Wing** is mainly described by level 5 of variable *egoposition\_imigration* (*Neutral*), people from East Germany (*Yes.EastGermany* for variable *f.eastGermany*), *high income satisfaction* and *medium political interest*.
- **Left Political Wing** is strongly connected with levels 0, 2 and 3 of variable *egoposition\_imigration* meaning that it is open to immigration issues, and *high salary satisfaction*

(Not sure if this makes sense, but we have no information for demographics and salaries of people voting left parties in Germany).

- **Right Political Wing** is mainly connected with levels 8 and 10 for *egoposition\_immigration* (far-right beliefs). Also, those observations are strongly connected with observations of *males*, with value No.EastGermany for *f.eastGermany* variable, with *low political interest* and *low to medium salary satisfaction*.

Concerning the profiling of target variables with quality metrics of the data set, like number of missing values, number of errors in data, number of univariate or multivariate outliers, is not included in detail while the data set do not contain missing or erroneous data. For the correlation of the target variables with outliers some results are presented during the profiling done by using FactoMineR (presented in Appendix) but the results are not so insightful.

## 2 Polytomous Modelling

In this section of the report, the creation and comparison of multiple models for the prediction of probabilities for voting each party or each political wing is completed. For the sake of this assignment, the goal is to provide *three final models* following the approaches: nominal response, ordinal response and hierarchical approach. In order to do so, for nominal response model, the variable *f.vote* containing the 6 different parties will be used. For ordinal response model, *f.vote* *factor* will be transformed to an ordinal factor creating an ordinal relationship from far-left parties to far-right ones. More specifically, the order is the following (*f.vote\_ord*) - The specific order was chosen based on page 3 of assignment's statement:

- LINKE > Gruene > SPD > FDP > CDU/CSU > AfD

Finally, for the hierarchical approach the target variable will be *f.political\_orientation* and in this case 2 nested binary outcome models will be created.

Before proceeding to modeling chapters, the split of the data set into training and test set is necessary and is conducted here.

### 2.1 Nominal Polytomous Modeling

#### 2.1.1 Comparison of Variables' Numerical and Categorical Representation

As a first step in this subsection, it is necessary to check if variables *egoposition\_immigration*, *political\_interest* and *income* provide better explanatory power when they are used as numerical or categorical variables. In order to do so, the following approach has been used:

1. Train a nominal polytomous target model containing only one of those variables in a continuous representation.
2. Train a nominal polytomous target model containing only one of those variables in a continuous representation, including second, cube and quadratic exponent of the variable.
3. Train a nominal polytomous target model containing only one of those variables in a categorical representation.
4. Compare those 3 models for each variable by using anova and AIC.
5. Keep each variable's representation that provide the best results in each case.

The results of the analysis are presented in the respective subsection of the Appendix for space saving reasons. Finally, during modelling procedure the above-mentioned variables will be used in the following forms, respectively:

- ***egoposition\_immigration***:  $\text{poly}(\text{egoposition\_immigration}, 3)$ , the cube form of this variable provides great discrimination between the different parties.
- ***political\_interest***:  $\text{poly}(\text{political\_interest}, 2)$ , even if the squared form of this variable does not provide significant explanatory power (null model had pretty much the same predictability).
- ***income*** : will be used just as a continuous variable, while it provides better results compared to the categorical representation.

## 2.2 Comparison of Nominal Models

```
##
##      AfD CDU/CSU      FDP  Gruene   LINKE     SPD
##      48    211      82    106      88     169

## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter   10 value 1184.278222
## final   value 1184.278203
## converged
```

## 2.3 Ordinal Polytomous Modeling

## 2.4 Hierarchical Modeling

# 3 Appendix

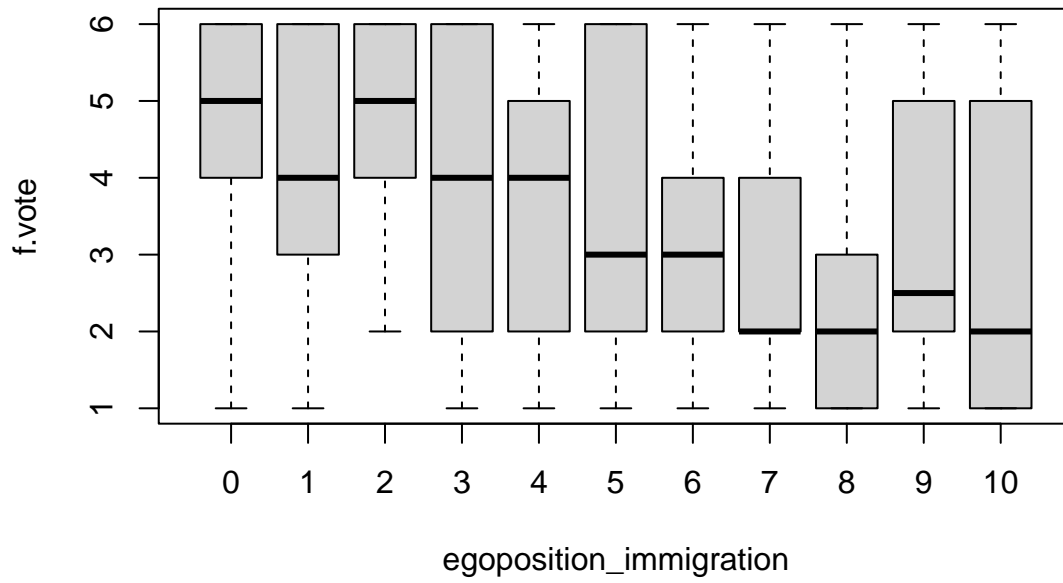
## 3.1 EDA

## 3.2 Profiling of Target Variable(s)

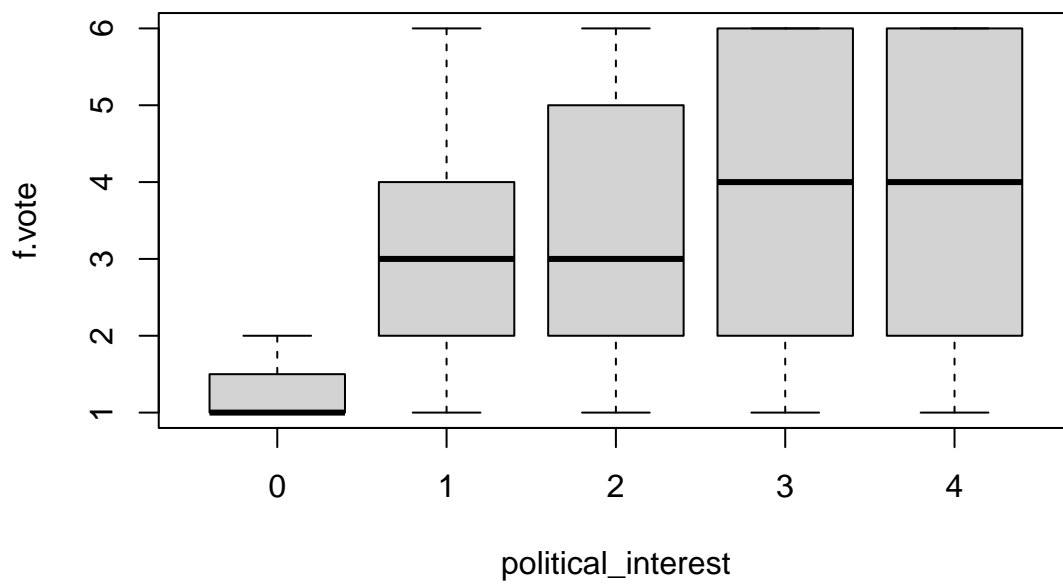
In the following plots the levels of variable *f.vote* and *f.political\_orientation* follow the structure presented below.

```
## [1] "Parties:"
## [1] 1 2 3 4 5 6
## [1] "AfD"      "CDU/CSU" "FDP"      "Gruene"   "LINKE"    "SPD"
## [1] "Political Wings:"
## [1] 1 2 3
## [1] "Center_Wing" "Left_Wing"  "Right_Wing"
```

**Association of f.vote and Egoposition Immigration**

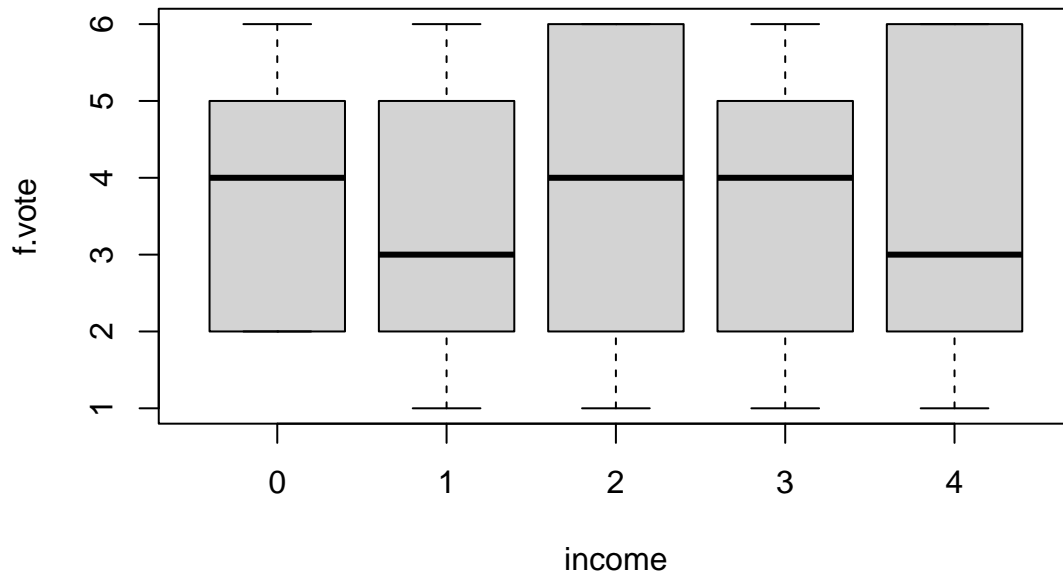


**Association of f.vote and Political Interest**

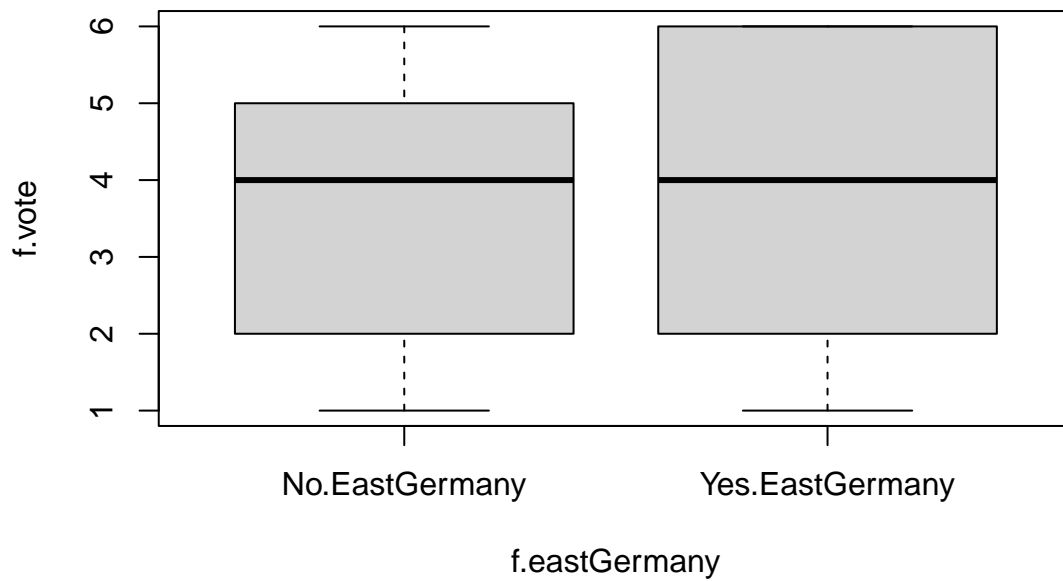




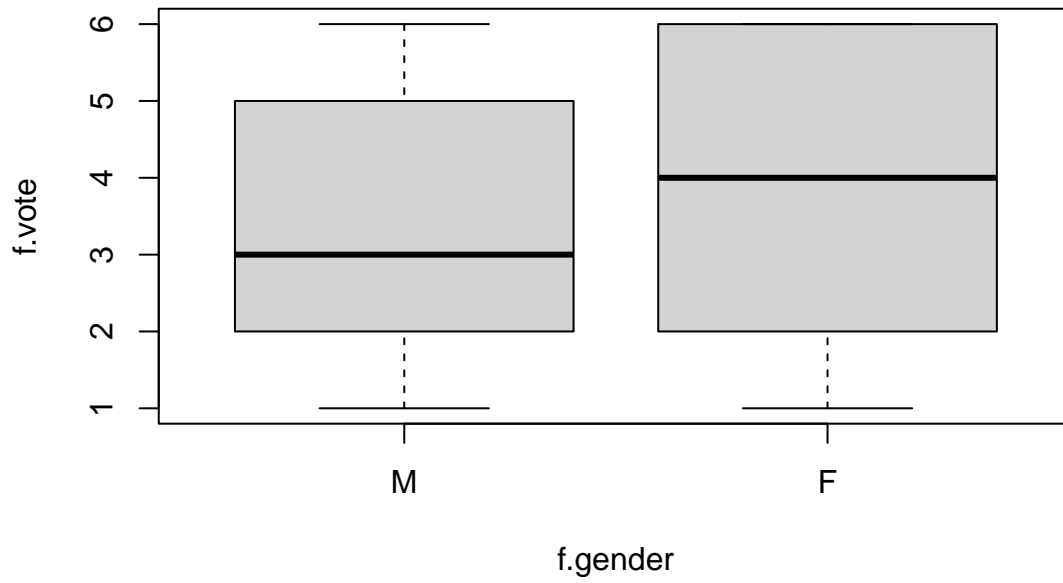
### Association of f.vote and Income Satisfaction



