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

Ander Barrio Campos, Odysseas Kyparissis

2023-01-05

Contents

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.

```r
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.

```r
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.

In the Polytomous Modelling chapter of the report the generation of new factors for those variables is taking place as well.

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(quantiData, 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
```
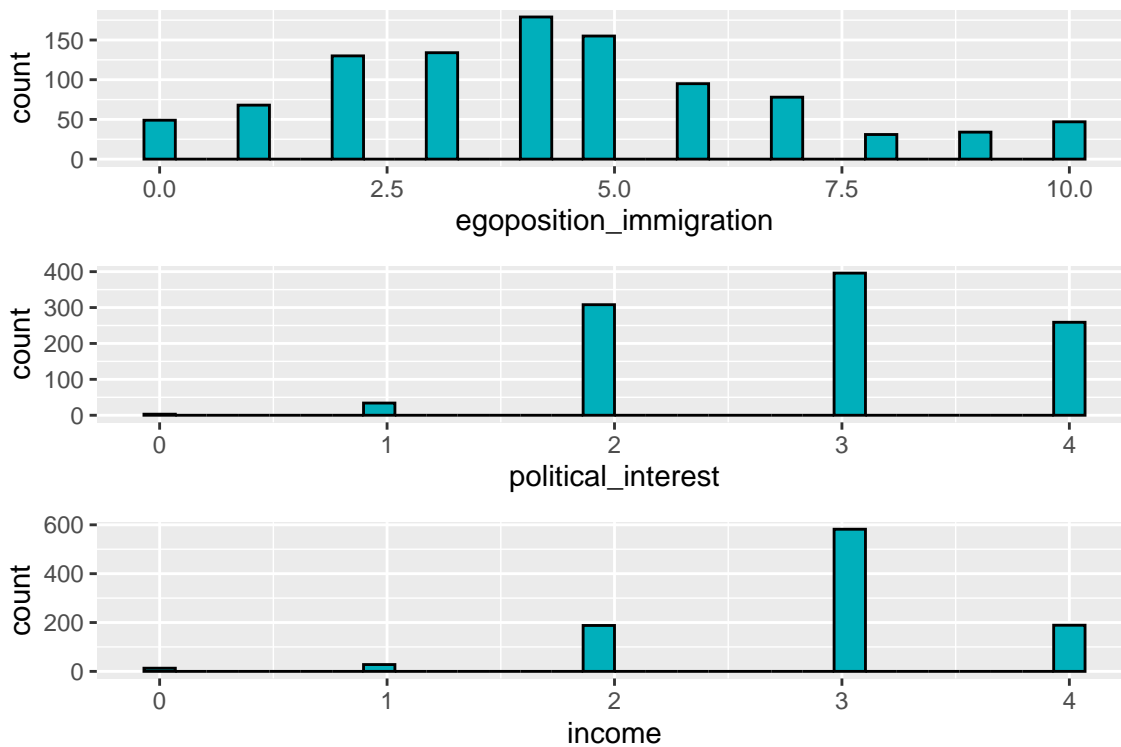
```
summary(gles$political_interest)
```

```
##    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
```
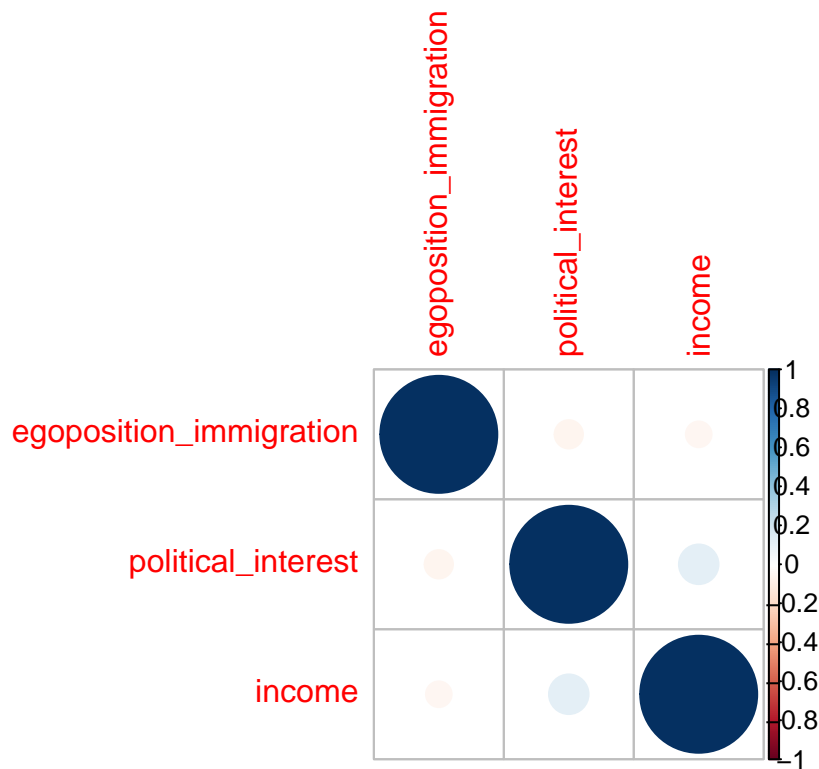
1.7.3 Descriptive Analysis for Categorial Variables

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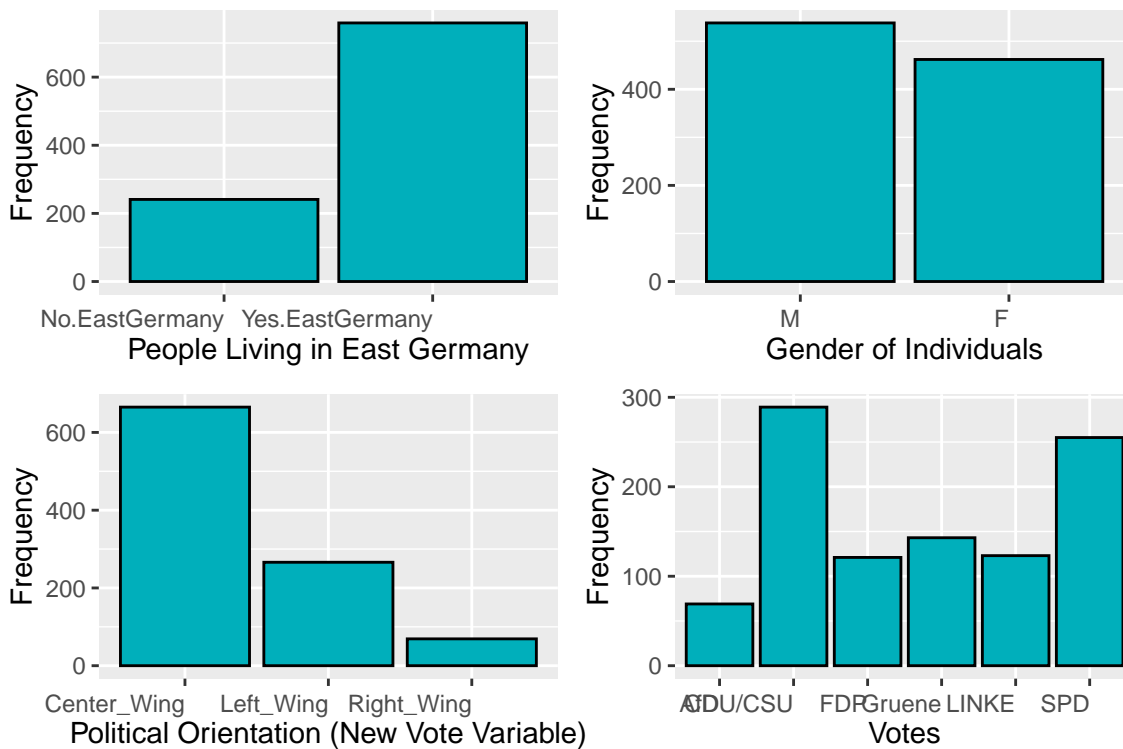
From the barplots, it is illustrated that most of the observations are from citizens of the Eastern

Gemany, 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 Inmigration
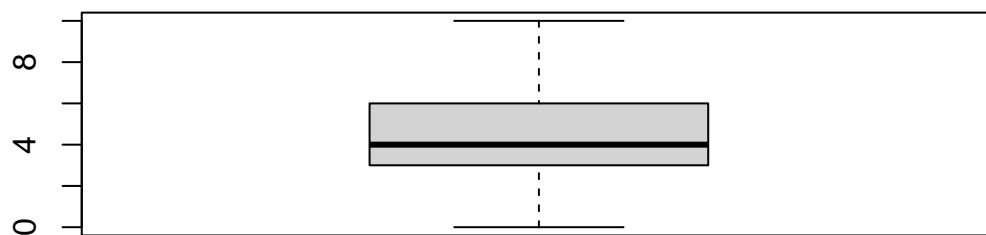

```
## [1] 0
```

Following by, the same approach is used for variable *political_interest*.

Boxplot of Variable Political Interest
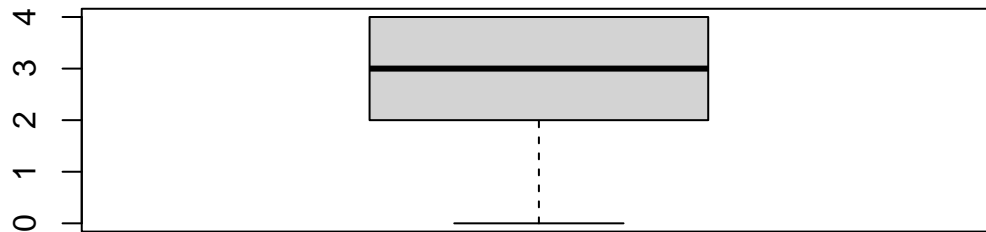

```
## [1] 0
```

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
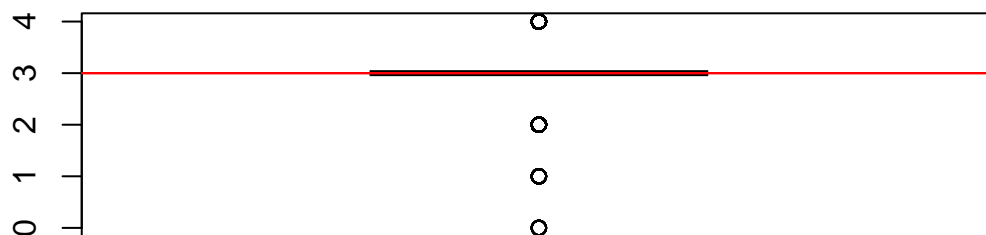

```
## [1] 418
```

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

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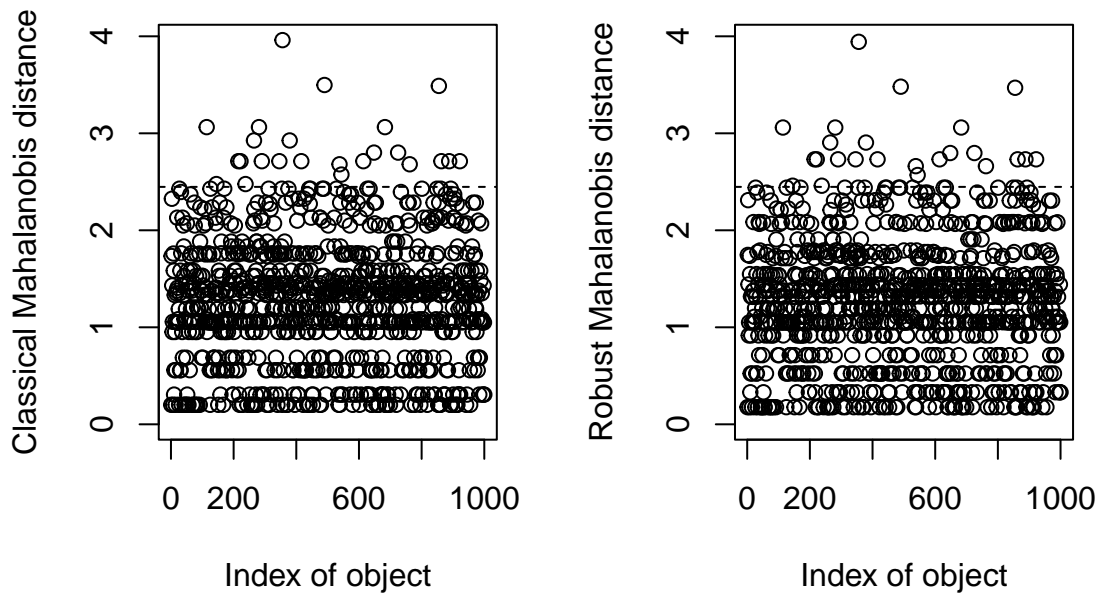
After calculating Mahalanobis distance at a 95% confidence interval, the cut off given is 2.447747.

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
```

10
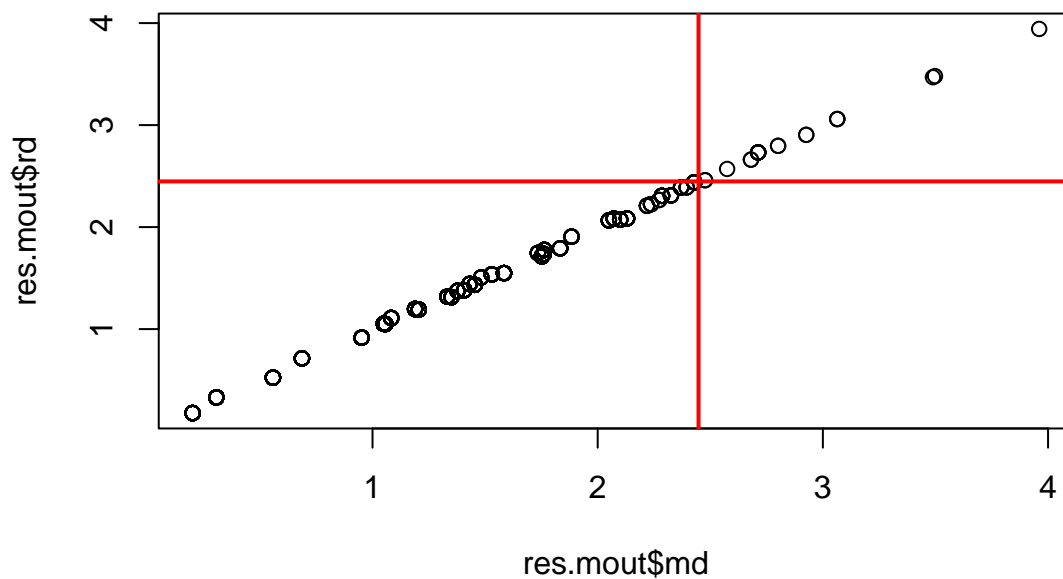
```
##  MvOut.No :976
##  MvOut.Yes: 24
```

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 are 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 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_imigration (*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. Derive new factor for each variable by combining some levels of the already existed factors, and train a new model with it. The new levels are chosen below, based on the allEffects plots.

5. Compare those 6 models and the NULL model for each variable by using anova for nested models reduction of deviance, Anova and AIC.

6. 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***: the new derived factor *f.Imm* will be used to represent this variable. In this case, the reduction in deviance is approximately equal to 172 units, the second biggest reduction after 224 units belonging to the original factor of the variable containing 10 levels. To continue with, by checking the explanatory power of the variable with Anova function, one can understand that it provides explanatory power to the model, in all of the forms (Appendix). Finally, by checking the allEffects plots for all the 5 models and the AIC comparison of them presented below, it is clear that *f.Imm* representation provides the better model.

```
## [1] 224.1982
```

```
## [1] 172.0104
```

```
##                   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_cat_new   25 2246.546
```

- ***political_interest***: poly(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). For picking this representation of this variable the same approach as before has been followed. AIC values for the 5 models are presented here, the remaining analysis can be found in Appendix. The only reason for using this variable in the squared form is that function Anova, indicates that the squared form of *political_interest* has a p-value smaller of 0.05, thus null hypothesis can be rejected.

```
##                     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_cat_new  15 2388.672
```

- ***income*** : the continuous representation (*income*) of first order will be used to represent this variable.

```
##                  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_cat_new 20 2386.946
```

2.1.2 Final Nominal Model

Once multiple different combinations of main effects and interactions of factors and the squared form of the numerical variable have been tested, the final model is presented below.

```
summary(nm_final)
```

```
## Call:
## multinom(formula = f.vote ~ poly(political_interest, 2) + income +
##     f.Imm + f.eastGermany + f.gender, data = train)
##
## Coefficients:
##          (Intercept) poly(political_interest, 2)1 poly(political_interest, 2)2
## CDU/CSU  -0.09257836                    -5.941845                   -0.8135103
## FDP     -13.10876866                    -4.007060                    3.6417160
## Gruene    0.51181473                     1.087766                   -8.9035984
## LINKE     3.11883232                    -0.199091                    1.0482878
## SPD       1.07507231                     3.036173                   -6.5510538
##            income f.Immlow_medium f.Immmedium f.Immmedium_high f.Immhigh
## CDU/CSU  0.30897594       0.3794200   1.0741356        -1.614876 -1.641185
## FDP      0.11260568      12.6063799  13.7919676        10.909124 10.608670
## Gruene   0.16462317       0.2443429  -0.4785748        -4.885834 -4.289655
## LINKE   -0.41228020      -0.5678470  -1.0749778        -4.304691 -3.474082
## SPD     -0.05034817       0.4244623   0.2317975        -2.549853 -2.465248
##         f.eastGermanyYes.EastGermany f.genderF
## CDU/CSU                    0.8480695  1.505285
## FDP                        1.0859395  1.327414
## Gruene                     0.7535584  1.970332
## LINKE                      0.2418049  1.588901
## SPD                        0.9076119  1.800443
##
## Std. Errors:
##          (Intercept) poly(political_interest, 2)1 poly(political_interest, 2)2
## CDU/CSU  1.3140067                     4.567882                     4.118287
## FDP      0.6787106                     5.003145                     4.386609
## Gruene   1.3574759                     5.469624                     5.342217
## LINKE    1.3003537                     5.120422                     4.653212
## SPD      1.3022998                     4.925334                     4.735253
##            income f.Immlow_medium f.Immmedium f.Immmedium_high f.Immhigh
## CDU/CSU 0.2396515       1.1883878   1.1701492        1.1253464 1.2027647
## FDP     0.2640849       0.4983665   0.4208022        0.3719566 0.5937215
## Gruene  0.2702383       1.1700810   1.1623876        1.3060775 1.5229222
## LINKE   0.2580925       1.1534082   1.1433739        1.1508066 1.2338791
## SPD     0.2447612       1.1670464   1.1536762        1.1165164 1.2146920
##         f.eastGermanyYes.EastGermany f.genderF
## CDU/CSU                    0.3742758 0.4247466
```

```
## FDP                          0.4389828 0.4618531
## Gruene                       0.4317185 0.4633330
## LINKE                        0.4172363 0.4637351
## SPD                          0.3919844 0.4346765
##
## Residual Deviance: 2119.625
## AIC: 2219.625
```

From the summary of the final nominal model, after executing the step function on the model containing all main effects and interactions of the factors and the numerical variables it can be concluded that the formula contains only the main effects of factors *f.Imm, f.eastGermany, f.gender*, the squared form of the numerical representation of variable *political_interest* and finally the first order of variable *income (numerical representation)*. Concerning the target variable *f.vote,* the party **AfD** is being used as the baseline category and then all the odds for the remaining parties are calculated based on this baseline category, as we have seen it in theory and labs sessions. The following plots indicate how the explanatory variables fluctuate throuhgout the different parties of the target variable. By the allEffects plot it is clear that the available explanatory variables are not enough to distinguish well the voting preferences of the German citizens.
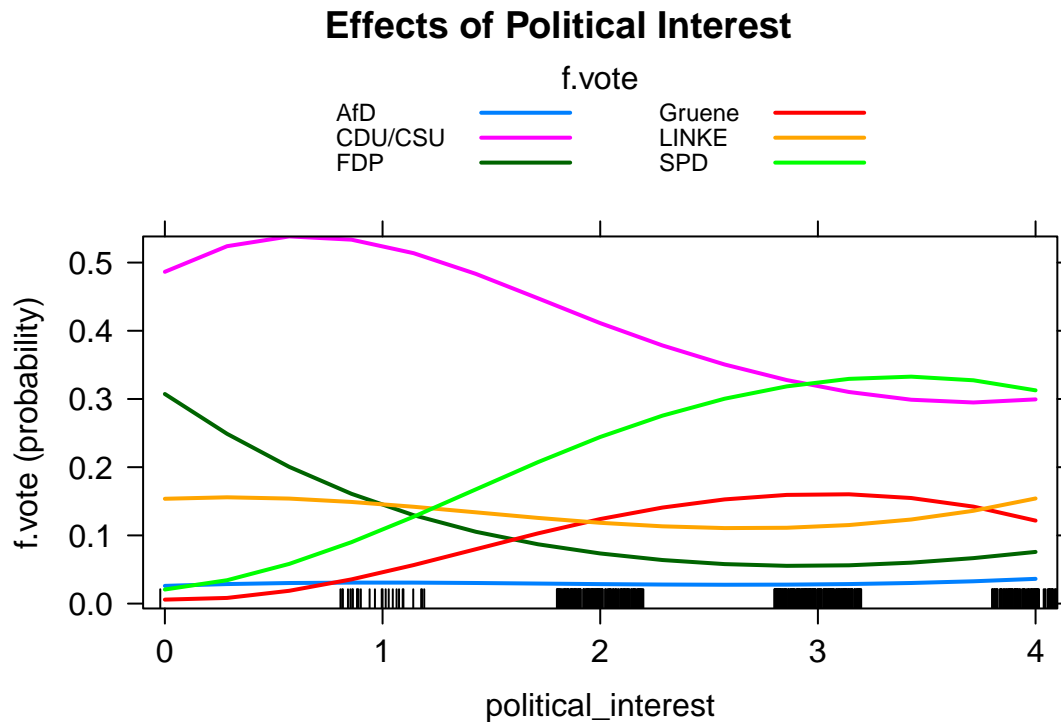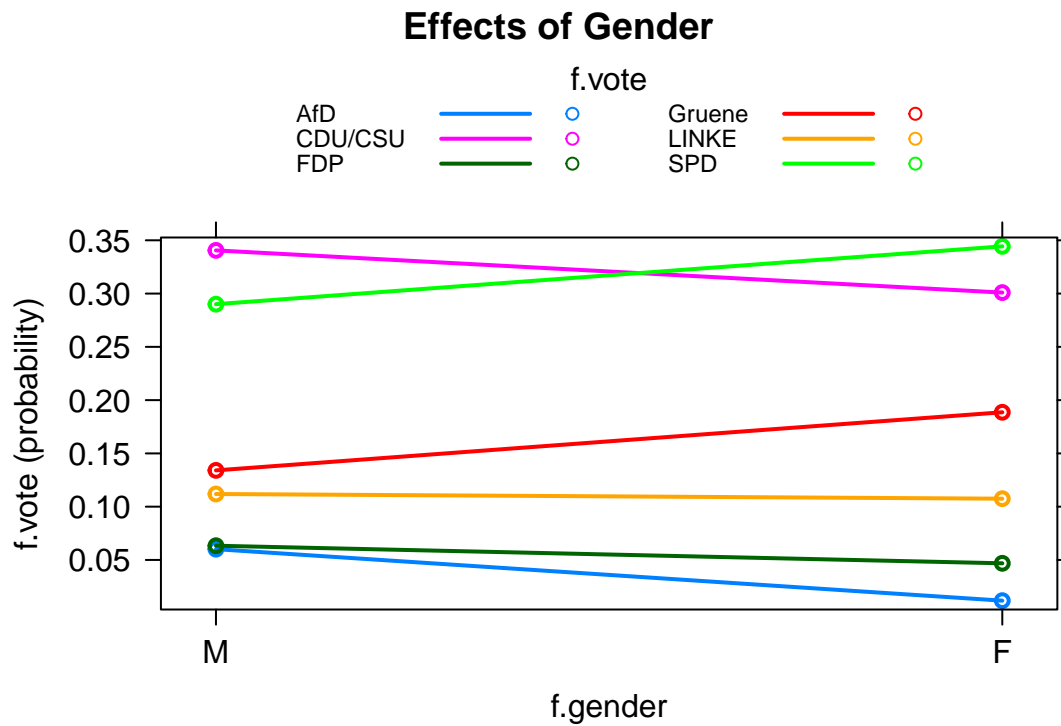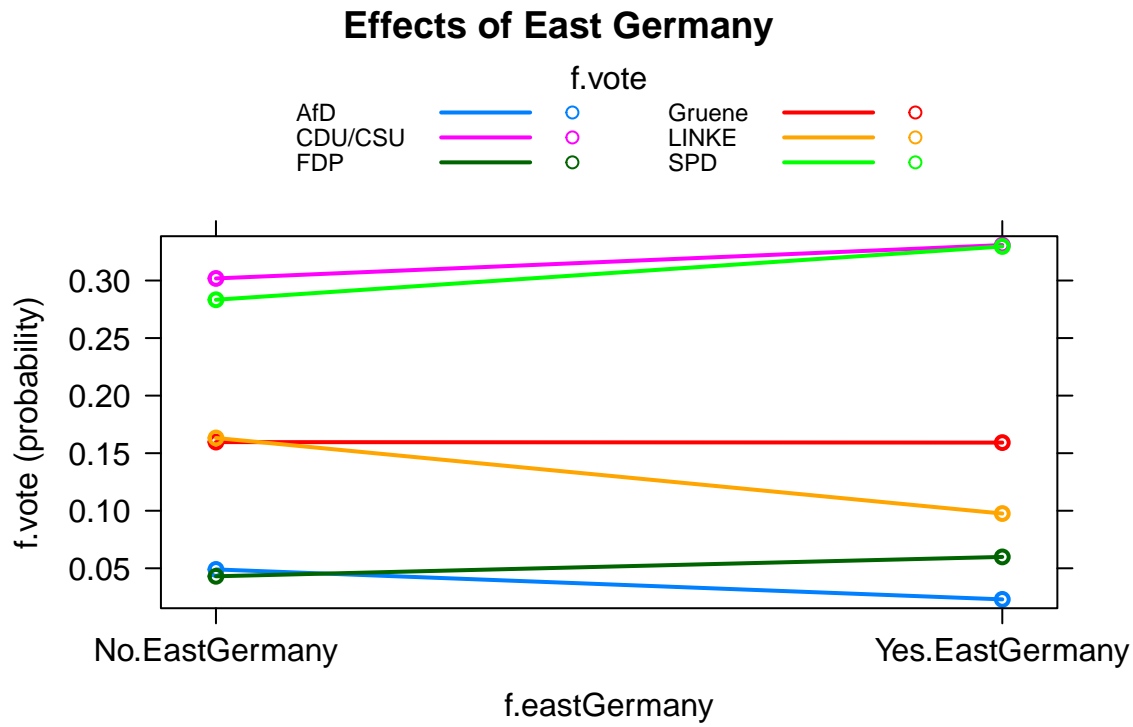
Effects of Income
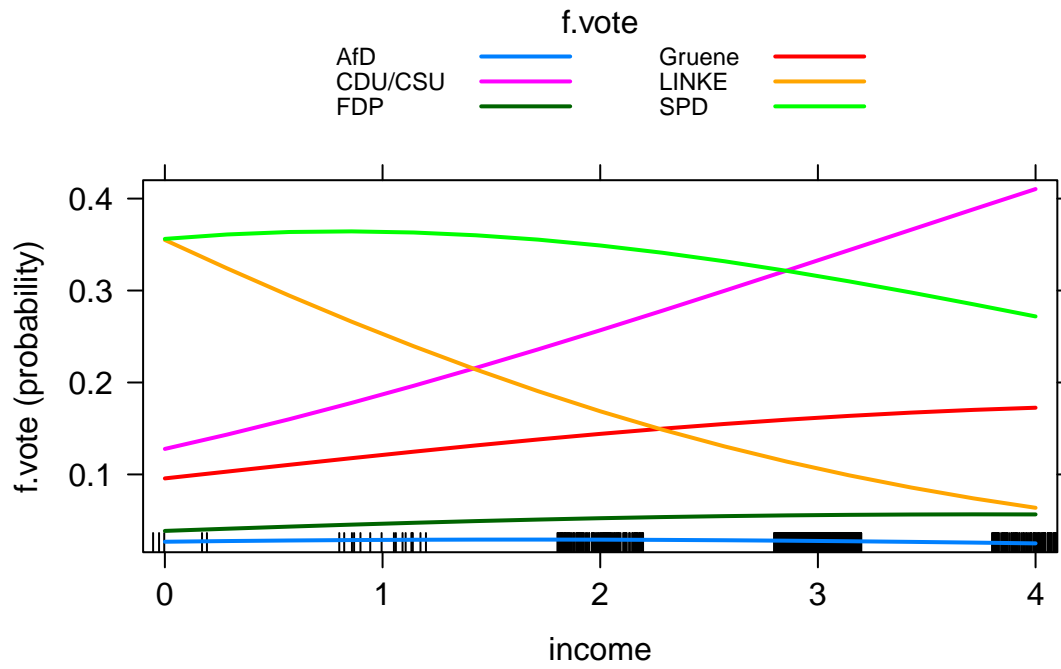
Effects of Egoposition Immigration

Effects of East Germany

Effects of Gender
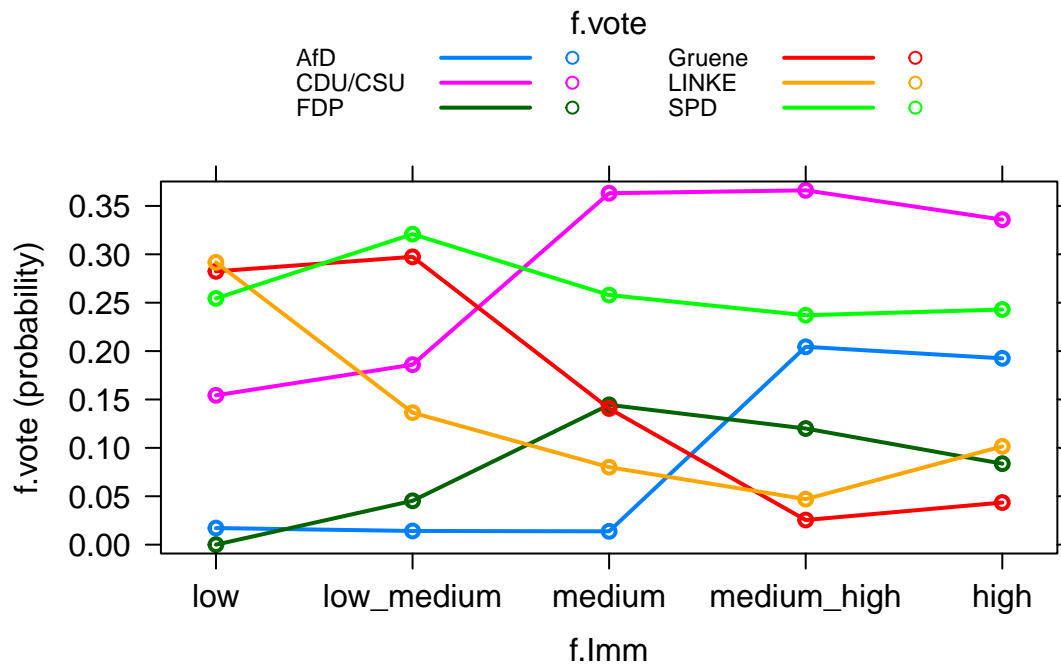
Finally, validation measures and graphs are generated for training and testing set here. Mainly, the confusion matrix has been used to calculate the accuracy, recall and precision of the model, while AUC plots have been generated as well. It can be seen that both training and testing set *FDP*, *Gruene* and *LINKE* cannot be predicted correctly. For those parties we need more variables that could distinguish them from the other parties.

2.1.2.1 Confusion Matrix and Metrics for Training Set   Here the confusion matrix and the appropriate metrics are presented for the training set.

```
##
##            AfD CDU/CSU FDP Gruene LINKE SPD
##    AfD      15      11   6      0     4   6
##    CDU/CSU  25     144  57     36    32  79
##    FDP       1       0   0      0     0   0
##    Gruene    0      12   3     22     8  20
##    LINKE     1       8   3     11    17  12
##    SPD       6      36  13     37    27  52

## [1] "Accuracy:"

## [1] 35.51136

## [1] "Precision:"

##       AfD   CDU/CSU       FDP     Gruene     LINKE       SPD
## 0.3571429 0.3860590 0.0000000 0.3384615 0.3269231 0.3040936

## [1] "MissClassification Rate:"

## [1] 64.48864
```
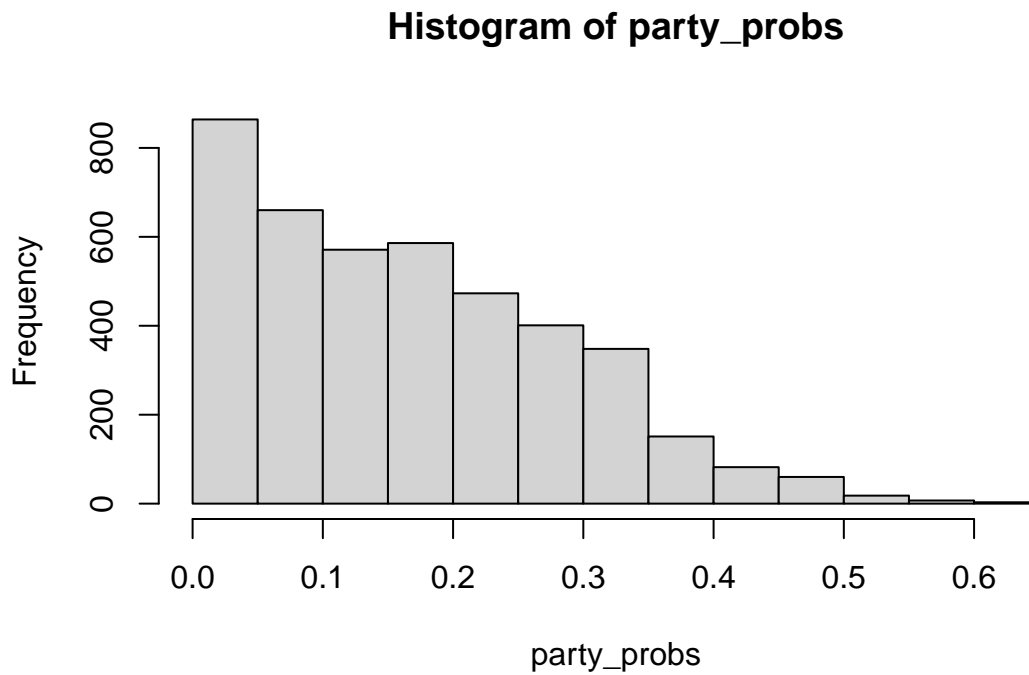
Moreover, the plot below depicts the distribution of the predicted probabilities for the training set.

Histogram of party_probs

2.1.2.2 Confusion Matrix and Metrics for Testing Set Here the confusion matrix and the appropriate metrics are presented for the testing set.

```
##
##            AfD CDU/CSU FDP Gruene LINKE SPD
##    AfD       9       5   3      0     2   3
##    CDU/CSU  10      53  25     17    14  37
##    FDP       1       0   0      0     0   0
```

```
##   Gruene    0       4   1       9     5  10
##   LINKE     0       4   1       2     4   8
##   SPD       1      12   9       9    10  28
```

```
## [1] "Accuracy:"
```

```
## [1] 34.7973
```

```
## [1] "Precision:"
```

```
##        AfD   CDU/CSU         FDP     Gruene      LINKE        SPD
## 0.4090909 0.3397436 0.0000000 0.3103448 0.2105263 0.4057971
```

```
## [1] "MissClassification Rate:"
```

```
## [1] 65.2027
```

2.2 Ordinal Polytomous Modeling

2.2.1 Comparison of Variables' Numerical and Categorical Representation

In this chapter, target variable will be *f.vote_ord* which contains the parties in an ordered factor starting from far-left parties to far-right ones. The same approach that has already been followed for nominal models will be applied here as well, in order to generate the optimal model based on the available explanatory variables. The baseline category in this case is party *LINKE* and it can be seen from the table of the new target variable. Consequently, all odds and cumulative probabilities will be calculated by the model, taking party *LINKE* as the first reference value of the target variable and continuing with the order indicated by the table below.

```
table(train$f.vote_ord)
```

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

The inclusion of different variables and the comparison of the models is taking place in the Appendix for space saving reasons. Below the final model and the validation phase are presented.

From the reduction of deviance and the comparison of the AIC for the different representations of the variable ***egoposition_immigration***, the same conclusions are derived with the analysis for the Nominal Models. Thus, again variable *egoposition_immigration* will be used with the format of the new vector generated (*f.Imm*). The results are presented here:

```
om0$dev - om1_imm_cat$dev
```

```
## [1] 121.6457
```

```
om0$dev - om1_imm_cat_new$dev
```

```
## [1] 111.2882
```

```
##                   df      AIC
## om0                5 2378.556
## om1_imm_con        6 2279.716
## om1_imm_con_sq     7 2280.979
## om1_imm_con_cb     8 2277.012
## om1_imm_con_qd     9 2277.038
```

```
## om1_imm_cat      15 2276.911
## om1_imm_cat_new   9 2275.268
```

Moreover, for variable **political_interest**, as shown below, the lowest AIC value is achieved for the squared form of the numerical representation of the variable, which is approximately the same with the AIC achieved by the new factor generated. Nevertheless, in this case Anova function does not indicate that any of those forms of the variable provide any explanatory power. Thus, in the following analysis, it is anticipated that when full model (with all effects and interactions) will be given as input to the step function will lead to the deletion of this variable.

```
##                    df     AIC
## om0                 5 2378.556
## om1_polint_con      6 2377.571
## om1_polint_con_sq   7 2377.477
## om1_polint_con_cb   8 2379.323
## om1_polint_con_qd   9 2378.822
## om1_polint_cat      9 2378.822
## om1_polint_cat_new  7 2377.716
```

Finally, for variable **income**, following the same analysis, taking into account the AIC values presented below, the lowest value is achieved when variable *income* is used in a squared form. On the other hand, while using the Anova function (Appendix), only the 1st order and the 2nd order of the variable have a p-value smaller than 0.05. Moreover, when comparing the models of 1st order and 2nd order with anova function, the result indicates that model with 1st order of the variable is better (p-value > 0.05, simpler model is better). For this reason, the first order of variable *income* will be used in this case.

```
##                 df     AIC
## om0              5 2378.556
## om1_inc_con      6 2375.977
## om1_inc_con_sq   7 2375.961
## om1_inc_con_cb   8 2377.332
## om1_inc_con_qd   9 2379.329
## om1_inc_cat      9 2379.329
## om1_inc_cat_new  8 2377.488

## Likelihood ratio tests of ordinal regression models
##
## Response: f.vote_ord
##            Model Resid. df Resid. Dev   Test    Df LR stat.   Pr(Chi)
## 1         income       698    2363.977
## 2 poly(income, 2)      697    2361.961 1 vs 2    1 2.016053 0.1556432
```

2.2.2 Final Ordinal Model

Once multiple different combinations of main effects and interactions of factors and the squared form of the numerical variable have been tested, the final model is presented below.

```
##
## Re-fitting to get Hessian

## Call:
## polr(formula = f.vote_ord ~ poly(political_interest, 2) + income +
```

```
##     f.Imm + f.gender + poly(political_interest, 2):f.Imm, data = train)
##
## Coefficients:
##                                                  Value Std. Error t value
## poly(political_interest, 2)1                   -18.0008    9.07021 -1.9846
## poly(political_interest, 2)2                     7.4740    9.04420  0.8264
## income                                           0.2949    0.09026  3.2678
## f.Immlow_medium                                  0.5918    0.33884  1.7466
## f.Immmedium                                      1.4948    0.33865  4.4140
## f.Immmedium_high                                 2.7165    0.38027  7.1437
## f.Immhigh                                        2.4998    0.48377  5.1674
## f.genderF                                       -0.4290    0.13942 -3.0771
## poly(political_interest, 2)1:f.Immlow_medium    13.6415    9.57548  1.4246
## poly(political_interest, 2)2:f.Immlow_medium     2.3692    9.51472  0.2490
## poly(political_interest, 2)1:f.Immmedium        11.4960    9.48140  1.2125
## poly(political_interest, 2)2:f.Immmedium        -9.8759    9.61089 -1.0276
## poly(political_interest, 2)1:f.Immmedium_high   17.3725   10.21368  1.7009
## poly(political_interest, 2)2:f.Immmedium_high  -12.7432   10.10649 -1.2609
## poly(political_interest, 2)1:f.Immhigh          37.5684   12.92239  2.9072
## poly(political_interest, 2)2:f.Immhigh          -7.2629   13.03251 -0.5573
##
## Intercepts:
##              Value    Std. Error t value
## LINKE|Gruene -0.2650   0.4222     -0.6276
## Gruene|SPD    0.8210   0.4226      1.9427
## SPD|FDP       2.0402   0.4286      4.7602
## FDP|CDU/CSU   2.5975   0.4320      6.0123
## CDU/CSU|AfD   4.9260   0.4595     10.7198
##
## Residual Deviance: 2212.405
## AIC: 2254.405
```

From the summary of the final ordinal model, after executing the step function on the model containing all main effects and interactions of the factors and the numerical variables it can be concluded that the formula contains the main effects of factors *f.Imm, f.gender*, the squared form of the numerical representation of variable *political_interest,* its interaction with factor *f.Imm* and finally the first order of variable *income (numerical representation).* The following plots indicate how the explanatory variables fluctuate throughout the different parties of the target variable. By the allEffects plot it is clear that the available explanatory variables are not enough to distinguish well the all the voting preferences of the German citizens, only specific parties can be differentiated, the far-right and far-left ones.
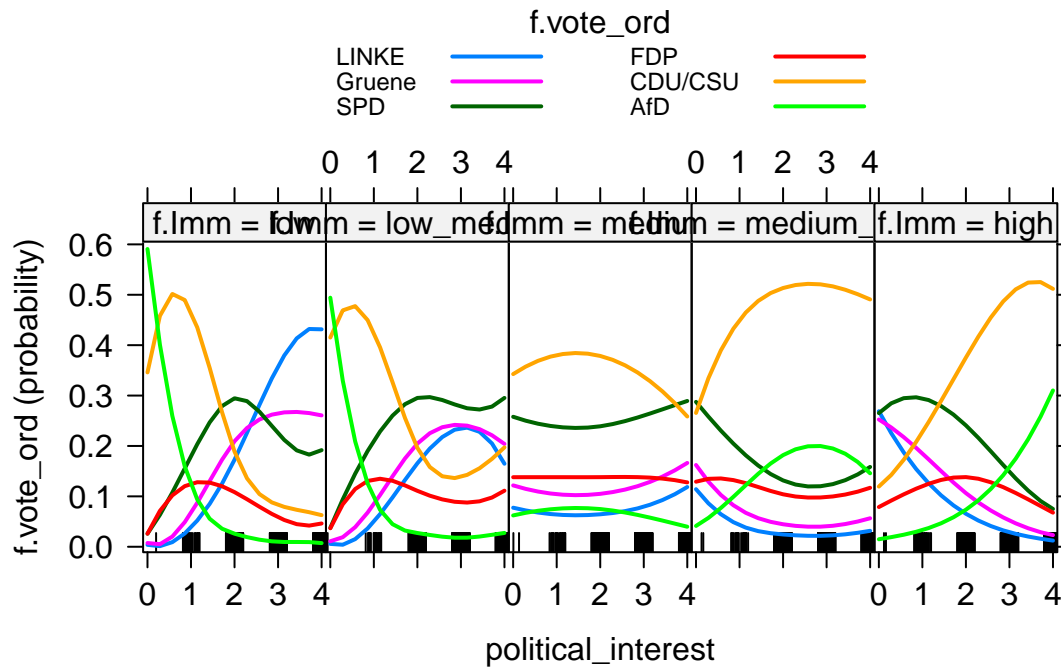
Effects of Income
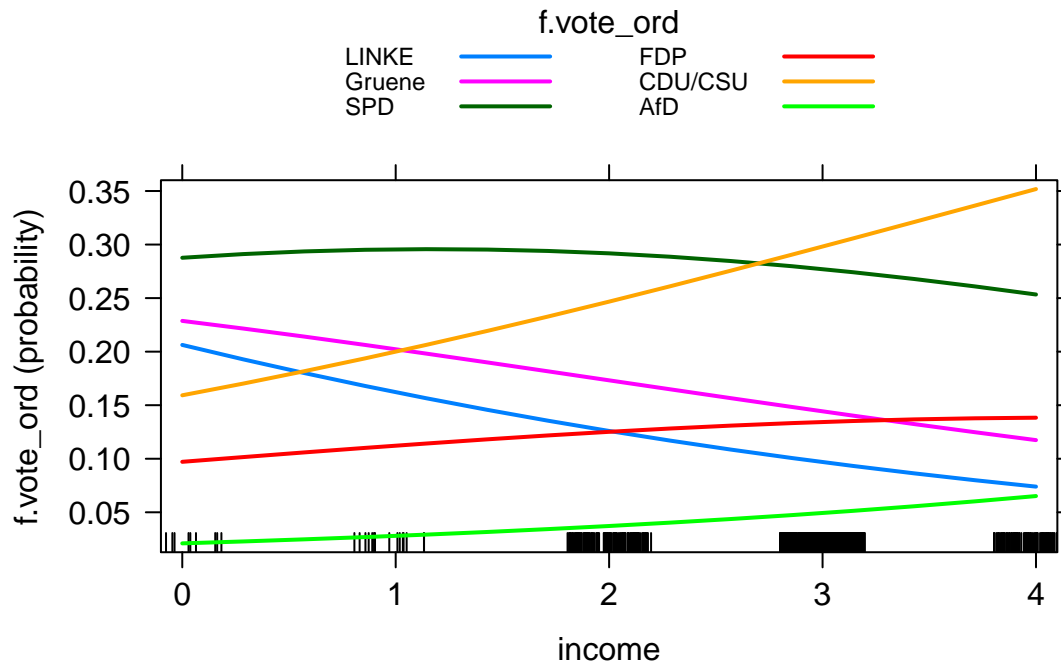
Effects of Gender
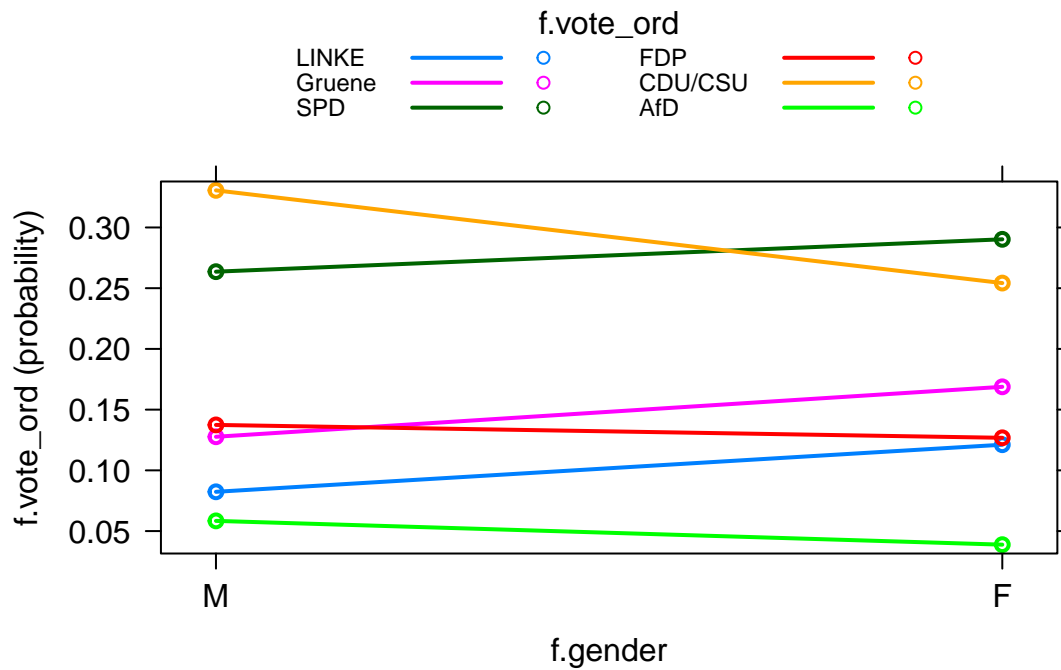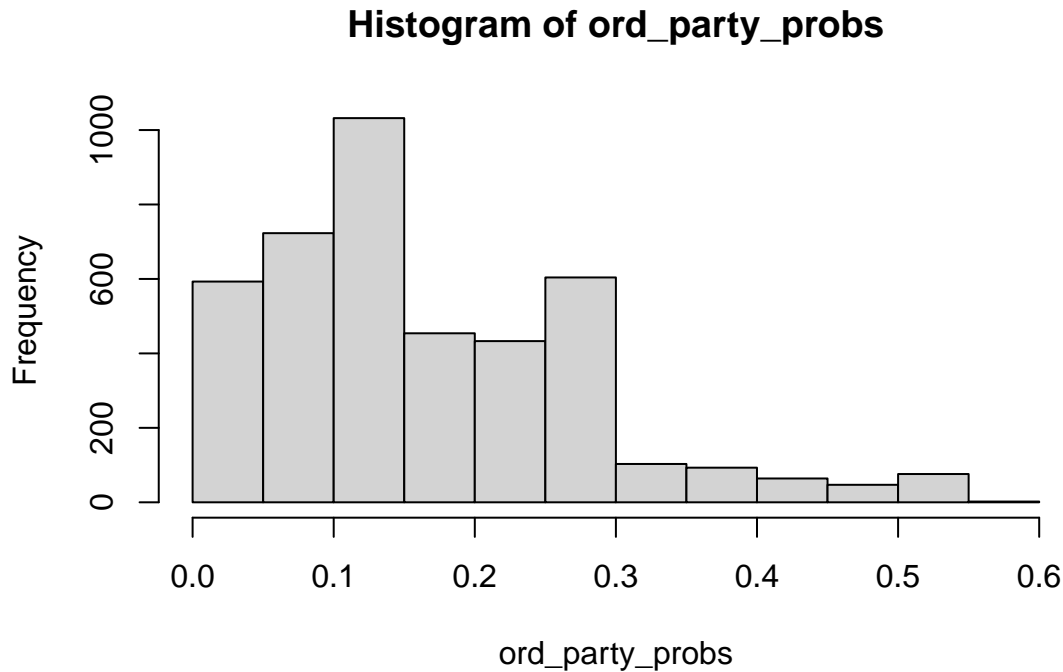
Effects of Interactions (Imm – PolInt)

2.2.2.1 Confusion Matrix and Metrics for Training Set Here the confusion matrix and the appropriate metrics are presented for the training set.

```
## 
##           LINKE Gruene SPD FDP CDU/CSU AfD
##   LINKE      20     22  14   1       9   1
##   Gruene      0      0   0   0       0   0
##   SPD        37     51  75  17      55   5
##   FDP         0      0   0   0       0   0
##   CDU/CSU    31     33  80  64     147  41
##   AfD         0      0   0   0       0   1
## [1] "Accuracy:"
## [1] 34.51705
## [1] "Precision:"
##     LINKE    Gruene       SPD       FDP   CDU/CSU       AfD
## 0.2985075       NaN 0.3125000       NaN 0.3712121 1.0000000
## [1] "MissClassification Rate:"
## [1] 65.48295
```

Moreover, the plot below depicts the distribution of the predicted probabilities for the training set.

23

Histogram of ord_party_probs

2.2.2.2 Confusion Matrix and Metrics for Testing Set Here the confusion matrix and the appropriate metrics are presented for the ord_testing set.

```
##
##          LINKE Gruene SPD FDP CDU/CSU AfD
##   LINKE      3      6  13   4       3   0
##   Gruene     0      0   0   0       0   0
##   SPD       18     17  35   6      18   2
##   FDP        0      0   0   0       0   0
##   CDU/CSU   14     14  38  29      57  19
##   AfD        0      0   0   0       0   0

## [1] "Accuracy:"

## [1] 32.09459

## [1] "Precision:"

##     LINKE    Gruene       SPD       FDP   CDU/CSU       AfD
## 0.1034483       NaN 0.3645833       NaN 0.3333333       NaN

## [1] "MissClassification Rate:"

## [1] 67.90541
```

2.3 Hierarchical Modeling

In order to follow the hierarchical approach, it is necessary to create a new variable which will enable the binary split of the data. By checking the table of the generated factor *f.politicalorientation* it is derived that *665* observations belong to center wing, *266* to left wing and *69* to the right political wing. For that reason the first layer of the hierarchical approach will deal with the separation of the observations to center wing versus others (left and

right), and the second layer will deal with the discrimination of observations between left and right. Consequently a new factor needs to be created for binary identification of center wing. Once the data is split into *Center_*Wing vs *Left_Right_Wings*, the same approach as before will be followed in order to choose the right representation of the explanatory variables. Due to repetition of the idea, the whole analysis of variables representation will take place in Appendix or the analysis chunks will not be included in this report (include=FALSE). Consequently the final model and its validation metrics will be presented directly.

2.3.1 First Layer of Hierarchical Approach

The format of the variables being used for training the first layer of the hierarchical approach is the following: *f.Imm, poly(political_interest,3), income.*
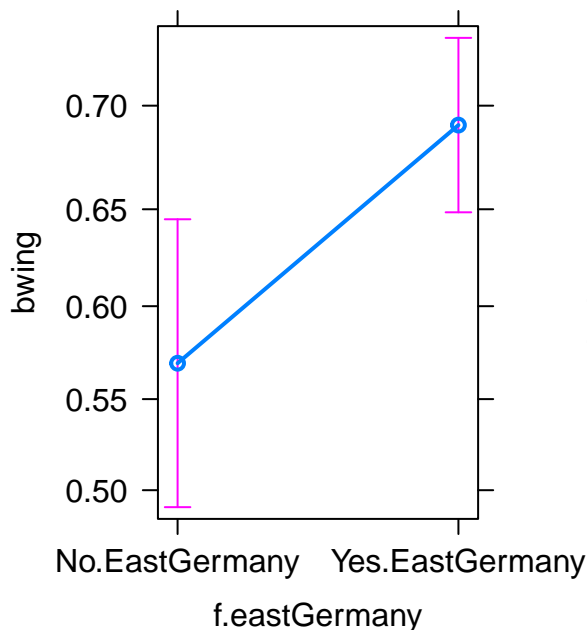
```
##
## Call:
## glm(formula = bwing ~ income + f.Imm + f.eastGermany + income:f.Imm,
##     family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8258  -1.1463   0.6878   0.8629   1.5708
##
## Coefficients:
##                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   -1.02051    1.33582  -0.764  0.44489
## income                         0.06552    0.44330   0.148  0.88249
## f.Immlow_medium               -0.75659    1.46862  -0.515  0.60644
## f.Immmedium                    1.89378    1.42596   1.328  0.18415
## f.Immmedium_high               0.10100    1.54920   0.065  0.94802
## f.Immhigh                      2.46921    1.87635   1.316  0.18819
## f.eastGermanyYes.EastGermany   0.52471    0.18879   2.779  0.00545 **
## income:f.Immlow_medium         0.47267    0.48693   0.971  0.33169
## income:f.Immmedium            -0.09122    0.47485  -0.192  0.84767
## income:f.Immmedium_high        0.38232    0.52346   0.730  0.46517
## income:f.Immhigh              -0.58147    0.63207  -0.920  0.35760
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 906.04  on 703  degrees of freedom
## Residual deviance: 849.75  on 693  degrees of freedom
## AIC: 871.75
##
## Number of Fisher Scoring iterations: 4
```

From the Anova analysis of the model and the all effects plot, we can see which explanatory variables are significant for the discrimination of central vs right and left wings, as well as how those variables affect the predictability of the first layer binary model.
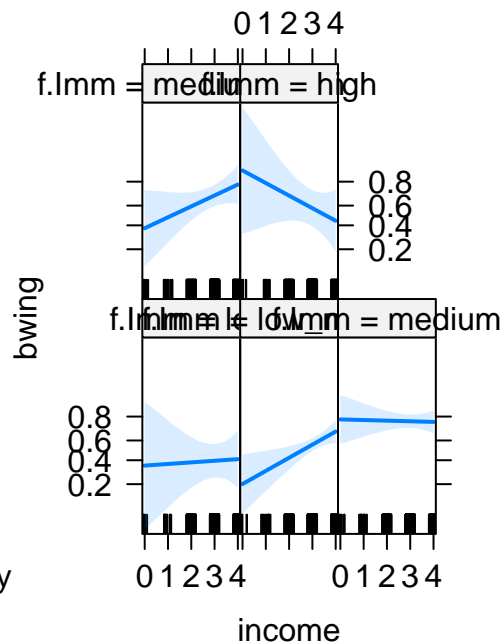
```
## Analysis of Deviance Table (Type II tests)
##
```

```
## Response: bwing
##                 LR Chisq Df Pr(>Chisq)
## income            3.261  1   0.070961 .
## f.Imm            38.445  4  9.069e-08 ***
## f.eastGermany     7.655  1   0.005663 **
## income:f.Imm      8.488  4   0.075244 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

f.eastGermany effect plot   **income*f.Imm effect plot**


2.3.2 Second Layer of Hierarchical Approach

For the second layer of the hierarchical approach the separation between right and left parties is necessary. The representations of the variables after the analysis for this step is: *poly(egoposition_immigration,4), f.PolInt (null model is better), poly(income,3) (null model is better)*.

```
bh2m0 <- glm( f.political_orientation ~ 1, family = binomial, data = train[train$bwing==
```

```
##
## Call:
## glm(formula = f.political_orientation ~ f.Imm + f.PolInt + f.gender,
##     family = binomial, data = train[train$bwing == "Left_Right_Wings",
##         ])
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.1494  -0.4360  -0.1862  -0.1317   2.3271
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)       15.53200 1455.39800   0.011 0.991485
```

```
## f.Immlow_medium      0.03407    1.16288    0.029 0.976628
## f.Immmedium          0.73118    1.13031    0.647 0.517710
## f.Immmedium_high     4.87808    1.18292    4.124 3.73e-05 ***
## f.Immhigh            3.57605    1.23106    2.905 0.003674 **
## f.PolIntmedium     -18.20467 1455.39764   -0.013 0.990020
## f.PolInthigh       -17.87140 1455.39766   -0.012 0.990203
## f.genderF           -2.10501    0.61681   -3.413 0.000643 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 241.08  on 241  degrees of freedom
## Residual deviance: 121.70  on 234  degrees of freedom
## AIC: 137.7
##
## Number of Fisher Scoring iterations: 14

## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##         LR Chisq Df Pr(>Chisq)
## f.Imm      97.782  4  < 2.2e-16 ***
## f.PolInt    5.371  2    0.06819 .
## f.gender   15.279  1  9.272e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```
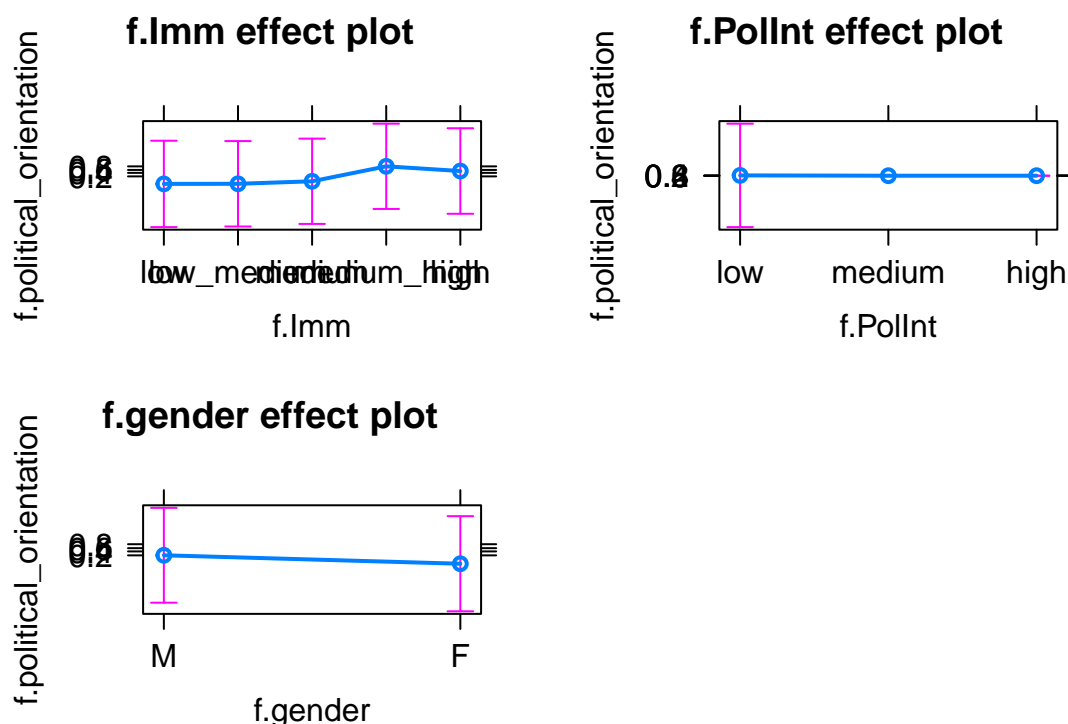

From the Anova analysis of the second layer of the hierarchical model and the all effects plot, we can see which explanatory variables are significant for the discrimination of right vs left wings,

as well as how those variables affect the predictability of the second layer of the binary model.

2.3.3 Confusion Matrix And Metrics for Training Set

```
##
##                   Left_Right_Wings Center_Wing
##    Center_Wing                 168         403
##    Left_Right_Wings             74          59

##               train_y
## train_pred   Center_Wing Left_Wing Right_Wing
##    Left_Wing            0       182         13
##    Right_Wing           0        12         35

## [1] "Accuracy:"

## [1] 35.79545
```

2.3.4 Confusion Matrix And Metrics for Testing Set

```
##
##                   Left_Right_Wings Center_Wing
##    Center_Wing                  74         165
##    Left_Right_Wings             19          38

##               test_y
## test_pred    Center_Wing Left_Wing Right_Wing
##    Left_Wing            0        68          7
##    Right_Wing           0         4         14

## [1] "Accuracy:"

## [1] 63.49614
```

3   Best Final Model

In order to select the final best model from the three different approaches, the comparison is completed by using the AIC method and by checking the accuracy of all the models. As it is depicted below, the best model is the Hierarchical Approach.

```
AIC(nm0,om0,nm_final,om_final)
```

```
##          df      AIC
## nm0       5 2378.556
## om0       5 2378.556
## nm_final 50 2219.625
## om_final 21 2254.405
```

```
AIC(layer1) + AIC(layer2)
```

```
## [1] 1009.448
```

Improvements to this work could be accomplished by adding more detailed influential data analysis and retraining of the models without them. In this version of the report influential data plots can be found in the last subsection of the Appendix for the hierarchical approach.

Also, better results could be generated by checking in more detail the interactions between all the variables and by creating new factors in all the different approaches followed.
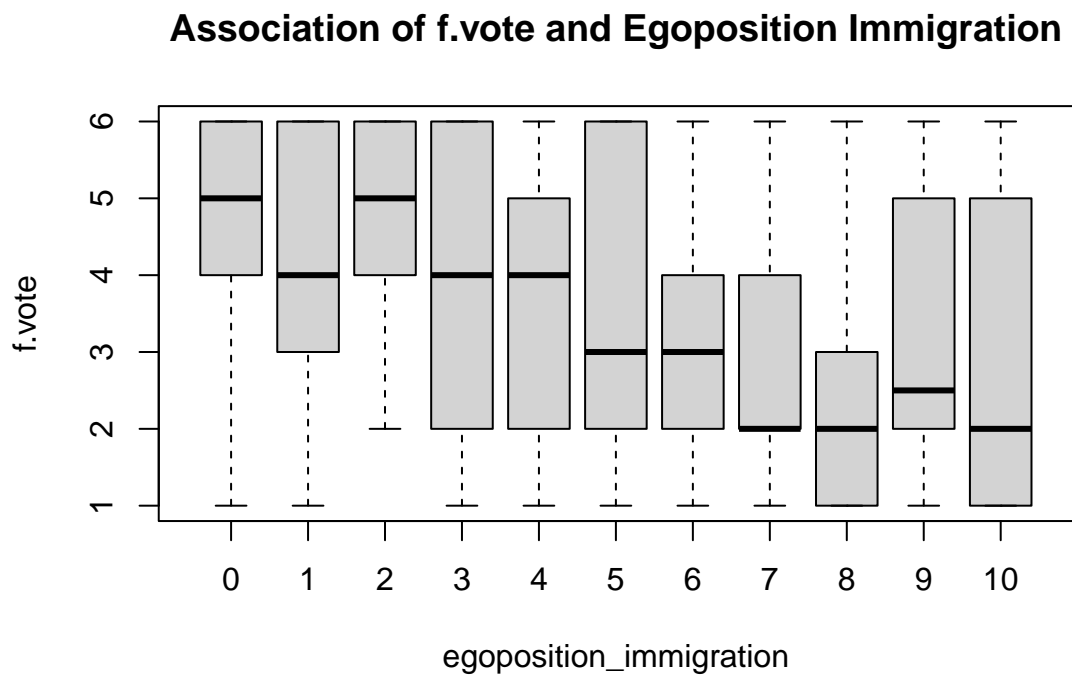
4 Appendix

4.1 EDA

4.2 Profiling of Target Variable(s)

In the following plots the levels of variable *f.vote* and *f.political_orientation* follow the structure presented below.
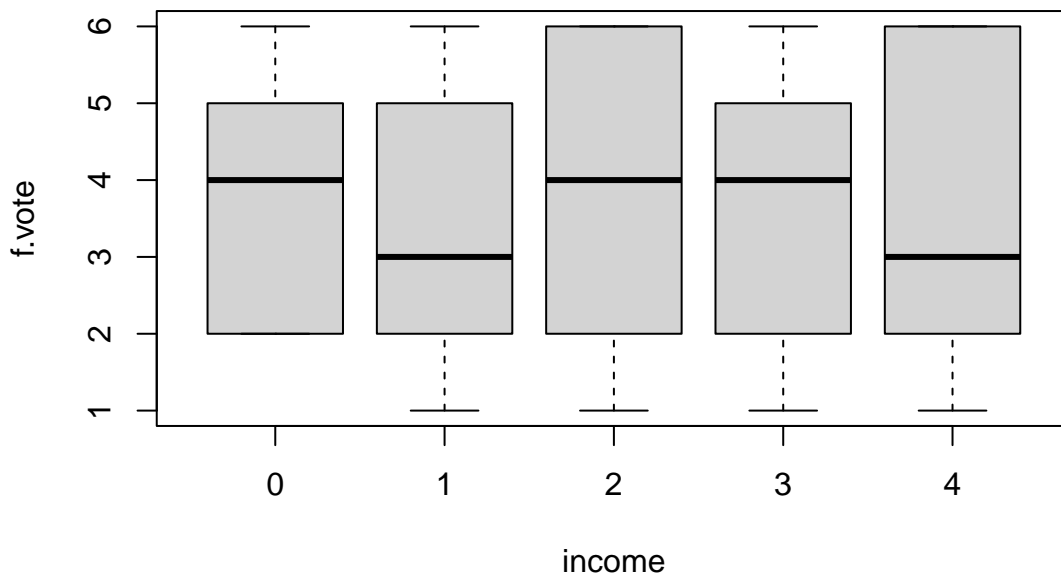
```
## [1] "Parties:"
```

```
## [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
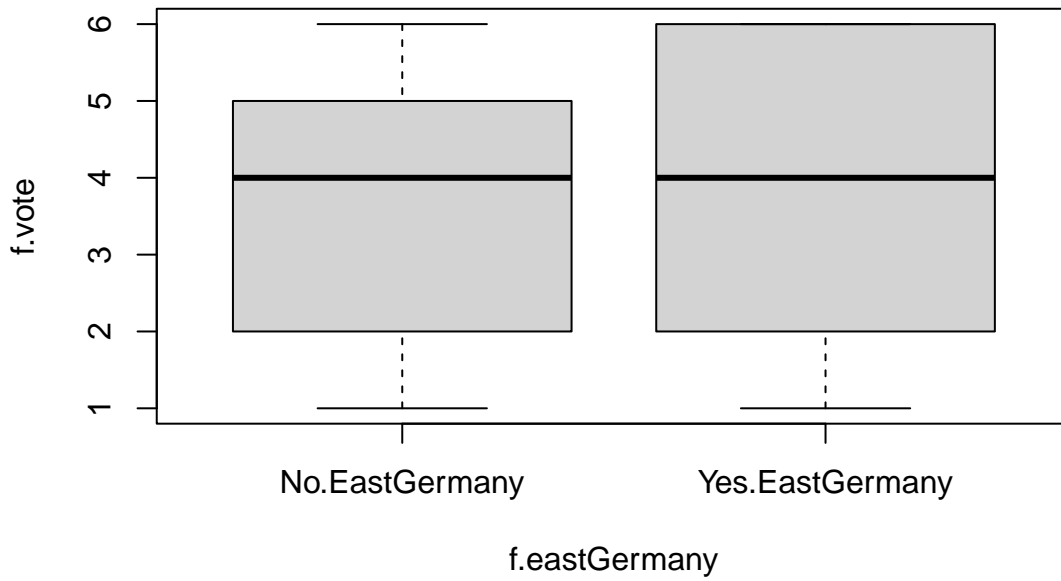
Association of f.vote and Political Interest
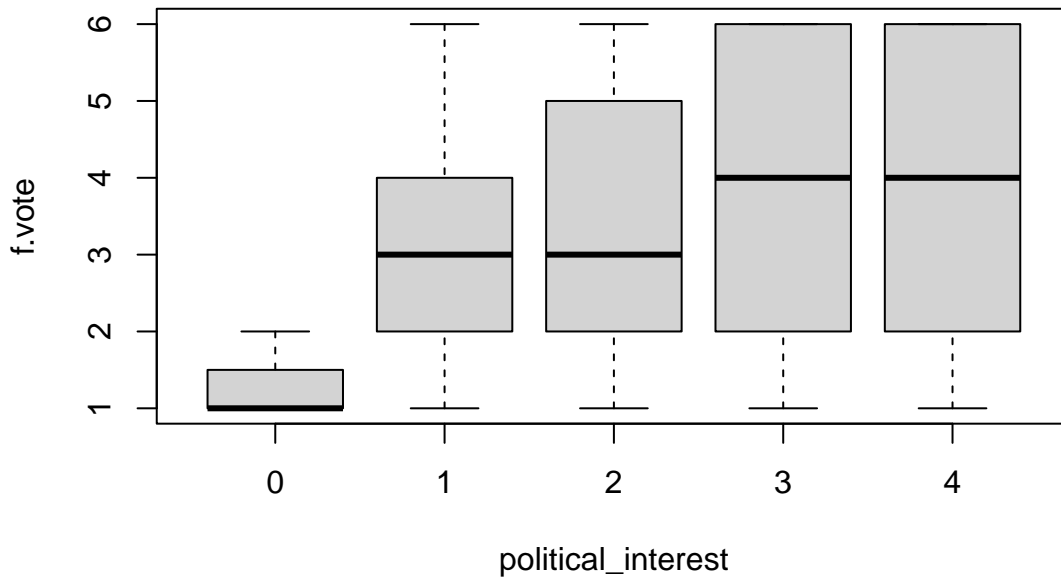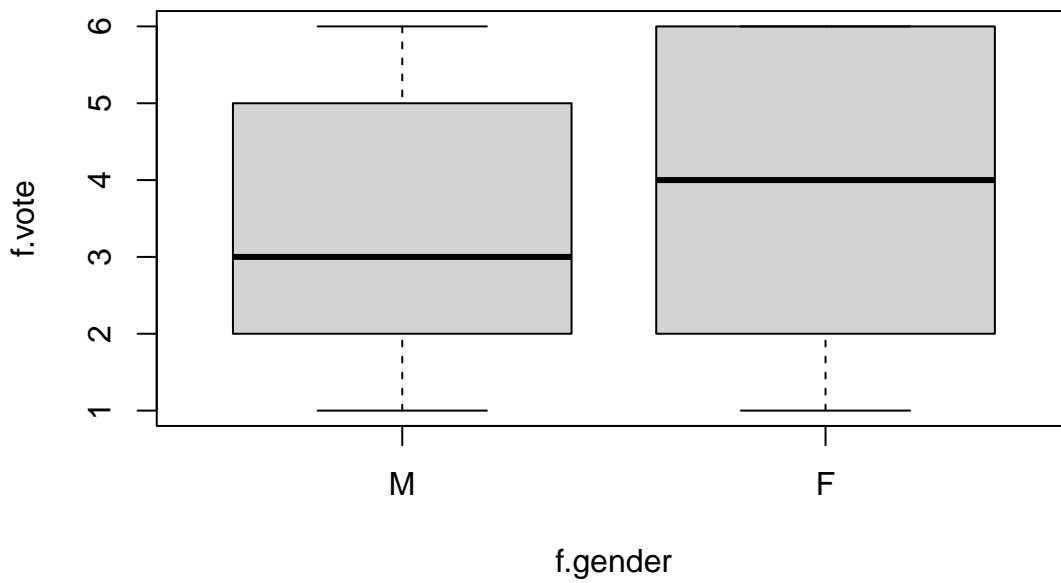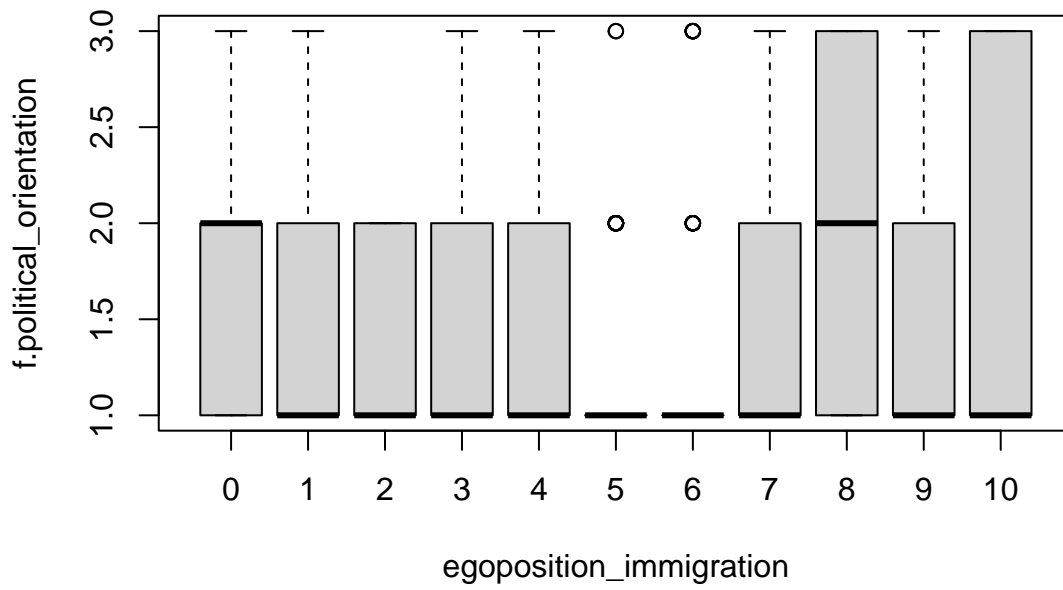

Association of f.vote and Income Satisfaction

Association of f.vote and East Germany

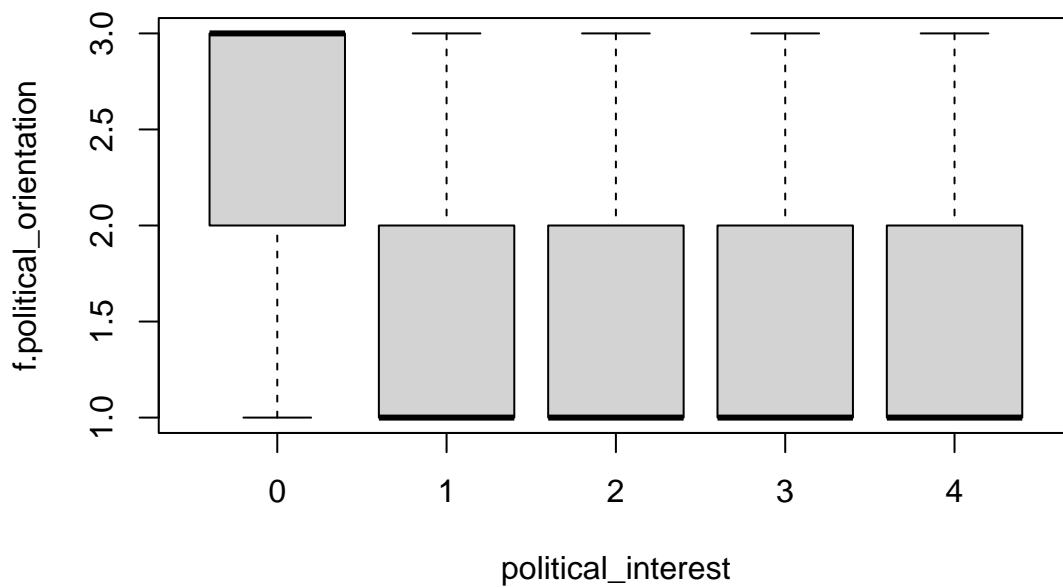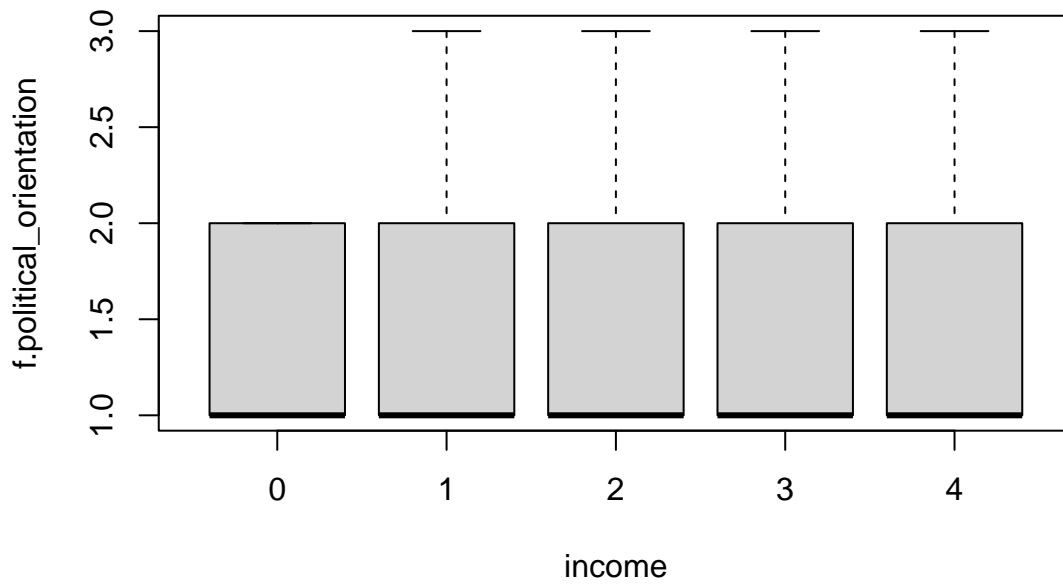## Association of f.vote and Gender

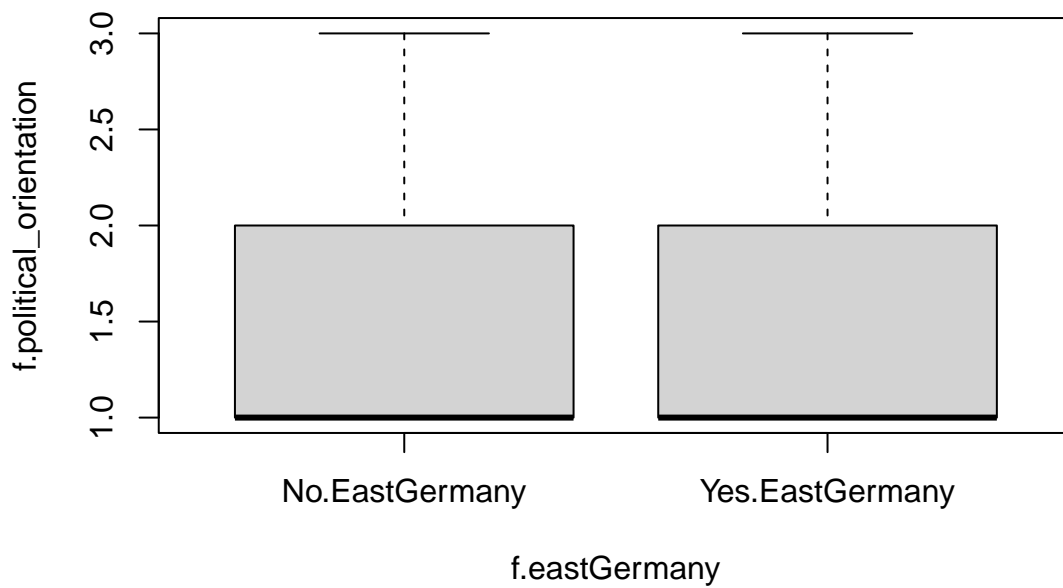**Association of Political Wings and Egoposition Immigration**

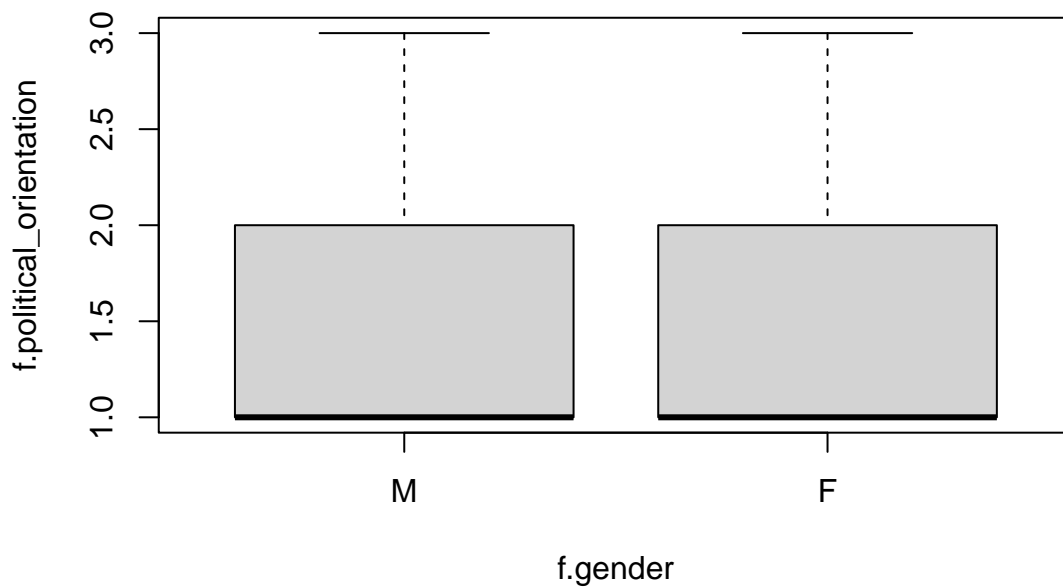**Association of Political Wings and Political Interest**

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)
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
## bwing=Left_Right_Wings                                  20.597015   100.000000
## f.Imm=medium_high                                       25.174825    52.173913
## f.egoposition_immigration=8_Level.Imm                   45.161290    20.289855
## f.Imm=high                                              34.042553    23.188406
## 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.PolInt=low                                            66.666667     2.898551
## f.political_interest=Low.Inter                          66.666667     2.898551
## f.IncSat=low_to_medium                                  17.857143     7.246377
## 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.Imm=medium                                                     2.564103  15.942029
## f.Imm=low_medium                                                 1.506024   7.246377
## 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
## bwing=Center_Wing                                                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
## bwing=Left_Right_Wings                                              33.5   9.958160e-36
## f.Imm=medium_high                                                   14.3   7.616170e-15
## f.egoposition_immigration=8_Level.Imm                               3.1   1.675803e-09
## f.Imm=high                                                          4.7   1.468400e-08
## 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.PolInt=low                                                        0.3   1.377478e-02
## f.political_interest=Low.Inter                                      0.3   1.377478e-02
## f.IncSat=low_to_medium                                              2.8   4.793709e-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.Imm=medium                                                       42.9   9.629260e-07
## f.Imm=low_medium                                                   33.2   1.727176e-07
## 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
## bwing=Center_Wing                                                  66.5   9.958160e-36
## 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
## bwing=Left_Right_Wings                                        12.477072
## f.Imm=medium_high                                              7.773807
## f.egoposition_immigration=8_Level.Imm                         6.026469
## f.Imm=high                                                     5.665215
## 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.PolInt=low                                                   2.463084
## f.political_interest=Low.Inter                                 2.463084
## f.IncSat=low_to_medium                                         1.977926
## 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.Imm=medium                                                  -4.899067
## f.Imm=low_medium                                              -5.226533
## f.vote_ord=SPD                                                -6.178794
## f.political_orientation=Left_Wing                             -6.346633
## f.vote_ord=CDU/CSU                                            -6.692711
## bwing=Center_Wing                                            -12.477072
## 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
## bwing=Center_Wing                              43.45865   100.000000   66.5
## f.political_orientation=Center_Wing            43.45865   100.000000   66.5
## f.Imm=medium                                   35.89744    53.287197   42.9
## 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
```