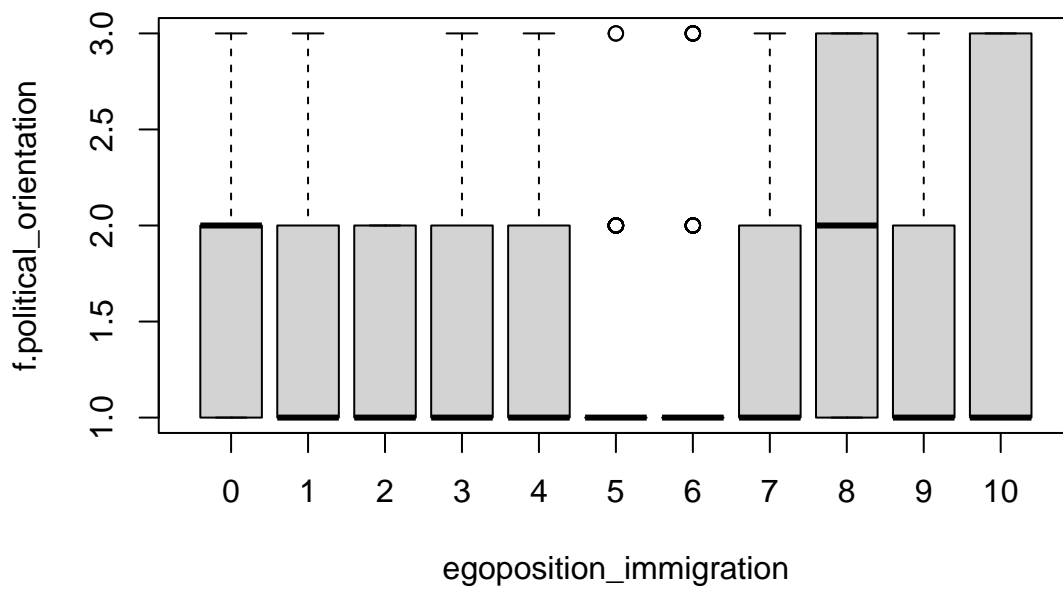
### Association of f.vote and East Germany



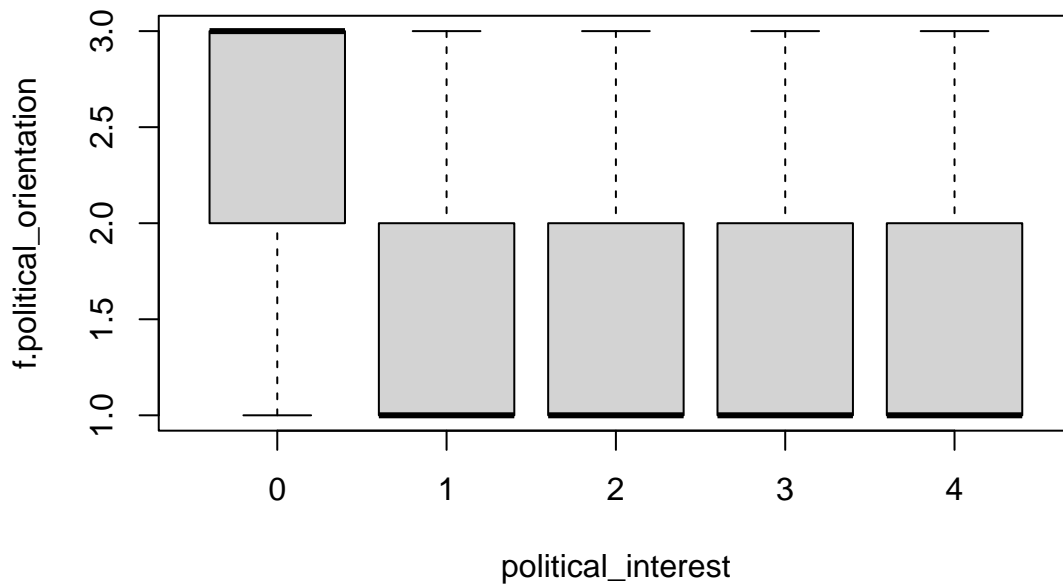
### Association of f.vote and Gender



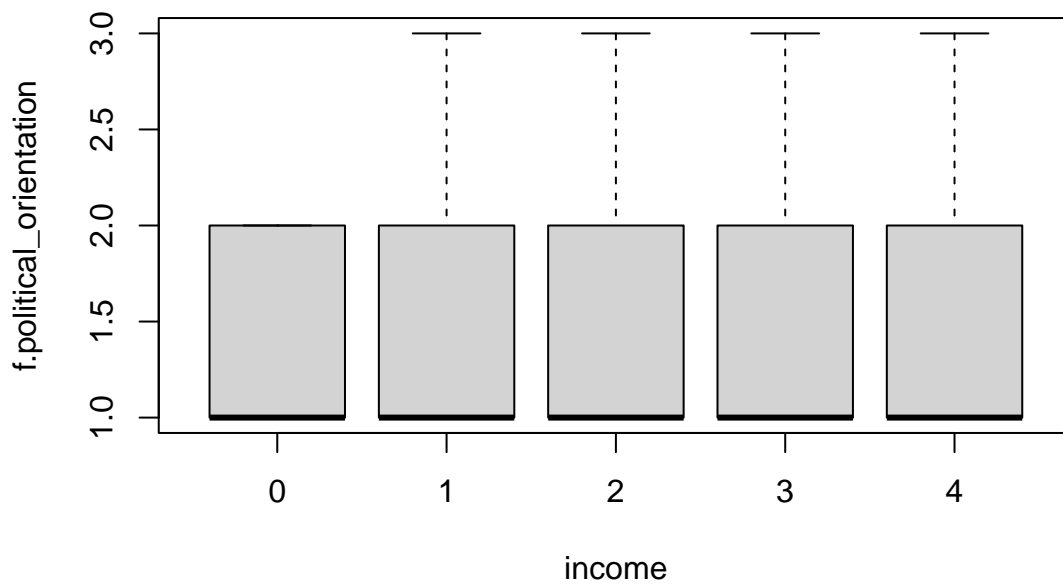
### Association of Political Wings and Egoposition Immigration



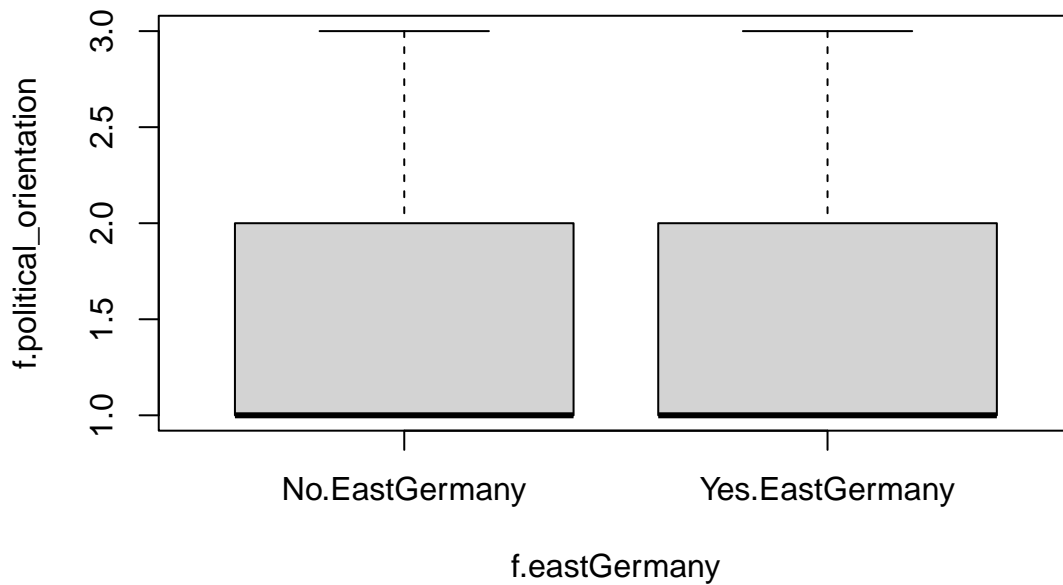
### Association of Political Wings and Political Interest



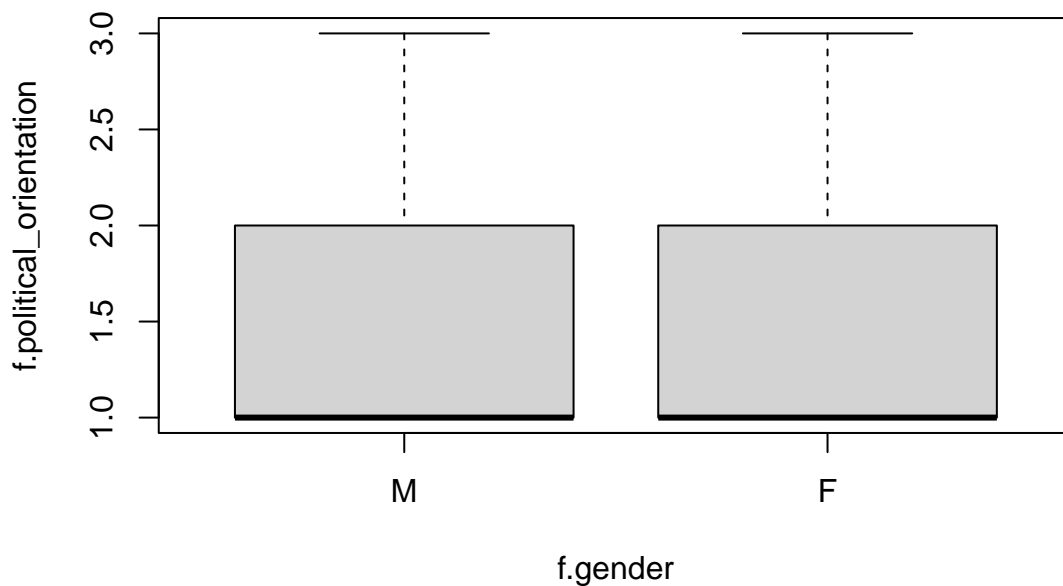
### Association of Political Wings and Income Satisfaction



### Association of Political Wings and East Germany



### Association of Political Wings and Gender



```
res.cat<-catdes(gles, 10) #11 for new factor
res.cat$category
```

```
## $AfD
##                               Cla/Mod   Mod/Cla
## f.vote_ord=AfD                100.000000 100.000000
## f.political_orientation=Right_Wing 100.000000 100.000000
## f.egoposition_immigration=8_Level.Imm 45.161290 20.289855
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm 34.042553 23.188406
```

## f.gender=M	10.408922	81.159420
## f.mout=MvOut.Yes	37.500000	13.043478
## f.duplicate=No.Duplicate	8.892356	82.608696
## f.egoposition_immigration=7_Level.Imm	17.948718	20.289855
## f.egoposition_immigration=9_Level.Imm	23.529412	11.594203
## f.eastGermany=No.EastGermany	11.618257	40.579710
## f.political_interest=Low.Inter	66.666667	2.898551
## f.income=Low_to_Medium.Sat	17.857143	7.246377
## f.egoposition_immigration=1_Level.Imm	1.470588	1.449275
## f.egoposition_immigration=3_Level.Imm	2.985075	5.797101
## f.eastGermany=Yes.EastGermany	5.401845	59.420290
## f.egoposition_immigration=5_Neutral_Level.Imm	1.290323	2.898551
## f.duplicate=Yes.Duplicate	3.342618	17.391304
## f.egoposition_immigration=4_Level.Imm	1.117318	2.898551
## f.vote_ord=FDP	0.000000	0.000000
## f.vote_ord=LINKE	0.000000	0.000000
## f.egoposition_immigration=2_Level.Imm	0.000000	0.000000
## f.vote_ord=Gruene	0.000000	0.000000
## f.mout=MvOut.No	6.147541	86.956522
## f.gender=F	2.813853	18.840580
## f.vote_ord=SPD	0.000000	0.000000
## f.political_orientation=Left_Wing	0.000000	0.000000
## f.vote_ord=CDU/CSU	0.000000	0.000000
## f.political_orientation=Center_Wing	0.000000	0.000000
##	Global	p.value
## f.vote_ord=AfD	6.9	1.889108e-108
## f.political_orientation=Right_Wing	6.9	1.889108e-108
## f.egoposition_immigration=8_Level.Imm	3.1	1.675803e-09
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm	4.7	1.468400e-08
## f.gender=M	53.8	1.101835e-06
## f.mout=MvOut.Yes	2.4	1.316568e-05
## f.duplicate=No.Duplicate	64.1	5.540764e-04
## f.egoposition_immigration=7_Level.Imm	7.8	5.783367e-04
## f.egoposition_immigration=9_Level.Imm	3.4	1.731296e-03
## f.eastGermany=No.EastGermany	24.1	1.731634e-03
## f.political_interest=Low.Inter	0.3	1.377478e-02
## f.income=Low_to_Medium.Sat	2.8	4.793709e-02
## f.egoposition_immigration=1_Level.Imm	6.8	4.815760e-02
## f.egoposition_immigration=3_Level.Imm	13.4	4.305493e-02
## f.eastGermany=Yes.EastGermany	75.9	1.731634e-03
## f.egoposition_immigration=5_Neutral_Level.Imm	15.5	6.970986e-04
## f.duplicate=Yes.Duplicate	35.9	5.540764e-04
## f.egoposition_immigration=4_Level.Imm	17.9	1.193747e-04
## f.vote_ord=FDP	12.1	9.721535e-05
## f.vote_ord=LINKE	12.3	8.254390e-05
## f.egoposition_immigration=2_Level.Imm	13.0	4.641675e-05
## f.vote_ord=Gruene	14.3	1.573110e-05
## f.mout=MvOut.No	97.6	1.316568e-05
## f.gender=F	46.2	1.101835e-06
## f.vote_ord=SPD	25.5	6.459324e-10

```

## f.political_orientation=Left_Wing                26.6  2.200779e-10
## f.vote_ord=CDU/CSU                               28.9  2.190738e-11
## f.political_orientation=Center_Wing              66.5  9.958160e-36
##                                                    v.test
## f.vote_ord=AfD                                    22.123229
## f.political_orientation=Right_Wing               22.123229
## f.egoposition_immigration=8_Level.Imm            6.026469
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm  5.665215
## f.gender=M                                         4.872520
## f.mout=MvOut.Yes                                  4.357333
## f.duplicate=No.Duplicate                          3.453152
## f.egoposition_immigration=7_Level.Imm            3.441576
## f.egoposition_immigration=9_Level.Imm            3.132830
## f.eastGermany=No.EastGermany                     3.132773
## f.political_interest=Low.Inter                   2.463084
## f.income=Low_to_Medium.Sat                       1.977926
## f.egoposition_immigration=1_Level.Imm            -1.975975
## f.egoposition_immigration=3_Level.Imm            -2.023177
## f.eastGermany=Yes.EastGermany                    -3.132773
## f.egoposition_immigration=5_Neutral_Level.Imm    -3.390718
## f.duplicate=Yes.Duplicate                        -3.453152
## f.egoposition_immigration=4_Level.Imm            -3.847407
## f.vote_ord=FDP                                    -3.897439
## f.vote_ord=LINKE                                  -3.936892
## f.egoposition_immigration=2_Level.Imm            -4.072973
## f.vote_ord=Gruene                                  -4.318194
## f.mout=MvOut.No                                  -4.357333
## f.gender=F                                         -4.872520
## f.vote_ord=SPD                                     -6.178794
## f.political_orientation=Left_Wing                -6.346633
## f.vote_ord=CDU/CSU                               -6.692711
## f.political_orientation=Center_Wing              -12.477072
##
## $`CDU/CSU`
##
## Cla/Mod      Mod/Cla Global
## f.vote_ord=CDU/CSU      100.00000 100.000000 28.9
## f.political_orientation=Center_Wing      43.45865 100.000000 66.5
## f.duplicate=Yes.Duplicate      36.21170 44.982699 35.9
## f.egoposition_immigration=5_Neutral_Level.Imm  39.35484 21.107266 15.5
## f.egoposition_immigration=7_Level.Imm      43.58974 11.764706 7.8
## f.egoposition_immigration=6_Level.Imm      40.00000 13.148789 9.5
## f.political_interest=Medium.Inter      33.44156 35.640138 30.8
## f.egoposition_immigration=1_Level.Imm      17.64706 4.152249 6.8
## f.income=Medium.Sat      22.34043 14.532872 18.8
## f.duplicate=No.Duplicate      24.80499 55.017301 64.1
## f.egoposition_immigration=2_Level.Imm      14.61538 6.574394 13.0
## f.vote_ord=AfD          0.00000 0.000000 6.9
## f.political_orientation=Right_Wing      0.00000 0.000000 6.9
## f.vote_ord=FDP          0.00000 0.000000 12.1
## f.vote_ord=LINKE        0.00000 0.000000 12.3

```

## f.vote_ord=Gruene	0.00000	0.000000	14.3
## f.vote_ord=SPD	0.00000	0.000000	25.5
## f.political_orientation=Left_Wing	0.00000	0.000000	26.6
##	p.value	v.test	
## f.vote_ord=CDU/CSU	2.718794e-260	34.464630	
## f.political_orientation=Center_Wing	4.312957e-64	16.902491	
## f.duplicate=Yes.Duplicate	1.578900e-04	3.778320	
## f.egoposition_immigration=5_Neutral_Level.Imm	2.326304e-03	3.045064	
## f.egoposition_immigration=7_Level.Imm	4.123963e-03	2.868521	
## f.egoposition_immigration=6_Level.Imm	1.484342e-02	2.436177	
## f.political_interest=Medium.Inter	3.612343e-02	2.095535	
## f.egoposition_immigration=1_Level.Imm	2.975586e-02	-2.173325	
## f.income=Medium.Sat	2.589708e-02	-2.227752	
## f.duplicate=No.Duplicate	1.578900e-04	-3.778320	
## f.egoposition_immigration=2_Level.Imm	5.395182e-05	-4.037813	
## f.vote_ord=AfD	2.190738e-11	-6.692711	
## f.political_orientation=Right_Wing	2.190738e-11	-6.692711	
## f.vote_ord=FDP	4.521871e-20	-9.174854	
## f.vote_ord=LINKE	2.036114e-20	-9.260430	
## f.vote_ord=Gruene	6.155171e-24	-10.089389	
## f.vote_ord=SPD	9.555546e-46	-14.197047	
## f.political_orientation=Left_Wing	4.116942e-48	-14.573901	
##			
## \$FDP			
##	Cla/Mod	Mod/Cla	Global
## f.vote_ord=FDP	100.000000	100.000000	12.1
## f.political_orientation=Center_Wing	18.195489	100.000000	66.5
## f.egoposition_immigration=6_Level.Imm	22.105263	17.3553719	9.5
## f.egoposition_immigration=0_Very_Open_Level.Imm	2.040816	0.8264463	4.9
## f.egoposition_immigration=2_Level.Imm	3.076923	3.3057851	13.0
## f.vote_ord=AfD	0.000000	0.000000	6.9
## f.political_orientation=Right_Wing	0.000000	0.000000	6.9
## f.vote_ord=LINKE	0.000000	0.000000	12.3
## f.vote_ord=Gruene	0.000000	0.000000	14.3
## f.vote_ord=SPD	0.000000	0.000000	25.5
## f.political_orientation=Left_Wing	0.000000	0.000000	26.6
## f.vote_ord=CDU/CSU	0.000000	0.000000	28.9
##	p.value	v.test	
## f.vote_ord=FDP	1.570479e-159	26.912447	
## f.political_orientation=Center_Wing	6.200298e-24	10.088671	
## f.egoposition_immigration=6_Level.Imm	3.784565e-03	2.895582	
## f.egoposition_immigration=0_Very_Open_Level.Imm	1.390975e-02	-2.459586	
## f.egoposition_immigration=2_Level.Imm	1.560324e-04	-3.781267	
## f.vote_ord=AfD	9.721535e-05	-3.897439	
## f.political_orientation=Right_Wing	9.721535e-05	-3.897439	
## f.vote_ord=LINKE	4.155458e-08	-5.484114	
## f.vote_ord=Gruene	2.059483e-09	-5.993045	
## f.vote_ord=SPD	2.177390e-17	-8.483916	
## f.political_orientation=Left_Wing	3.054680e-18	-8.709407	
## f.vote_ord=CDU/CSU	4.521871e-20	-9.174854	

```

##
## $Gruene
##
## Cla/Mod      Mod/Cla
## f.vote_ord=Gruene      100.000000 100.000000
## f.political_orientation=Left_Wing      53.759398 100.000000
## f.egoposition_immigration=2_Level.Imm      28.461538 25.8741259
## f.gender=F      17.748918 57.3426573
## f.political_interest=Medium_to_High.Inter      17.676768 48.9510490
## f.egoposition_immigration=1_Level.Imm      25.000000 11.8881119
## f.egoposition_immigration=6_Level.Imm      7.368421 4.8951049
## f.egoposition_immigration=8_Level.Imm      0.000000 0.000000
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm      2.127660 0.6993007
## f.egoposition_immigration=9_Level.Imm      0.000000 0.000000
## f.gender=M      11.338290 42.6573427
## f.egoposition_immigration=7_Level.Imm      2.564103 1.3986014
## f.vote_ord=AfD      0.000000 0.000000
## f.political_orientation=Right_Wing      0.000000 0.000000
## f.vote_ord=FDP      0.000000 0.000000
## f.vote_ord=LINKE      0.000000 0.000000
## f.vote_ord=SPD      0.000000 0.000000
## f.vote_ord=CDU/CSU      0.000000 0.000000
## f.political_orientation=Center_Wing      0.000000 0.000000
##
## Global      p.value
## f.vote_ord=Gruene      14.3 1.663892e-177
## f.political_orientation=Left_Wing      26.6 4.555935e-99
## f.egoposition_immigration=2_Level.Imm      13.0 5.773018e-06
## f.gender=F      46.2 4.072838e-03
## f.political_interest=Medium_to_High.Inter      39.6 1.459058e-02
## f.egoposition_immigration=1_Level.Imm      6.8 1.540367e-02
## f.egoposition_immigration=6_Level.Imm      9.5 3.395532e-02
## f.egoposition_immigration=8_Level.Imm      3.1 7.725865e-03
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm      4.7 6.044056e-03
## f.egoposition_immigration=9_Level.Imm      3.4 4.782805e-03
## f.gender=M      53.8 4.072838e-03
## f.egoposition_immigration=7_Level.Imm      7.8 4.551511e-04
## f.vote_ord=AfD      6.9 1.573110e-05
## f.political_orientation=Right_Wing      6.9 1.573110e-05
## f.vote_ord=FDP      12.1 2.059483e-09
## f.vote_ord=LINKE      12.3 1.443577e-09
## f.vote_ord=SPD      25.5 1.039117e-20
## f.vote_ord=CDU/CSU      28.9 6.155171e-24
## f.political_orientation=Center_Wing      66.5 1.406134e-79
##
## v.test
## f.vote_ord=Gruene      28.406856
## f.political_orientation=Left_Wing      21.126332
## f.egoposition_immigration=2_Level.Imm      4.534536
## f.gender=F      2.872465
## f.political_interest=Medium_to_High.Inter      2.442385
## f.egoposition_immigration=1_Level.Imm      2.422746
## f.egoposition_immigration=6_Level.Imm      -2.120602

```



```

## f.egoposition_immigration=8_Level.Imm -2.663821
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm -2.745382
## f.egoposition_immigration=9_Level.Imm -2.821309
## f.gender=M -2.872465
## f.egoposition_immigration=7_Level.Imm -3.505850
## f.vote_ord=AfD -4.318194
## f.political_orientation=Right_Wing -4.318194
## f.vote_ord=FDP -5.993045
## f.vote_ord=LINKE -6.050544
## f.vote_ord=SPD -9.331980
## f.vote_ord=CDU/CSU -10.089389
## f.political_orientation=Center_Wing -18.888951
##
## $LINKE
##
## Cla/Mod Mod/Cla Global
## f.vote_ord=LINKE 100.000000 100.000000 12.3
## f.political_orientation=Left_Wing 46.240602 100.000000 26.6
## f.eastGermany=No.EastGermany 19.087137 37.398374 24.1
## f.egoposition_immigration=0_Very_Open_Level.Imm 28.571429 11.382114 4.9
## f.egoposition_immigration=3_Level.Imm 19.402985 21.138211 13.4
## f.duplicate=No.Duplicate 14.196568 73.983740 64.1
## f.income=Medium.Sat 17.553191 26.829268 18.8
## f.duplicate=Yes.Duplicate 8.913649 26.016260 35.9
## f.egoposition_immigration=6_Level.Imm 4.210526 3.252033 9.5
## f.egoposition_immigration=5_Neutral_Level.Imm 5.161290 6.504065 15.5
## f.eastGermany=Yes.EastGermany 10.144928 62.601626 75.9
## f.income=High.Sat 4.761905 7.317073 18.9
## f.vote_ord=AfD 0.000000 0.000000 6.9
## f.political_orientation=Right_Wing 0.000000 0.000000 6.9
## f.vote_ord=FDP 0.000000 0.000000 12.1
## f.vote_ord=Gruene 0.000000 0.000000 14.3
## f.vote_ord=SPD 0.000000 0.000000 25.5
## f.vote_ord=CDU/CSU 0.000000 0.000000 28.9
## f.political_orientation=Center_Wing 0.000000 0.000000 66.5
##
## p.value v.test
## f.vote_ord=LINKE 3.053611e-161 27.058260
## f.political_orientation=Left_Wing 8.361150e-83 19.277115
## f.eastGermany=No.EastGermany 4.265885e-04 3.523064
## f.egoposition_immigration=0_Very_Open_Level.Imm 1.737035e-03 3.131859
## f.egoposition_immigration=3_Level.Imm 1.099556e-02 2.542840
## f.duplicate=No.Duplicate 1.345692e-02 2.471442
## f.income=Medium.Sat 1.925059e-02 2.340643
## f.duplicate=Yes.Duplicate 1.345692e-02 -2.471442
## f.egoposition_immigration=6_Level.Imm 6.136722e-03 -2.740385
## f.egoposition_immigration=5_Neutral_Level.Imm 1.585127e-03 -3.158630
## f.eastGermany=Yes.EastGermany 4.265885e-04 -3.523064
## f.income=High.Sat 1.536281e-04 -3.785130
## f.vote_ord=AfD 8.254390e-05 -3.936892
## f.political_orientation=Right_Wing 8.254390e-05 -3.936892
## f.vote_ord=FDP 4.155458e-08 -5.484114