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```
## f.egoposition_immigration=2_Level.Imm              14.61538   6.574394   13.0
## f.Imm=low_medium                                   18.67470  21.453287   33.2
## 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
## bwing=Left_Right_Wings                               0.00000   0.000000   33.5
##                                                         p.value      v.test
## f.vote_ord=CDU/CSU                                 2.718794e-260   34.464630
## bwing=Center_Wing                                   4.312957e-64   16.902491
## f.political_orientation=Center_Wing                 4.312957e-64   16.902491
## f.Imm=medium                                        2.568896e-05    4.208660
## 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.Imm=low_medium                                    2.862253e-07   -5.132298
## 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
## bwing=Left_Right_Wings                              4.312957e-64  -16.902491
##
## $FDP
##                                                    Cla/Mod      Mod/Cla  Global
## f.vote_ord=FDP                                   100.000000  100.0000000   12.1
## bwing=Center_Wing                                 18.195489  100.0000000   66.5
## f.political_orientation=Center_Wing               18.195489  100.0000000   66.5
## f.Imm=medium                                      17.016317   60.3305785   42.9
## f.egoposition_immigration=6_Level.Imm             22.105263   17.3553719    9.5
## f.Imm=low                                          2.040816    0.8264463    4.9
## f.egoposition_immigration=0_Very_Open_Level.Imm    2.040816    0.8264463    4.9
## f.Imm=low_medium                                   6.927711   19.0082645   33.2
## f.egoposition_immigration=2_Level.Imm              3.076923    3.3057851   13.0
## f.vote_ord=AfD                                     0.000000    0.0000000    6.9
## f.political_orientation=Right_Wing                 0.000000    0.0000000    6.9
## f.vote_ord=LINKE                                   0.000000    0.0000000   12.3
## f.vote_ord=Gruene                                  0.000000    0.0000000   14.3
## f.vote_ord=SPD                                     0.000000    0.0000000   25.5
```

```
## f.political_orientation=Left_Wing                     0.000000   0.0000000   26.6
## f.vote_ord=CDU/CSU                                     0.000000   0.0000000   28.9
## bwing=Left_Right_Wings                                 0.000000   0.0000000   33.5
##                                                           p.value      v.test
## f.vote_ord=FDP                                    1.570479e-159   26.912447
## bwing=Center_Wing                                  6.200298e-24   10.088671
## f.political_orientation=Center_Wing                6.200298e-24   10.088671
## f.Imm=medium                                       4.272470e-05    4.092229
## f.egoposition_immigration=6_Level.Imm              3.784565e-03    2.895582
## f.Imm=low                                          1.390975e-02   -2.459586
## f.egoposition_immigration=0_Very_Open_Level.Imm    1.390975e-02   -2.459586
## f.Imm=low_medium                                   2.581352e-04   -3.654051
## 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
## bwing=Left_Right_Wings                             6.200298e-24  -10.088671
##
## $Gruene
##                                                             Cla/Mod       Mod/Cla
## f.vote_ord=Gruene                                        100.000000   100.0000000
## f.political_orientation=Left_Wing                         53.759398   100.0000000
## bwing=Left_Right_Wings                                    42.686567   100.0000000
## f.Imm=low_medium                                          23.795181    55.2447552
## 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     0.0000000
## f.Imm=high                                                 2.127660     0.6993007
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm    2.127660     0.6993007
## f.egoposition_immigration=9_Level.Imm                      0.000000     0.0000000
## f.gender=M                                                11.338290    42.6573427
## f.egoposition_immigration=7_Level.Imm                      2.564103     1.3986014
## f.vote_ord=AfD                                             0.000000     0.0000000
## f.political_orientation=Right_Wing                         0.000000     0.0000000
## f.Imm=medium_high                                          1.398601     1.3986014
## f.vote_ord=FDP                                             0.000000     0.0000000
## f.vote_ord=LINKE                                           0.000000     0.0000000
## f.vote_ord=SPD                                             0.000000     0.0000000
## f.vote_ord=CDU/CSU                                         0.000000     0.0000000
## bwing=Center_Wing                                          0.000000     0.0000000
## f.political_orientation=Center_Wing                        0.000000     0.0000000
##                                                             Global       p.value
## f.vote_ord=Gruene                                             14.3   1.663892e-177
```

```
## f.political_orientation=Left_Wing                                26.6  4.555935e-99
## bwing=Left_Right_Wings                                           33.5  1.406134e-79
## f.Imm=low_medium                                                 33.2  4.705371e-09
## 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.Imm=high                                                        4.7  6.044056e-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.Imm=medium_high                                                14.3  1.816764e-08
## 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
## bwing=Center_Wing                                                66.5  1.406134e-79
## 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
## bwing=Left_Right_Wings                                           18.888951
## f.Imm=low_medium                                                  5.857270
## 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.Imm=high                                                       -2.745382
## 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.Imm=medium_high                                                -5.628602
## 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
## bwing=Center_Wing                                               -18.888951
## 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
## bwing=Left_Right_Wings                               36.716418 100.000000   33.5
## f.eastGermany=No.EastGermany                         19.087137  37.398374   24.1
## f.Imm=low                                            28.571429  11.382114    4.9
## f.egoposition_immigration=0_Very_Open_Level.Imm      28.571429  11.382114    4.9
## f.IncSat=medium                                      13.896104  86.991870   77.0
## f.Imm=low_medium                                     16.566265  44.715447   33.2
## 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.Imm=medium_high                                     6.993007   8.130081   14.3
## f.duplicate=Yes.Duplicate                             8.913649  26.016260   35.9
## f.Imm=medium                                          9.324009  32.520325   42.9
## 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.IncSat=high                                         4.761905   7.317073   18.9
## 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
## bwing=Center_Wing                                     0.000000   0.000000   66.5
## 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
## bwing=Left_Right_Wings                                6.141124e-67  17.284633
## f.eastGermany=No.EastGermany                          4.265885e-04   3.523064
## f.Imm=low                                             1.737035e-03   3.131859
## f.egoposition_immigration=0_Very_Open_Level.Imm       1.737035e-03   3.131859
## f.IncSat=medium                                       3.395906e-03   2.929424
## f.Imm=low_medium                                      4.615992e-03   2.832678
## 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.Imm=medium_high                                     3.007057e-02  -2.169160
## f.duplicate=Yes.Duplicate                             1.345692e-02  -2.471442
## f.Imm=medium                                          1.252121e-02  -2.497104
## 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.IncSat=high                                         1.536281e-04  -3.785130
## 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
## bwing=Center_Wing                                   6.141124e-67 -17.284633
## 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
## bwing=Center_Wing                     38.345865 100.0000000   66.5
## f.political_orientation=Center_Wing   38.345865 100.0000000   66.5
## f.Imm=low_medium                      32.530120  42.3529412   33.2
## 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.Imm=medium_high                     16.783217   9.4117647   14.3
## 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
## bwing=Left_Right_Wings                 0.000000   0.0000000   33.5
##                                            p.value      v.test
## f.vote_ord=SPD                       9.178288e-246   33.480784
## bwing=Center_Wing                     5.401466e-55   15.619038
## f.political_orientation=Center_Wing   5.401466e-55   15.619038
## f.Imm=low_medium                      3.909839e-04    3.546096
## 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.Imm=medium_high                     7.988755e-03   -2.652545
## 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
## bwing=Left_Right_Wings                5.401466e-55  -15.619038
```

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

```
## $Center_Wing
```

```
##                                                 Cla/Mod   Mod/Cla Global
## bwing=Center_Wing                               100.00000 100.000000   66.5
## 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.Imm=medium                                     76.22378  49.172932   42.9
## 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.IncSat=high                                    74.07407  21.052632   18.9
## 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.Imm=low                                        48.97959   3.609023    4.9
## 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.Imm=low_medium                                 58.13253  29.022556   33.2
## 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
## bwing=Left_Right_Wings                            0.00000   0.000000   33.5
##                                                      p.value     v.test
## bwing=Center_Wing                               4.360677e-276  35.503370
## 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.Imm=medium                                     1.257853e-08   5.691694
## 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.IncSat=high                                    1.331258e-02   2.475296
## 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.Imm=low                                        1.008813e-02  -2.572794
## 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.Imm=low_medium                                             9.076070e-05  -3.914050
## 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
## bwing=Left_Right_Wings                                      4.360677e-276 -35.503370
##
## $Left_Wing
##                                                                 Cla/Mod      Mod/Cla
## bwing=Left_Right_Wings                                        79.402985 100.0000000
## 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.Imm=low_medium                                             40.361446   50.3759398
## f.egoposition_immigration=2_Level.Imm                        45.384615   22.1804511
## f.Imm=low                                                    48.979592    9.0225564
## 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.IncSat=medium                                              28.311688   81.9548872
## f.gender=M                                                   23.605948   47.7443609
## f.IncSat=high                                                19.576720   13.9097744
## f.income=High.Sat                                            19.576720   13.9097744
## f.Imm=high                                                   10.638298    1.8796992
## 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.Imm=medium                                                 21.212121   34.2105263
## 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.Imm=medium_high                                             8.391608    4.5112782
## 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
## bwing=Center_Wing                                             0.000000    0.0000000
##                                                                 Global      p.value
## bwing=Left_Right_Wings                                           33.5 5.080116e-178
## 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.Imm=low_medium                                             33.2  9.856340e-12
## f.egoposition_immigration=2_Level.Imm                        13.0  7.347278e-07
## f.Imm=low                                                     4.9  6.479798e-04
## 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.IncSat=medium                                              77.0  2.344145e-02
## f.gender=M                                                   53.8  2.119615e-02
## f.IncSat=high                                                18.9  1.362802e-02
## f.income=High.Sat                                            18.9  1.362802e-02
## f.Imm=high                                                    4.7  7.300975e-03
## 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.Imm=medium                                                 42.9  7.895011e-04
## 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.Imm=medium_high                                            14.3  6.708713e-09
## 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
## bwing=Center_Wing                                            66.5 5.080116e-178
##                                                                    v.test
## bwing=Left_Right_Wings                                      28.448539
## f.vote_ord=Gruene                                           21.126332
## f.vote=Gruene                                               21.126332
## f.vote_ord=LINKE                                            19.277115
## f.vote=LINKE                                                19.277115
## f.Imm=low_medium                                             6.808585
## f.egoposition_immigration=2_Level.Imm                        4.951952
## f.Imm=low                                                    3.410693
## f.egoposition_immigration=0_Very_Open_Level.Imm              3.410693
## f.egoposition_immigration=3_Level.Imm                        3.121644
## f.gender=F                                                   2.304472
## f.IncSat=medium                                              2.266162
## f.gender=M                                                  -2.304472
## f.IncSat=high                                               -2.466922
## f.income=High.Sat                                           -2.466922
## f.Imm=high                                                  -2.682795
## 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.Imm=medium                                               -3.356450
## 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.Imm=medium_high                                          -5.798058
## 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
## bwing=Center_Wing                                         -28.448539
##
## $Right_Wing
##                                                             Cla/Mod    Mod/Cla
## f.vote_ord=AfD                                            100.000000 100.000000
## f.vote=AfD                                                100.000000 100.000000
## bwing=Left_Right_Wings                                     20.597015 100.000000
## f.Imm=medium_high                                          25.174825  52.173913
## f.egoposition_immigration=8_Level.Imm                      45.161290  20.289855
## f.Imm=high                                                 34.042553  23.188406
## 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.PolInt=low                                               66.666667   2.898551
## f.political_interest=Low.Inter                             66.666667   2.898551
## f.IncSat=low_to_medium                                     17.857143   7.246377
## 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.Imm=medium                                                2.564103  15.942029
```

```
## f.Imm=low_medium                                              1.506024   7.246377
## 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
## bwing=Center_Wing                                             0.000000   0.000000
##                                                               Global      p.value
## f.vote_ord=AfD                                                   6.9 1.889108e-108
## f.vote=AfD                                                       6.9 1.889108e-108
## bwing=Left_Right_Wings                                          33.5   9.958160e-36
## f.Imm=medium_high                                               14.3   7.616170e-15
## f.egoposition_immigration=8_Level.Imm                            3.1   1.675803e-09
## f.Imm=high                                                       4.7   1.468400e-08
## 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.PolInt=low                                                     0.3   1.377478e-02
## f.political_interest=Low.Inter                                   0.3   1.377478e-02
## f.IncSat=low_to_medium                                           2.8   4.793709e-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.Imm=medium                                                    42.9   9.629260e-07
## f.Imm=low_medium                                                33.2   1.727176e-07
## 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
## bwing=Center_Wing                                               66.5   9.958160e-36
##                                                                 v.test
## f.vote_ord=AfD                                                22.123229
## f.vote=AfD                                                    22.123229
## bwing=Left_Right_Wings                                        12.477072
```

```
## f.Imm=medium_high                                      7.773807
## f.egoposition_immigration=8_Level.Imm                  6.026469
## f.Imm=high                                             5.665215
## 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.PolInt=low                                           2.463084
## f.political_interest=Low.Inter                         2.463084
## f.IncSat=low_to_medium                                 1.977926
## 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.Imm=medium                                          -4.899067
## f.Imm=low_medium                                      -5.226533
## f.vote_ord=SPD                                        -6.178794
## f.vote=SPD                                            -6.178794
## f.vote_ord=CDU/CSU                                    -6.692711
## f.vote=CDU/CSU                                        -6.692711
## bwing=Center_Wing                                    -12.477072
```

4.3 Modelling

4.3.1 Nominal Models

Comparison of Variables' Numerical and Categorical Representation for Nominal Models

```
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
```

```
nm0$dev - nm1_imm_cat_new$dev
```

```
## [1] 172.0104
```

```
anova(nm1_imm_con, nm1_imm_con_sq, test="Chisq")
```

```
## Likelihood ratio tests of Multinomial Models
##
## Response: f.vote
##                                 Model Resid. df Resid. Dev    Test    Df LR stat.
## 1          egoposition_immigration      3510   2236.832
## 2 poly(egoposition_immigration, 2)      3505   2223.027 1 vs 2     5 13.80457
##      Pr(Chi)
## 1
## 2 0.01689968
```

```
anova(nm1_imm_con_sq, nm1_imm_con_cb, test="Chisq")
```

```
## Likelihood ratio tests of Multinomial Models
##
## Response: f.vote
##                                 Model Resid. df Resid. Dev    Test    Df LR stat.
## 1 poly(egoposition_immigration, 2)      3505   2223.027
## 2 poly(egoposition_immigration, 3)      3500   2206.187 1 vs 2     5 16.83944
##        Pr(Chi)
## 1
## 2 0.004814587
```

```
anova(nm1_imm_con_cb, nm1_imm_con_qd, test="Chisq")
```

```
## Likelihood ratio tests of Multinomial Models
##
## Response: f.vote
##                                 Model Resid. df Resid. Dev    Test    Df LR stat.
## 1 poly(egoposition_immigration, 3)      3500   2206.187
## 2 poly(egoposition_immigration, 4)      3495   2197.456 1 vs 2     5 8.731158
##      Pr(Chi)
## 1
## 2 0.1202799
```

```
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
```

```
Anova(nm1_imm_cat_new, 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.Imm    172.01 20  < 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")
```

Effects Imm Continuous
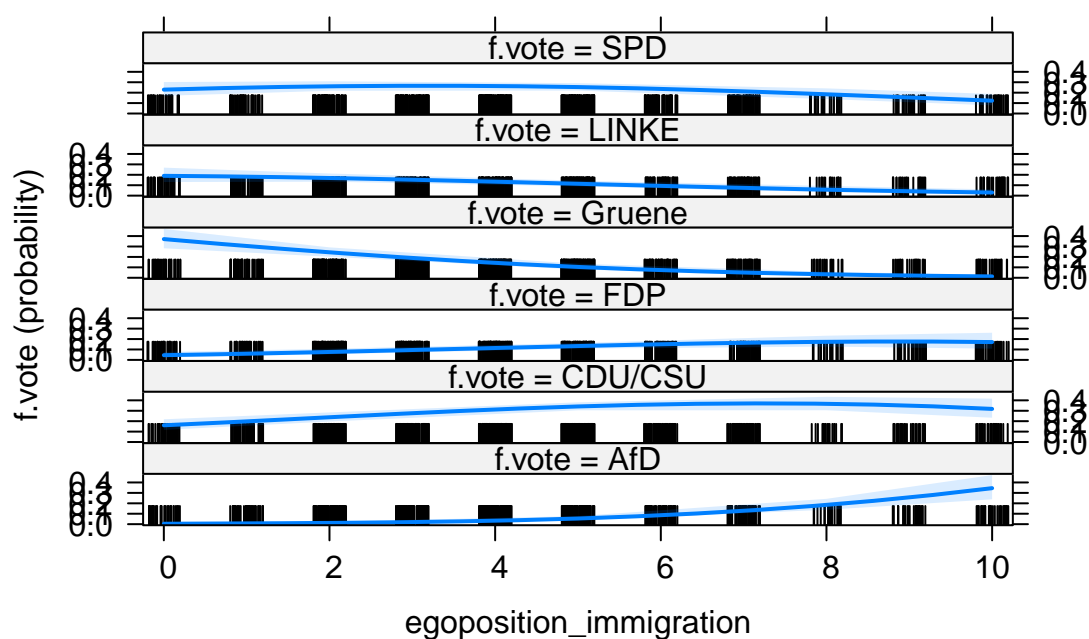

```
plot(allEffects(nm1_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```

Effects Imm Continuous Squared
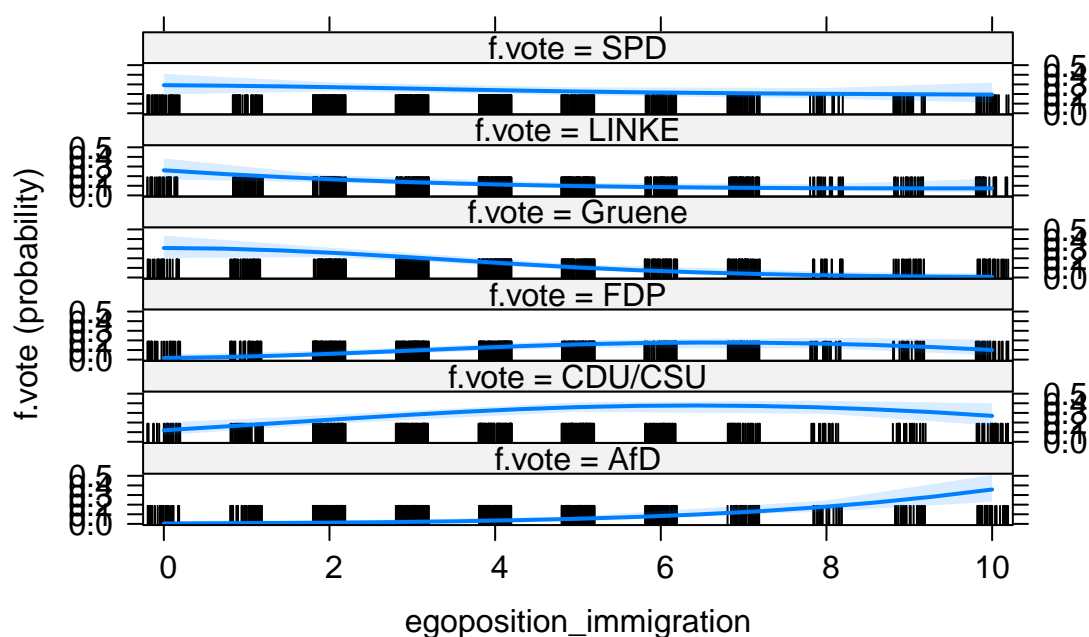

```
plot(allEffects(nm1_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```

Effects Imm Continuous Cubed
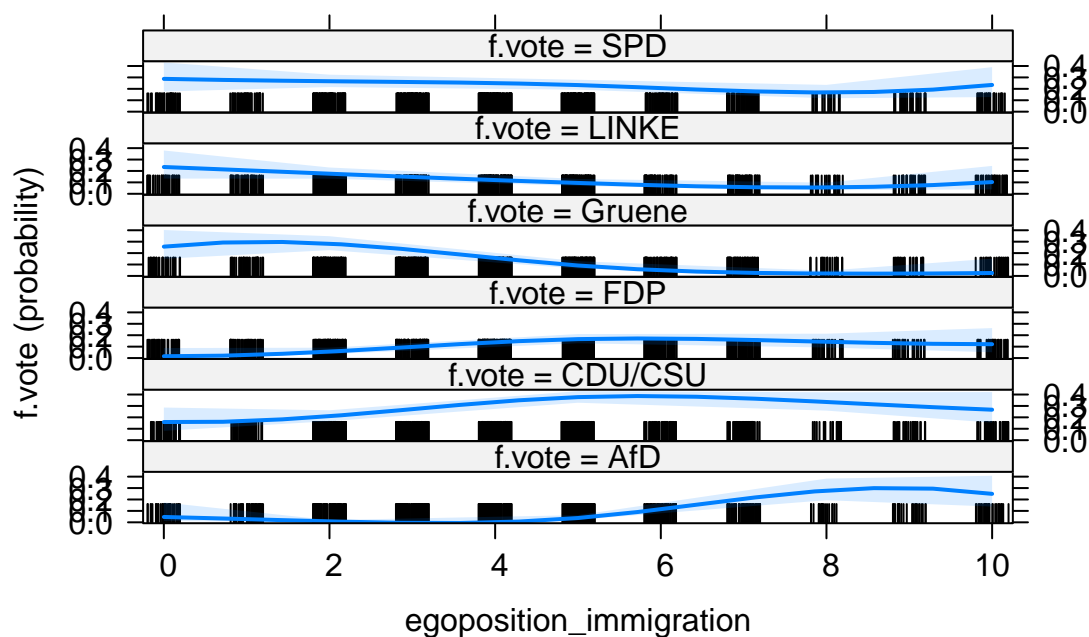

```
plot(allEffects(nm1_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```

Effects Imm Continuous Quadratic
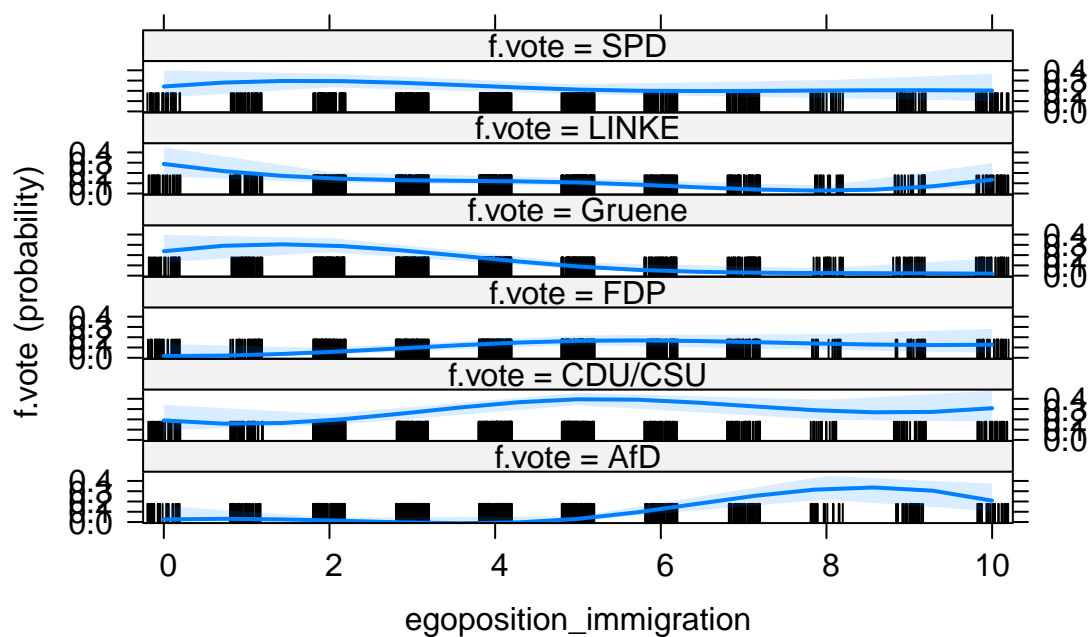

```
plot(allEffects(nm1_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

Effects Imm Categorical
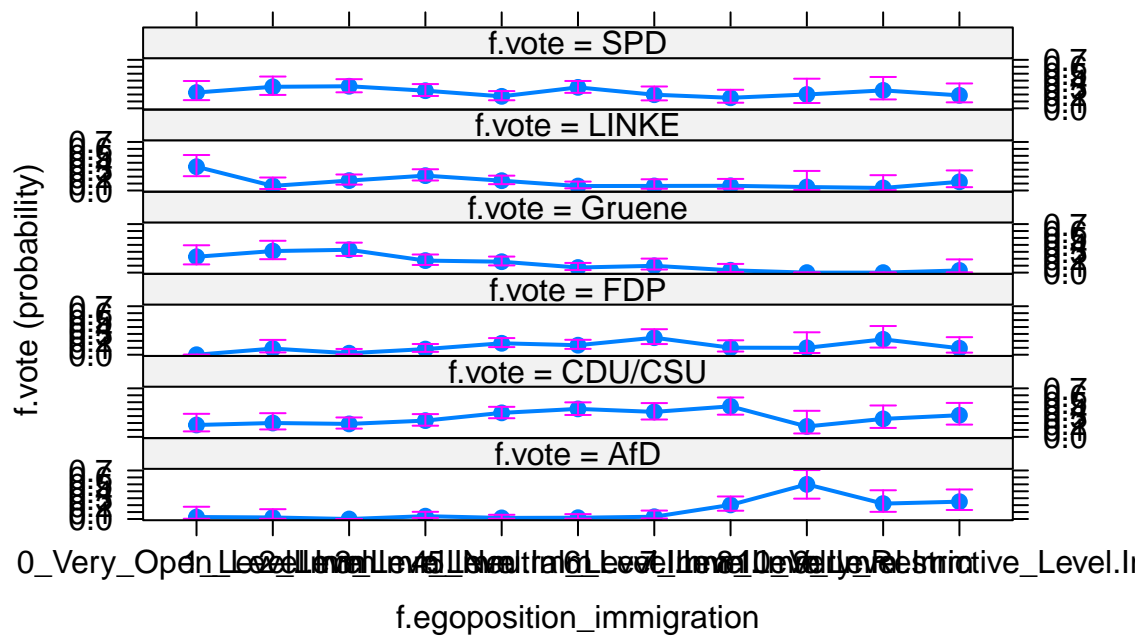

```
plot(allEffects(nm1_imm_cat_new),ask=FALSE, main="Effects Imm Categorical")
```

Effects Imm Categorical
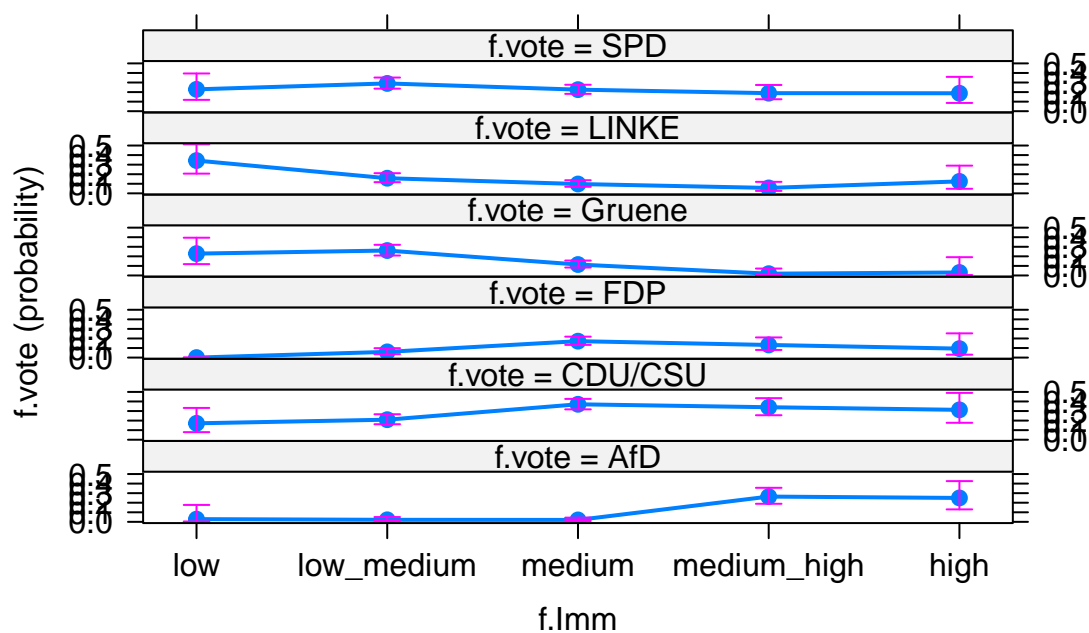

```
# nm1_imm_con_cb is better concerning AIC but we lose 5 df that compared to new factor
#step(nm1_imm_cat_new)
```

```
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
```

```
nm0$dev - nm1_polint_cat_new$dev
```

```
## [1] 9.884028
```

```
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
```

```
Anova(nm1_polint_cat_new, 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.PolInt     9.884 10     0.4507
```

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

Effects Pol Int Continuous
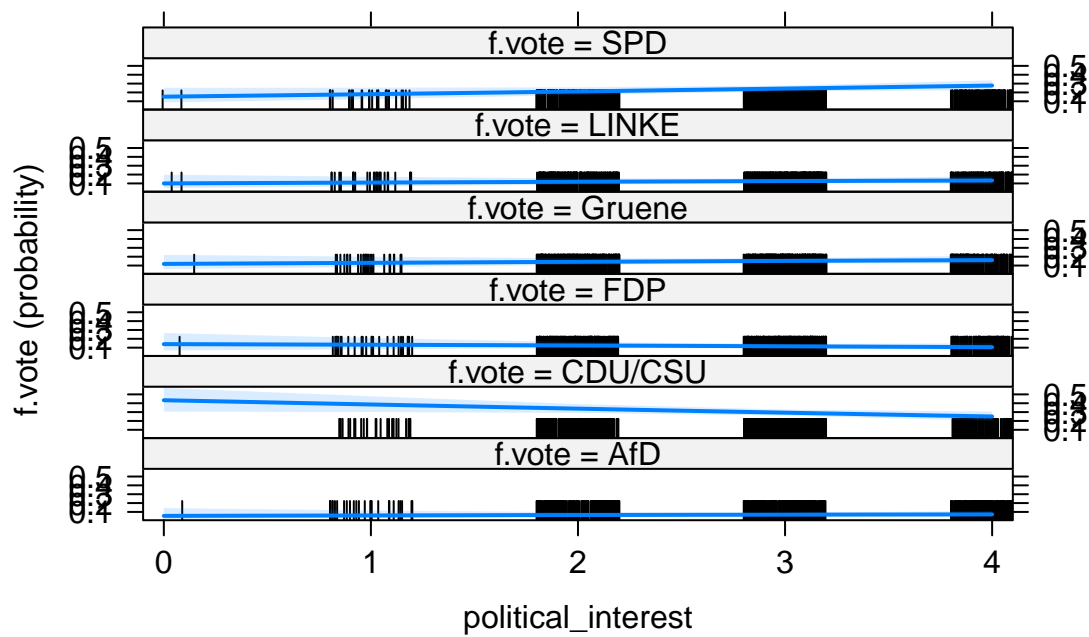

```
plot(allEffects(nm1_polint_con_sq),ask=FALSE,main="Effects Pol Int Continuous Squared")
```

Effects Pol Int Continuous Squared
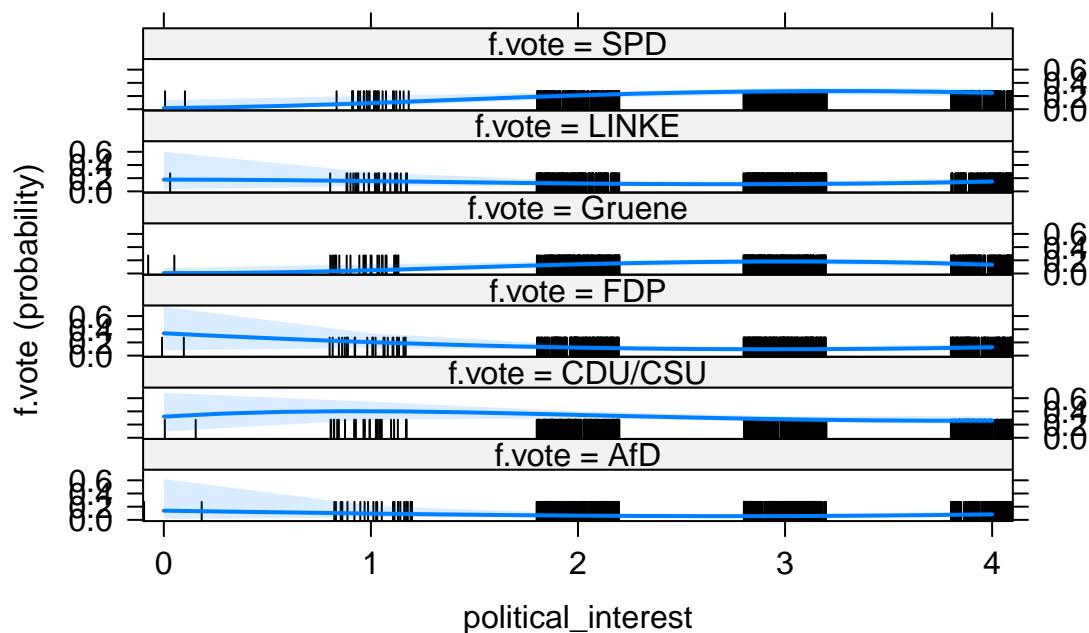

```
plot(allEffects(nm1_polint_con_cb),ask=FALSE, main="Effects Pol Int Continuous Cubed")
```

Effects Pol Int Continuous Cubed
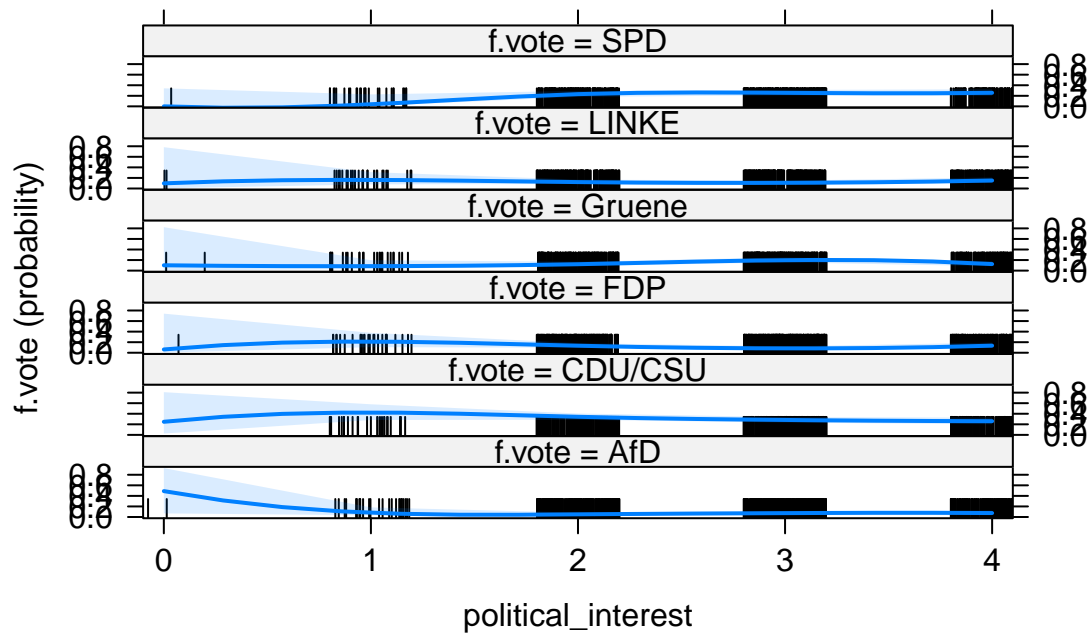

```
plot(allEffects(nm1_polint_con_qd),ask=FALSE, main="Effects Pol Int Continuous Quadratic
```

Effects Pol Int Continuous Quadratic
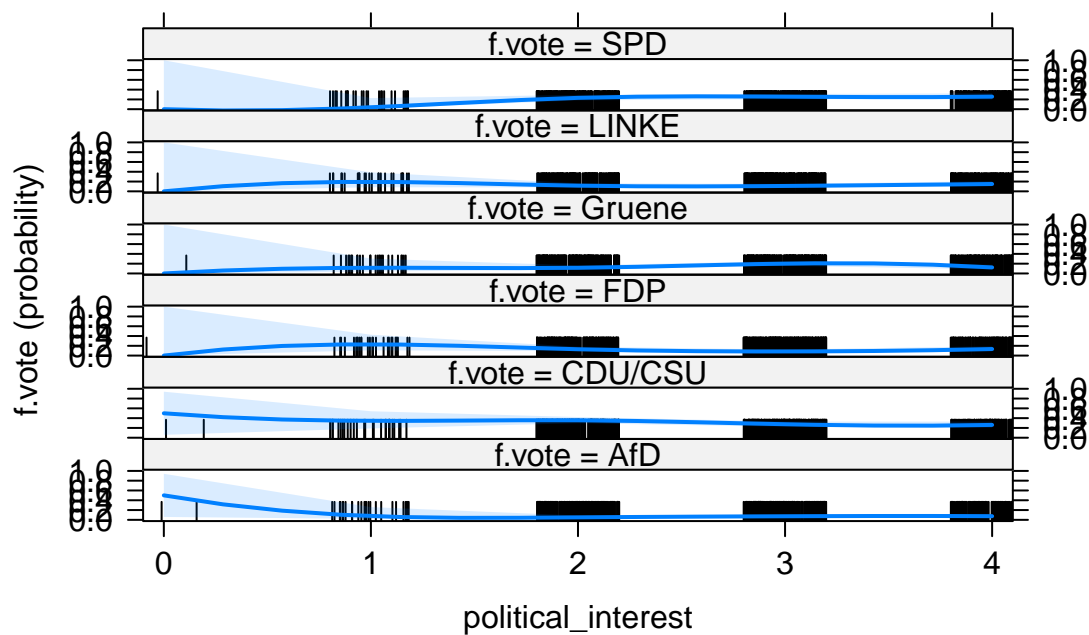

```
plot(allEffects(nm1_polint_cat),ask=FALSE, main="Effects Pol Int Categorical")
```

Effects Pol Int Categorical
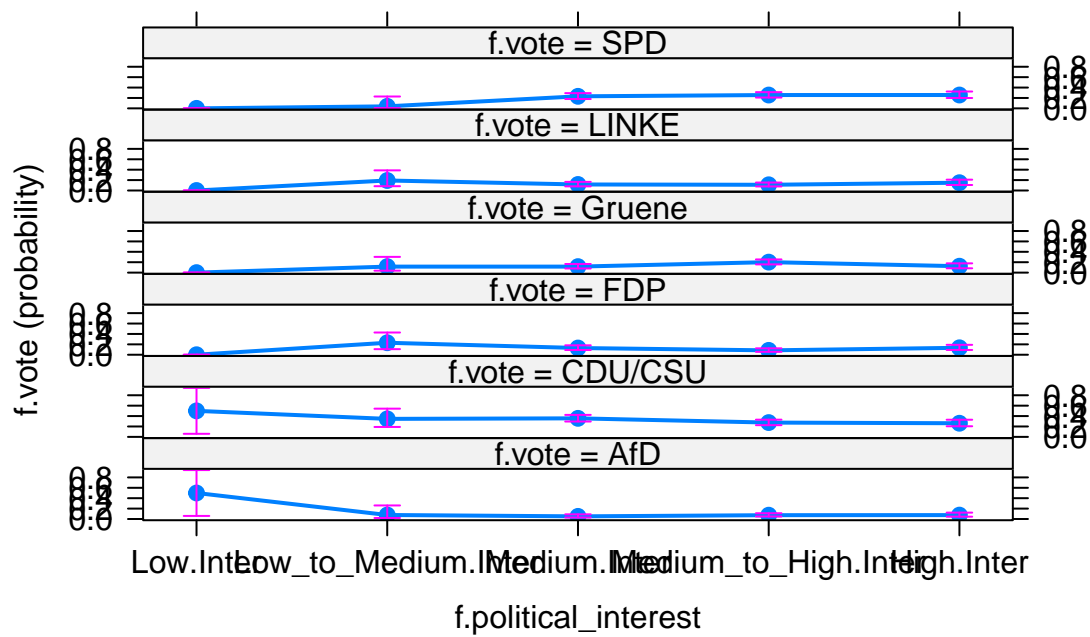

```
plot(allEffects(nm1_polint_cat_new),ask=FALSE, main="Effects Pol Int Categorical")
```

Effects Pol Int Categorical
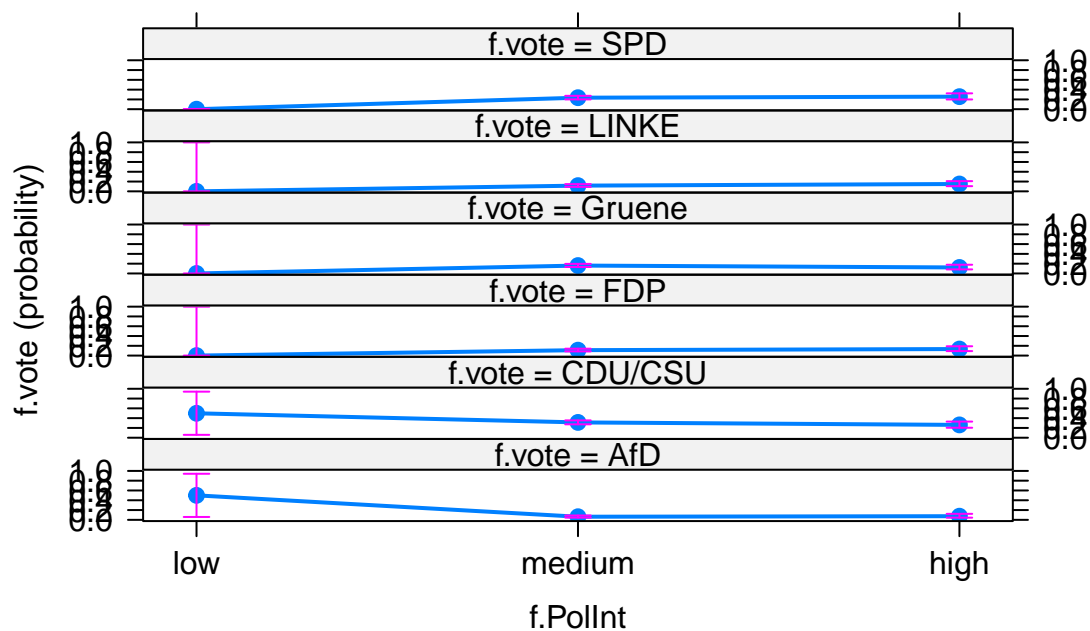

```
#step(nm1_polint_con_sq)
```

```
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
```

```
nm0$dev - nm1_inc_cat_new$dev
```

```
## [1] 21.60993
```

```
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
```

```r
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
```

```r
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
```

```r
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
```

```
Anova(nm1_inc_cat_new, 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.IncSat   21.61 15     0.1184
```

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


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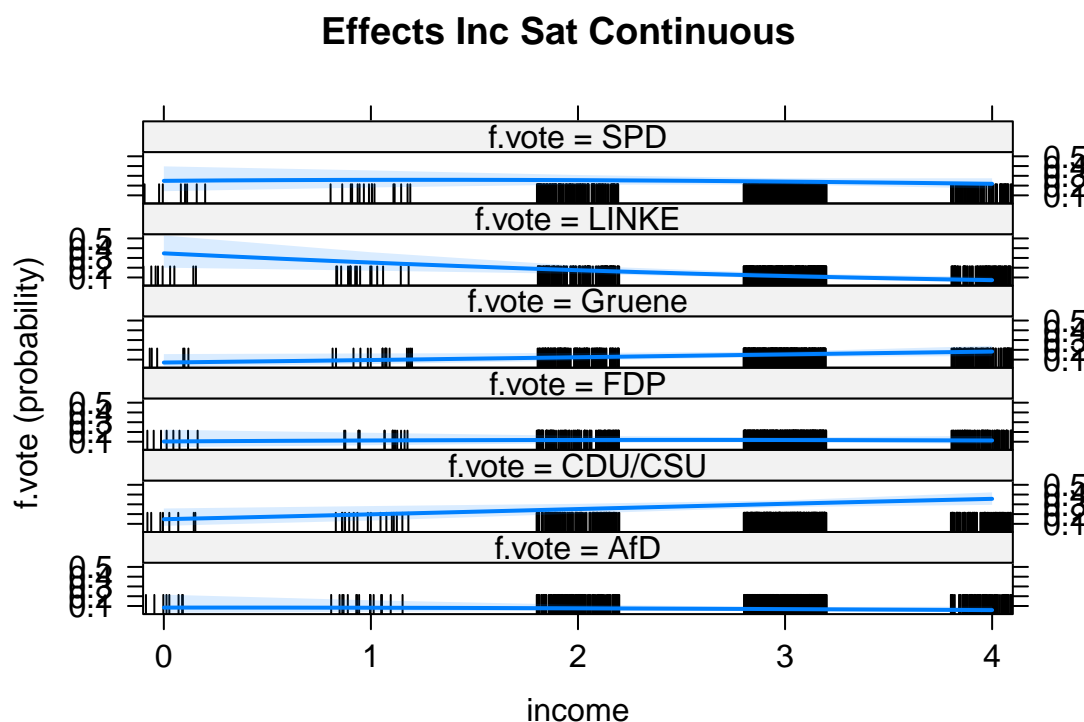
```
plot(allEffects(nm1_inc_con_sq),ask=FALSE,main="Effects Inc Sat Continuous Squared")
```

Effects Inc Sat Continuous Squared
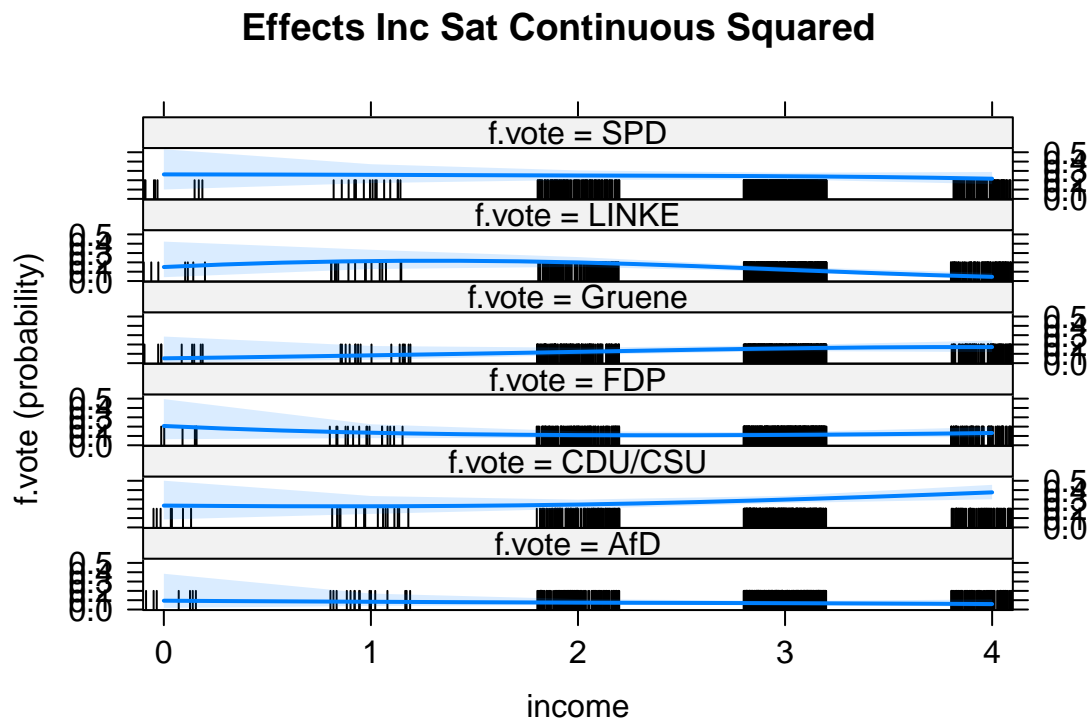

```
plot(allEffects(nm1_inc_con_cb),ask=FALSE, main="Effects Inc Sat Continuous Cubed")
```

Effects Inc Sat Continuous Cubed
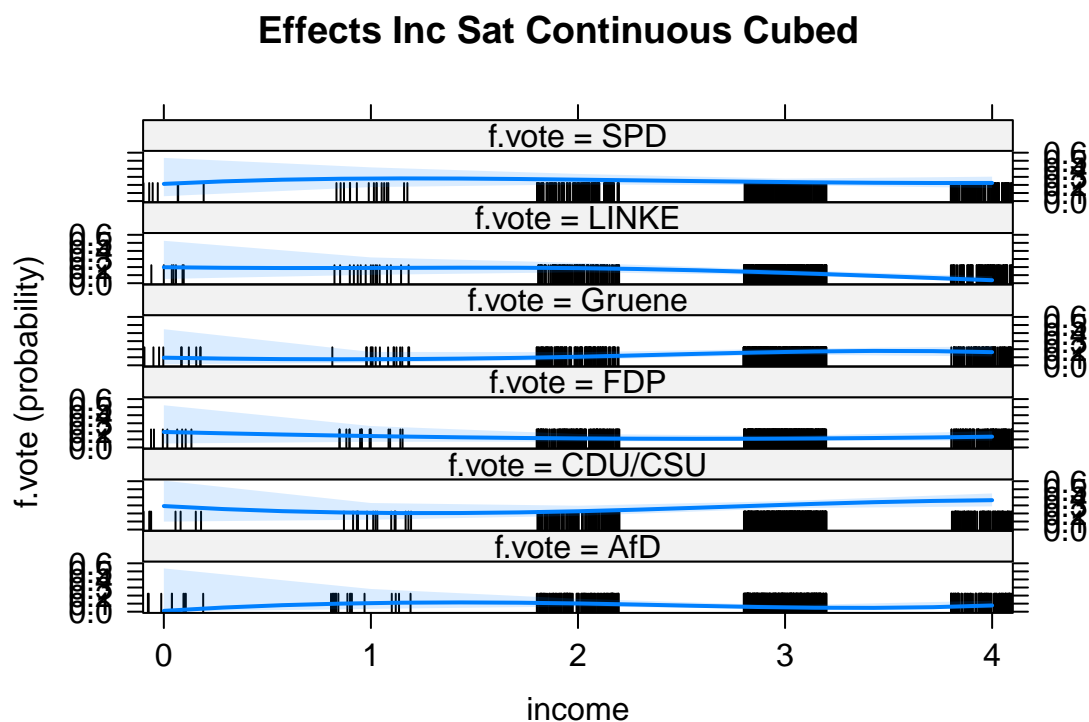

```
plot(allEffects(nm1_inc_con_qd),ask=FALSE, main="Effects Inc Sat Continuous Quadratic")
```

Effects Inc Sat Continuous Quadratic
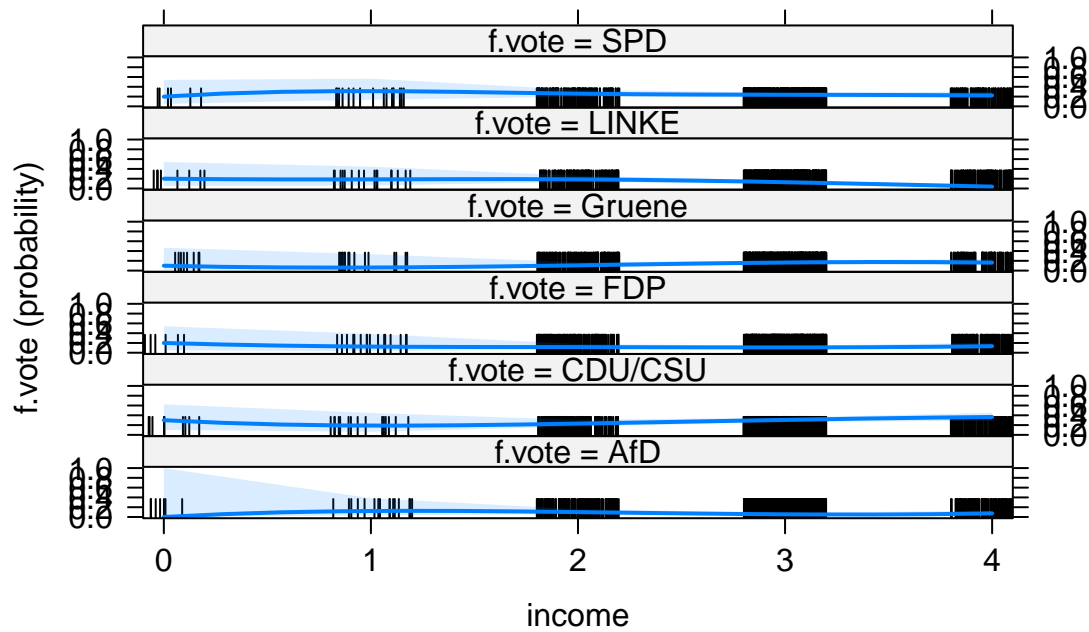

```
plot(allEffects(nm1_inc_cat),ask=FALSE, main="Effects Inc Sat Categorical")
```

Effects Inc Sat Categorical
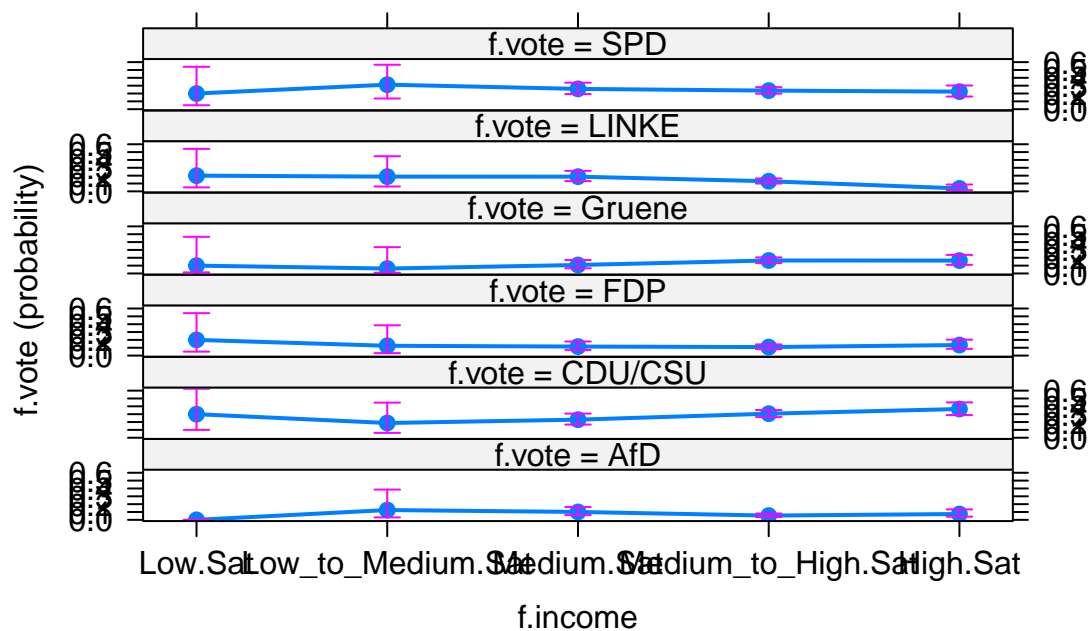

```
plot(allEffects(nm1_inc_cat_new),ask=FALSE, main="Effects Inc Sat Categorical")
```

Effects Inc Sat Categorical
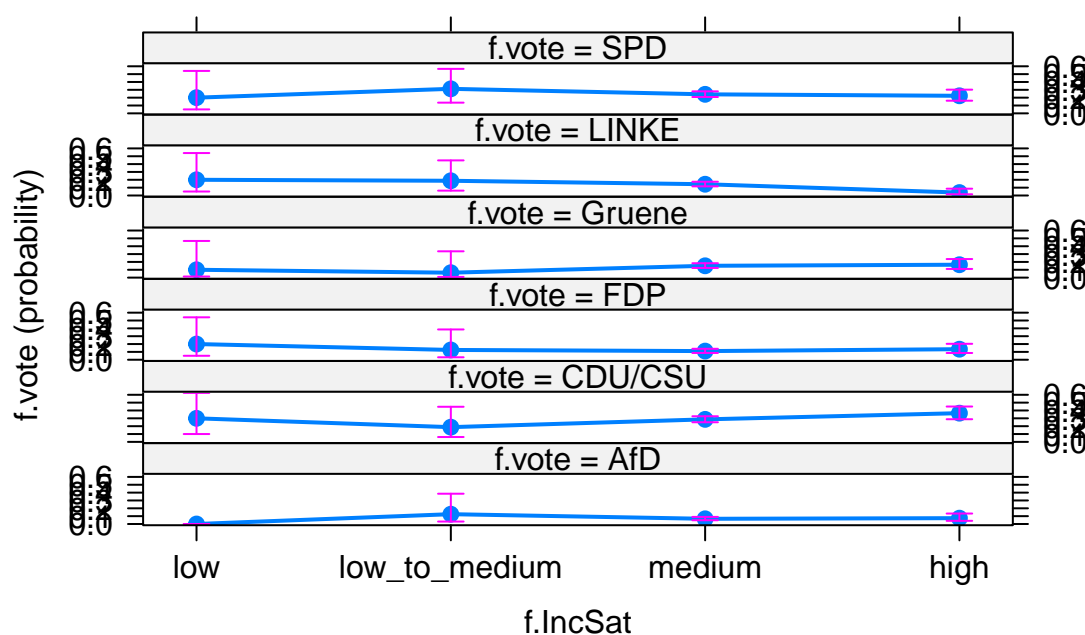

```
#step(nm1_imm_cat_new)
```

4.3.2 Ordinal Models

Comparison of Variables' Numerical and Categorical Representation for Ordinal Models

```
om0$dev - om1_imm_con$dev
```

```
## [1] 100.8407
```

```
om0$dev - om1_imm_con_sq$dev
```

```
## [1] 101.5774
```

```
om0$dev - om1_imm_con_cb$dev
```

```
## [1] 107.5449
```

```
om0$dev - om1_imm_con_qd$dev
```

```
## [1] 109.5187
```

```
anova(om1_imm_con, om1_imm_con_sq, test="Chisq")
```

```
## Likelihood ratio tests of ordinal regression models
##
## Response: f.vote_ord
##                               Model Resid. df Resid. Dev   Test   Df  LR stat.
## 1          egoposition_immigration       698    2267.716
## 2 poly(egoposition_immigration, 2)       697    2266.979 1 vs 2    1 0.7367148
##    Pr(Chi)
## 1
## 2 0.3907153
```

```
anova(om1_imm_con_sq, om1_imm_con_cb, test="Chisq")
```

```
## Likelihood ratio tests of ordinal regression models
##
## Response: f.vote_ord
##                                 Model Resid. df Resid. Dev   Test    Df LR stat.
## 1 poly(egoposition_immigration, 2)        697    2266.979
## 2 poly(egoposition_immigration, 3)        696    2261.012 1 vs 2     1 5.967445
##      Pr(Chi)
## 1
## 2 0.01457238
```

```
anova(om1_imm_con_cb, om1_imm_con_qd, test="Chisq")
```

```
## Likelihood ratio tests of ordinal regression models
##
## Response: f.vote_ord
##                                 Model Resid. df Resid. Dev   Test    Df LR stat.
## 1 poly(egoposition_immigration, 3)        696    2261.012
## 2 poly(egoposition_immigration, 4)        695    2259.038 1 vs 2     1 1.973788
##      Pr(Chi)
## 1
## 2 0.1600463
```

```
Anova(om1_imm_con, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                        LR Chisq Df Pr(>Chisq)
## egoposition_immigration   100.84  1  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(om1_imm_con_sq, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                                  LR Chisq Df Pr(>Chisq)
## poly(egoposition_immigration, 2)   101.58  2  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(om1_imm_con_cb, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                                  LR Chisq Df Pr(>Chisq)
## poly(egoposition_immigration, 3)   107.55  3  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(om1_imm_con_qd, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                                 LR Chisq Df Pr(>Chisq)
## poly(egoposition_immigration, 4)   109.52  4  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(om1_imm_cat, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                           LR Chisq Df Pr(>Chisq)
## f.egoposition_immigration   121.65 10  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(om1_imm_cat_new, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##         LR Chisq Df Pr(>Chisq)
## f.Imm     111.29  4  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(allEffects(om1_imm_con),ask=FALSE, main="Effects Imm Continuous")
```

```
##
## Re-fitting to get Hessian
```

Effects Imm Continuous
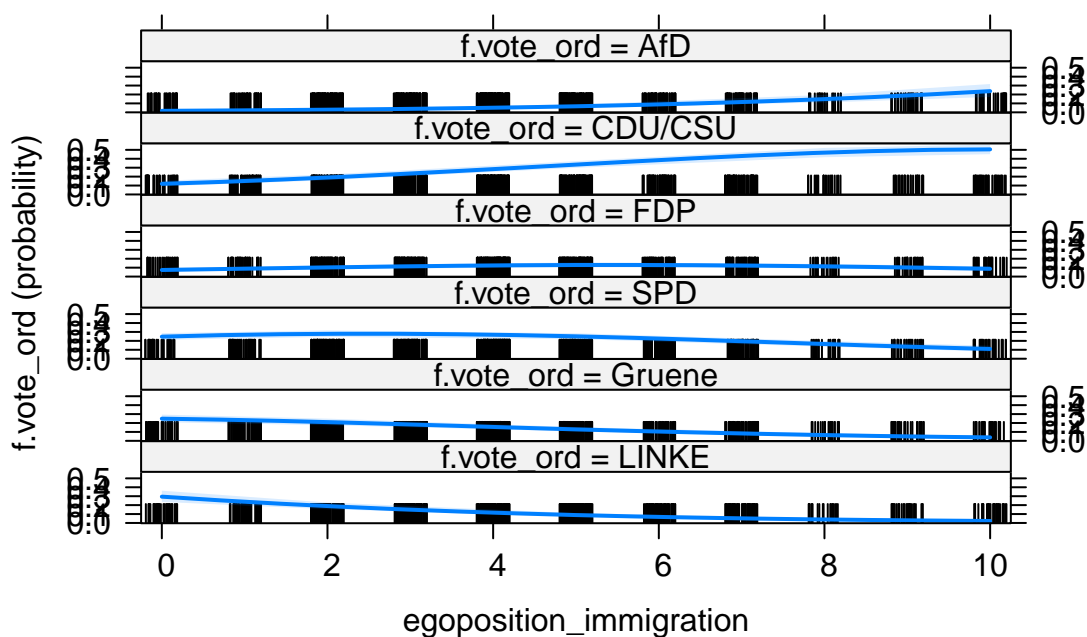

```
plot(allEffects(om1_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```

```
##
## Re-fitting to get Hessian
```

Effects Imm Continuous Squared
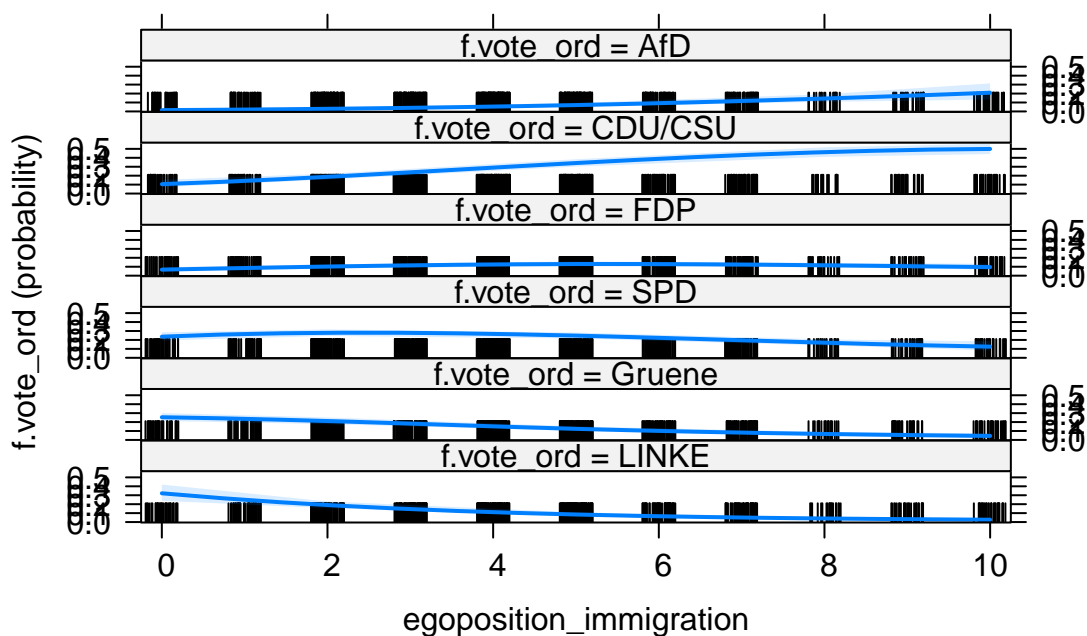

```
plot(allEffects(om1_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```

```
##
## Re-fitting to get Hessian
```

Effects Imm Continuous Cubed
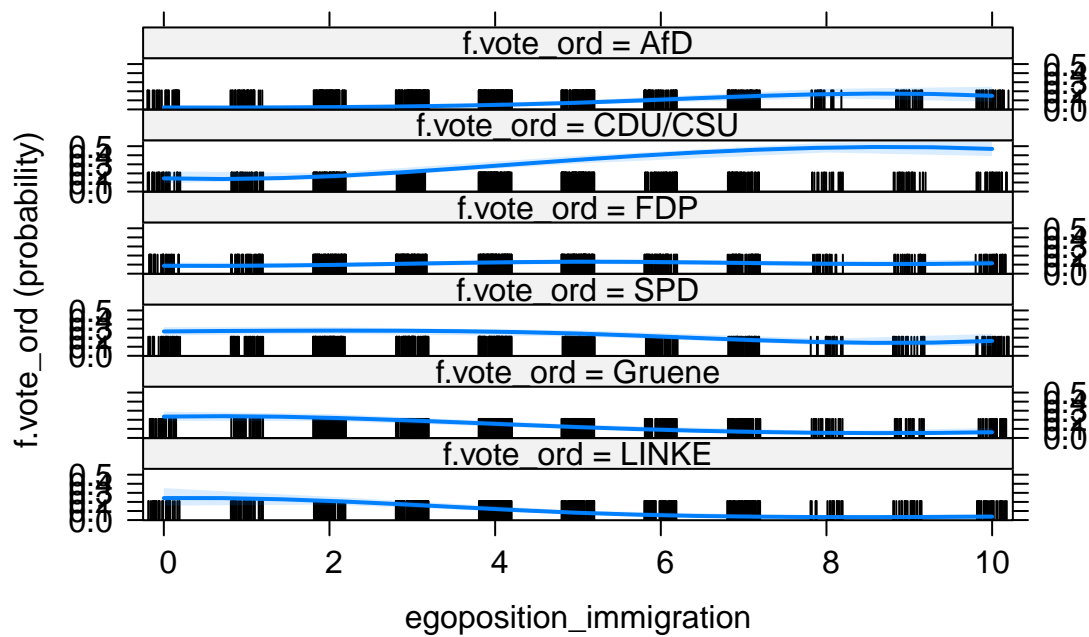

```
plot(allEffects(om1_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```

```
##
## Re-fitting to get Hessian
```

Effects Imm Continuous Quadratic
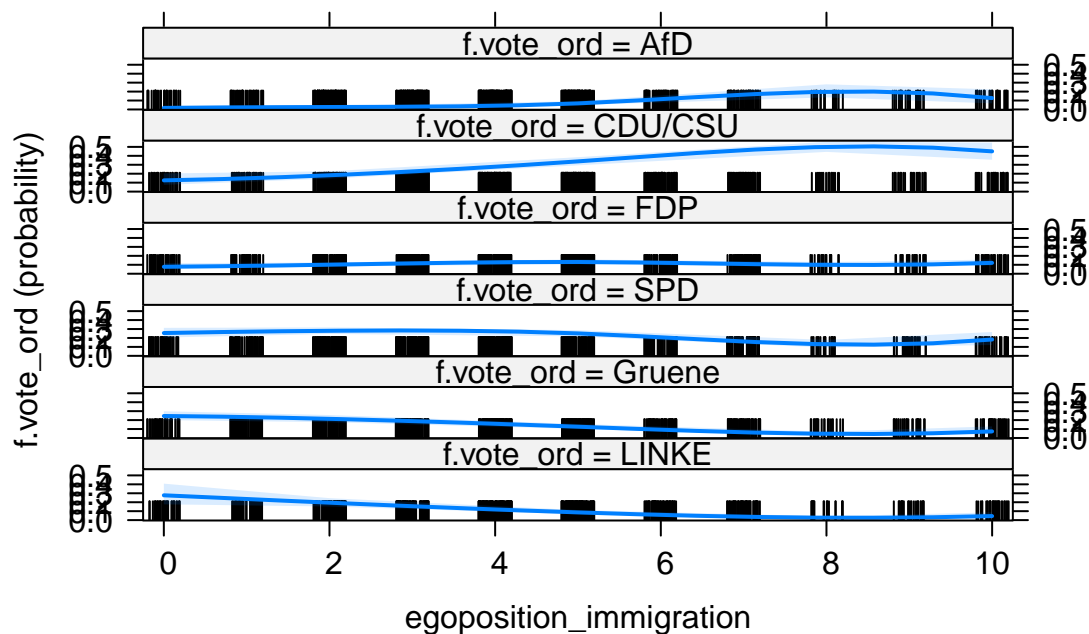

```
plot(allEffects(om1_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