```

```
## f.vote_ord=Gruene 1.443577e-09 -6.050544
## f.vote_ord=SPD 1.096795e-17 -8.563303
## f.vote_ord=CDU/CSU 2.036114e-20 -9.260430
## f.political_orientation=Center_Wing 6.141124e-67 -17.284633
```

```
##
```

```
## $SPD
```

```
##
## Cla/Mod Mod/Cla Global
## f.vote_ord=SPD 100.000000 100.0000000 25.5
## f.political_orientation=Center_Wing 38.345865 100.0000000 66.5
## f.egoposition_immigration=2_Level.Imm 36.923077 18.8235294 13.0
## f.mout=MvOut.No 26.024590 99.6078431 97.6
## f.egoposition_immigration=1_Level.Imm 38.235294 10.1960784 6.8
## f.political_interest=Low_to_Medium.Inter 8.823529 1.1764706 3.4
## f.mout=MvOut.Yes 4.166667 0.3921569 2.4
## f.vote_ord=AfD 0.000000 0.0000000 6.9
## f.political_orientation=Right_Wing 0.000000 0.0000000 6.9
## f.vote_ord=FDP 0.000000 0.0000000 12.1
## f.vote_ord=LINKE 0.000000 0.0000000 12.3
## f.vote_ord=Gruene 0.000000 0.0000000 14.3
## f.political_orientation=Left_Wing 0.000000 0.0000000 26.6
## f.vote_ord=CDU/CSU 0.000000 0.0000000 28.9
```

```
## p.value v.test
## f.vote_ord=SPD 9.178288e-246 33.480784
## f.political_orientation=Center_Wing 5.401466e-55 15.619038
## f.egoposition_immigration=2_Level.Imm 1.985233e-03 3.092433
## f.mout=MvOut.No 8.131457e-03 2.646562
## f.egoposition_immigration=1_Level.Imm 1.674243e-02 2.392316
## f.political_interest=Low_to_Medium.Inter 1.626155e-02 -2.402992
## f.mout=MvOut.Yes 8.131457e-03 -2.646562
## f.vote_ord=AfD 6.459324e-10 -6.178794
## f.political_orientation=Right_Wing 6.459324e-10 -6.178794
## f.vote_ord=FDP 2.177390e-17 -8.483916
## f.vote_ord=LINKE 1.096795e-17 -8.563303
## f.vote_ord=Gruene 1.039117e-20 -9.331980
## f.political_orientation=Left_Wing 2.115265e-41 -13.477726
## f.vote_ord=CDU/CSU 9.555546e-46 -14.197047
```

```
res.cat<-catdes(gles, 11) #11 for new factor
res.cat$category
```

```
## $Center_Wing
```

```
##
## Cla/Mod Mod/Cla Global
## f.vote_ord=CDU/CSU 100.00000 43.458647 28.9
## f.vote=CDU/CSU 100.00000 43.458647 28.9
## f.vote_ord=SPD 100.00000 38.345865 25.5
## f.vote=SPD 100.00000 38.345865 25.5
## f.vote_ord=FDP 100.00000 18.195489 12.1
## f.vote=FDP 100.00000 18.195489 12.1
## f.egoposition_immigration=5_Neutral_Level.Imm 83.22581 19.398496 15.5
## f.eastGermany=Yes.EastGermany 69.43347 79.248120 75.9
## f.duplicate=Yes.Duplicate 73.25905 39.548872 35.9
```

## f.egoposition_immigration=6_Level.Imm	81.05263	11.578947	9.5
## f.income=High.Sat	74.07407	21.052632	18.9
## f.political_interest=Medium.Inter	71.75325	33.233083	30.8
## f.egoposition_immigration=8_Level.Imm	48.38710	2.255639	3.1
## f.egoposition_immigration=0_Very_Open_Level.Imm	48.97959	3.609023	4.9
## f.egoposition_immigration=2_Level.Imm	54.61538	10.676692	13.0
## f.duplicate=No.Duplicate	62.71451	60.451128	64.1
## f.eastGermany=No.EastGermany	57.26141	20.751880	24.1
## f.vote_ord=AfD	0.00000	0.000000	6.9
## f.vote=AfD	0.00000	0.000000	6.9
## f.vote_ord=LINKE	0.00000	0.000000	12.3
## f.vote=LINKE	0.00000	0.000000	12.3
## f.vote_ord=Gruene	0.00000	0.000000	14.3
## f.vote=Gruene	0.00000	0.000000	14.3
##	p.value	v.test	
## f.vote_ord=CDU/CSU	4.312957e-64	16.902491	
## f.vote=CDU/CSU	4.312957e-64	16.902491	
## f.vote_ord=SPD	5.401466e-55	15.619038	
## f.vote=SPD	5.401466e-55	15.619038	
## f.vote_ord=FDP	6.200298e-24	10.088671	
## f.vote=FDP	6.200298e-24	10.088671	
## f.egoposition_immigration=5_Neutral_Level.Imm	5.513189e-07	5.007534	
## f.eastGermany=Yes.EastGermany	5.849772e-04	3.438486	
## f.duplicate=Yes.Duplicate	6.507953e-04	3.409511	
## f.egoposition_immigration=6_Level.Imm	1.102026e-03	3.263095	
## f.income=High.Sat	1.331258e-02	2.475296	
## f.political_interest=Medium.Inter	1.837781e-02	2.357917	
## f.egoposition_immigration=8_Level.Imm	3.695876e-02	-2.086219	
## f.egoposition_immigration=0_Very_Open_Level.Imm	1.008813e-02	-2.572794	
## f.egoposition_immigration=2_Level.Imm	2.600362e-03	-3.011411	
## f.duplicate=No.Duplicate	6.507953e-04	-3.409511	
## f.eastGermany=No.EastGermany	5.849772e-04	-3.438486	
## f.vote_ord=AfD	9.958160e-36	-12.477072	
## f.vote=AfD	9.958160e-36	-12.477072	
## f.vote_ord=LINKE	6.141124e-67	-17.284633	
## f.vote=LINKE	6.141124e-67	-17.284633	
## f.vote_ord=Gruene	1.406134e-79	-18.888951	
## f.vote=Gruene	1.406134e-79	-18.888951	
##			
## \$Left_Wing			
##	Cla/Mod	Mod/Cla	
## f.vote_ord=Gruene	100.000000	53.7593985	
## f.vote=Gruene	100.000000	53.7593985	
## f.vote_ord=LINKE	100.000000	46.2406015	
## f.vote=LINKE	100.000000	46.2406015	
## f.egoposition_immigration=2_Level.Imm	45.384615	22.1804511	
## f.egoposition_immigration=0_Very_Open_Level.Imm	48.979592	9.0225564	
## f.egoposition_immigration=3_Level.Imm	38.059701	19.1729323	
## f.gender=F	30.086580	52.2556391	
## f.gender=M	23.605948	47.7443609	

## f.income=High.Sat	19.576720	13.9097744
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm	10.638298	1.8796992
## f.egoposition_immigration=8_Level.Imm	6.451613	0.7518797
## f.egoposition_immigration=9_Level.Imm	5.882353	0.7518797
## f.egoposition_immigration=5_Neutral_Level.Imm	15.483871	9.0225564
## f.egoposition_immigration=7_Level.Imm	10.256410	3.0075188
## f.egoposition_immigration=6_Level.Imm	11.578947	4.1353383
## f.vote_ord=AfD	0.000000	0.0000000
## f.vote=AfD	0.000000	0.0000000
## f.vote_ord=FDP	0.000000	0.0000000
## f.vote=FDP	0.000000	0.0000000
## f.vote_ord=SPD	0.000000	0.0000000
## f.vote=SPD	0.000000	0.0000000
## f.vote_ord=CDU/CSU	0.000000	0.0000000
## f.vote=CDU/CSU	0.000000	0.0000000
##	Global	p.value
## f.vote_ord=Gruene	14.3	4.555935e-99
## f.vote=Gruene	14.3	4.555935e-99
## f.vote_ord=LINKE	12.3	8.361150e-83
## f.vote=LINKE	12.3	8.361150e-83
## f.egoposition_immigration=2_Level.Imm	13.0	7.347278e-07
## f.egoposition_immigration=0_Very_Open_Level.Imm	4.9	6.479798e-04
## f.egoposition_immigration=3_Level.Imm	13.4	1.798442e-03
## f.gender=F	46.2	2.119615e-02
## f.gender=M	53.8	2.119615e-02
## f.income=High.Sat	18.9	1.362802e-02
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm	4.7	7.300975e-03
## f.egoposition_immigration=8_Level.Imm	3.1	5.282681e-03
## f.egoposition_immigration=9_Level.Imm	3.4	2.382574e-03
## f.egoposition_immigration=5_Neutral_Level.Imm	15.5	4.059018e-04
## f.egoposition_immigration=7_Level.Imm	7.8	2.687651e-04
## f.egoposition_immigration=6_Level.Imm	9.5	2.154814e-04
## f.vote_ord=AfD	6.9	2.200779e-10
## f.vote=AfD	6.9	2.200779e-10
## f.vote_ord=FDP	12.1	3.054680e-18
## f.vote=FDP	12.1	3.054680e-18
## f.vote_ord=SPD	25.5	2.115265e-41
## f.vote=SPD	25.5	2.115265e-41
## f.vote_ord=CDU/CSU	28.9	4.116942e-48
## f.vote=CDU/CSU	28.9	4.116942e-48
##	v.test	
## f.vote_ord=Gruene	21.126332	
## f.vote=Gruene	21.126332	
## f.vote_ord=LINKE	19.277115	
## f.vote=LINKE	19.277115	
## f.egoposition_immigration=2_Level.Imm	4.951952	
## f.egoposition_immigration=0_Very_Open_Level.Imm	3.410693	
## f.egoposition_immigration=3_Level.Imm	3.121644	
## f.gender=F	2.304472	
## f.gender=M	-2.304472	

## f.income=High.Sat	-2.466922	
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm	-2.682795	
## f.egoposition_immigration=8_Level.Imm	-2.789271	
## f.egoposition_immigration=9_Level.Imm	-3.037869	
## f.egoposition_immigration=5_Neutral_Level.Imm	-3.536217	
## f.egoposition_immigration=7_Level.Imm	-3.643682	
## f.egoposition_immigration=6_Level.Imm	-3.700139	
## f.vote_ord=AfD	-6.346633	
## f.vote=AfD	-6.346633	
## f.vote_ord=FDP	-8.709407	
## f.vote=FDP	-8.709407	
## f.vote_ord=SPD	-13.477726	
## f.vote=SPD	-13.477726	
## f.vote_ord=CDU/CSU	-14.573901	
## f.vote=CDU/CSU	-14.573901	
##		
## \$Right_Wing		
##		
	Cla/Mod	Mod/Cla
## f.vote_ord=AfD	100.000000	100.000000
## f.vote=AfD	100.000000	100.000000
## f.egoposition_immigration=8_Level.Imm	45.161290	20.289855
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm	34.042553	23.188406
## f.gender=M	10.408922	81.159420
## f.mout=MvOut.Yes	37.500000	13.043478
## f.duplicate=No.Duplicate	8.892356	82.608696
## f.egoposition_immigration=7_Level.Imm	17.948718	20.289855
## f.egoposition_immigration=9_Level.Imm	23.529412	11.594203
## f.eastGermany=No.EastGermany	11.618257	40.579710
## f.political_interest=Low.Inter	66.666667	2.898551
## f.income=Low_to_Medium.Sat	17.857143	7.246377
## f.egoposition_immigration=1_Level.Imm	1.470588	1.449275
## f.egoposition_immigration=3_Level.Imm	2.985075	5.797101
## f.eastGermany=Yes.EastGermany	5.401845	59.420290
## f.egoposition_immigration=5_Neutral_Level.Imm	1.290323	2.898551
## f.duplicate=Yes.Duplicate	3.342618	17.391304
## f.egoposition_immigration=4_Level.Imm	1.117318	2.898551
## f.vote_ord=FDP	0.000000	0.000000
## f.vote=FDP	0.000000	0.000000
## f.vote_ord=LINKE	0.000000	0.000000
## f.vote=LINKE	0.000000	0.000000
## f.egoposition_immigration=2_Level.Imm	0.000000	0.000000
## f.vote_ord=Gruene	0.000000	0.000000
## f.vote=Gruene	0.000000	0.000000
## f.mout=MvOut.No	6.147541	86.956522
## f.gender=F	2.813853	18.840580
## f.vote_ord=SPD	0.000000	0.000000
## f.vote=SPD	0.000000	0.000000
## f.vote_ord=CDU/CSU	0.000000	0.000000
## f.vote=CDU/CSU	0.000000	0.000000
##	Global	p.value

## f.vote_ord=AfD	6.9	1.889108e-108
## f.vote=AfD	6.9	1.889108e-108
## f.egoposition_immigration=8_Level.Imm	3.1	1.675803e-09
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm	4.7	1.468400e-08
## f.gender=M	53.8	1.101835e-06
## f.mout=MvOut.Yes	2.4	1.316568e-05
## f.duplicate=No.Duplicate	64.1	5.540764e-04
## f.egoposition_immigration=7_Level.Imm	7.8	5.783367e-04
## f.egoposition_immigration=9_Level.Imm	3.4	1.731296e-03
## f.eastGermany=No.EastGermany	24.1	1.731634e-03
## f.political_interest=Low.Inter	0.3	1.377478e-02
## f.income=Low_to_Medium.Sat	2.8	4.793709e-02
## f.egoposition_immigration=1_Level.Imm	6.8	4.815760e-02
## f.egoposition_immigration=3_Level.Imm	13.4	4.305493e-02
## f.eastGermany=Yes.EastGermany	75.9	1.731634e-03
## f.egoposition_immigration=5_Neutral_Level.Imm	15.5	6.970986e-04
## f.duplicate=Yes.Duplicate	35.9	5.540764e-04
## f.egoposition_immigration=4_Level.Imm	17.9	1.193747e-04
## f.vote_ord=FDP	12.1	9.721535e-05
## f.vote=FDP	12.1	9.721535e-05
## f.vote_ord=LINKE	12.3	8.254390e-05
## f.vote=LINKE	12.3	8.254390e-05
## f.egoposition_immigration=2_Level.Imm	13.0	4.641675e-05
## f.vote_ord=Gruene	14.3	1.573110e-05
## f.vote=Gruene	14.3	1.573110e-05
## f.mout=MvOut.No	97.6	1.316568e-05
## f.gender=F	46.2	1.101835e-06
## f.vote_ord=SPD	25.5	6.459324e-10
## f.vote=SPD	25.5	6.459324e-10
## f.vote_ord=CDU/CSU	28.9	2.190738e-11
## f.vote=CDU/CSU	28.9	2.190738e-11
##		v.test
## f.vote_ord=AfD	22.123229	
## f.vote=AfD	22.123229	
## f.egoposition_immigration=8_Level.Imm	6.026469	
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm	5.665215	
## f.gender=M	4.872520	
## f.mout=MvOut.Yes	4.357333	
## f.duplicate=No.Duplicate	3.453152	
## f.egoposition_immigration=7_Level.Imm	3.441576	
## f.egoposition_immigration=9_Level.Imm	3.132830	
## f.eastGermany=No.EastGermany	3.132773	
## f.political_interest=Low.Inter	2.463084	
## f.income=Low_to_Medium.Sat	1.977926	
## f.egoposition_immigration=1_Level.Imm	-1.975975	
## f.egoposition_immigration=3_Level.Imm	-2.023177	
## f.eastGermany=Yes.EastGermany	-3.132773	
## f.egoposition_immigration=5_Neutral_Level.Imm	-3.390718	
## f.duplicate=Yes.Duplicate	-3.453152	
## f.egoposition_immigration=4_Level.Imm	-3.847407	

```
## f.vote_ord=FDP -3.897439
## f.vote=FDP -3.897439
## f.vote_ord=LINKE -3.936892
## f.vote=LINKE -3.936892
## f.egoposition_immigration=2_Level.Imm -4.072973
## f.vote_ord=Gruene -4.318194
## f.vote=Gruene -4.318194
## f.mout=MvOut.No -4.357333
## f.gender=F -4.872520
## f.vote_ord=SPD -6.178794
## f.vote=SPD -6.178794
## f.vote_ord=CDU/CSU -6.692711
## f.vote=CDU/CSU -6.692711
```