```
##
## Re-fitting to get Hessian
```

Effects Imm Categorical
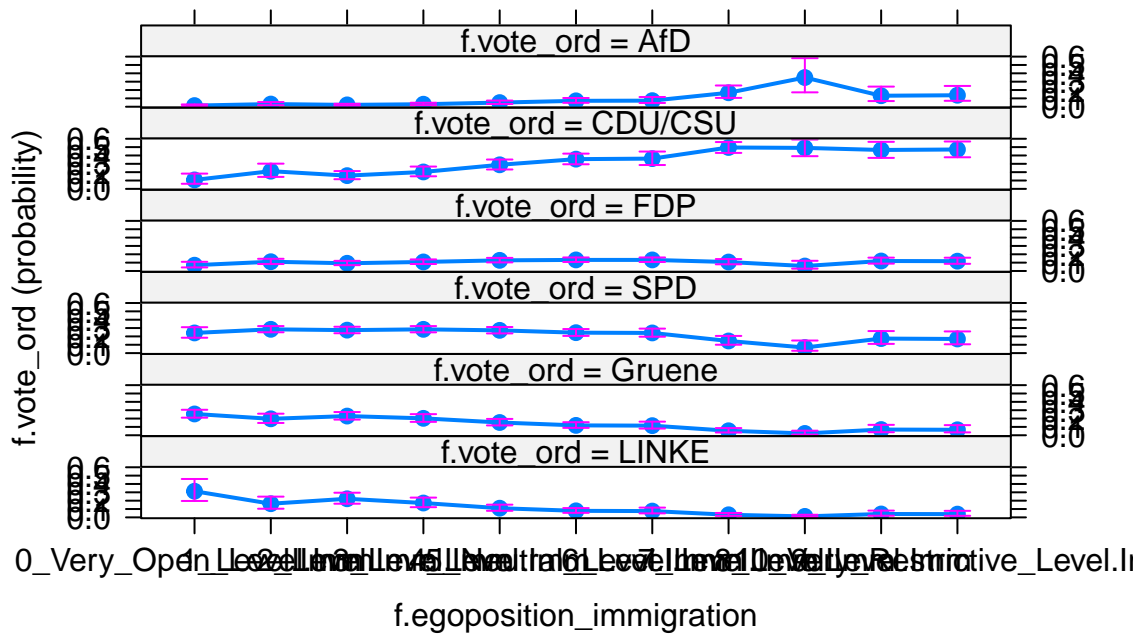

```
plot(allEffects(om1_imm_cat_new),ask=FALSE, main="Effects Imm Categorical")
```

```
##
## Re-fitting to get Hessian
```

Effects Imm Categorical
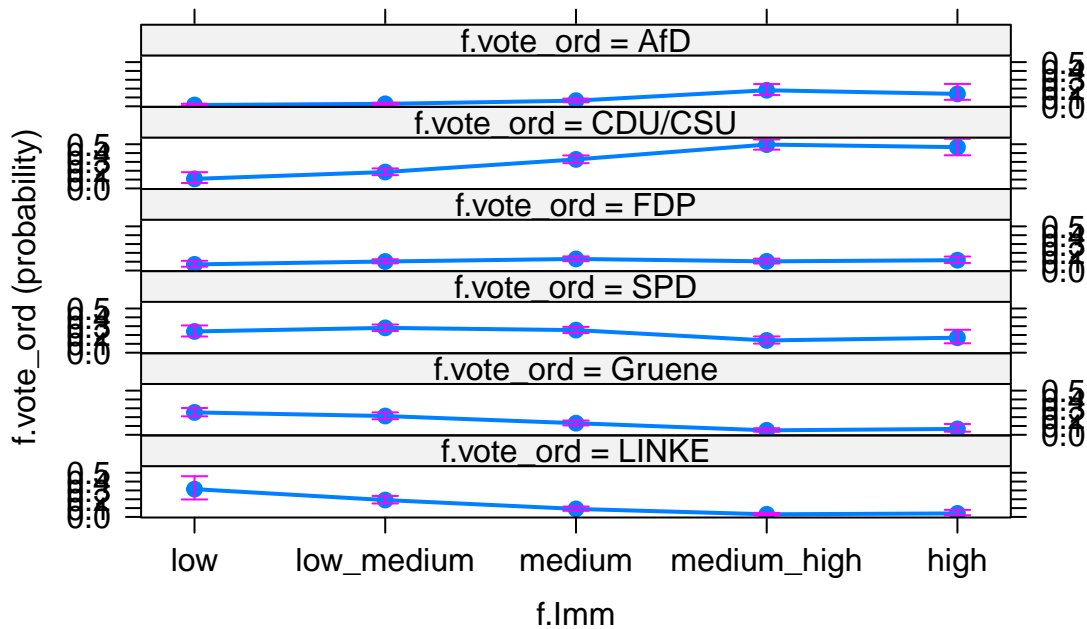

```
# om1_imm_con_cb is better concerning AIC but we lose 5 df that compared to new factor
#step(om1_imm_cat_new)
```

```
om0$dev - om1_polint_con$dev
```

```
## [1] 2.985803
```

```
om0$dev - om1_polint_con_sq$dev
```

```
## [1] 5.079863
```

```
om0$dev - om1_polint_con_cb$dev
```

```
## [1] 5.232933
```

```
om0$dev - om1_polint_con_qd$dev
```

```
## [1] 7.734318
```

```
om0$dev - om1_polint_cat$dev
```

```
## [1] 7.73432
```

```
om0$dev - om1_polint_cat_new$dev
```

```
## [1] 4.840537
```

```
anova(om1_polint_con, om1_polint_con_sq, test="Chisq")
```

```
## Likelihood ratio tests of ordinal regression models
##
## Response: f.vote_ord
##                          Model Resid. df Resid. Dev    Test    Df LR stat.
## 1          political_interest       698    2365.571
## 2 poly(political_interest, 2)       697    2363.477 1 vs 2     1 2.094061
##     Pr(Chi)
## 1
## 2 0.1478726
```

```
anova(om1_polint_con_sq, om1_polint_con_cb, test="Chisq")
```

```
## Likelihood ratio tests of ordinal regression models
##
## Response: f.vote_ord
##                          Model Resid. df Resid. Dev    Test    Df  LR stat.
## 1 poly(political_interest, 2)       697    2363.477
## 2 poly(political_interest, 3)       696    2363.323 1 vs 2     1 0.1530697
##     Pr(Chi)
## 1
## 2 0.6956189
```

```
anova(om1_polint_con_cb, om1_polint_con_qd, test="Chisq")
```

```
## Likelihood ratio tests of ordinal regression models
##
## Response: f.vote_ord
##                          Model Resid. df Resid. Dev    Test    Df LR stat.
## 1 poly(political_interest, 3)       696    2363.323
## 2 poly(political_interest, 4)       695    2360.822 1 vs 2     1 2.501385
```

```
##      Pr(Chi)
## 1
## 2 0.1137462
```

```r
Anova(om1_polint_con, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                    LR Chisq Df Pr(>Chisq)
## political_interest   2.9858  1      0.084 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
Anova(om1_polint_con_sq, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                         LR Chisq Df Pr(>Chisq)
## poly(political_interest, 2)   5.0799  2    0.07887 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
Anova(om1_polint_con_cb, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                         LR Chisq Df Pr(>Chisq)
## poly(political_interest, 3)   5.2329  3     0.1555
```

```r
Anova(om1_polint_con_qd, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                          LR Chisq Df Pr(>Chisq)
## poly(political_interest, 4)   7.7343  4     0.1018
```

```r
Anova(om1_polint_cat, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                    LR Chisq Df Pr(>Chisq)
## f.political_interest   7.7343  4     0.1018
```

```r
Anova(om1_polint_cat_new, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##           LR Chisq Df Pr(>Chisq)
## f.PolInt    4.8405  2     0.0889 .
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
plot(allEffects(om1_polint_con),ask=FALSE, main="Effects Pol Int Continuous")

##
## Re-fitting to get Hessian
```

Effects Pol Int Continuous
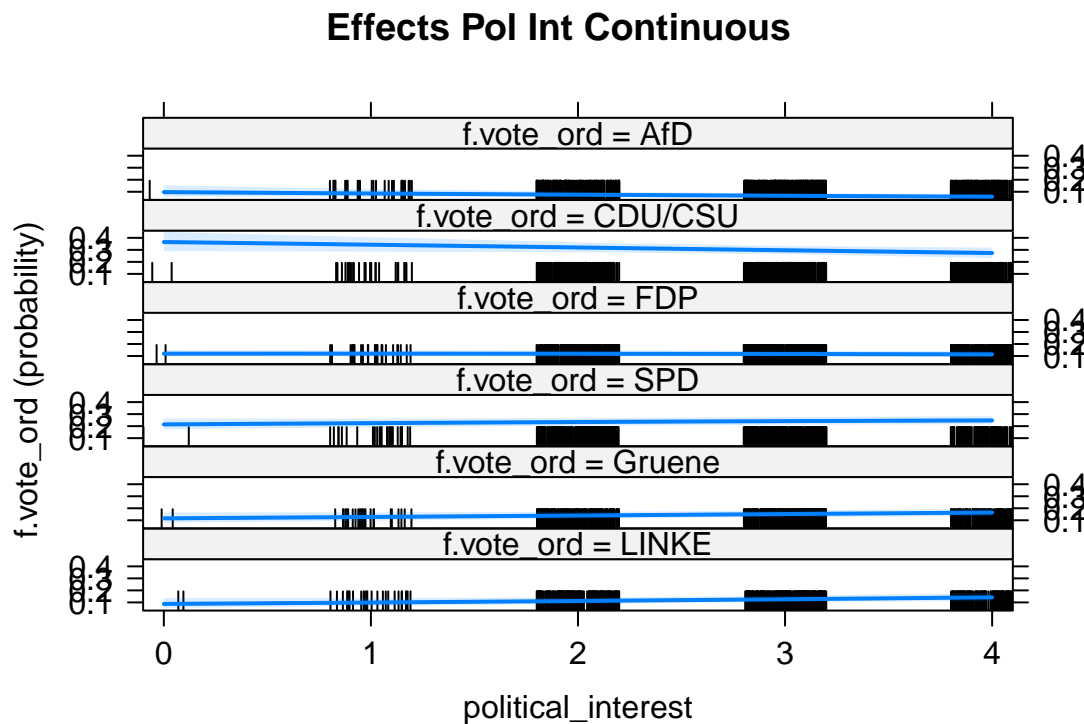

```
plot(allEffects(om1_polint_con_sq),ask=FALSE,main="Effects Pol Int Continuous Squared")

##
## Re-fitting to get Hessian
```

Effects Pol Int Continuous Squared
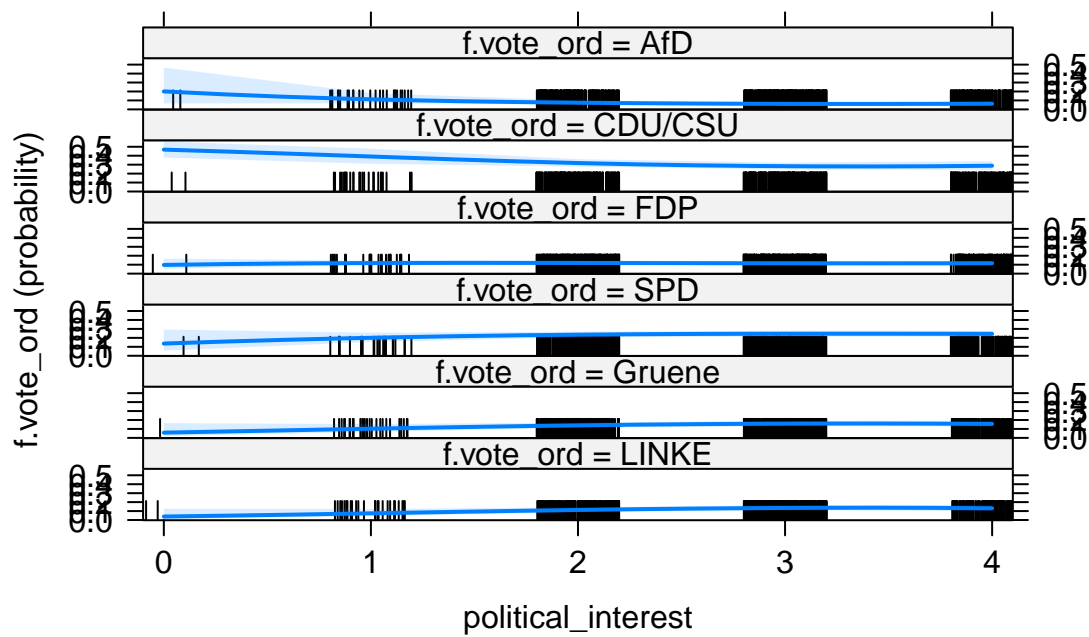

```
plot(allEffects(om1_polint_con_cb),ask=FALSE, main="Effects Pol Int Continuous Cubed")
```

```
##
## Re-fitting to get Hessian
```

Effects Pol Int Continuous Cubed
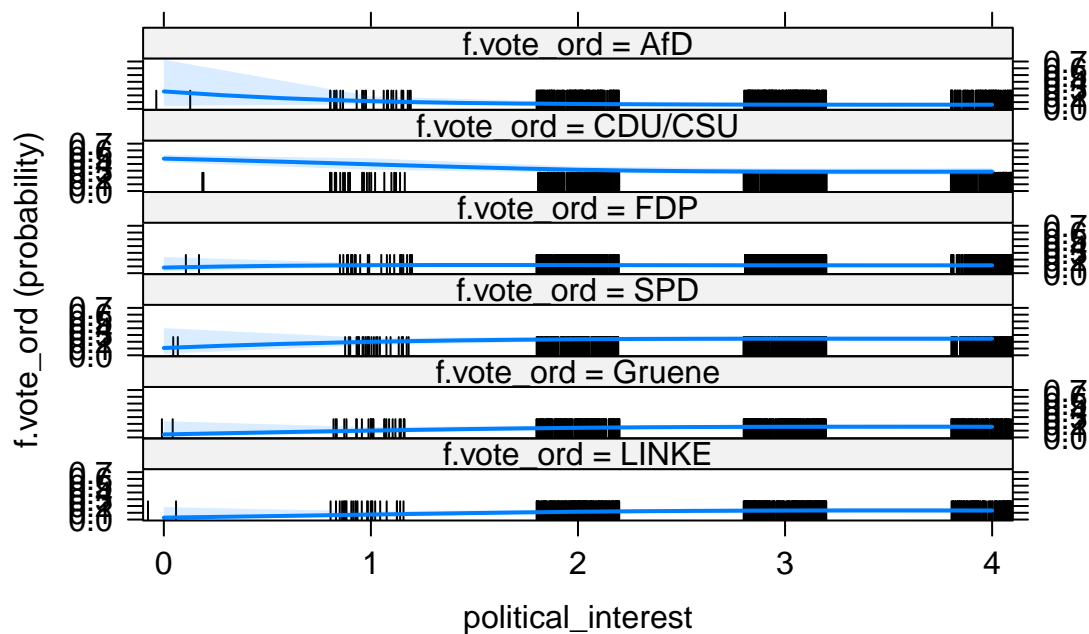

```
plot(allEffects(om1_polint_con_qd),ask=FALSE, main="Effects Pol Int Continuous Quadratic
```

```
##
## Re-fitting to get Hessian
```

Effects Pol Int Continuous Quadratic
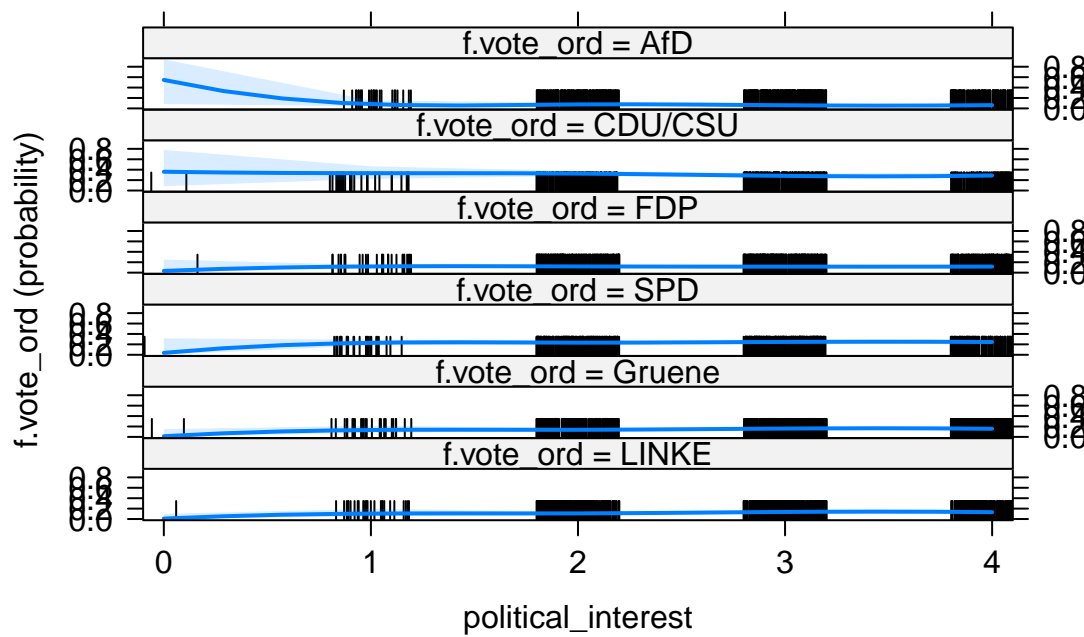

```
plot(allEffects(om1_polint_cat),ask=FALSE, main="Effects Pol Int Categorical")
```

```
##
## Re-fitting to get Hessian
```

Effects Pol Int Categorical
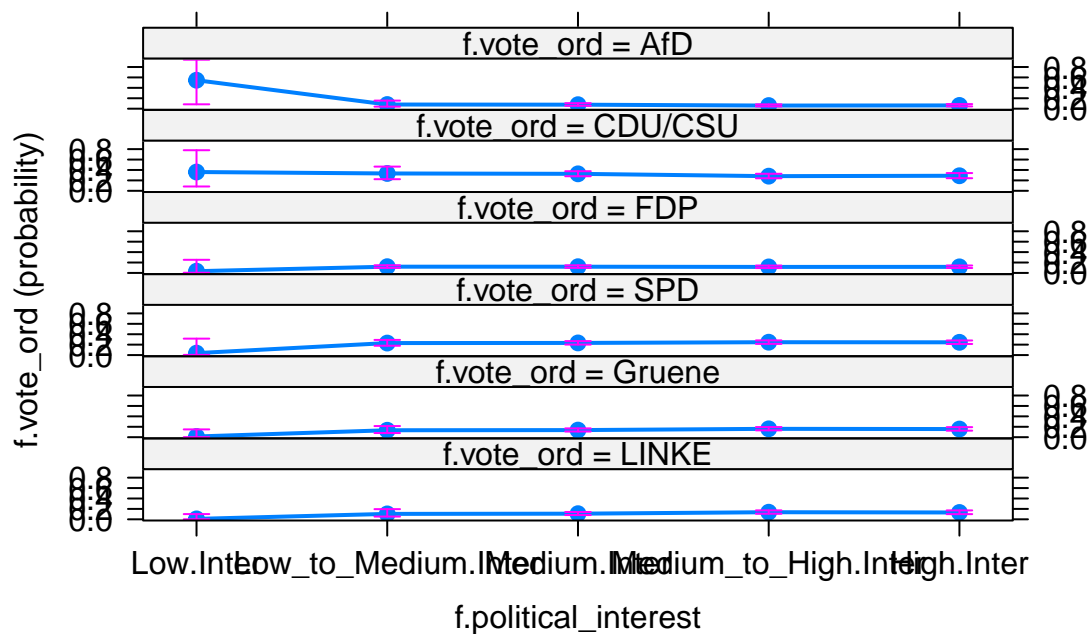

```
plot(allEffects(om1_polint_cat_new),ask=FALSE, main="Effects Pol Int Categorical")
```

```
##
## Re-fitting to get Hessian
```

Effects Pol Int Categorical
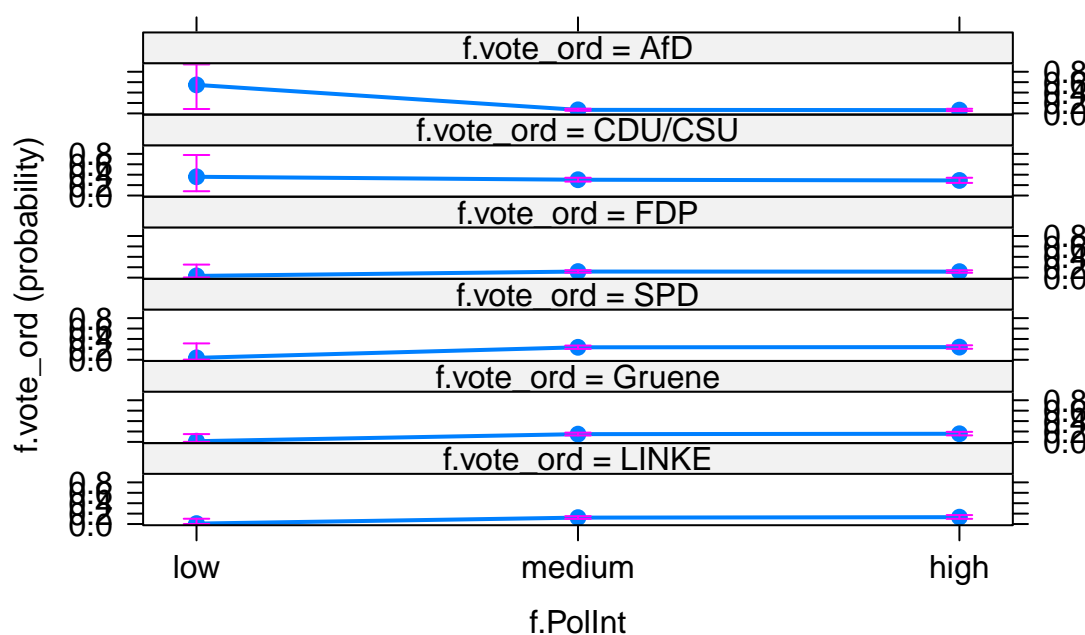

```
om0$dev - om1_inc_con$dev
```

```
## [1] 4.579493
```

```
om0$dev - om1_inc_con_sq$dev
```

```
## [1] 6.595547
```

```
om0$dev - om1_inc_con_cb$dev
```

```
## [1] 7.224751
```

```
om0$dev - om1_inc_con_qd$dev
```

```
## [1] 7.226956
```

```
om0$dev - om1_inc_cat$dev
```

```
## [1] 7.226959
```

```
om0$dev - om1_inc_cat_new$dev
```

```
## [1] 7.068024
```

```
anova(om1_inc_con_sq, om1_inc_con_cb, test="Chisq")
```

```
## Likelihood ratio tests of ordinal regression models
##
## Response: f.vote_ord
##              Model Resid. df Resid. Dev   Test   Df  LR stat.   Pr(Chi)
## 1 poly(income, 2)       697   2361.961
## 2 poly(income, 3)       696   2361.332 1 vs 2     1 0.6292041 0.4276474
```

```
anova(om1_inc_con_cb, om1_inc_con_qd, test="Chisq")
```

```
## Likelihood ratio tests of ordinal regression models
##
## Response: f.vote_ord
##              Model Resid. df Resid. Dev   Test   Df    LR stat.   Pr(Chi)
## 1 poly(income, 3)      696    2361.332
## 2 poly(income, 4)      695    2361.329 1 vs 2    1 0.002204762 0.9625492
```

Anova(om1_inc_con, test="Chisq")

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##        LR Chisq Df Pr(>Chisq)
## income   4.5795  1    0.03236 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Anova(om1_inc_con_sq, test="Chisq")

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                LR Chisq Df Pr(>Chisq)
## poly(income, 2)   6.5955  2    0.03697 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Anova(om1_inc_con_cb, test="Chisq")

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                LR Chisq Df Pr(>Chisq)
## poly(income, 3)   7.2248  3    0.06507 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Anova(om1_inc_con_qd, test="Chisq")

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                LR Chisq Df Pr(>Chisq)
## poly(income, 4)    7.227  4     0.1244
```

Anova(om1_inc_cat, test="Chisq")

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##          LR Chisq Df Pr(>Chisq)
## f.income    7.227  4     0.1244
```

```
Anova(om1_inc_cat_new, test="Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##          LR Chisq Df Pr(>Chisq)
## f.IncSat    7.068  3    0.06976 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(allEffects(om1_inc_con),ask=FALSE, main="Effects Inc Sat Continuous")
```

```
##
## Re-fitting to get Hessian
```

Effects Inc Sat Continuous
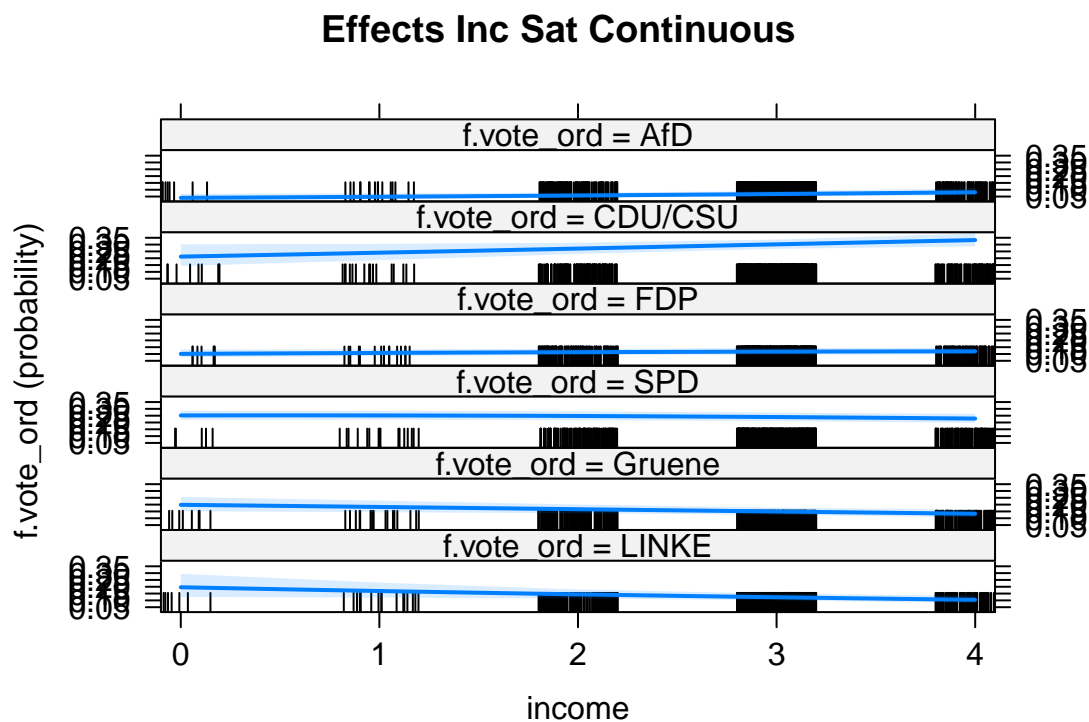

```
plot(allEffects(om1_inc_con_sq),ask=FALSE,main="Effects Inc Sat Continuous Squared")
```

```
##
## Re-fitting to get Hessian
```

Effects Inc Sat Continuous Squared
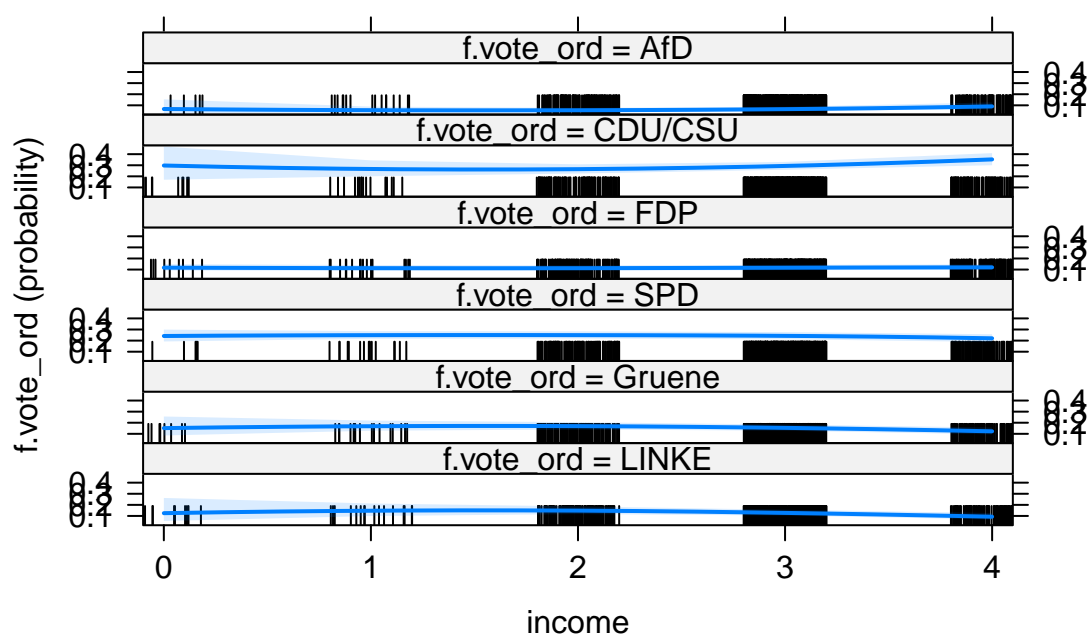

```
plot(allEffects(om1_inc_con_cb),ask=FALSE, main="Effects Inc Sat Continuous Cubed")
```

```
##
## Re-fitting to get Hessian
```

Effects Inc Sat Continuous Cubed
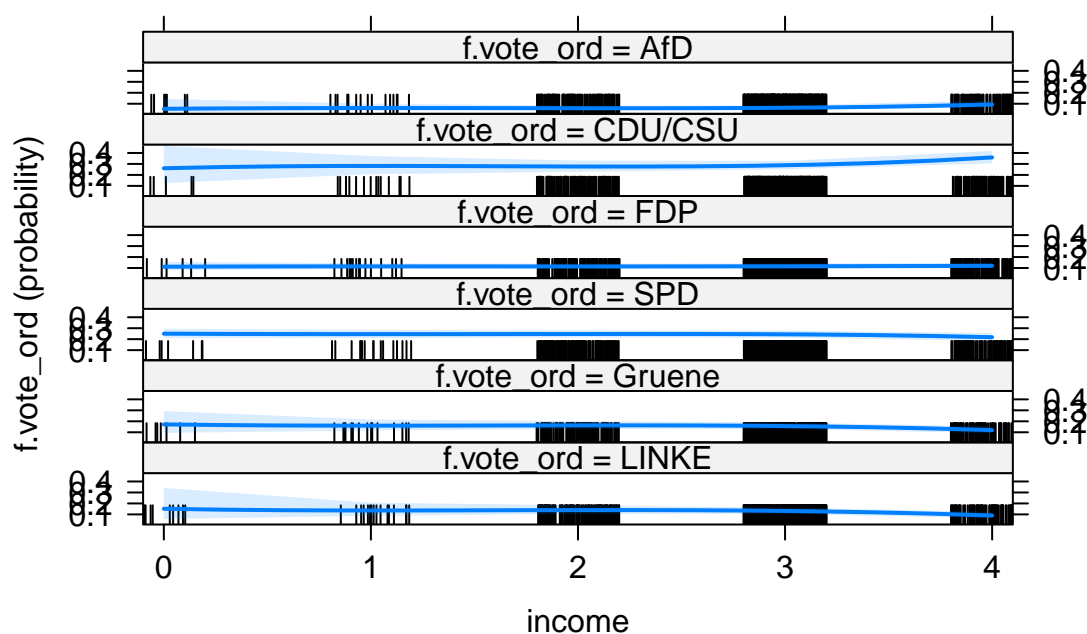

```
plot(allEffects(om1_inc_con_qd),ask=FALSE, main="Effects Inc Sat Continuous Quadratic")
```

```
##
## Re-fitting to get Hessian
```

Effects Inc Sat Continuous Quadratic
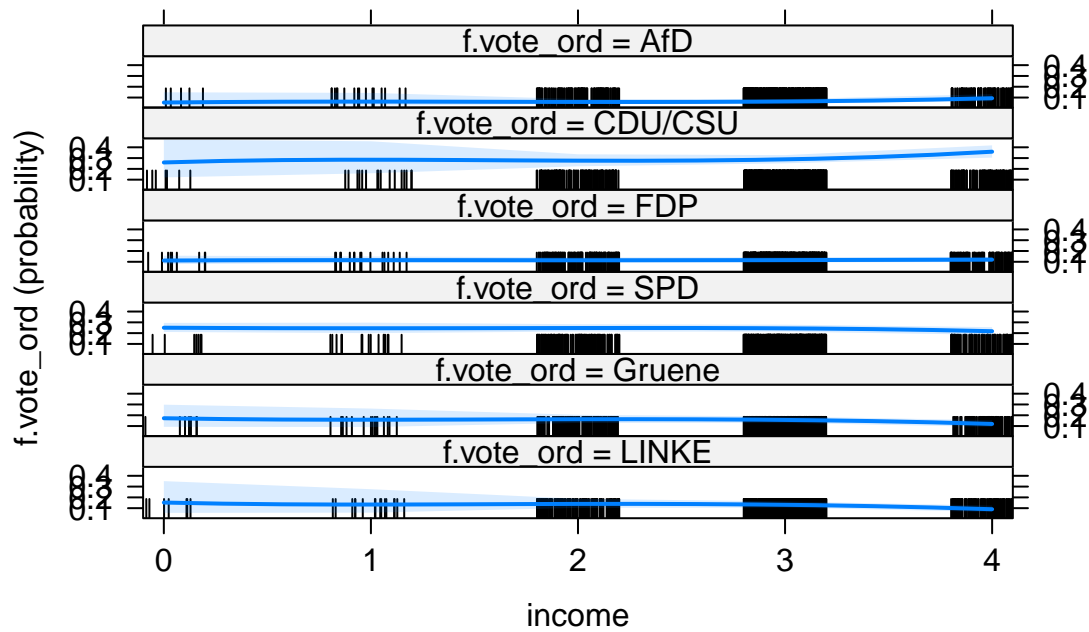

```
plot(allEffects(om1_inc_cat),ask=FALSE, main="Effects Inc Sat Categorical")
```

```
##
## Re-fitting to get Hessian
```

Effects Inc Sat Categorical
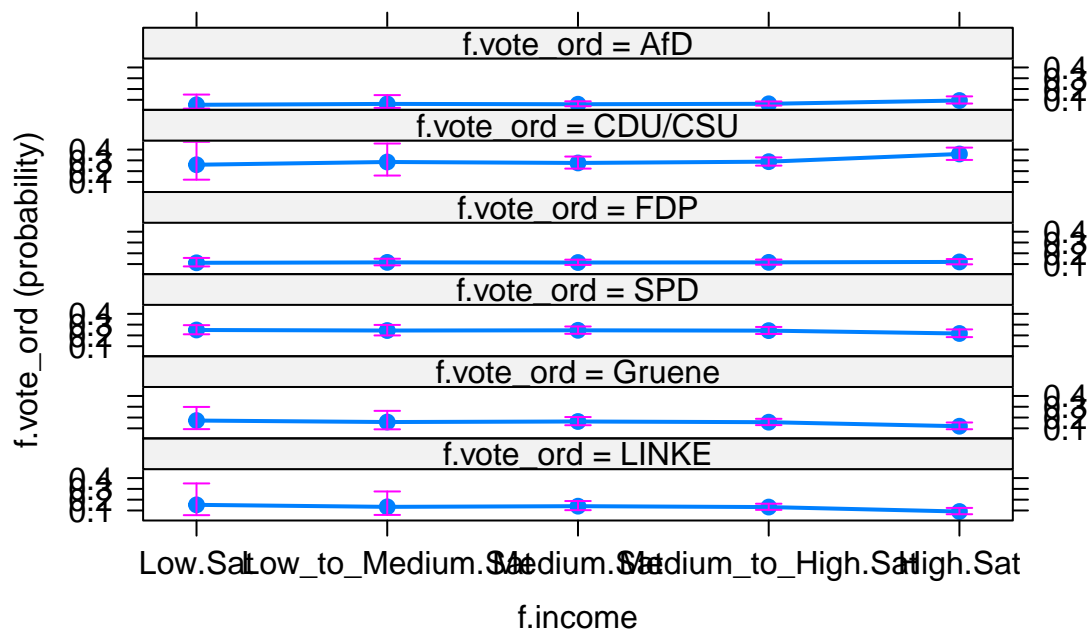

```
plot(allEffects(om1_inc_cat_new),ask=FALSE, main="Effects Inc Sat Categorical")
```

```
##
## Re-fitting to get Hessian
```

Effects Inc Sat Categorical
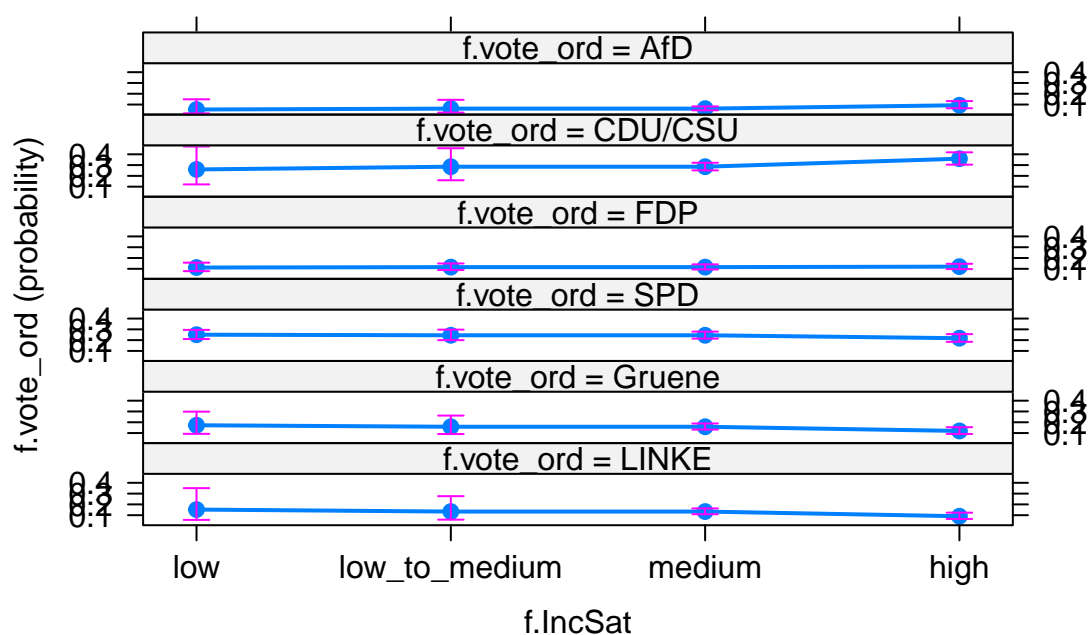
4.3.3 Hierarchical Models

```
bhm0$dev - bhm1_imm_con$dev
```

```
## [1] 11.06988
```

```
bhm0$dev - bhm1_imm_con_sq$dev
```

```
## [1] 28.21052
```

```
bhm0$dev - bhm1_imm_con_cb$dev
```

```
## [1] 29.49081
```

```
bhm0$dev - bhm1_imm_con_qd$dev
```

```
## [1] 32.86867
```

```
anova(bhm1_imm_con, bhm1_imm_con_sq, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: bwing ~ egoposition_immigration
## Model 2: bwing ~ poly(egoposition_immigration, 2)
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1       702     894.97
## 2       701     877.83  1   17.141 3.471e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(bhm1_imm_con_sq, bhm1_imm_con_cb, test="Chisq")
```

```
## Analysis of Deviance Table
```

```
##
## Model 1: bwing ~ poly(egoposition_immigration, 2)
## Model 2: bwing ~ poly(egoposition_immigration, 3)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      701     877.83
## 2      700     876.55  1   1.2803   0.2578
```

```
anova(bhm1_imm_con_cb, bhm1_imm_con_qd, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: bwing ~ poly(egoposition_immigration, 3)
## Model 2: bwing ~ poly(egoposition_immigration, 4)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      700     876.55
## 2      699     873.17  1   3.3779  0.06608 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm1_imm_con, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                        Df  Chisq Pr(>Chisq)
## egoposition_immigration  1 10.701   0.001071 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm1_imm_con_sq, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                                Df  Chisq Pr(>Chisq)
## poly(egoposition_immigration, 2)  2 27.359   1.145e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm1_imm_con_cb, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                                Df  Chisq Pr(>Chisq)
## poly(egoposition_immigration, 3)  3 28.743   2.536e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm1_imm_con_qd, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
```

```
##                               Df  Chisq Pr(>Chisq)
## poly(egoposition_immigration, 4)  4 32.007  1.907e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm1_imm_cat, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                          Df  Chisq Pr(>Chisq)
## f.egoposition_immigration 10 46.032  1.415e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm1_imm_cat_new, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##        Df  Chisq Pr(>Chisq)
## f.Imm   4 35.157  4.313e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(allEffects(bhm1_imm_con),ask=FALSE, main="Effects Imm Continuous")
```

Effects Imm Continuous
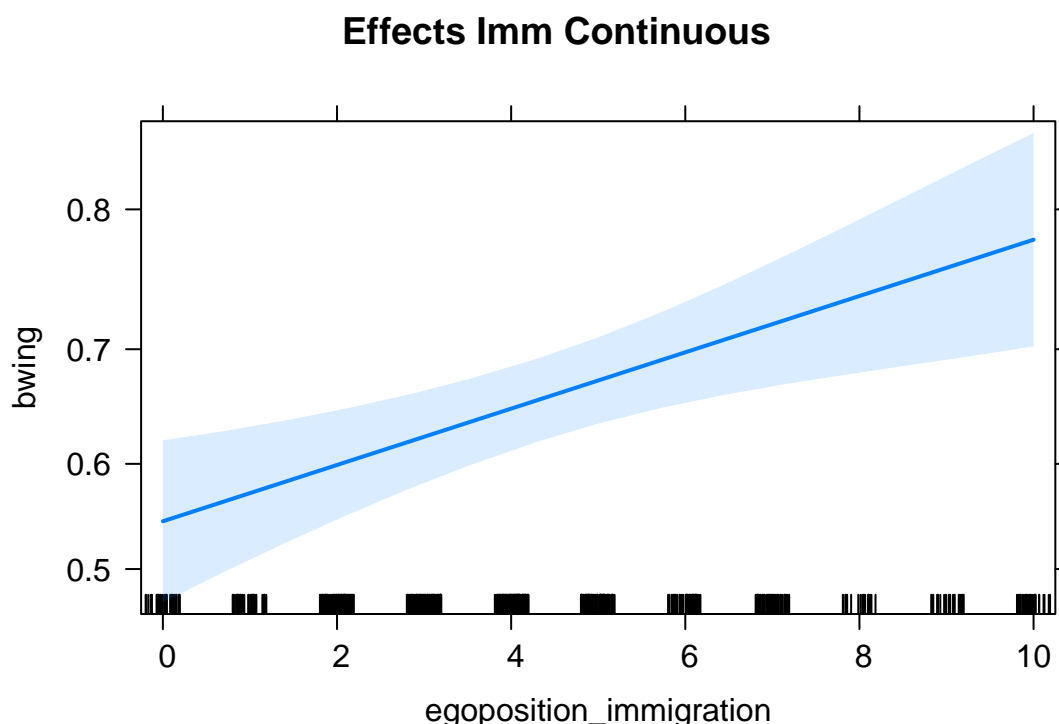

```
plot(allEffects(bhm1_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```

Effects Imm Continuous Squared
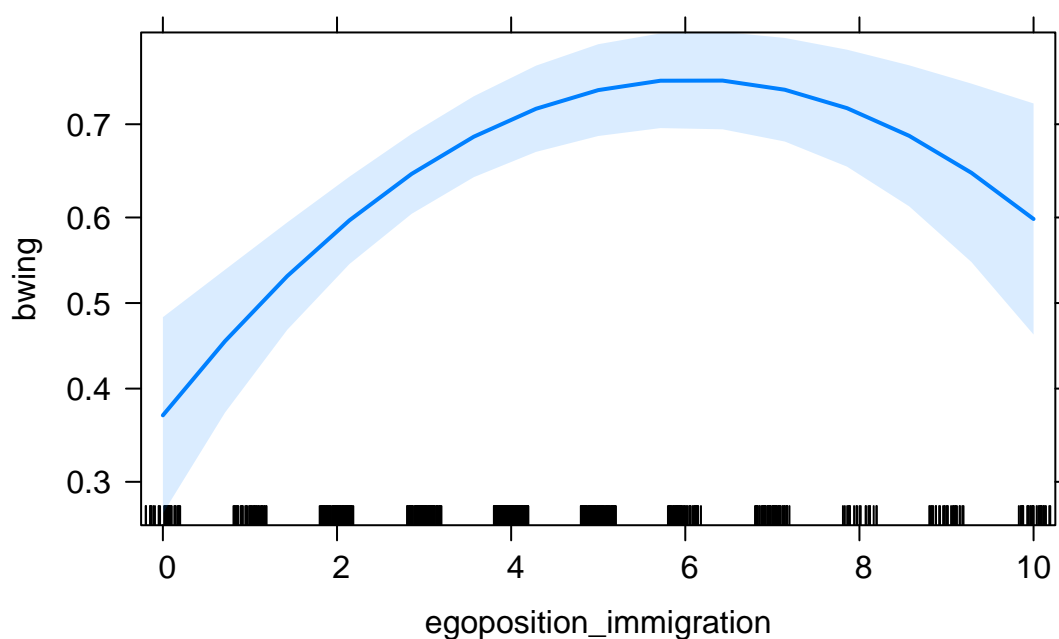

```
plot(allEffects(bhm1_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```

Effects Imm Continuous Cubed
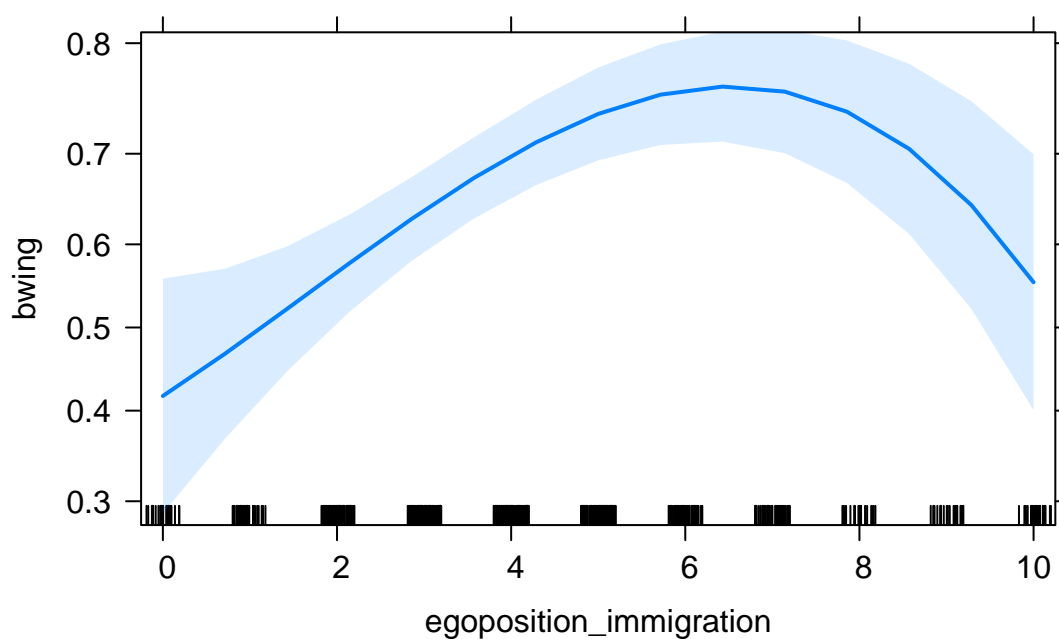

```
plot(allEffects(bhm1_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```

Effects Imm Continuous Quadratic
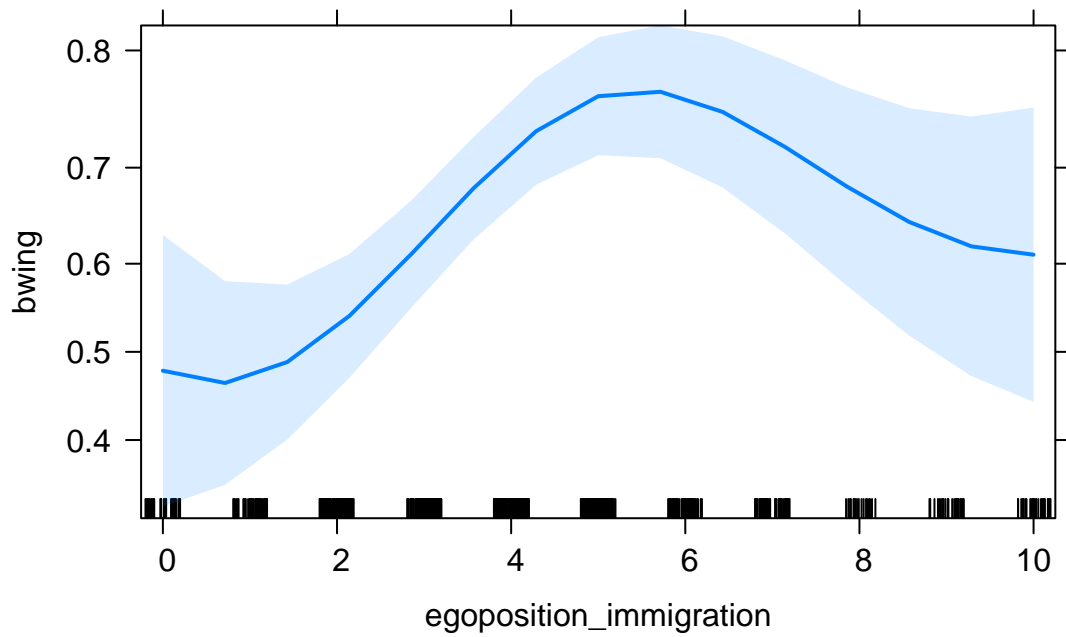

```
plot(allEffects(bhm1_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

Effects Imm Categorical
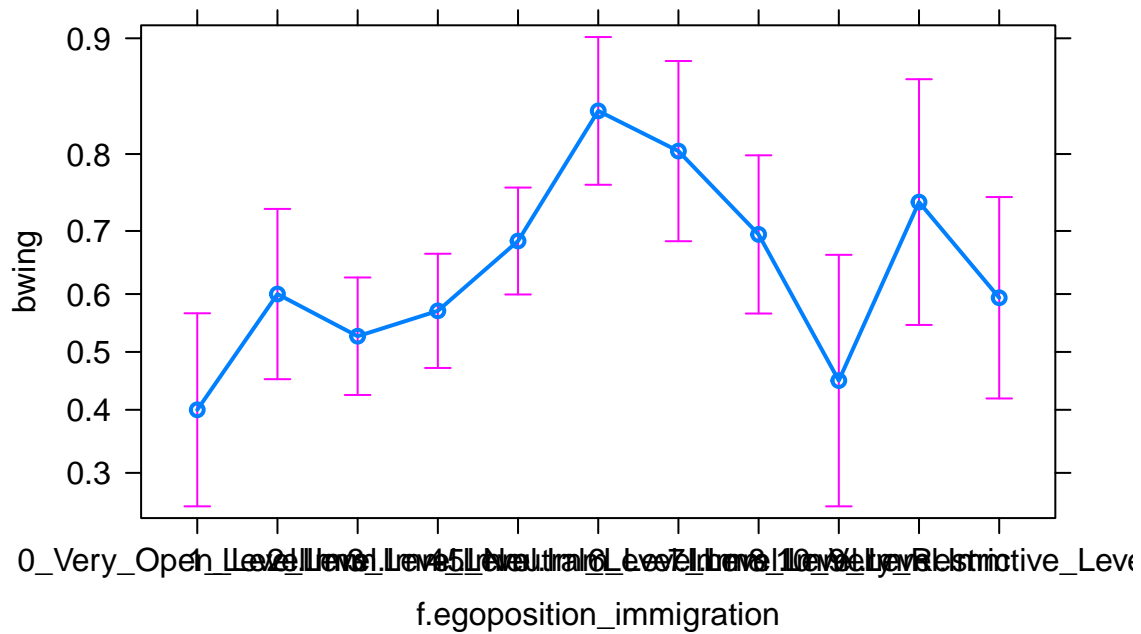

```
plot(allEffects(bhm1_imm_cat_new),ask=FALSE, main="Effects Imm Categorical")
```

Effects Imm Categorical
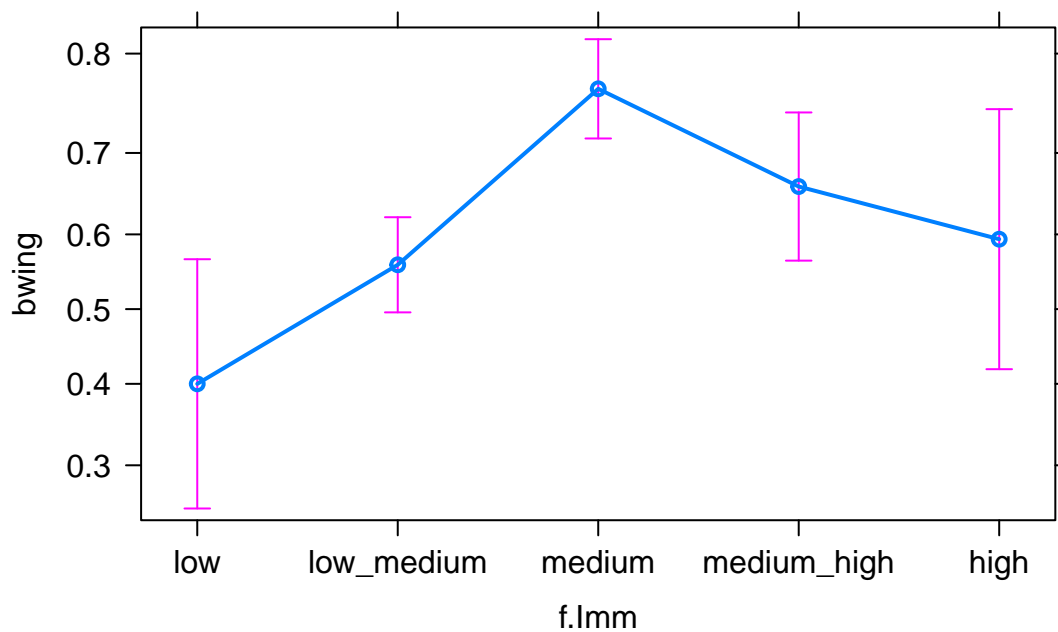

```
bhm0$dev - bhm1_polint_con$dev
```

```
## [1] 1.027896
```
```
bhm0$dev - bhm1_polint_con_sq$dev
```

```
## [1] 1.034385
```
```
bhm0$dev - bhm1_polint_con_cb$dev
```

```
## [1] 5.069252
```
```
bhm0$dev - bhm1_polint_con_qd$dev
```

```
## [1] 6.113992
```
```
bhm0$dev - bhm1_polint_cat$dev
```

```
## [1] 6.113992
```
```
bhm0$dev - bhm1_polint_cat_new$dev
```

```
## [1] 0.2269066
```
```
anova(bhm1_polint_con, bhm1_polint_con_sq, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: bwing ~ political_interest
## Model 2: bwing ~ poly(political_interest, 2)
##   Resid. Df Resid. Dev Df  Deviance Pr(>Chi)
## 1       702     905.01
## 2       701     905.00  1 0.0064891   0.9358
```

```
anova(bhm1_polint_con_sq, bhm1_polint_con_cb, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: bwing ~ poly(political_interest, 2)
## Model 2: bwing ~ poly(political_interest, 3)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       701     905.00
## 2       700     900.97  1   4.0349  0.04457 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(bhm1_polint_con_cb, bhm1_polint_con_qd, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: bwing ~ poly(political_interest, 3)
## Model 2: bwing ~ poly(political_interest, 4)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       700     900.97
## 2       699     899.92  1   1.0447   0.3067
```

```
Anova(bhm1_polint_con, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                    Df  Chisq Pr(>Chisq)
## political_interest  1 1.0241     0.3115
```

```
Anova(bhm1_polint_con_sq, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                            Df  Chisq Pr(>Chisq)
## poly(political_interest, 2)  2 1.0277     0.5982
```

```
Anova(bhm1_polint_con_cb, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                            Df  Chisq Pr(>Chisq)
## poly(political_interest, 3)  3 4.8836     0.1805
```

```
Anova(bhm1_polint_con_qd, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                            Df  Chisq Pr(>Chisq)
## poly(political_interest, 4)  4 6.0009     0.1991
```

```
Anova(bhm1_polint_cat, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                     Df  Chisq Pr(>Chisq)
## f.political_interest  4 6.0009     0.1991
```

```
Anova(bhm1_polint_cat_new, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##          Df  Chisq Pr(>Chisq)
## f.PolInt  2 0.2305     0.8912
```

```
plot(allEffects(bhm1_polint_con),ask=FALSE, main="Effects Political Interest Continuous"
```

Effects Political Interest Continuous
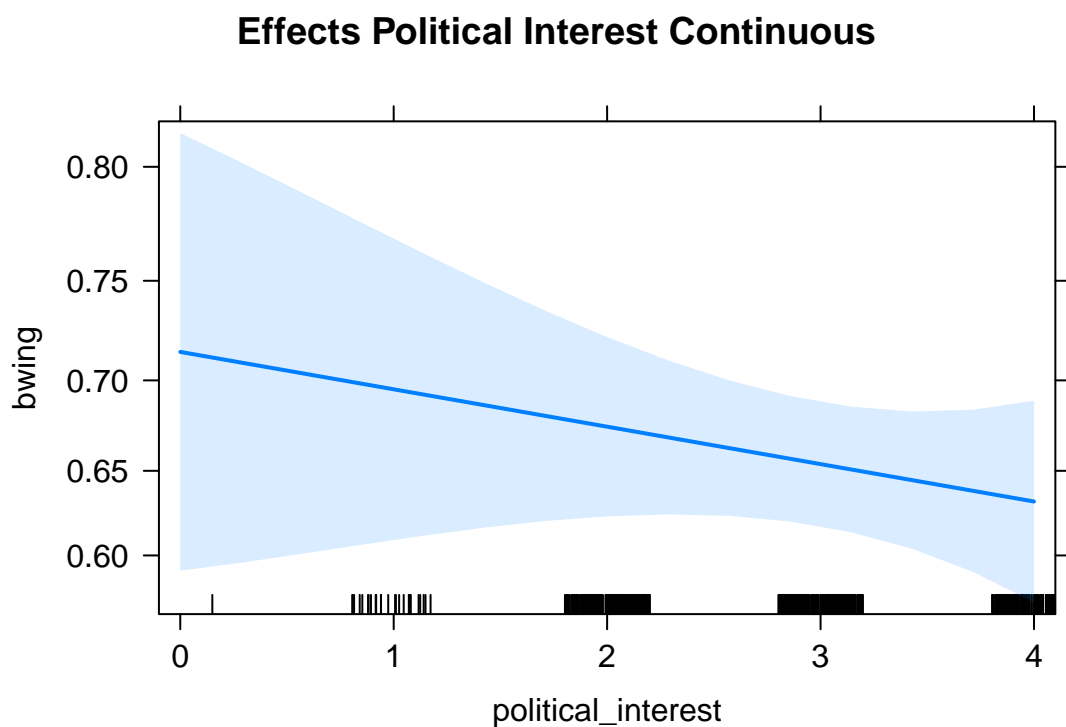

```
plot(allEffects(bhm1_polint_con_sq),ask=FALSE,main="Effects Political Interest Continuou
```

Effects Political Interest Continuous Squared
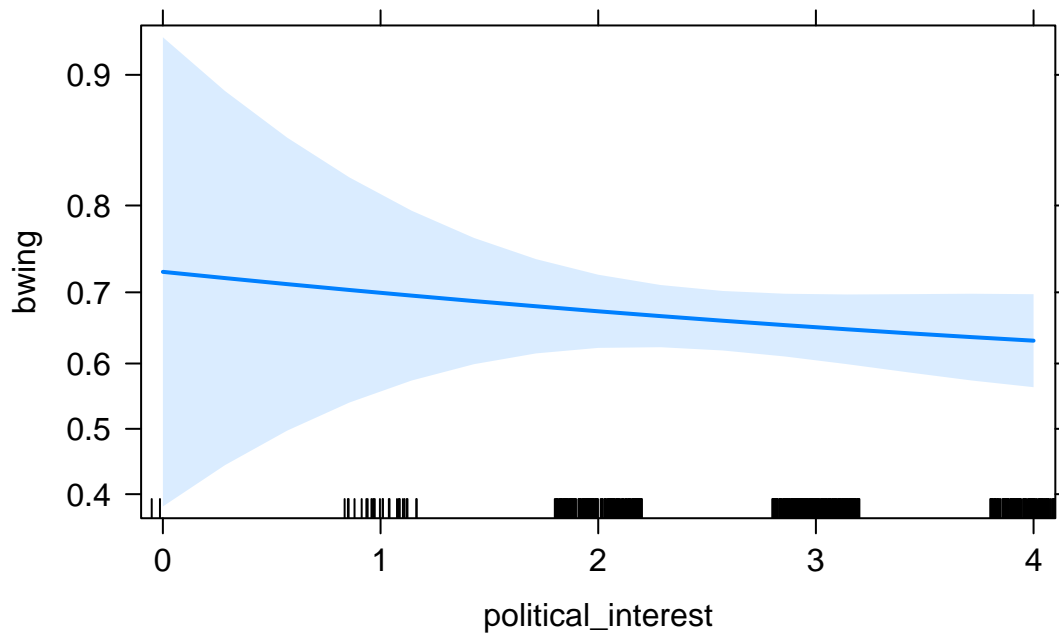

```
plot(allEffects(bhm1_polint_con_cb),ask=FALSE, main="Effects Political Interest Continuo
```

Effects Political Interest Continuous Cubed
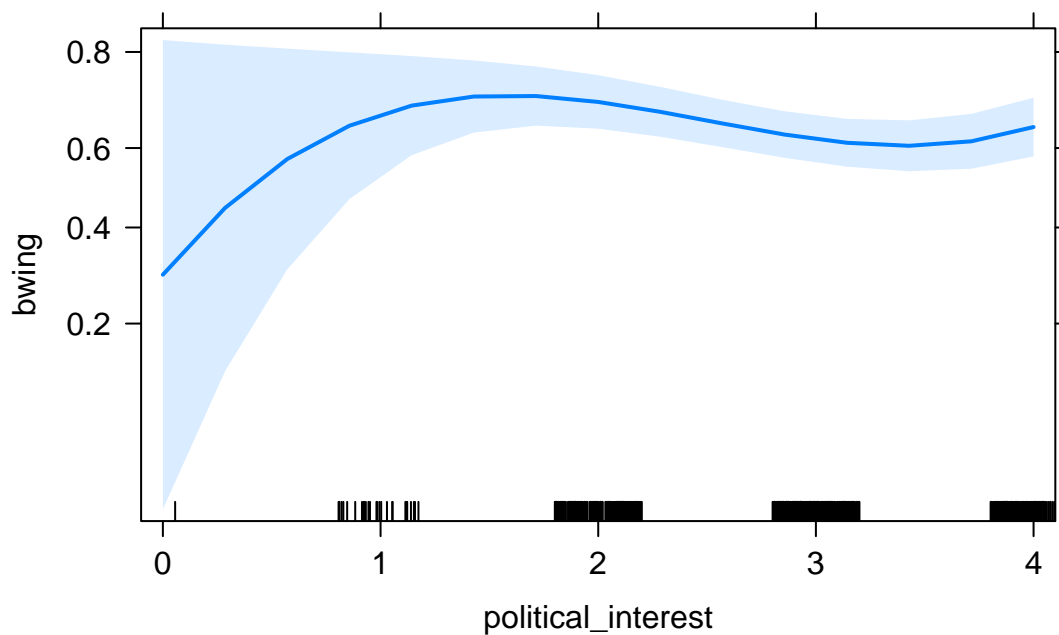

```
plot(allEffects(bhm1_polint_con_qd),ask=FALSE, main="Effects Political Interest Continuo
```

# Effects Political Interest Continuous Quadratic
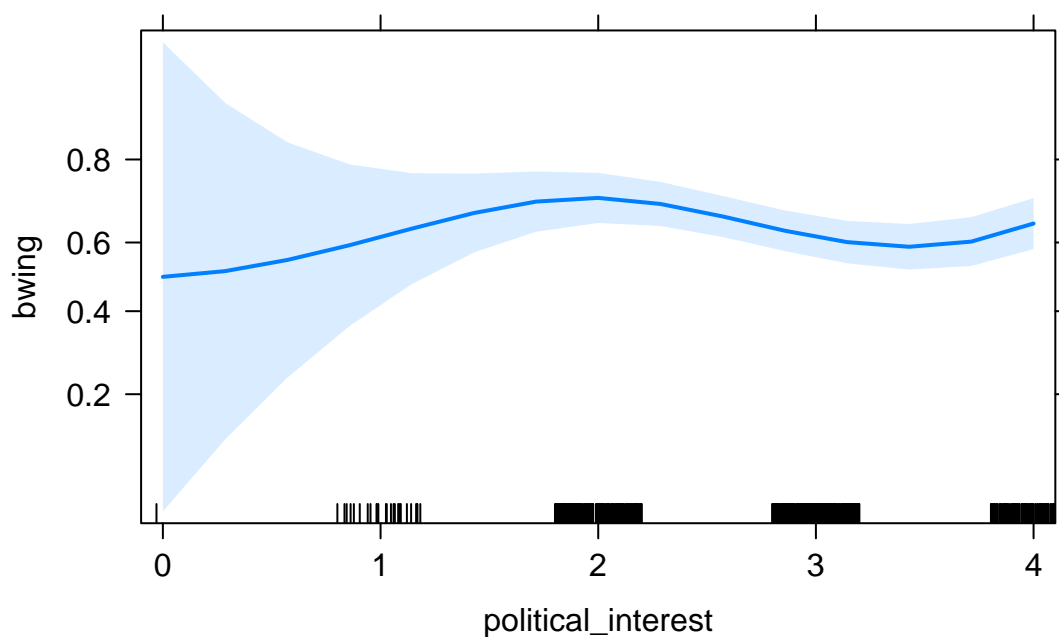

```
plot(allEffects(bhm1_polint_cat),ask=FALSE, main="Effects Political Interest Categorical
```

Effects Political Interest Categorical
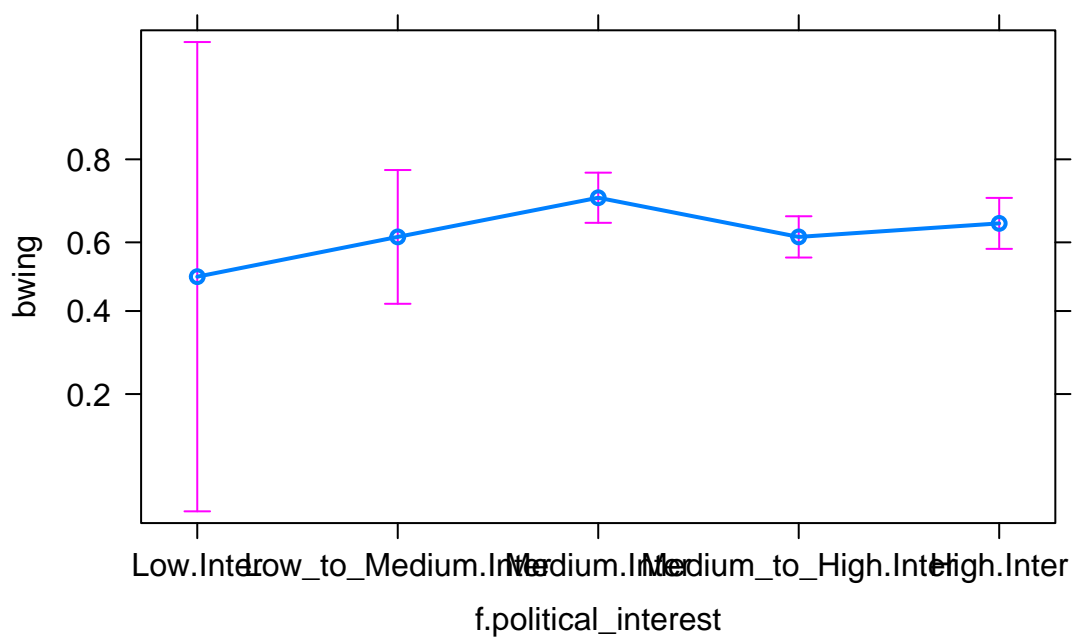

```
plot(allEffects(bhm1_polint_cat_new),ask=FALSE, main="Effects Political Interest Categor
```

Effects Political Interest Categorical
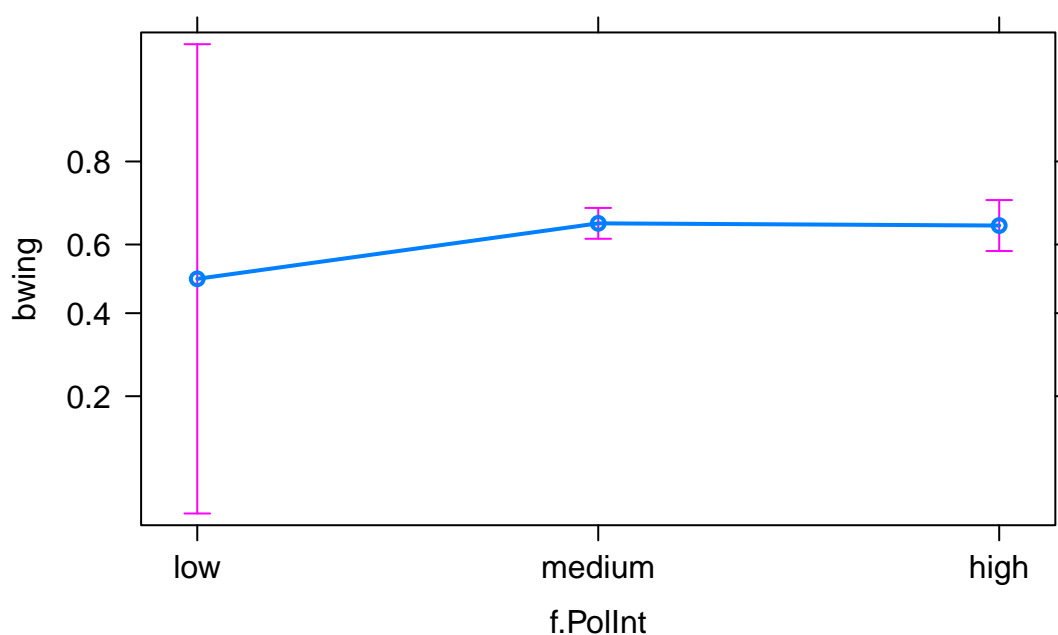

```
bhm0$dev - bhm1_inc_con$dev
```

```
## [1] 2.66419
```

```
bhm0$dev - bhm1_inc_con_sq$dev
```

```
## [1] 4.560265
```

```
bhm0$dev - bhm1_inc_con_cb$dev
```

```
## [1] 4.625955
```

```
bhm0$dev - bhm1_inc_con_qd$dev
```

```
## [1] 4.632596
```

```
bhm0$dev - bhm1_inc_cat$dev
```

```
## [1] 4.632596
```

```
bhm0$dev - bhm1_inc_cat_new$dev
```

```
## [1] 3.626678
```

```
anova(bhm1_inc_con, bhm1_inc_con_sq, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: bwing ~ income
## Model 2: bwing ~ poly(income, 2)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       702     903.37
## 2       701     901.48  1   1.8961   0.1685
```

```
anova(bhm1_inc_con_sq, bhm1_inc_con_cb, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: bwing ~ poly(income, 2)
## Model 2: bwing ~ poly(income, 3)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       701      901.48
## 2       700      901.41  1 0.065689   0.7977
```

```
anova(bhm1_inc_con_cb, bhm1_inc_con_qd, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: bwing ~ poly(income, 3)
## Model 2: bwing ~ poly(income, 4)
##   Resid. Df Resid. Dev Df  Deviance Pr(>Chi)
## 1       700      901.41
## 2       699      901.40  1 0.0066418    0.935
```

```
Anova(bhm1_inc_con, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##         Df  Chisq Pr(>Chisq)
## income   1 2.6707     0.1022
```

```
Anova(bhm1_inc_con_sq, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                 Df  Chisq Pr(>Chisq)
## poly(income, 2)  2 4.4295     0.1092
```

```
Anova(bhm1_inc_con_cb, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                 Df  Chisq Pr(>Chisq)
## poly(income, 3)  3 4.5237     0.2102
```

```
Anova(bhm1_inc_con_qd, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                 Df  Chisq Pr(>Chisq)
## poly(income, 4)  4 4.5337     0.3386
```

```
Anova(bhm1_inc_cat, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##          Df  Chisq Pr(>Chisq)
## f.income  4 4.5337     0.3386
```

```
Anova(bhm1_inc_cat_new, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##          Df  Chisq Pr(>Chisq)
## f.IncSat  3 3.5048     0.3201
```

```
plot(allEffects(bhm1_inc_con),ask=FALSE, main="Effects Income Continuous")
```


Effects Income Continuous
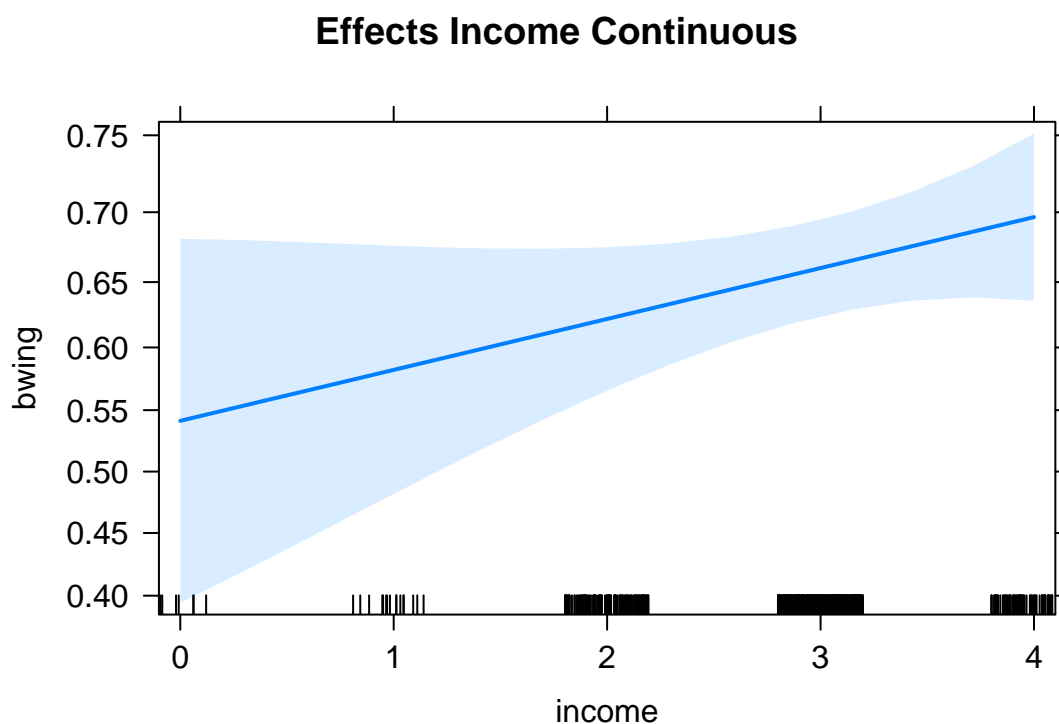
```
plot(allEffects(bhm1_inc_con_sq),ask=FALSE,main="Effects Income Continuous Squared")
```

Effects Income Continuous Squared
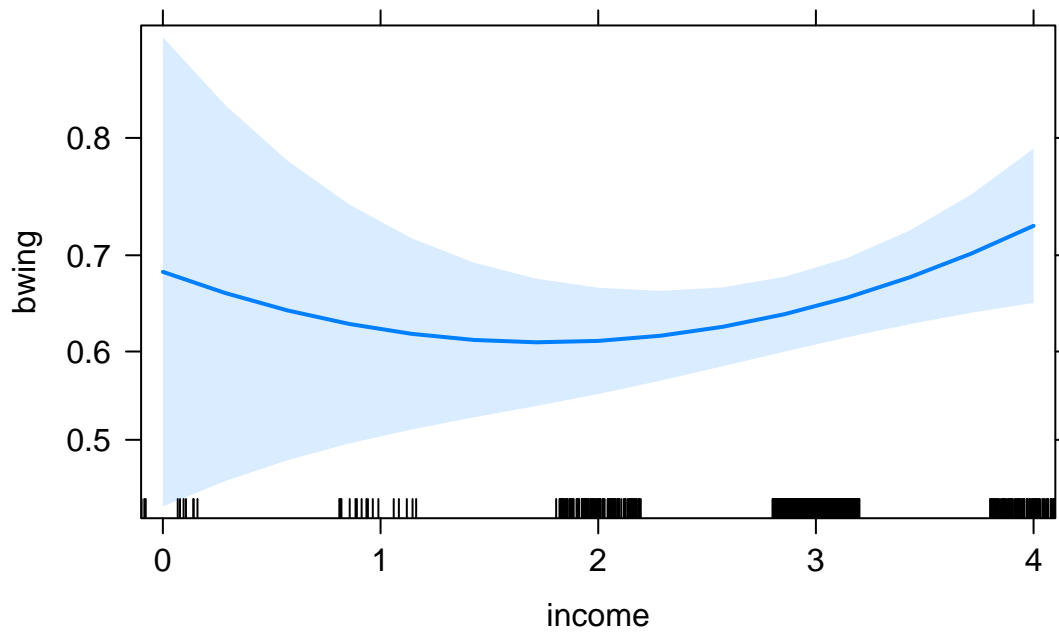