### 3.3 Modelling

#### 3.3.1 Comparison of Variables' Numerical and Categorical Representation

```
nm1_imm_con <- multinom(f.vote~ egoposition_immigration, data=train)

## # weights: 18 (10 variable)
## initial value 1261.398666
## iter 10 value 1148.327092
## final value 1118.415750
## converged

nm1_imm_con_sq <- multinom(f.vote~ poly(egoposition_immigration,2), data=train)

## # weights: 24 (15 variable)
## initial value 1261.398666
## iter 10 value 1138.305498
## iter 20 value 1114.794463
## iter 30 value 1112.561822
## iter 40 value 1112.001598
## iter 50 value 1111.674468
## iter 60 value 1111.561069
## iter 70 value 1111.518668
## iter 80 value 1111.514694
## iter 90 value 1111.513727
## final value 1111.513467
## converged

nm1_imm_con_cb <- multinom(f.vote~ poly(egoposition_immigration,3), data=train)

## # weights: 30 (20 variable)
## initial value 1261.398666
## iter 10 value 1135.510008
## iter 20 value 1107.179662
## iter 30 value 1103.188553
## iter 40 value 1103.096228
## final value 1103.093747
## converged
```

```

nm1_imm_con_qd <- multinom(f.vote~ poly(egoposition_immigration,4), data=train)

## # weights:  36 (25 variable)
## initial  value 1261.398666
## iter   10 value 1131.200848
## iter   20 value 1100.878825
## iter   30 value 1099.110493
## iter   40 value 1098.830119
## iter   50 value 1098.728526
## final   value 1098.728168
## converged

nm1_imm_cat <- multinom(f.vote~ f.egoposition_immigration, data=train)

## # weights:  72 (55 variable)
## initial  value 1261.398666
## iter   10 value 1102.799382
## iter   20 value 1076.003232
## iter   30 value 1073.394913
## iter   40 value 1072.372161
## iter   50 value 1072.311475
## iter   60 value 1072.180511
## final   value 1072.179111
## converged

nm0$dev - nm1_imm_con$dev

## [1] 131.7249

nm0$dev - nm1_imm_con_sq$dev

## [1] 145.5295

nm0$dev - nm1_imm_con_cb$dev

## [1] 162.3689

nm0$dev - nm1_imm_con_qd$dev

## [1] 171.1001

nm0$dev - nm1_imm_cat$dev

## [1] 224.1982

Anova(nm1_imm_con, test="Chisq")

## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter   10 value 1184.278222
## final   value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote

```



```

##                                LR Chisq Df Pr(>Chisq)
## egoposition_immigration    131.72  5  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Anova(nm1_imm_con_sq, test="Chisq")

## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter  10 value 1184.278222
## final  value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##                                LR Chisq Df Pr(>Chisq)
## poly(egoposition_immigration, 2)    145.53 10  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Anova(nm1_imm_con_cb, test="Chisq")

## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter  10 value 1184.278222
## final  value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##                                LR Chisq Df Pr(>Chisq)
## poly(egoposition_immigration, 3)    162.37 15  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Anova(nm1_imm_con_qd, test="Chisq")

## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter  10 value 1184.278222
## final  value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##                                LR Chisq Df Pr(>Chisq)
## poly(egoposition_immigration, 4)    171.1 20  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
Anova(nm1_imm_cat, test="Chisq")
```

```
## # weights: 12 (5 variable)
## initial value 1261.398666
## iter 10 value 1184.278222
## final value 1184.278203
## converged
```

```
## Analysis of Deviance Table (Type II tests)
```

```
##
```

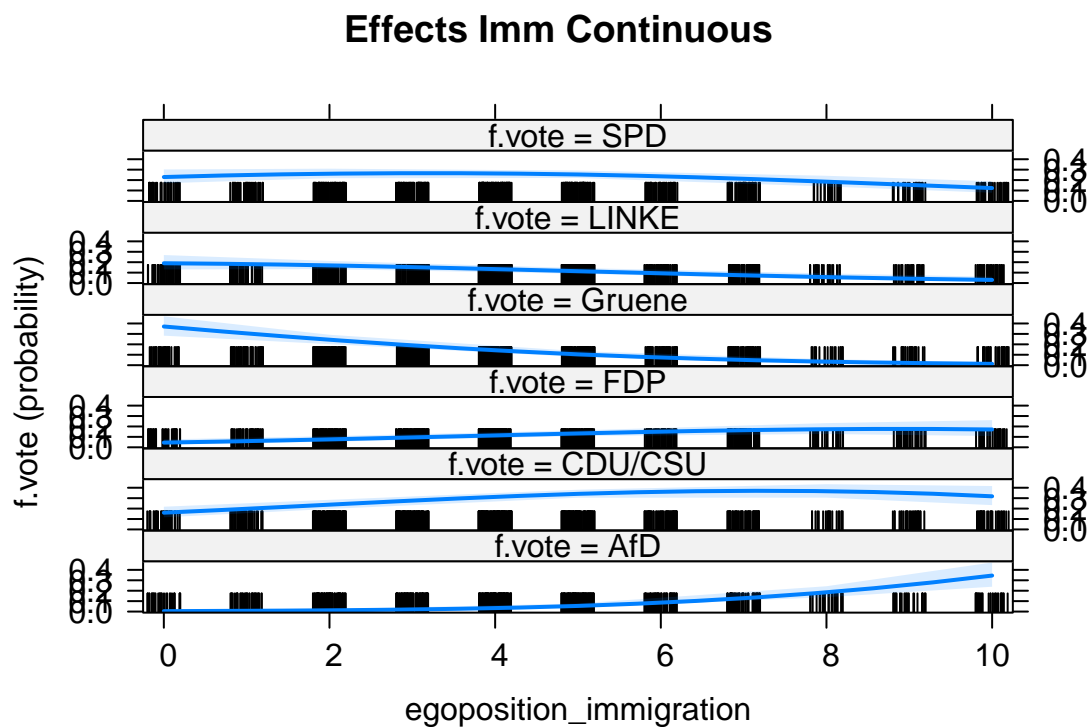
```
## Response: f.vote
```

```
##              LR Chisq Df Pr(>Chisq)
## f.egoposition_immigration    224.2  50  < 2.2e-16 ***
```

```
## ---
```

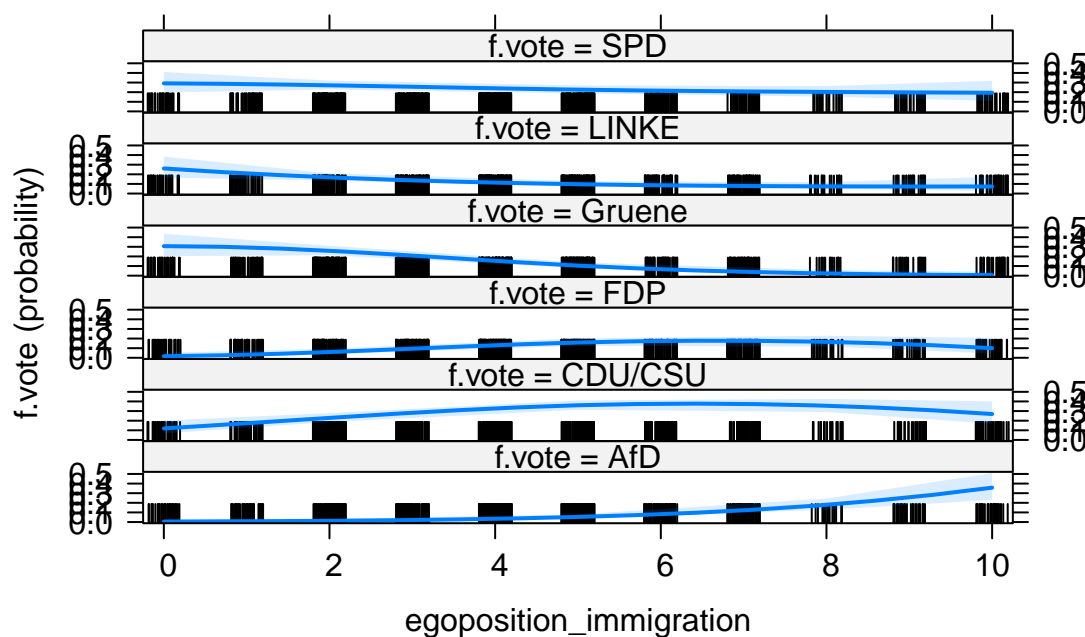
```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(allEffects(nm1_imm_con),ask=FALSE, main="Effects Imm Continuous")
```



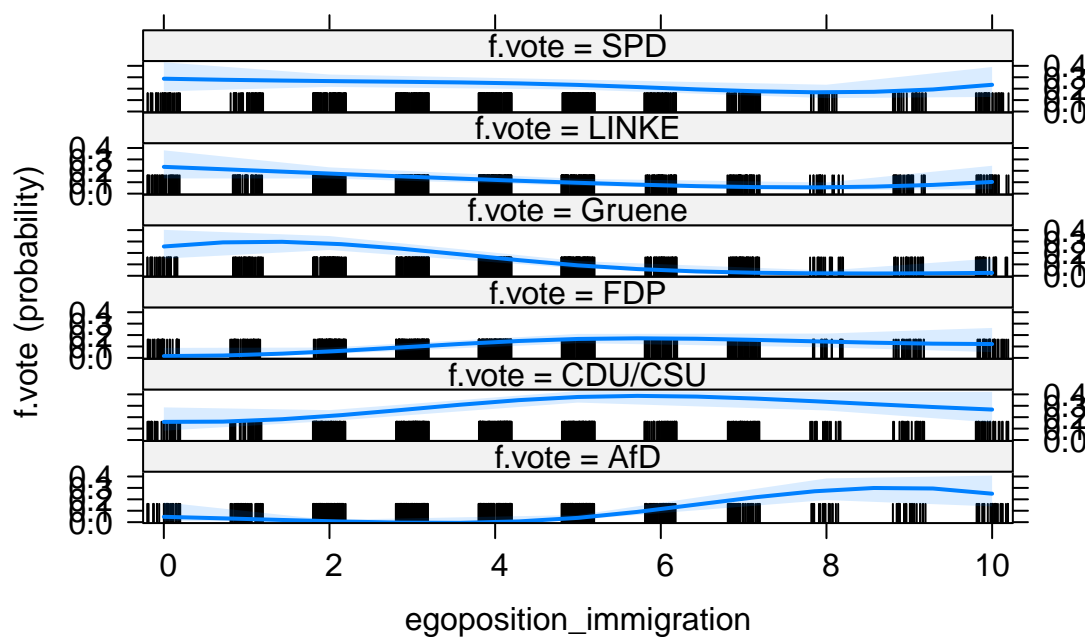
```
plot(allEffects(nm1_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```

## Effects Imm Continuous Squared



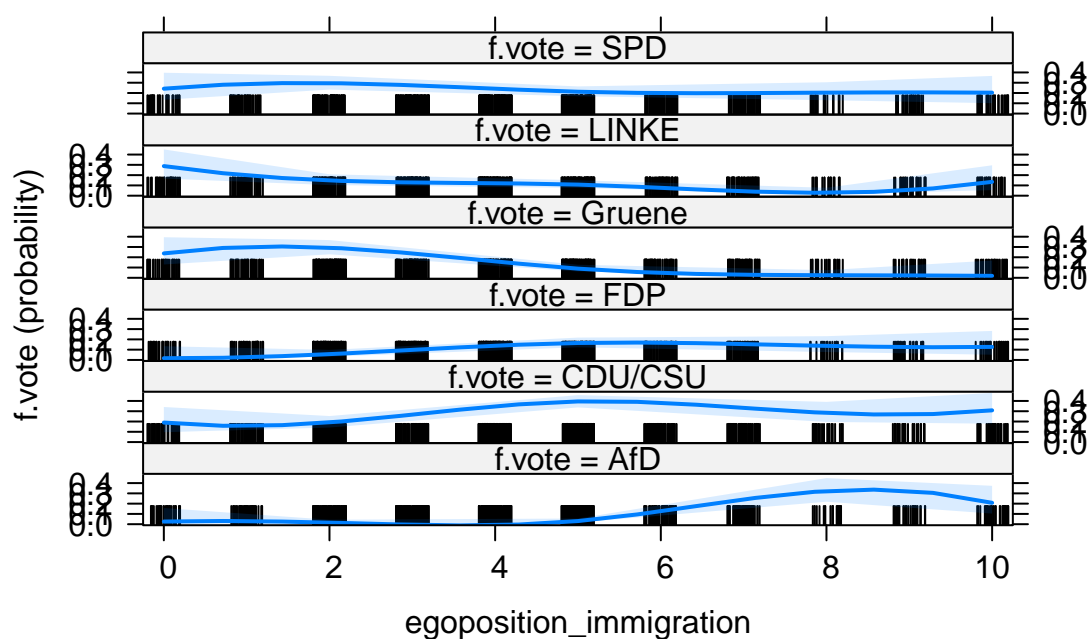
```
plot(allEffects(nm1_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```