```
plot(allEffects(bhm1_inc_con_cb),ask=FALSE, main="Effects Income Continuous Cubed")
```

Effects Income Continuous Cubed
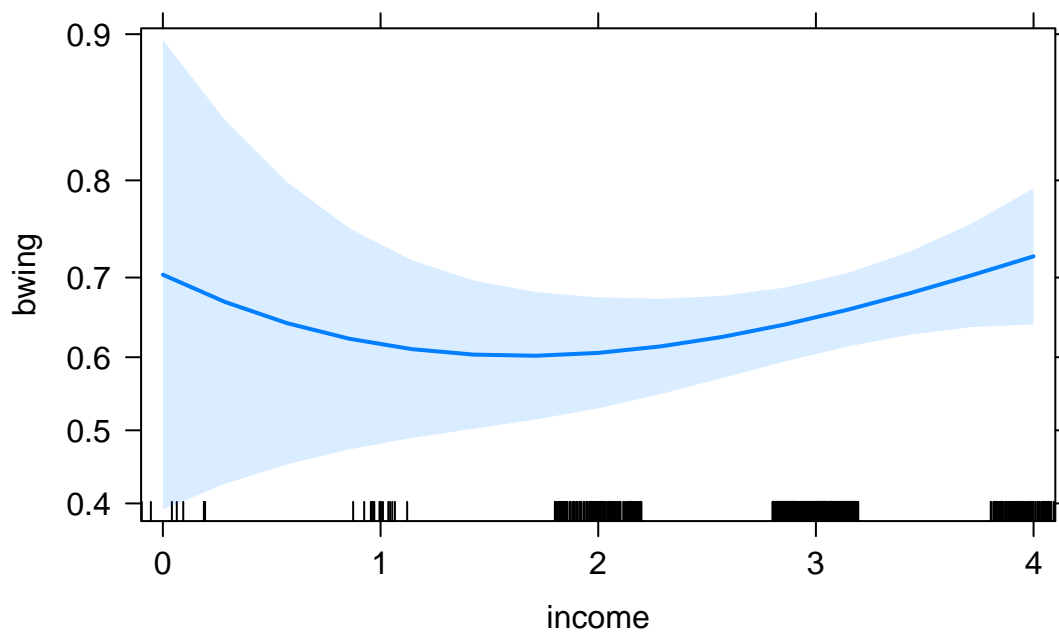

```
plot(allEffects(bhm1_inc_con_qd),ask=FALSE, main="Effects Income Interest Continuous Qua
```

Effects Income Interest Continuous Quadratic
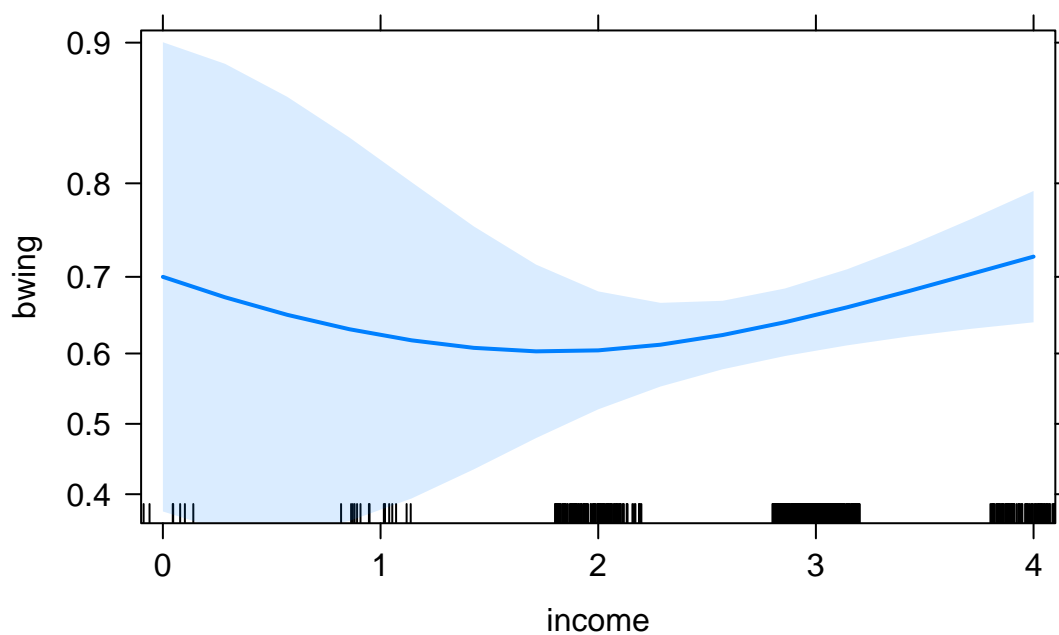
```
plot(allEffects(bhm1_inc_cat),ask=FALSE, main="Effects Income Interest Categorical")
```


Effects Income Interest Categorical
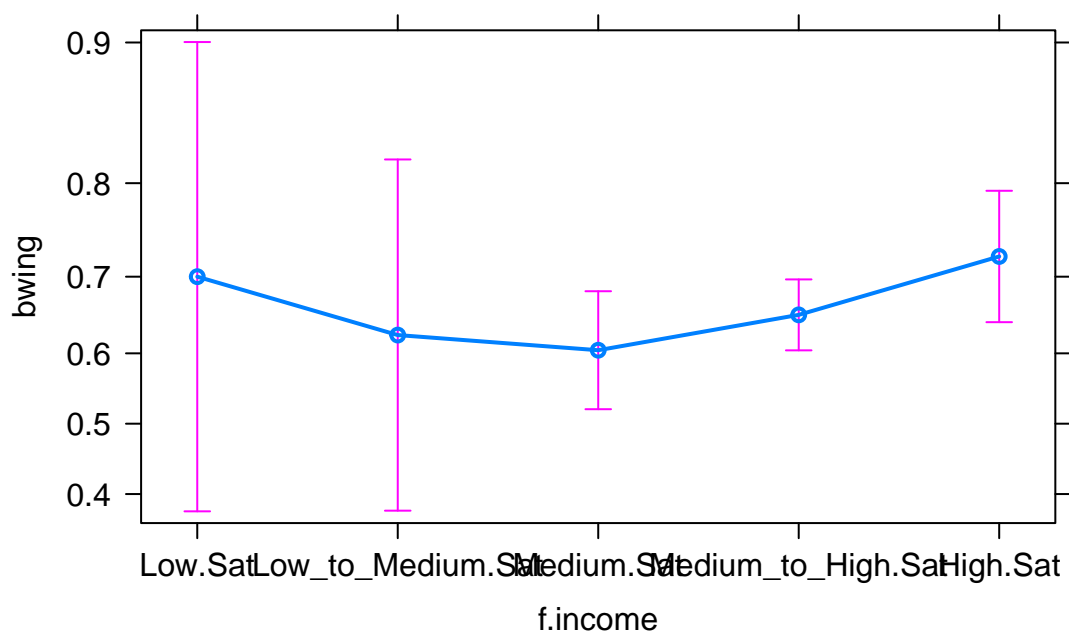
```
plot(allEffects(bhm1_inc_cat_new),ask=FALSE, main="Effects Income Interest Categorical")
```

Effects Income Interest Categorical
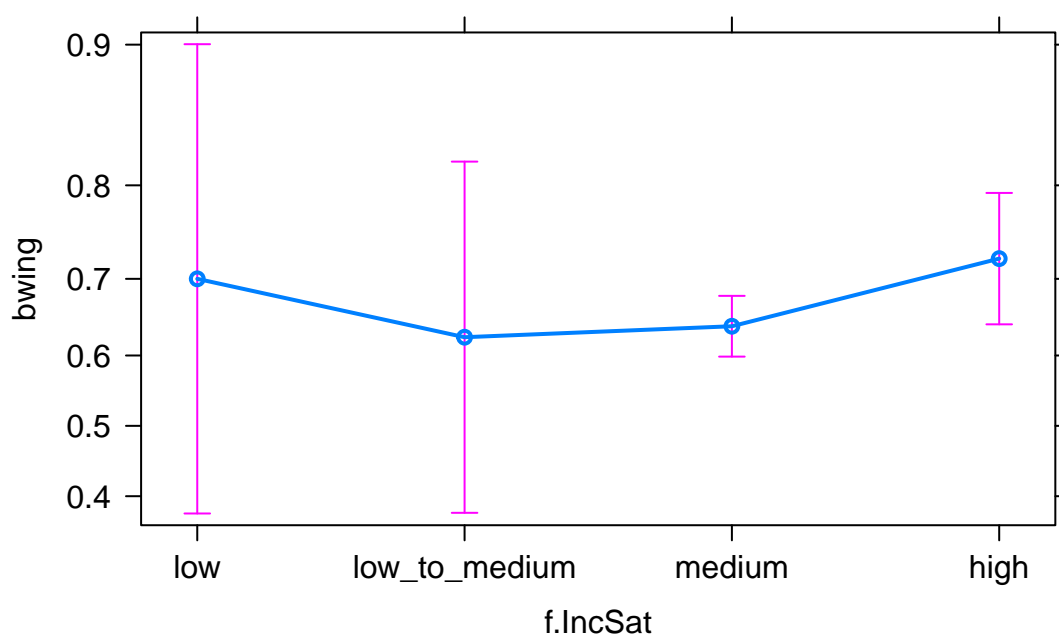

```
bh2m0$dev - bhm2_imm_con$dev
```

```
## [1] 84.36461
```

```
bh2m0$dev - bhm2_imm_con_sq$dev
```

```
## [1] 84.40058
```

```
bh2m0$dev - bhm2_imm_con_cb$dev
```

```
## [1] 95.40436
```

```
bh2m0$dev - bhm2_imm_con_qd$dev
```

```
## [1] 99.30075
```

```
anova(bhm2_imm_con, bhm2_imm_con_sq, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: f.political_orientation ~ egoposition_immigration
## Model 2: f.political_orientation ~ poly(egoposition_immigration, 2)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       240     156.72
## 2       239     156.68  1 0.035967   0.8496
```

```
anova(bhm2_imm_con_sq, bhm2_imm_con_cb, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: f.political_orientation ~ poly(egoposition_immigration, 2)
## Model 2: f.political_orientation ~ poly(egoposition_immigration, 3)
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1       239     156.68
```

```
## 2        238      145.68  1   11.004 0.0009093 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(bhm2_imm_con_cb, bhm2_imm_con_qd, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: f.political_orientation ~ poly(egoposition_immigration, 3)
## Model 2: f.political_orientation ~ poly(egoposition_immigration, 4)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       238     145.68
## 2       237     141.78  1   3.8964  0.04839 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm2_imm_con, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##                         Df  Chisq Pr(>Chisq)
## egoposition_immigration  1 52.916  3.482e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm2_imm_con_sq, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##                                Df  Chisq Pr(>Chisq)
## poly(egoposition_immigration, 2)  2 52.537  3.906e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm2_imm_con_cb, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##                                Df  Chisq Pr(>Chisq)
## poly(egoposition_immigration, 3)  3 61.847  2.369e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm2_imm_con_qd, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##                                Df Chisq Pr(>Chisq)
## poly(egoposition_immigration, 4)  4 65.88  1.679e-13 ***
## ---
```

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

```
Anova(bhm2_imm_cat, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##                              Df  Chisq Pr(>Chisq)
## f.egoposition_immigration 10 56.757   1.48e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(bhm2_imm_cat_new, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##        Df  Chisq Pr(>Chisq)
## f.Imm   4 70.592  1.702e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(allEffects(bhm2_imm_con),ask=FALSE, main="Effects Imm Continuous")
```

Effects Imm Continuous
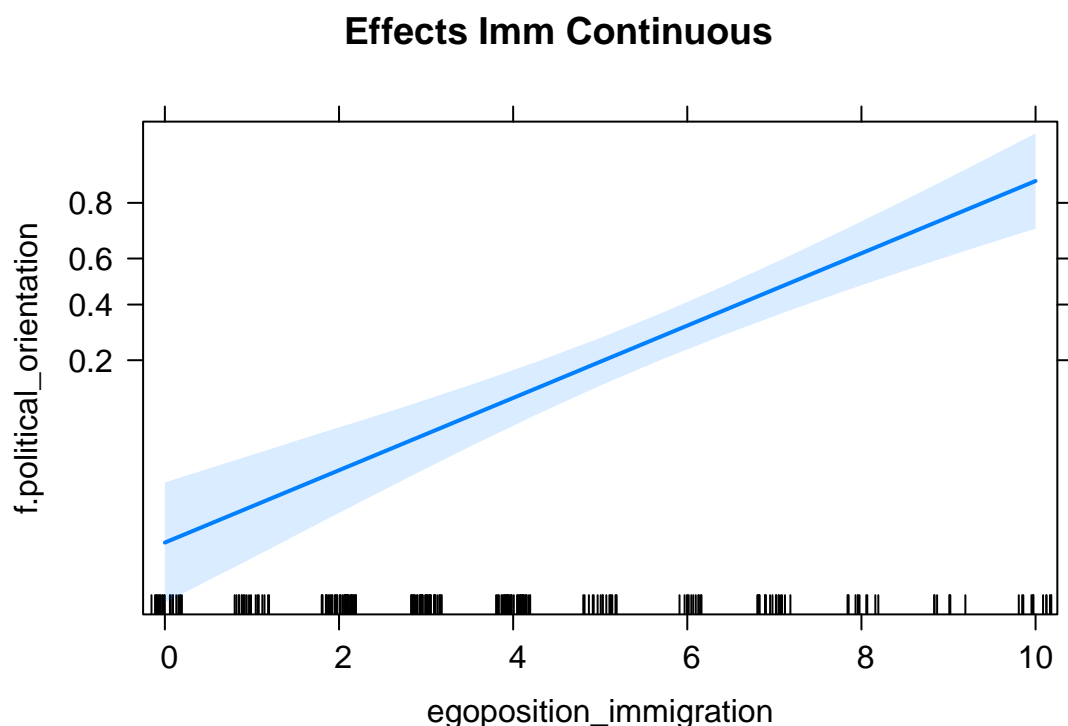

```
plot(allEffects(bhm2_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```

Effects Imm Continuous Squared
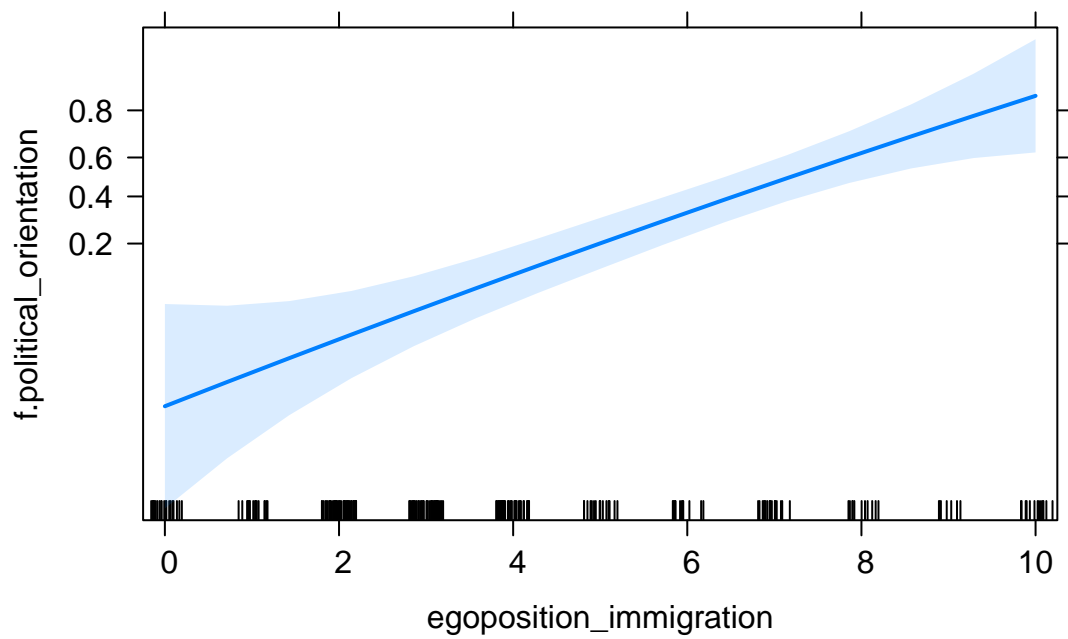

```
plot(allEffects(bhm2_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```

Effects Imm Continuous Cubed
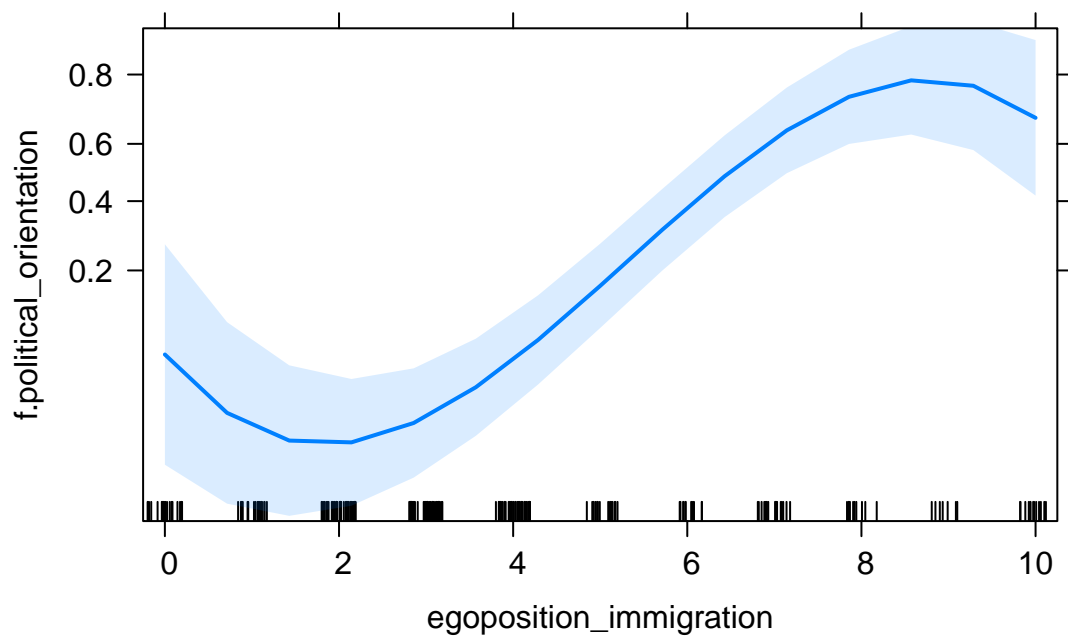

```
plot(allEffects(bhm2_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```

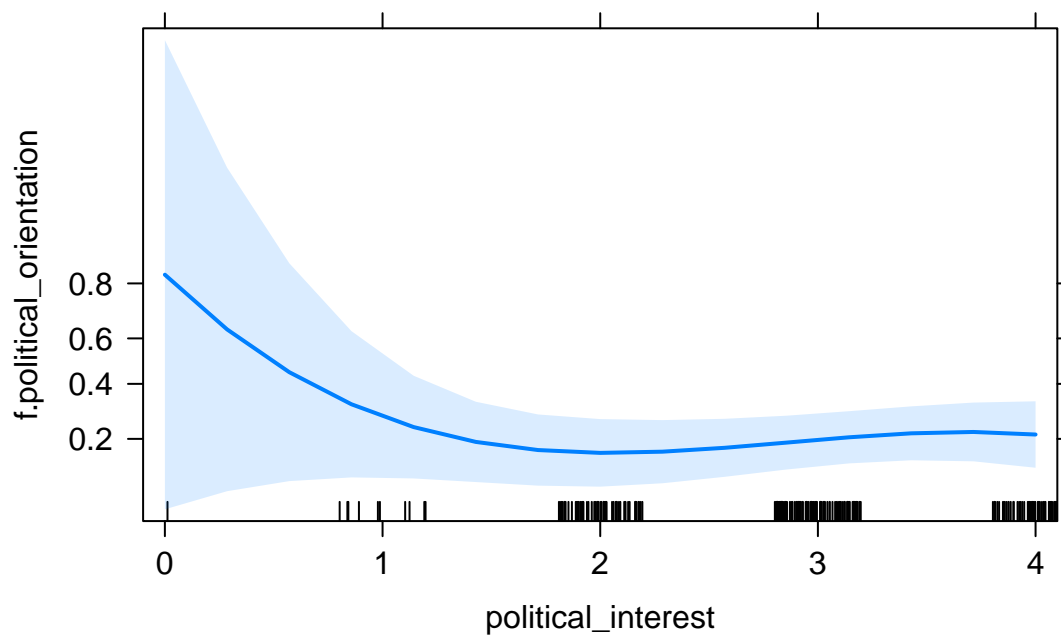## Effects Imm Continuous Quadratic
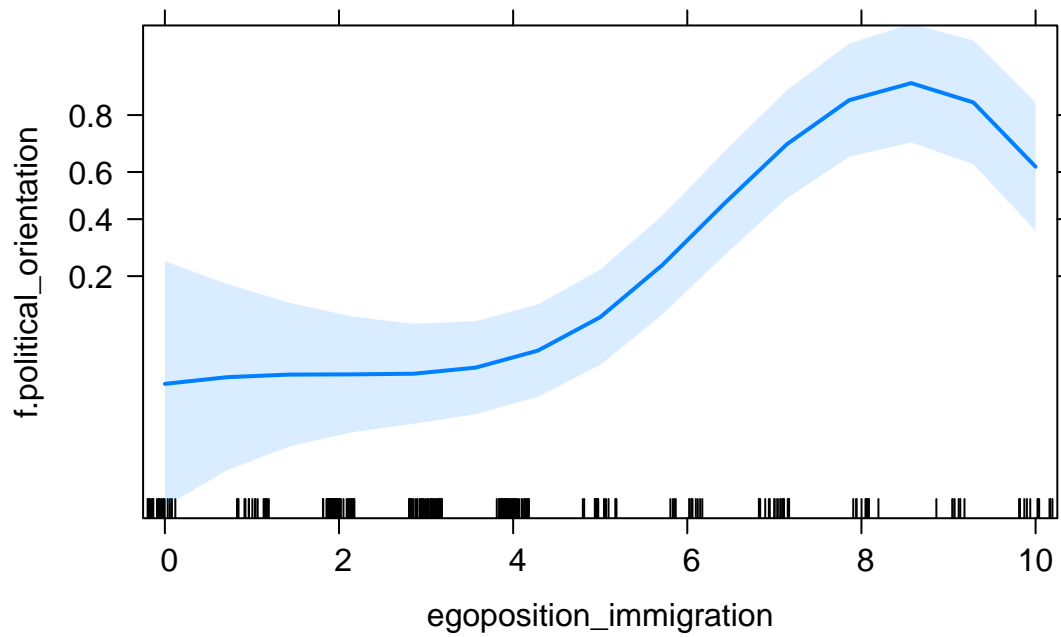

```
plot(allEffects(bhm2_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

Effects Imm Categorical
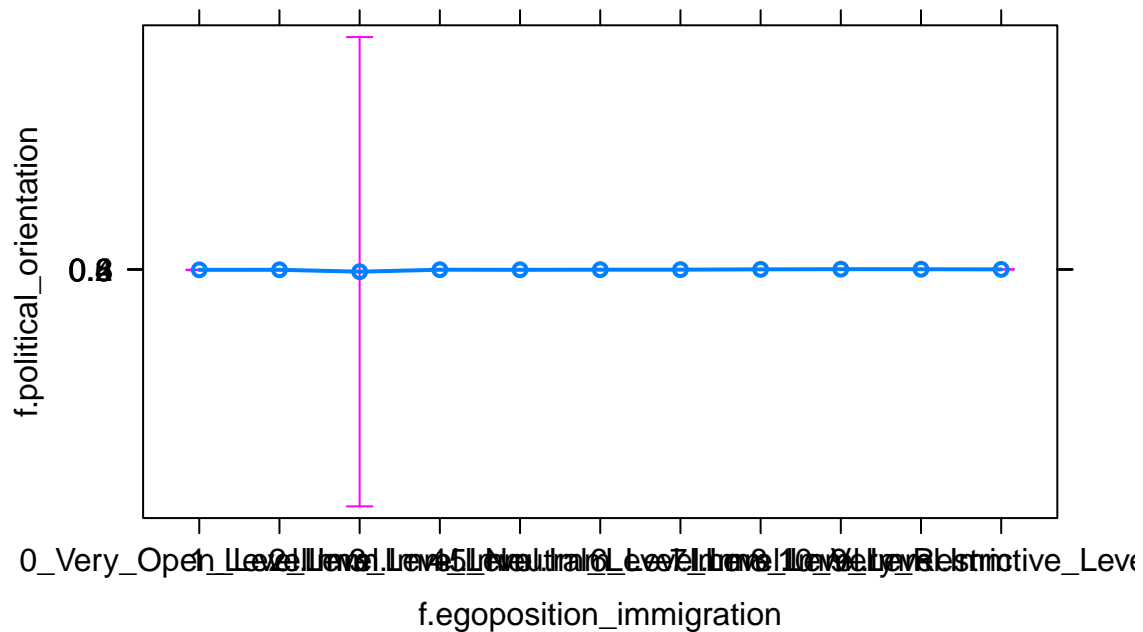

```
plot(allEffects(bhm2_imm_cat_new),ask=FALSE, main="Effects Imm Categorical")
```

Effects Imm Categorical
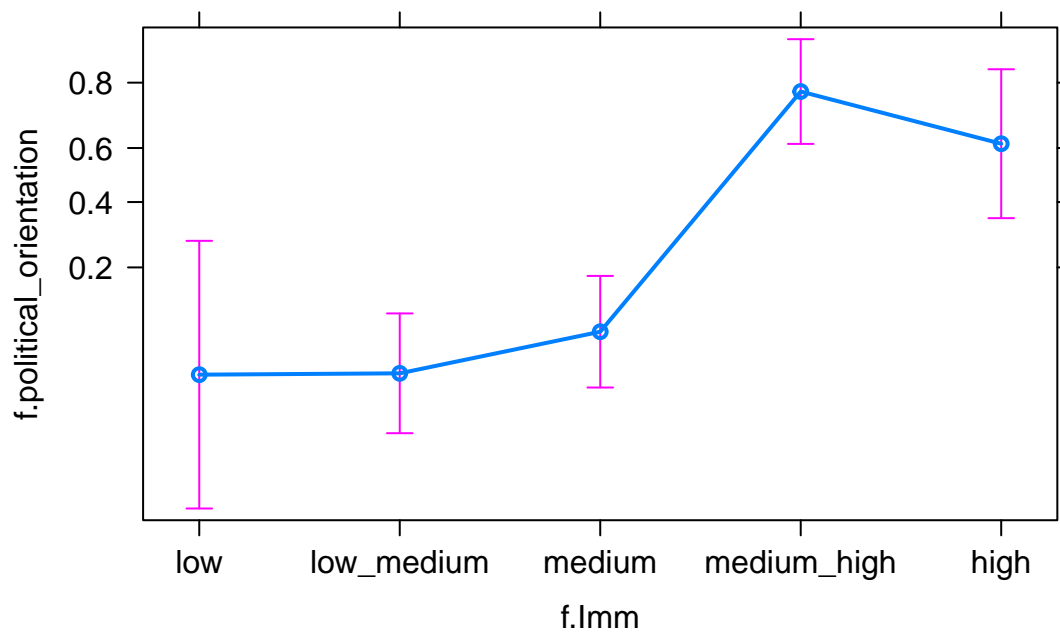

```
# bhm2_imm_con_qd is better concerning AIC
```

```
bh2m0$dev - bhm2_polint_con$dev
```

```
## [1] 0.001939783
```

```
bh2m0$dev - bhm2_polint_con_sq$dev
```

```
## [1] 1.531539
```

```
bh2m0$dev - bhm2_polint_con_cb$dev
```

```
## [1] 2.700847
```

```
bh2m0$dev - bhm2_polint_con_qd$dev
```

```
## [1] 3.520738
```

```
anova(bhm2_polint_con, bhm2_polint_con_sq, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: f.political_orientation ~ political_interest
## Model 2: f.political_orientation ~ poly(political_interest, 2)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       240     241.08
## 2       239     239.55  1   1.5296   0.2162
```

```
anova(bhm2_polint_con_sq, bhm2_polint_con_cb, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: f.political_orientation ~ poly(political_interest, 2)
## Model 2: f.political_orientation ~ poly(political_interest, 3)
```

```
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       239     239.55
## 2       238     238.38  1   1.1693   0.2795
```

```
anova(bhm2_polint_con_cb, bhm2_polint_con_qd, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: f.political_orientation ~ poly(political_interest, 3)
## Model 2: f.political_orientation ~ poly(political_interest, 4)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       238     238.38
## 2       237     237.56  1  0.81989   0.3652
```

```
Anova(bhm2_polint_con, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##                   Df  Chisq Pr(>Chisq)
## political_interest  1 0.0019     0.9649
```

```
Anova(bhm2_polint_con_sq, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##                          Df  Chisq Pr(>Chisq)
## poly(political_interest, 2)  2 1.5906     0.4514
```

```
Anova(bhm2_polint_con_cb, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##                          Df  Chisq Pr(>Chisq)
## poly(political_interest, 3)  3 2.1387     0.5441
```

```
Anova(bhm2_polint_con_qd, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##                          Df  Chisq Pr(>Chisq)
## poly(political_interest, 4)  4 0.2708     0.9916
```

```
Anova(bhm2_polint_cat, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##                    Df  Chisq Pr(>Chisq)
## f.political_interest  4 0.2708     0.9916
```

```
Anova(bhm2_polint_cat_new, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##            Df  Chisq Pr(>Chisq)
## f.PolInt   2 0.2351     0.8891
```

```
plot(allEffects(bhm2_polint_con),ask=FALSE, main="Effects polint Continuous")
```

Effects polint Continuous
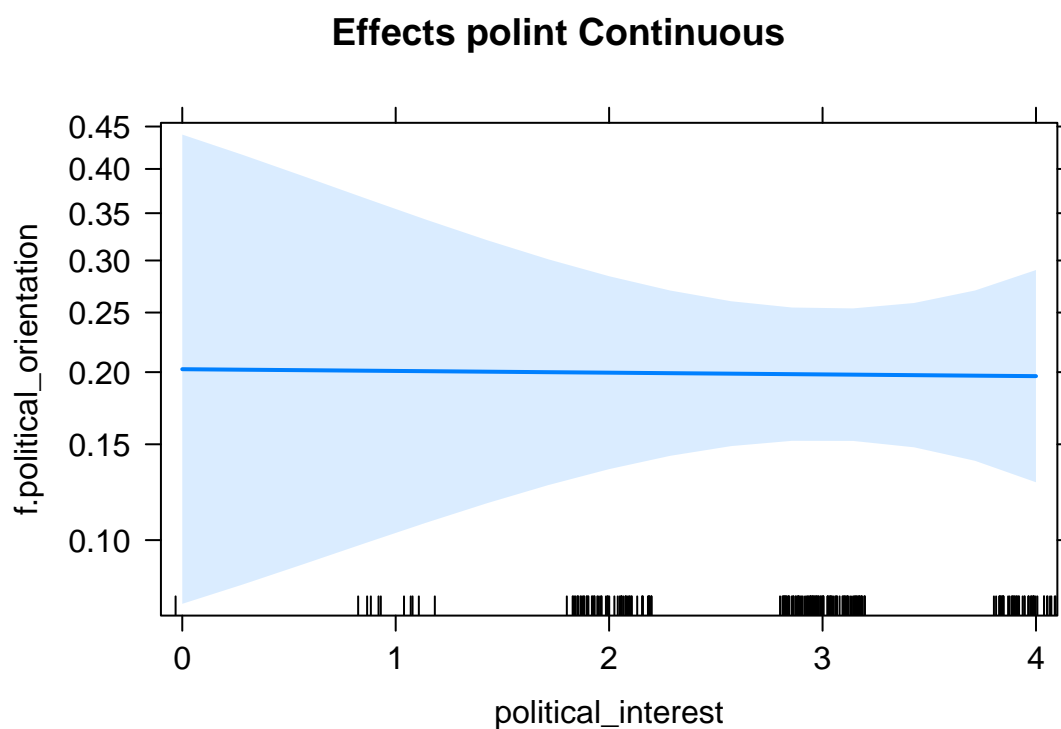

```
plot(allEffects(bhm2_polint_con_sq),ask=FALSE,main="Effects polint Continuous Squared")
```

Effects polint Continuous Squared
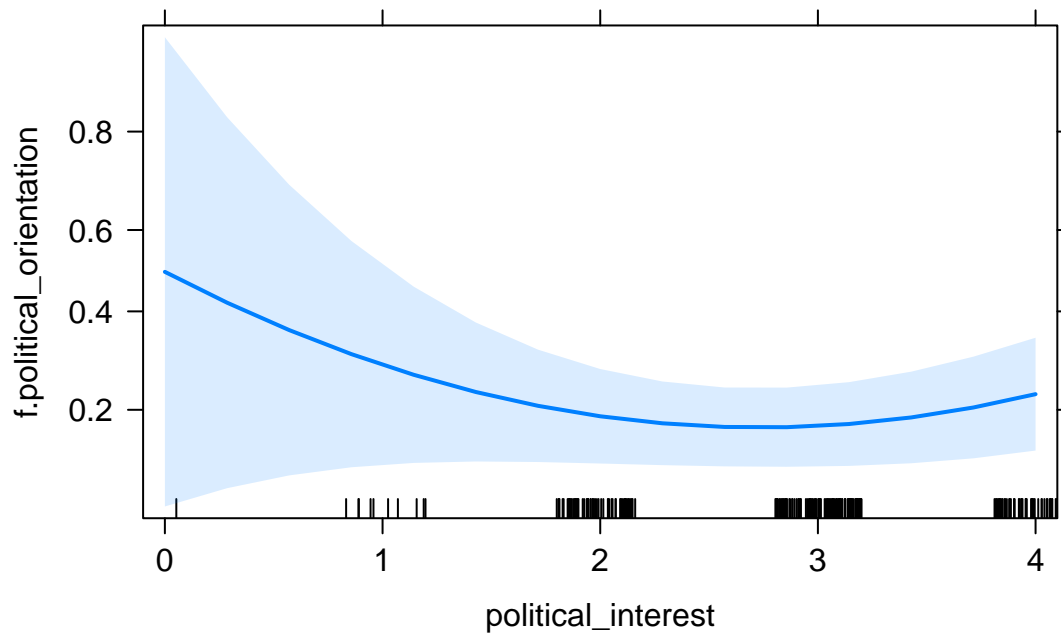

```
plot(allEffects(bhm2_polint_con_cb),ask=FALSE, main="Effects polint Continuous Cubed")
```

Effects polint Continuous Cubed


```
plot(allEffects(bhm2_polint_con_qd),ask=FALSE, main="Effects polint Continuous Quadratic
```

Effects polint Continuous Quadratic
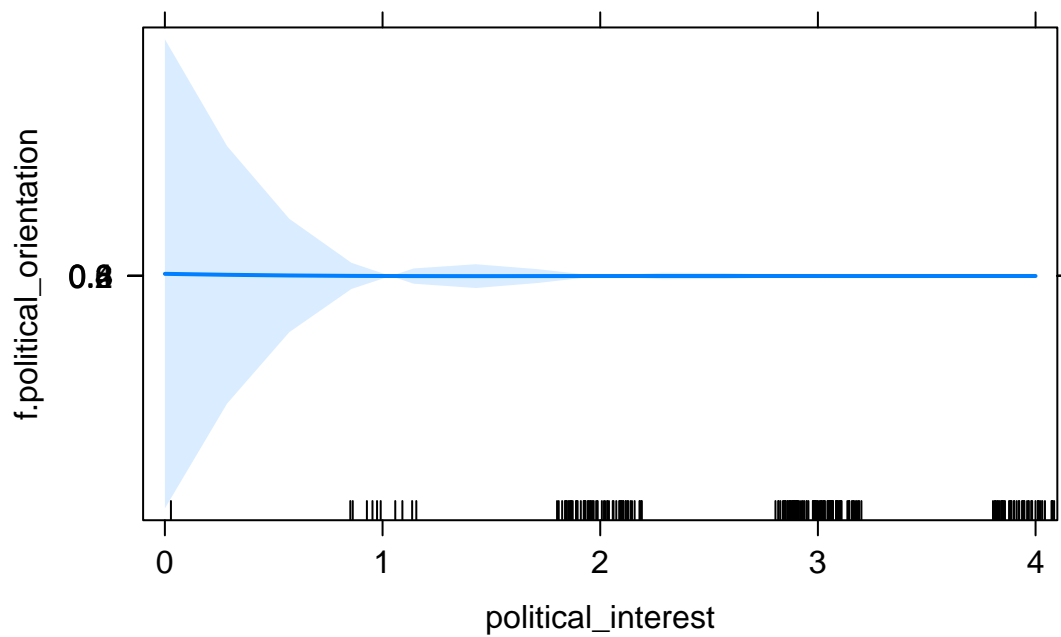

```
plot(allEffects(bhm2_polint_cat),ask=FALSE, main="Effects polint Categorical")
```

Effects polint Categorical
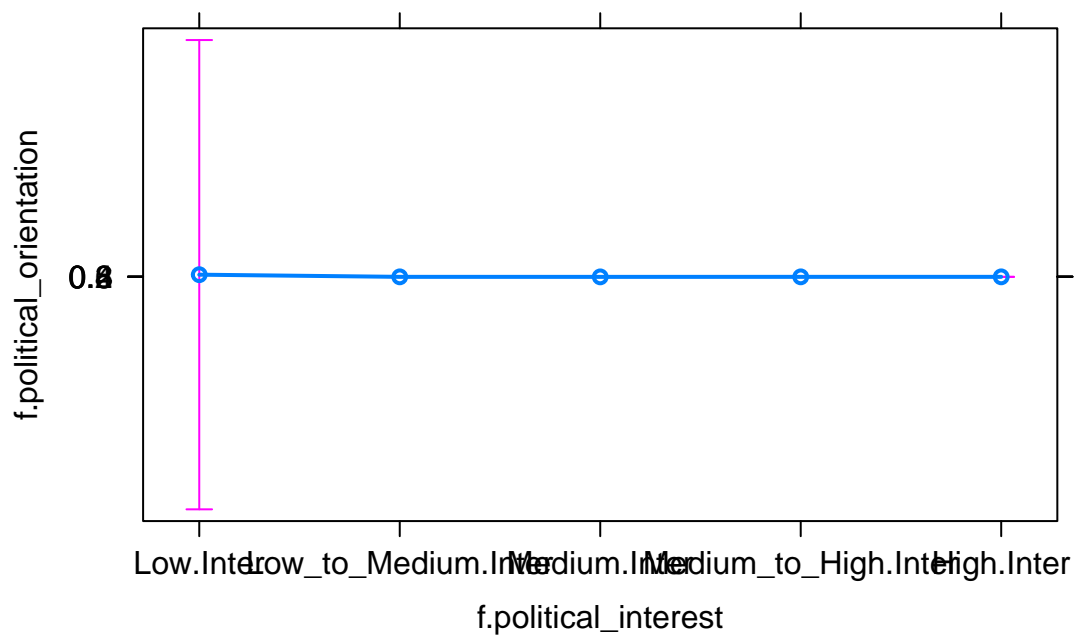