## Effects Imm Continuous Cubed



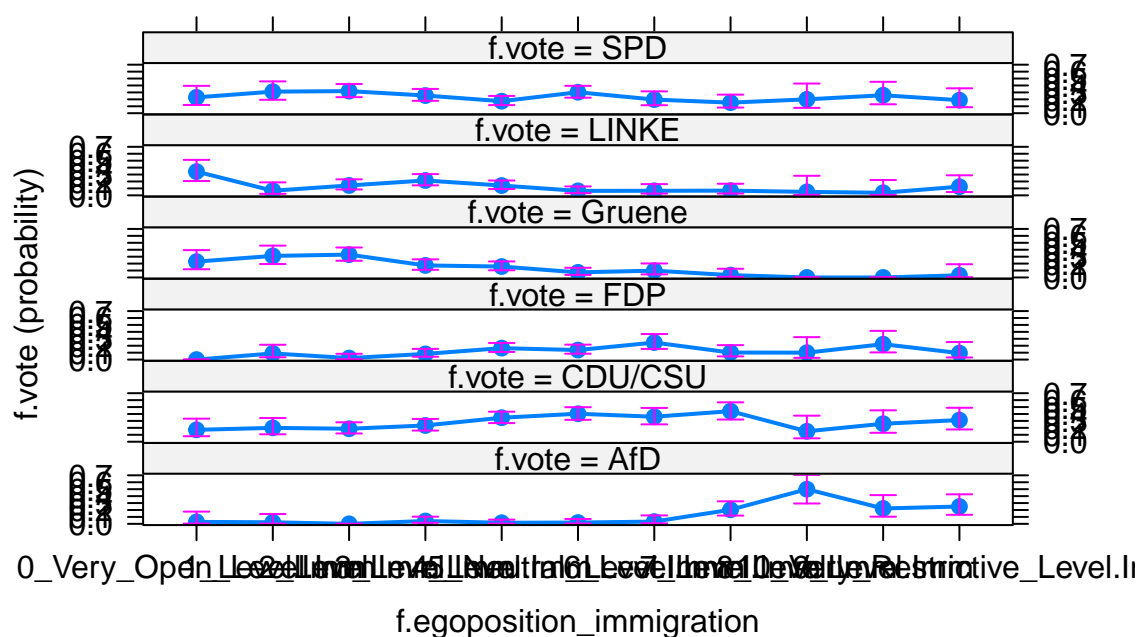
```
plot(allEffects(nm1_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```

## Effects Imm Continuous Quadratic



```
plot(allEffects(nm1_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

## Effects Imm Categorical



```
AIC(nm0, nm1_imm_con, nm1_imm_con_sq, nm1_imm_con_cb, nm1_imm_con_qd, nm1_imm_cat)
```

##		df	AIC
##	nm0	5	2378.556
##	nm1_imm_con	10	2256.832
##	nm1_imm_con_sq	15	2253.027
##	nm1_imm_con_cb	20	2246.187

```

## nm1_imm_con_qd 25 2247.456
## nm1_imm_cat 55 2254.358
# nm1_imm_con_cb is better, egoposition immigration will be used in a cube form as a c
step(nm1_imm_con_cb)

## Start: AIC=2246.19
## f.vote ~ poly(egoposition_immigration, 3)
##
## trying - poly(egoposition_immigration, 3)
## # weights: 12 (5 variable)
## initial value 1261.398666
## iter 10 value 1184.278222
## final value 1184.278203
## converged
##
## Df AIC
## <none> 20 2246.187
## - poly(egoposition_immigration, 3) 5 2378.556

## Call:
## multinom(formula = f.vote ~ poly(egoposition_immigration, 3),
## data = train)
##
## Coefficients:
## (Intercept) poly(egoposition_immigration, 3)1
## CDU/CSU 2.198448 -21.42693
## FDP 1.137774 -13.80769
## Gruene 1.235675 -48.97938
## LINKE 1.281049 -35.92971
## SPD 2.003310 -29.65495
## poly(egoposition_immigration, 3)2 poly(egoposition_immigration, 3)3
## CDU/CSU -14.344612 13.49973
## FDP -20.411339 16.08179
## Gruene -10.916255 21.42471
## LINKE -5.740813 18.12012
## SPD -8.740119 16.31465
##
## Residual Deviance: 2206.187
## AIC: 2246.187
nm1_polint_con <- multinom(f.vote~ political_interest, data=train)

## # weights: 18 (10 variable)
## initial value 1261.398666
## iter 10 value 1182.635003
## final value 1180.874975
## converged
nm1_polint_con_sq <- multinom(f.vote~ poly(political_interest,2), data=train)

## # weights: 24 (15 variable)
## initial value 1261.398666
## iter 10 value 1174.985083

```

```

## iter 20 value 1173.880322
## iter 30 value 1173.724037
## final value 1173.724020
## converged
nm1_polint_con_cb <- multinom(f.vote~ poly(political_interest,3), data=train)

## # weights: 30 (20 variable)
## initial value 1261.398666
## iter 10 value 1172.052121
## iter 20 value 1169.148902
## iter 30 value 1169.103863
## iter 40 value 1169.098649
## final value 1169.098573
## converged
nm1_polint_con_qd <- multinom(f.vote~ poly(political_interest,4), data=train)

## # weights: 36 (25 variable)
## initial value 1261.398666
## iter 10 value 1170.486692
## iter 20 value 1168.082554
## iter 30 value 1167.788799
## iter 40 value 1167.784779
## iter 50 value 1167.782195
## final value 1167.780538
## converged
nm1_polint_cat <- multinom(f.vote~ f.political_interest, data=train)

## # weights: 36 (25 variable)
## initial value 1261.398666
## iter 10 value 1172.572840
## iter 20 value 1169.778510
## iter 30 value 1167.829523
## iter 40 value 1167.778829
## final value 1167.778457
## converged
nm0$dev - nm1_polint_con$dev

## [1] 6.806457
nm0$dev - nm1_polint_con_sq$dev

## [1] 21.10837
nm0$dev - nm1_polint_con_cb$dev

## [1] 30.35926
nm0$dev - nm1_polint_con_qd$dev

## [1] 32.99533

```

```

nm0$dev - nm1_polint_cat$dev

## [1] 32.99949
anova(nm1_polint_con, nm1_polint_con_sq, test="Chisq")

## Likelihood ratio tests of Multinomial Models
##
## Response: f.vote
##
##           Model Resid. df Resid. Dev   Test    Df LR stat.
## 1           political_interest      3510    2361.750
## 2 poly(political_interest, 2)      3505    2347.448 1 vs 2      5 14.30191
##      Pr(Chi)
## 1
## 2 0.01380121
anova(nm1_polint_con_sq, nm1_polint_con_cb, test="Chisq")

## Likelihood ratio tests of Multinomial Models
##
## Response: f.vote
##
##           Model Resid. df Resid. Dev   Test    Df LR stat.
## 1 poly(political_interest, 2)      3505    2347.448
## 2 poly(political_interest, 3)      3500    2338.197 1 vs 2      5 9.250894
##      Pr(Chi)
## 1
## 2 0.09946569
anova(nm1_polint_con_cb, nm1_polint_con_qd, test="Chisq")

## Likelihood ratio tests of Multinomial Models
##
## Response: f.vote
##
##           Model Resid. df Resid. Dev   Test    Df LR stat.
## 1 poly(political_interest, 3)      3500    2338.197
## 2 poly(political_interest, 4)      3495    2335.561 1 vs 2      5 2.636069
##      Pr(Chi)
## 1
## 2 0.7558777
Anova(nm1_polint_con, test="Chisq")

## # weights: 12 (5 variable)
## initial value 1261.398666
## iter 10 value 1184.278222
## final value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##
##           LR Chisq Df Pr(>Chisq)
## political_interest  6.8065 5    0.2354

```

```
Anova(nm1_polint_con_sq, test="Chisq")
```

```
## # weights: 12 (5 variable)
## initial value 1261.398666
## iter 10 value 1184.278222
## final value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##
## LR Chisq Df Pr(>Chisq)
## poly(political_interest, 2) 21.108 10 0.02035 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(nm1_polint_con_cb, test="Chisq")
```

```
## # weights: 12 (5 variable)
## initial value 1261.398666
## iter 10 value 1184.278222
## final value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##
## LR Chisq Df Pr(>Chisq)
## poly(political_interest, 3) 30.359 15 0.01069 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(nm1_polint_con_qd, test="Chisq")
```

```
## # weights: 12 (5 variable)
## initial value 1261.398666
## iter 10 value 1184.278222
## final value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##
## LR Chisq Df Pr(>Chisq)
## poly(political_interest, 4) 32.995 20 0.03378 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

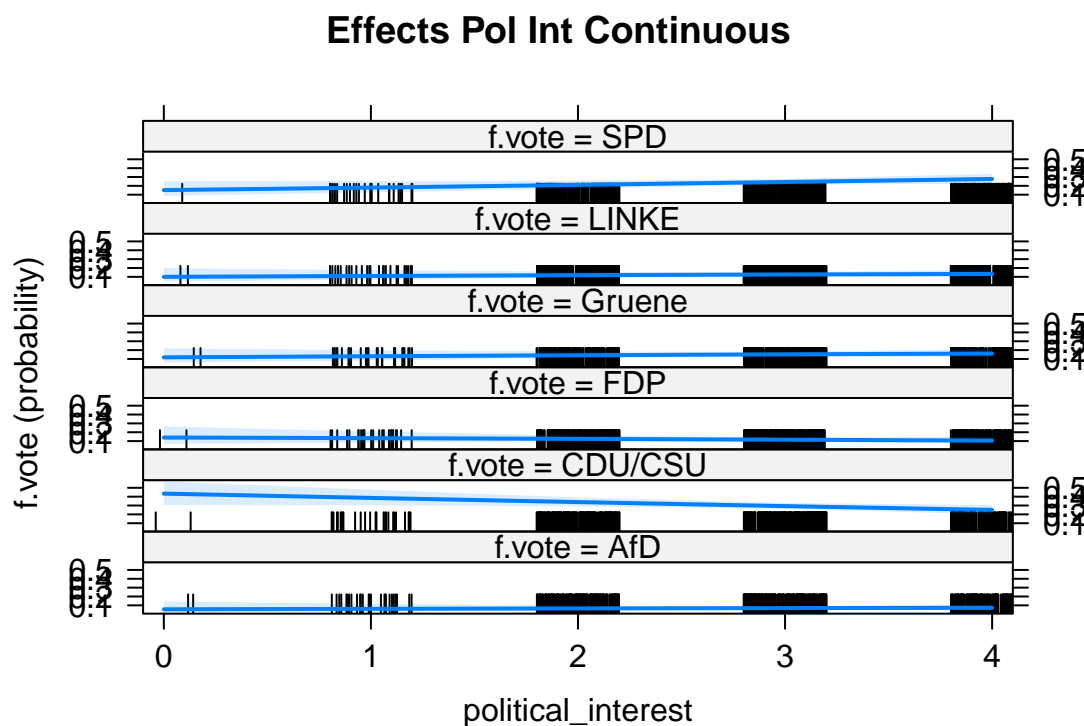
```
Anova(nm1_polint_cat, test="Chisq")
```

```
## # weights: 12 (5 variable)
## initial value 1261.398666
## iter 10 value 1184.278222
## final value 1184.278203
```



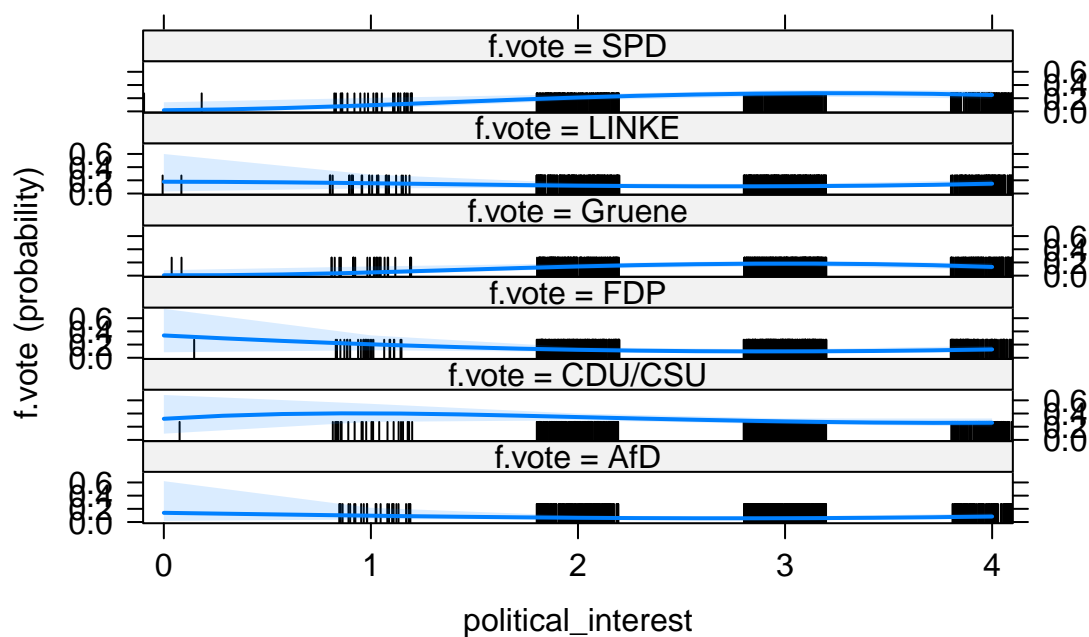
```
## converged
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##               LR Chisq Df Pr(>Chisq)
## f.political_interest 32.999 20 0.03375 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

plot(allEffects(nm1_polint_con),ask=FALSE, main="Effects Pol Int Continuous")
```



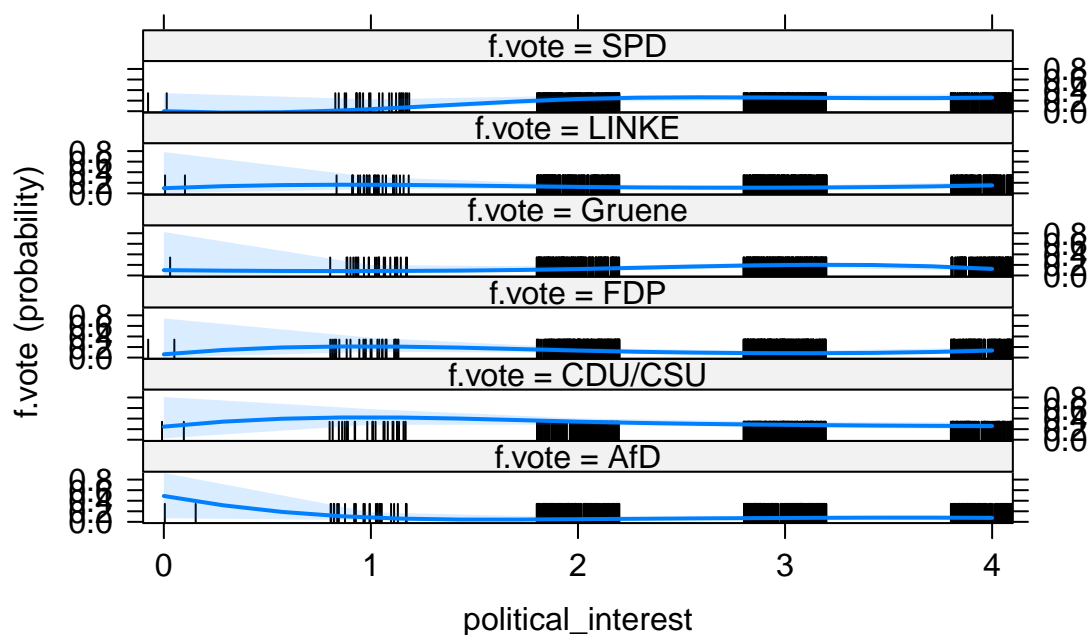
```
plot(allEffects(nm1_polint_con_sq),ask=FALSE,main="Effects Pol Int Continuous Squared")
```

## Effects Pol Int Continuous Squared



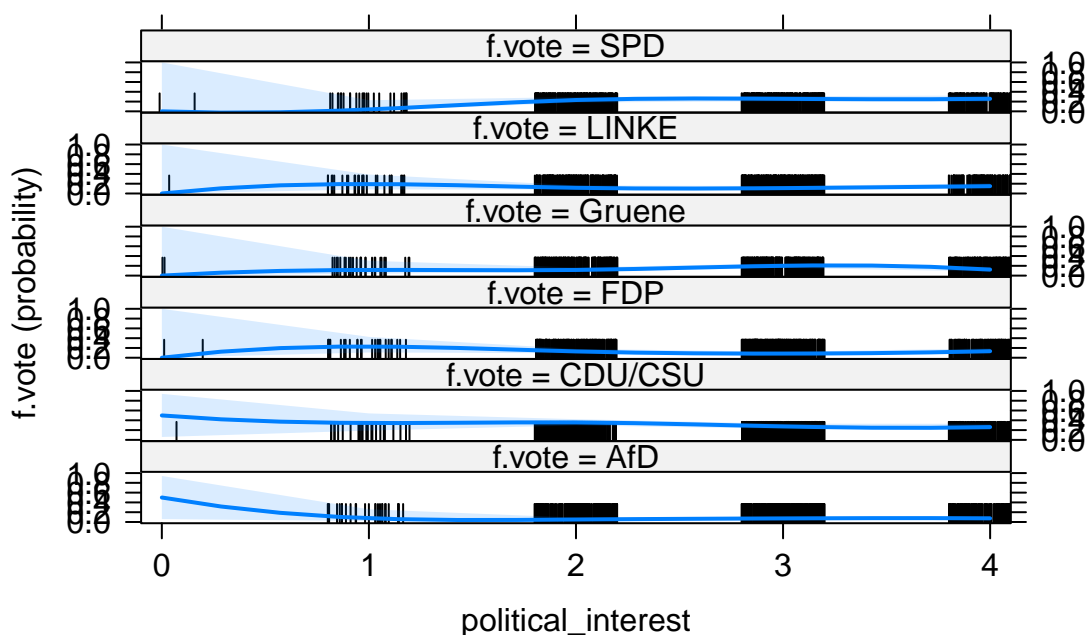
```
plot(allEffects(nm1_polint_con_cb),ask=FALSE, main="Effects Pol Int Continuous Cubed")
```

## Effects Pol Int Continuous Cubed



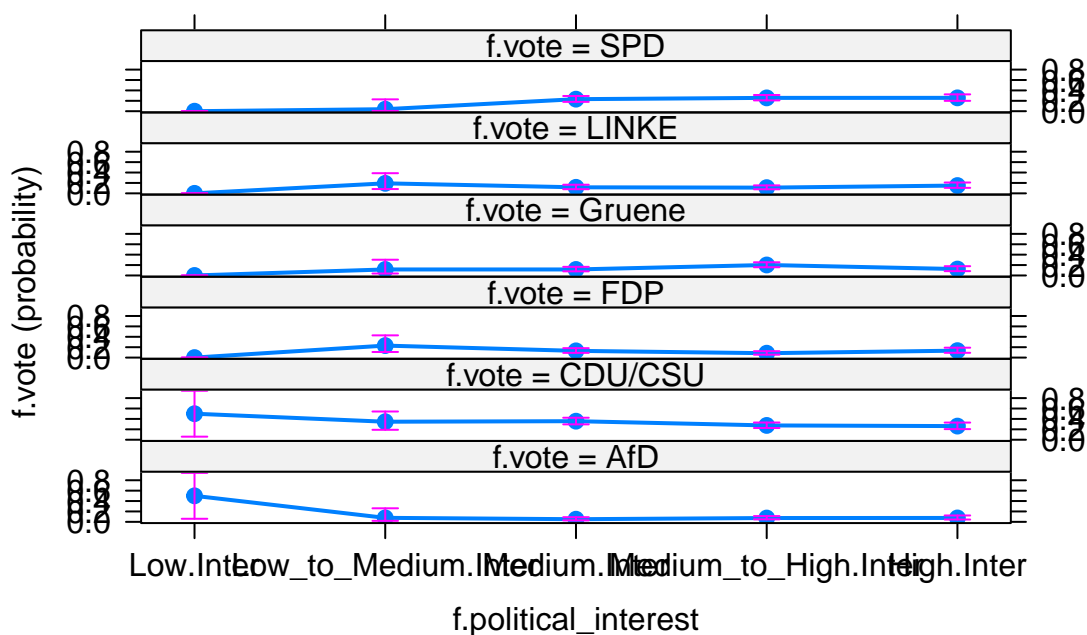
```
plot(allEffects(nm1_polint_con_qd),ask=FALSE, main="Effects Pol Int Continuous Quadratic")
```

## Effects Pol Int Continuous Quadratic



```
plot(allEffects(nm1_polint_cat), ask=FALSE, main="Effects Pol Int Categorical")
```

## Effects Pol Int Categorical



```
AIC(nm0, nm1_polint_con, nm1_polint_con_sq, nm1_polint_con_cb, nm1_polint_con_qd, nm1_po
```

```
##          df      AIC
## nm0          5 2378.556
## nm1_polint_con 10 2381.750
## nm1_polint_con_sq 15 2377.448
## nm1_polint_con_cb 20 2378.197
```

```
## nm1_polint_con_qd 25 2385.561
## nm1_polint_cat 25 2385.557
# nm1_polint_con_sq is better, but in general politican interest does not provide pred
step(nm1_polint_con_sq)

## Start: AIC=2377.45
## f.vote ~ poly(political_interest, 2)
##
## trying - poly(political_interest, 2)
## # weights: 12 (5 variable)
## initial value 1261.398666
## iter 10 value 1184.278222
## final value 1184.278203
## converged
##
## Df AIC
## <none> 15 2377.448
## - poly(political_interest, 2) 5 2378.556

## Call:
## multinom(formula = f.vote ~ poly(political_interest, 2), data = train)
##
## Coefficients:
## (Intercept) poly(political_interest, 2)1 poly(political_interest, 2)2
## CDU/CSU 1.4873661 -4.50161649 -3.8855984
## FDP 0.5336771 -2.50425803 0.1110844
## Gruene 0.7732454 1.75300389 -11.9503766
## LINKE 0.6123860 0.05763351 -1.1297075
## SPD 1.2507984 3.06573651 -9.3148235
##
## Residual Deviance: 2347.448
## AIC: 2377.448

nm1_inc_con <- multinom(f.vote~ income, data=train)

## # weights: 18 (10 variable)
## initial value 1261.398666
## iter 10 value 1176.331976
## final value 1175.313945
## converged

nm1_inc_con_sq <- multinom(f.vote~ poly(income,2), data=train)

## # weights: 24 (15 variable)
## initial value 1261.398666
## iter 10 value 1172.962842
## iter 20 value 1172.190380
## iter 30 value 1172.160700
## final value 1172.160646
## converged

nm1_inc_con_cb <- multinom(f.vote~ poly(income,3), data=train)

## # weights: 30 (20 variable)
```

```

## initial value 1261.398666
## iter 10 value 1172.105064
## iter 20 value 1169.192288
## iter 30 value 1168.668686
## iter 40 value 1168.590284
## final value 1168.588764
## converged

nm1_inc_con_qd <- multinom(f.vote~ poly(income,4), data=train)

## # weights: 36 (25 variable)
## initial value 1261.398666
## iter 10 value 1172.012151
## iter 20 value 1169.101645
## iter 30 value 1168.546076
## iter 40 value 1168.440566
## iter 50 value 1168.365116
## iter 60 value 1168.347278
## iter 70 value 1168.341156
## iter 80 value 1168.340870
## iter 90 value 1168.340223
## iter 100 value 1168.337397
## final value 1168.337397
## stopped after 100 iterations

nm1_inc_cat <- multinom(f.vote~ f.income, data=train)

## # weights: 36 (25 variable)
## initial value 1261.398666
## iter 10 value 1174.099089
## iter 20 value 1169.290127
## iter 30 value 1168.381969
## iter 40 value 1168.331831
## final value 1168.331584
## converged

nm0$dev - nm1_inc_con$dev

## [1] 17.92852

nm0$dev - nm1_inc_con_sq$dev

## [1] 24.23512

nm0$dev - nm1_inc_con_cb$dev

## [1] 31.37888

nm0$dev - nm1_inc_con_qd$dev

## [1] 31.88161

nm0$dev - nm1_inc_cat$dev

## [1] 31.89324

```

```

anova(nm1_inc_con, nm1_inc_con_sq, test="Chisq")

## Likelihood ratio tests of Multinomial Models
##
## Response: f.vote
##           Model Resid. df Resid. Dev   Test    Df LR stat.   Pr(Chi)
## 1           income      3510    2350.628
## 2 poly(income, 2)      3505    2344.321 1 vs 2     5 6.306599 0.2775181
anova(nm1_inc_con_sq, nm1_inc_con_cb, test="Chisq")

## Likelihood ratio tests of Multinomial Models
##
## Response: f.vote
##           Model Resid. df Resid. Dev   Test    Df LR stat.   Pr(Chi)
## 1 poly(income, 2)      3505    2344.321
## 2 poly(income, 3)      3500    2337.178 1 vs 2     5 7.143764 0.2101661
anova(nm1_inc_con_cb, nm1_inc_con_qd, test="Chisq")

## Likelihood ratio tests of Multinomial Models
##
## Response: f.vote
##           Model Resid. df Resid. Dev   Test    Df LR stat.   Pr(Chi)
## 1 poly(income, 3)      3500    2337.178
## 2 poly(income, 4)      3495    2336.675 1 vs 2     5 0.5027325 0.9920229
Anova(nm1_inc_con, test="Chisq")

## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter  10 value 1184.278222
## final   value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##           LR Chisq Df Pr(>Chisq)
## income    17.928  5  0.003037 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Anova(nm1_inc_con_sq, test="Chisq")

## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter  10 value 1184.278222
## final   value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote

```

```

##               LR Chisq Df Pr(>Chisq)
## poly(income, 2)  24.235 10      0.007 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Anova(nm1_inc_con_cb, test="Chisq")

## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter  10 value 1184.278222
## final  value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##               LR Chisq Df Pr(>Chisq)
## poly(income, 3)  31.379 15   0.007814 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Anova(nm1_inc_con_qd, test="Chisq")

## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter  10 value 1184.278222
## final  value 1184.278203
## converged

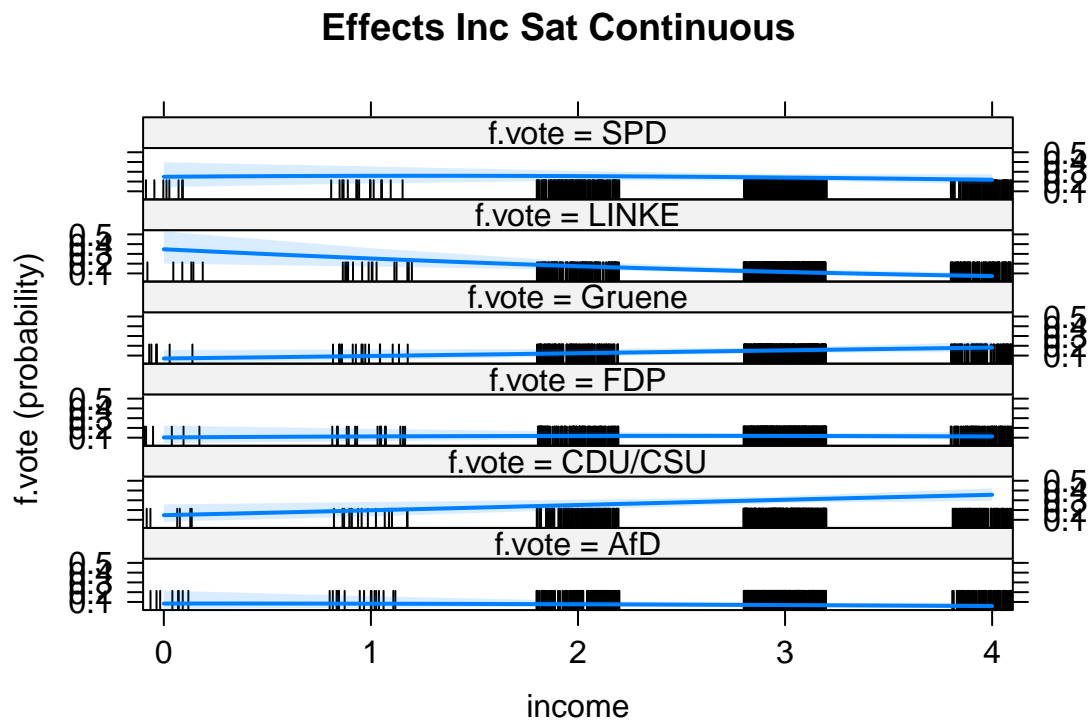
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##               LR Chisq Df Pr(>Chisq)
## poly(income, 4)  31.882 20   0.04458 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Anova(nm1_inc_cat, test="Chisq")

## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter  10 value 1184.278222
## final  value 1184.278203
## converged

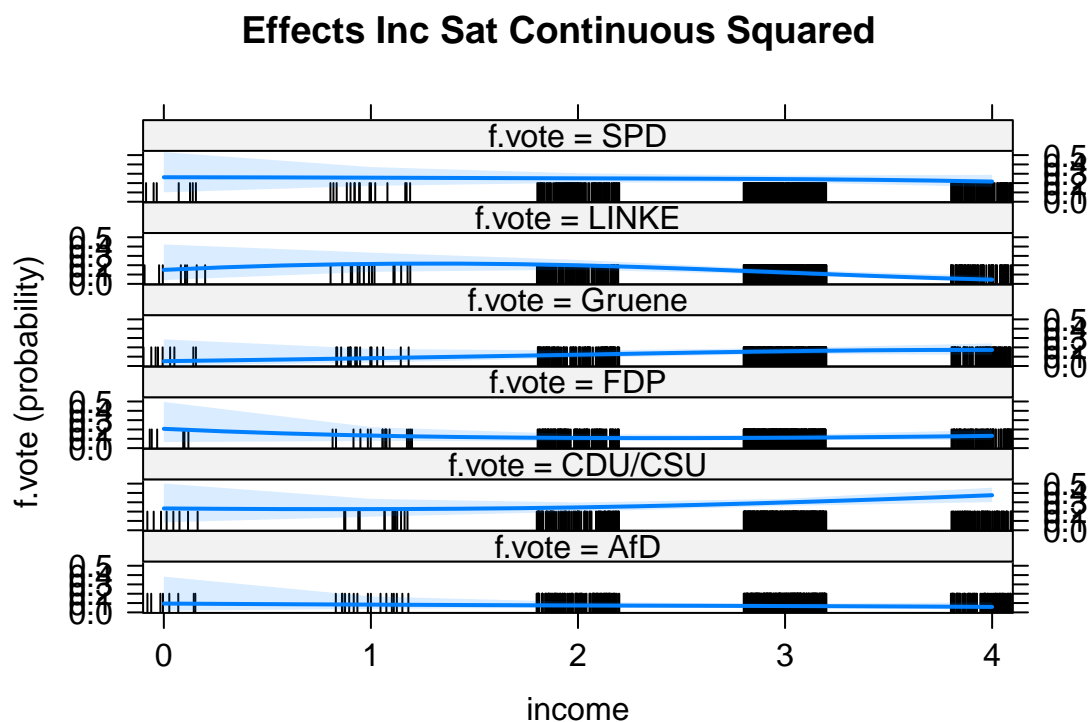
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##               LR Chisq Df Pr(>Chisq)
## f.income  31.893 20   0.04445 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
plot(allEffects(nm1_inc_con),ask=FALSE, main="Effects Inc Sat Continuous")
```



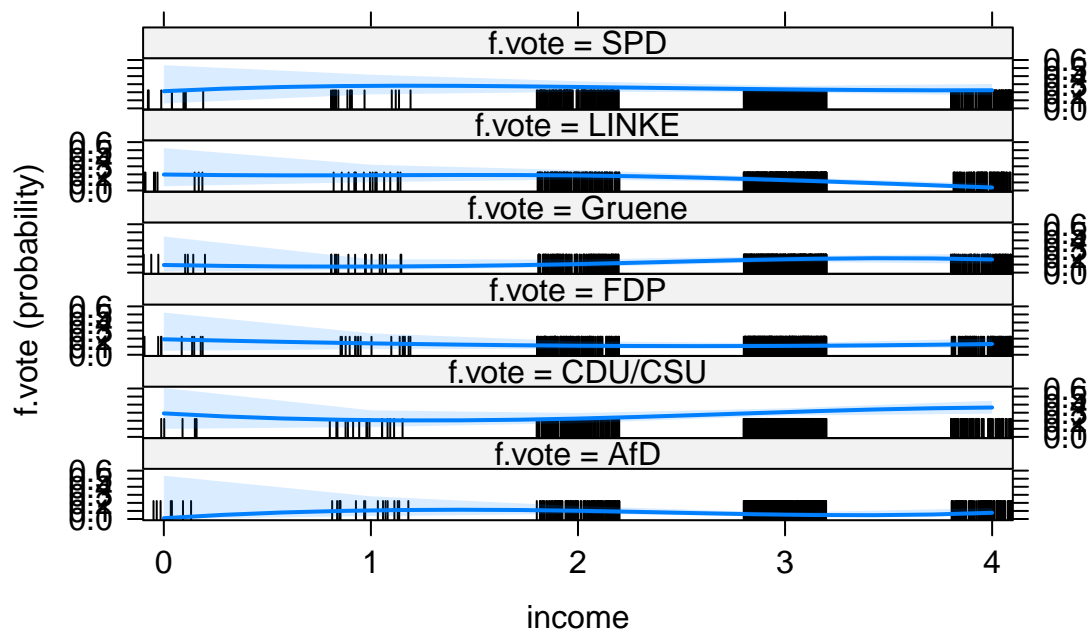
```
plot(allEffects(nm1_inc_con_sq),ask=FALSE,main="Effects Inc Sat Continuous Squared")
```



```
plot(allEffects(nm1_inc_con_cb),ask=FALSE, main="Effects Inc Sat Continuous Cubed")
```

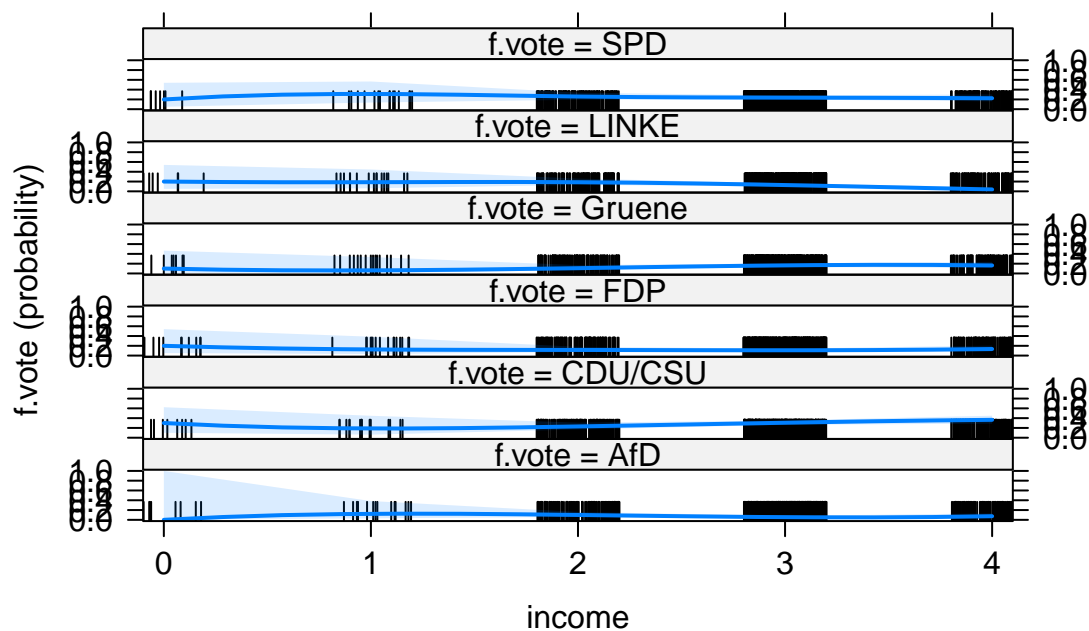


## Effects Inc Sat Continuous Cubed



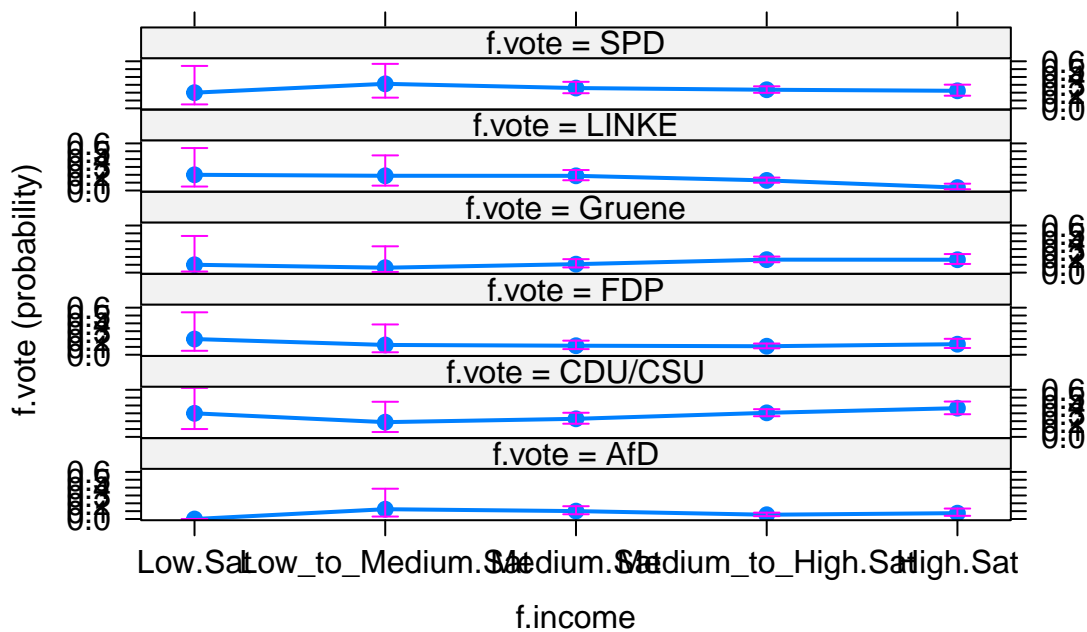
```
plot(allEffects(nm1_inc_con_qd),ask=FALSE, main="Effects Inc Sat Continuous Quadratic")
```

## Effects Inc Sat Continuous Quadratic



```
plot(allEffects(nm1_inc_cat),ask=FALSE, main="Effects Pol Int Categorical")
```

## Effects Pol Int Categorical



```
AIC(nm0, nm1_inc_con, nm1_inc_con_sq, nm1_inc_con_cb, nm1_inc_con_qd, nm1_inc_cat)
```

```
##          df      AIC
## nm0          5 2378.556
## nm1_inc_con   10 2370.628
## nm1_inc_con_sq 15 2374.321
## nm1_inc_con_cb 20 2377.178
## nm1_inc_con_qd 25 2386.675
## nm1_inc_cat   25 2386.663
```

*# nm1\_inc\_con is better, income satisfaction will be used as numerical in first order step(nm1\_inc\_con)*

```
## Start: AIC=2370.63
## f.vote ~ income
##
## trying - income
## # weights: 12 (5 variable)
## initial value 1261.398666
## iter 10 value 1184.278222
## final value 1184.278203
## converged
##          Df      AIC
## <none>    10 2370.628
## - income   5 2378.556
##
## Call:
## multinom(formula = f.vote ~ income, data = train)
##
## Coefficients:
##          (Intercept)          income
```

```
## CDU/CSU    0.5669786  0.3124576
## FDP        0.2040125  0.1155575
## Gruene     -0.1766037  0.3307659
## LINKE      1.4228335 -0.2987874
## SPD        1.0878742  0.0599093
##
## Residual Deviance: 2350.628
## AIC: 2370.628
```

### 3.3.2 Quality Info Model m0