```
plot(allEffects(bhm2_polint_cat_new),ask=FALSE, main="Effects polint Categorical")
```

Effects polint Categorical
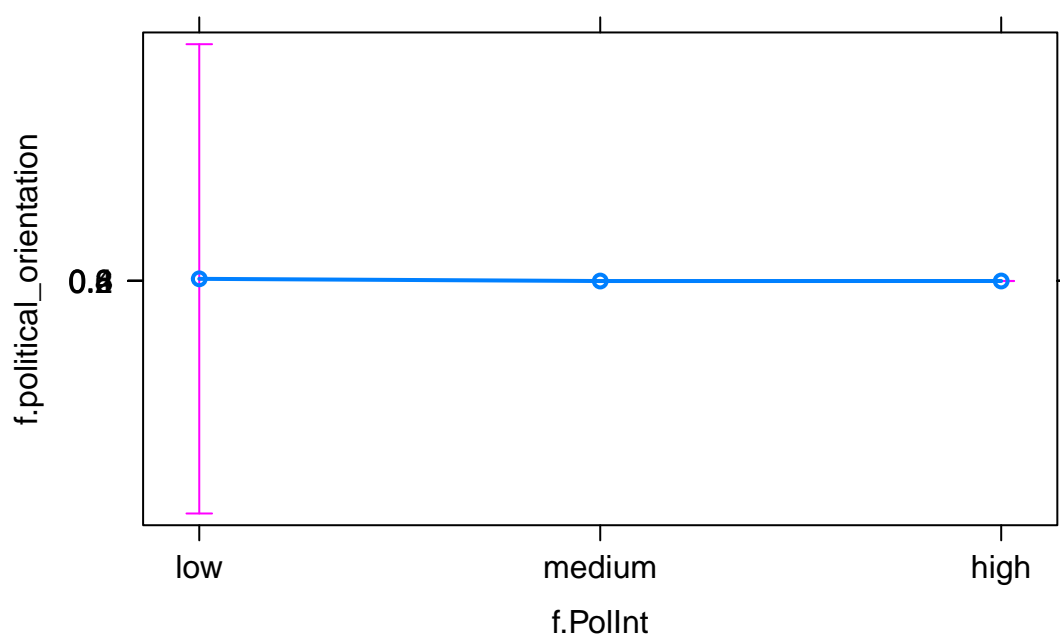

```
bh2m0$dev - bhm2_inc_con$dev
```

```
## [1] 0.003212806
```

```
bh2m0$dev - bhm2_inc_con_sq$dev
```

```
## [1] 0.2958203
```

```
bh2m0$dev - bhm2_inc_con_cb$dev
```

```
## [1] 5.451673
```

```
bh2m0$dev - bhm2_inc_con_qd$dev
```

```
## [1] 5.749227
```

```
anova(bhm2_inc_con, bhm2_inc_con_sq, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: f.political_orientation ~ income
## Model 2: f.political_orientation ~ poly(income, 2)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       240     241.08
## 2       239     240.79  1  0.29261   0.5886
```

```
anova(bhm2_inc_con_sq, bhm2_inc_con_cb, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: f.political_orientation ~ poly(income, 2)
## Model 2: f.political_orientation ~ poly(income, 3)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       239     240.79
```

```
## 2         238     235.63  1   5.1559  0.02317 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(bhm2_inc_con_cb, bhm2_inc_con_qd, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: f.political_orientation ~ poly(income, 3)
## Model 2: f.political_orientation ~ poly(income, 4)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       238     235.63
## 2       237     235.33  1  0.29755   0.5854
```

```
Anova(bhm2_inc_con, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##        Df  Chisq Pr(>Chisq)
## income  1 0.0032     0.9548
```

```
Anova(bhm2_inc_con_sq, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##               Df Chisq Pr(>Chisq)
## poly(income, 2)  2  0.31     0.8564
```

```
Anova(bhm2_inc_con_cb, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##               Df  Chisq Pr(>Chisq)
## poly(income, 3)  3 5.0218     0.1702
```

```
Anova(bhm2_inc_con_qd, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##               Df  Chisq Pr(>Chisq)
## poly(income, 4)  4 4.4184     0.3523
```

```
Anova(bhm2_inc_cat, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##         Df  Chisq Pr(>Chisq)
## f.income  4 4.4184     0.3523
```

```
Anova(bhm2_inc_cat_new, test="Wald")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##          Df  Chisq Pr(>Chisq)
## f.IncSat  3 2.0817     0.5556
```

```
plot(allEffects(bhm2_inc_con),ask=FALSE, main="Effects inc Continuous")
```

Effects inc Continuous
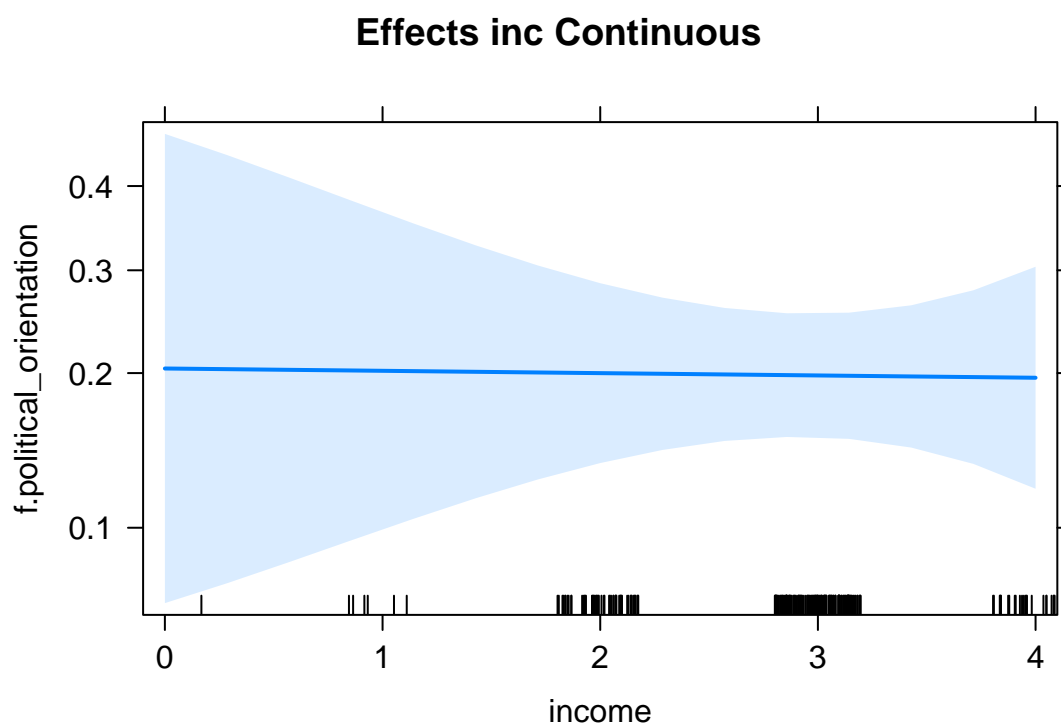

```
plot(allEffects(bhm2_inc_con_sq),ask=FALSE,main="Effects inc Continuous Squared")
```

Effects inc Continuous Squared
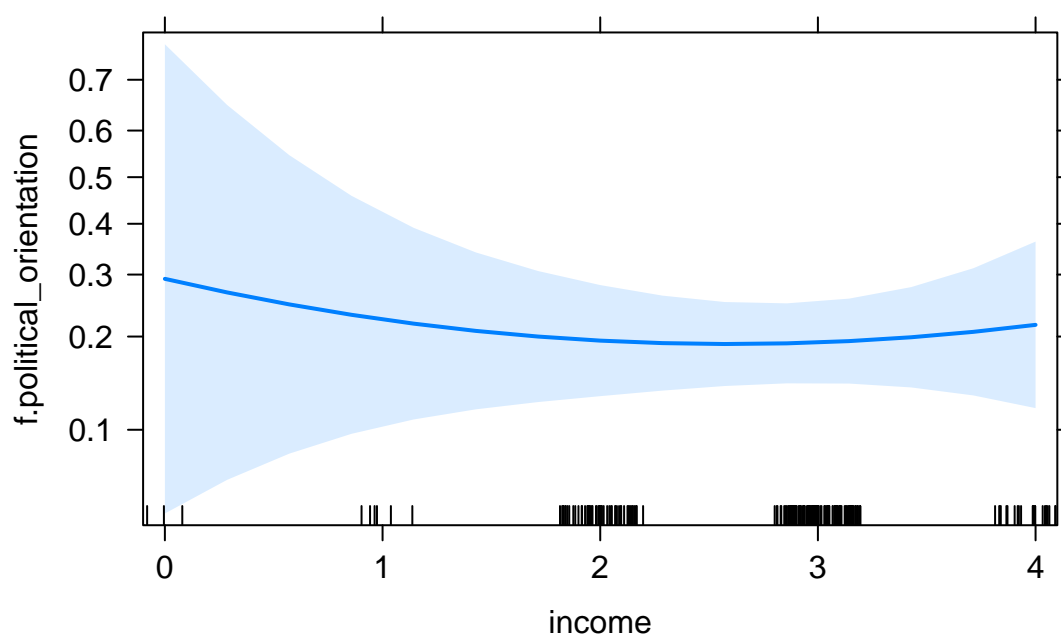

```
plot(allEffects(bhm2_inc_con_cb),ask=FALSE, main="Effects inc Continuous Cubed")
```

Effects inc Continuous Cubed
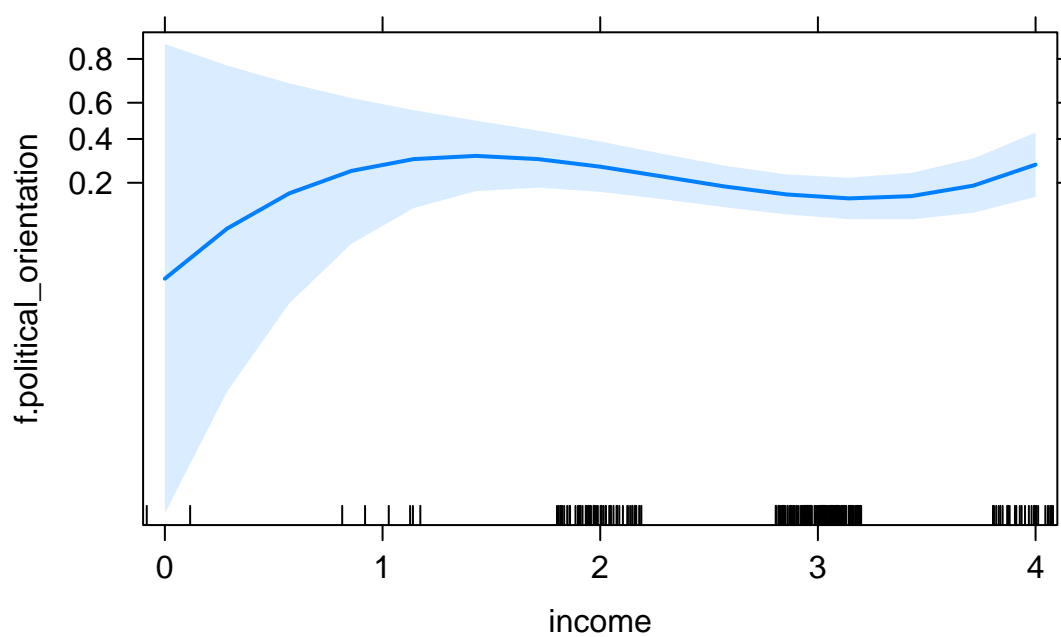

```
plot(allEffects(bhm2_inc_con_qd),ask=FALSE, main="Effects inc Continuous Quadratic")
```

Effects inc Continuous Quadratic
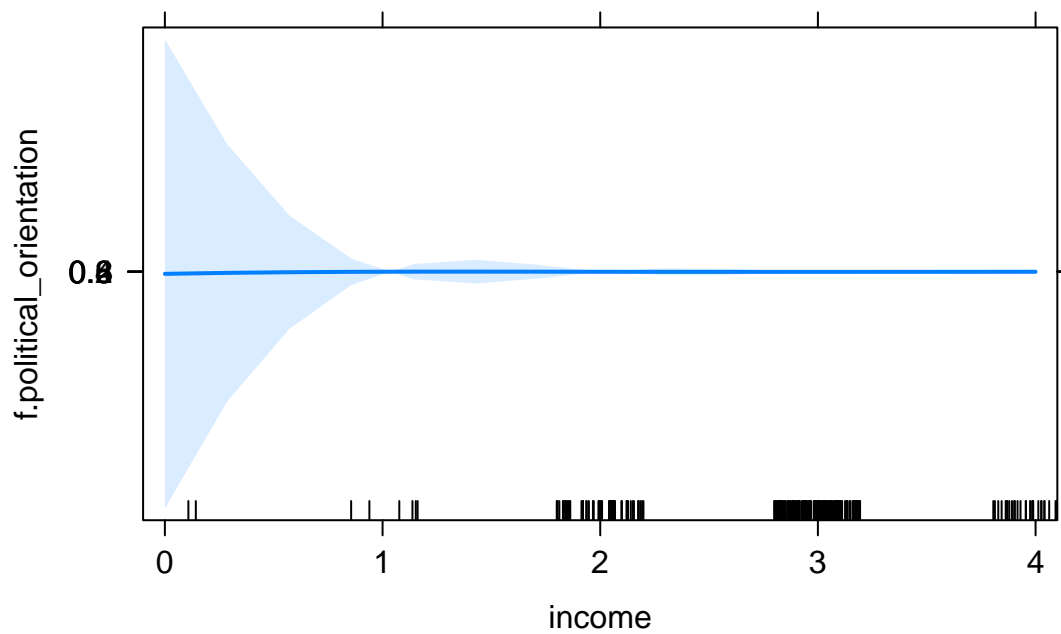

```
plot(allEffects(bhm2_inc_cat),ask=FALSE, main="Effects inc Categorical")
```

Effects inc Categorical
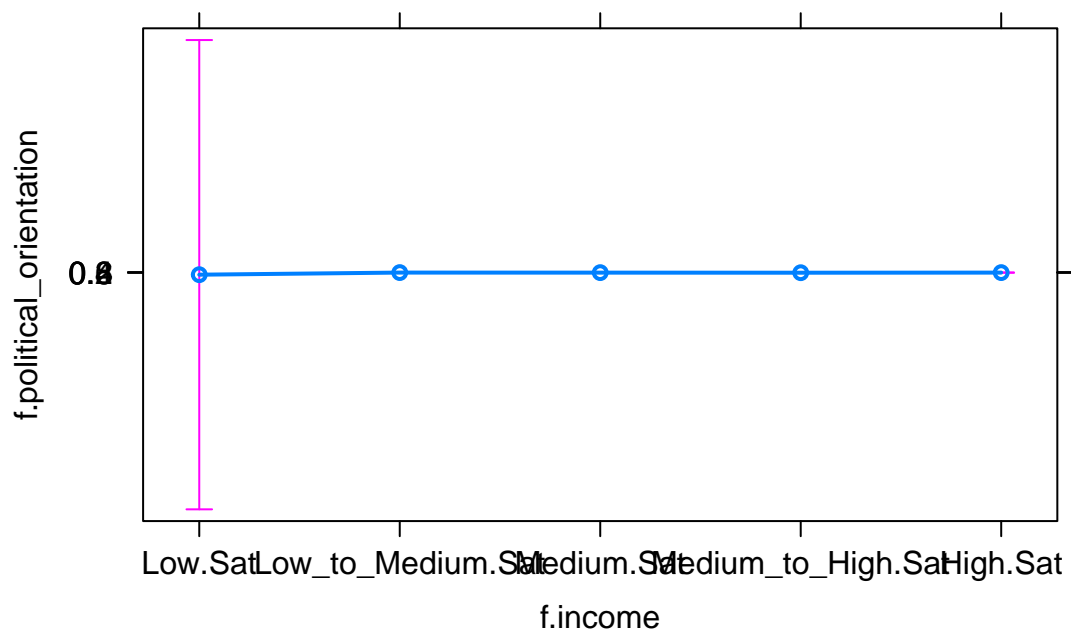

```
plot(allEffects(bhm2_inc_cat_new),ask=FALSE, main="Effects inc Categorical")
```

Effects inc Categorical
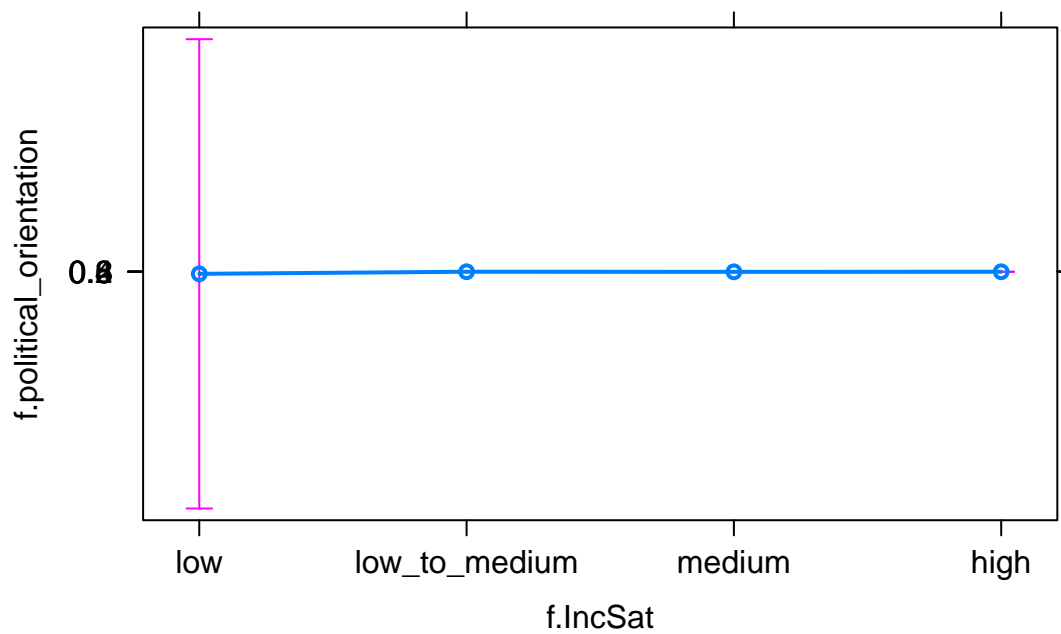
4.3.4 Influential Data

LAYER 1

```
residualPlots(layer1, layout=c(2, 1))
```
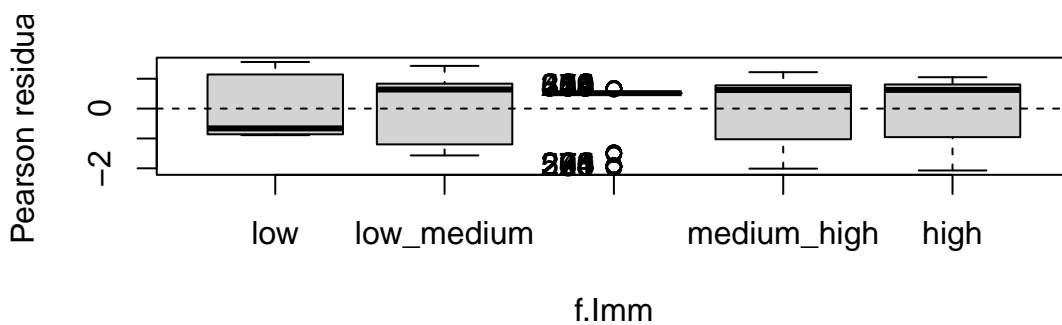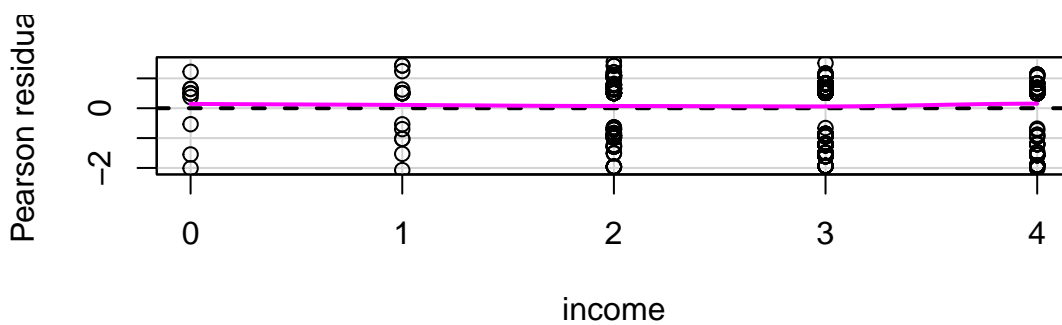


```
##                 Test stat Pr(>|Test stat|)
## income            0.3272           0.5673
## f.Imm
## f.eastGermany
```

```
avPlots(layer1,id=list(n=5))
```
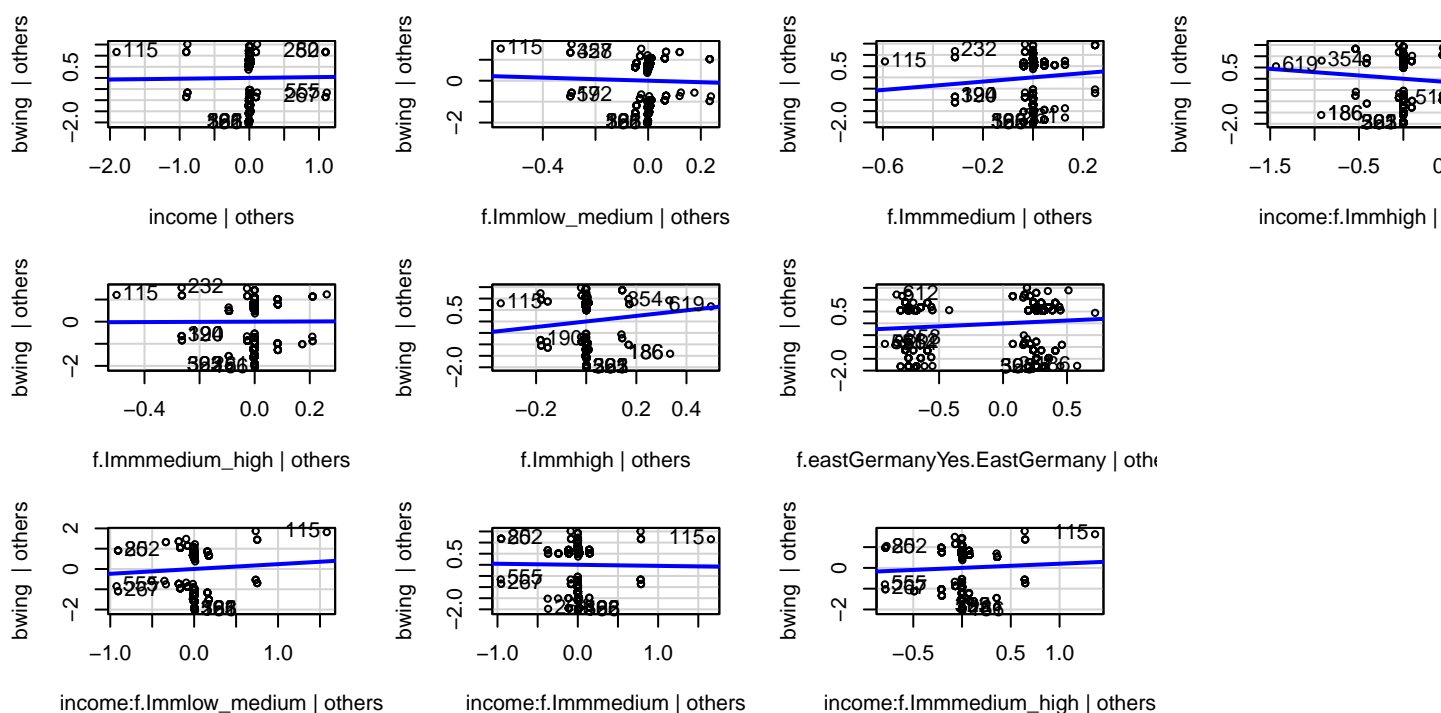


```
influenceIndexPlot(layer1,id=list(n=20),vars=c("Cook", "Student","hat"))
```



```
influencePlot(layer1,id=list(method="noteworthy"))
```
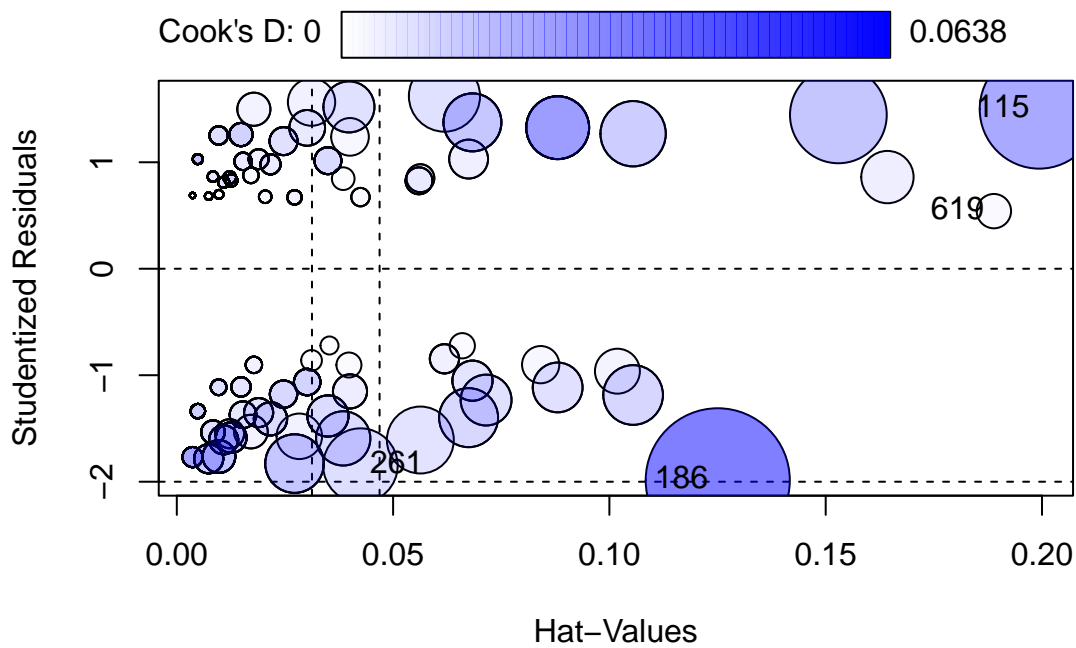
```
##          StudRes        Hat        CookD
## 115   1.4984544  0.19935318  0.043472427
## 186  -1.9868059  0.12504695  0.063779519
## 261  -1.8485185  0.04245303  0.017034566
## 619   0.5409559  0.18888395  0.003627381
```
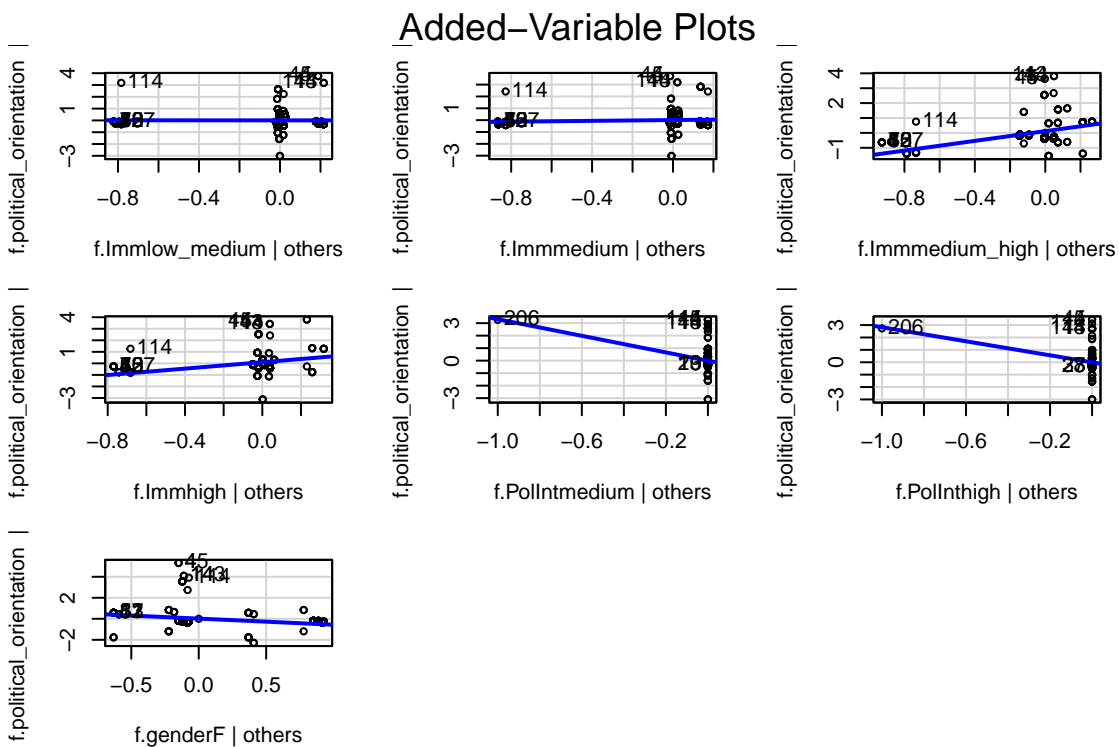
LAYER 2

```
residualPlots(layer2, layout=c(2, 1))
```
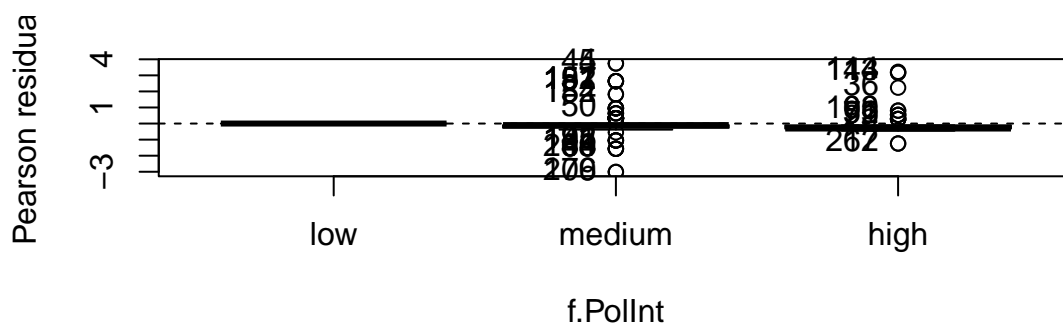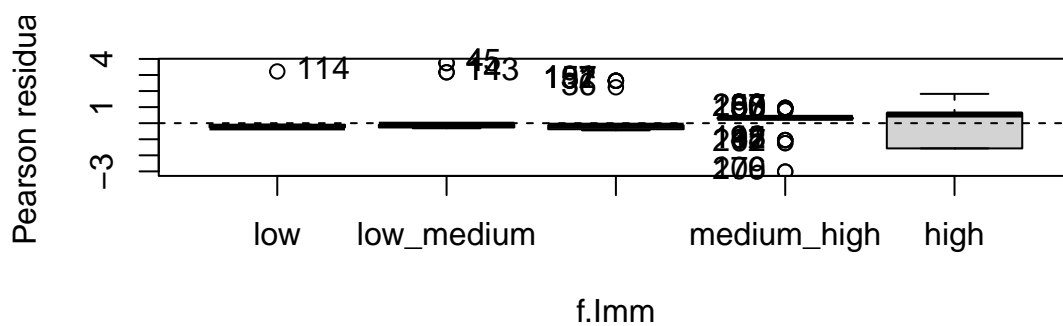
```
## Warning in residualPlots.default(model, ...): No possible lack-of-fit tests
```
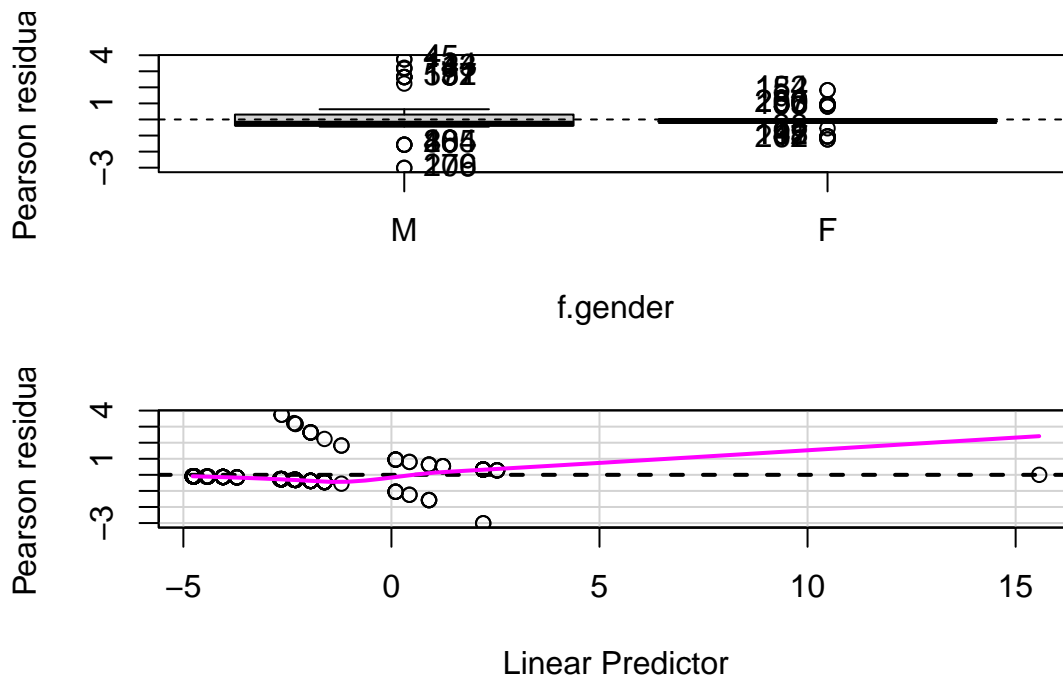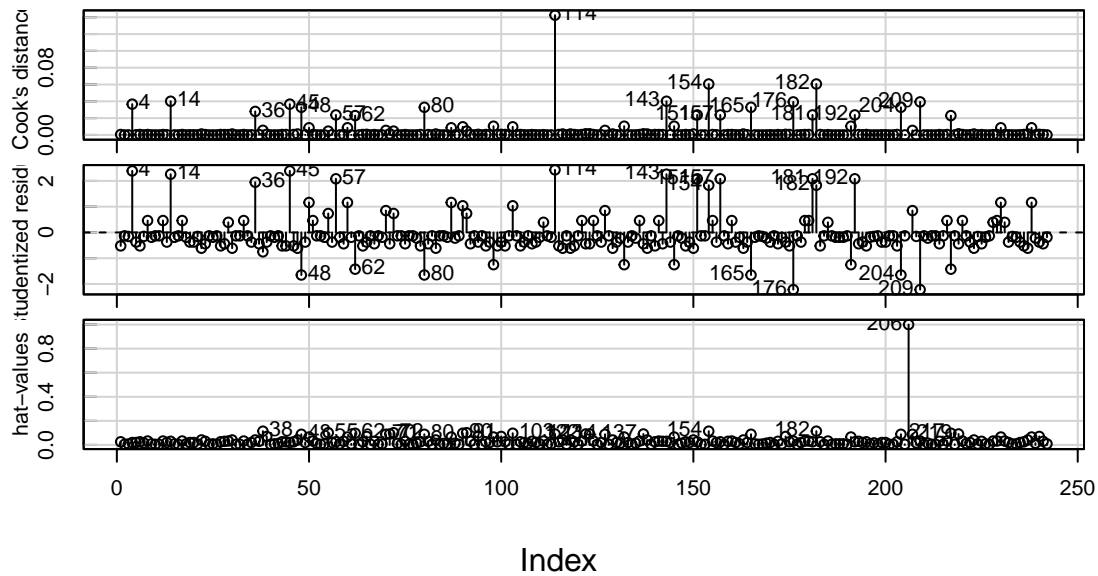


```
avPlots(layer2,id=list(n=5))
```
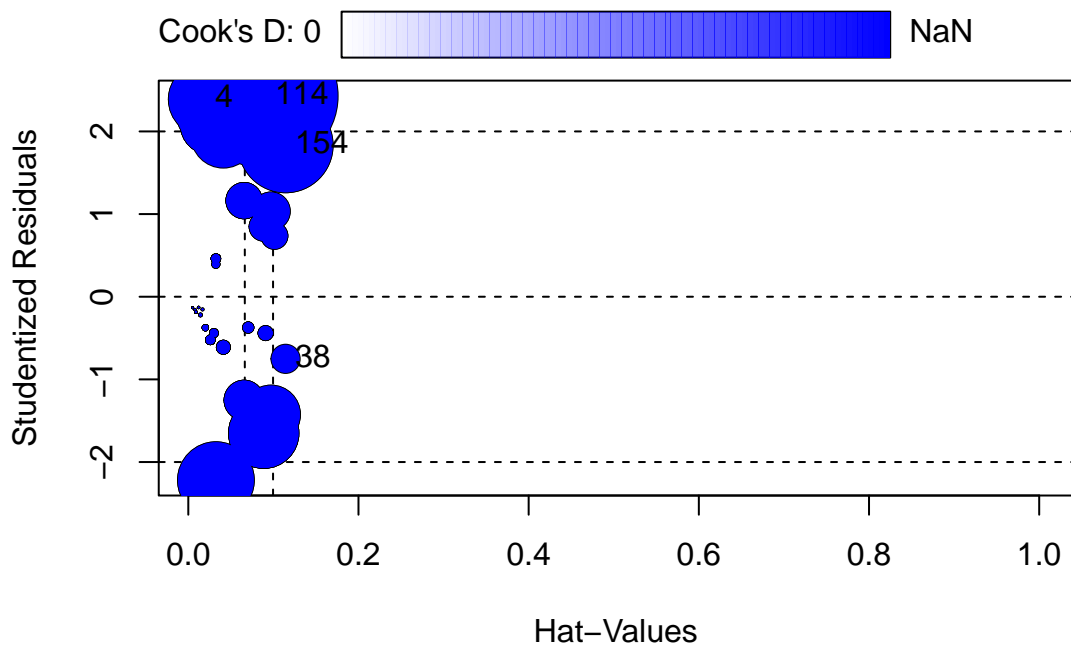

Added−Variable Plots

```
influenceIndexPlot(layer2,id=list(n=20),vars=c("Cook", "Student","hat"))
```

Diagnostic Plots

```
influencePlot(layer2,id=list(method="noteworthy"))
```



```
##        StudRes        Hat       CookD
## 4    2.3879624 0.02010491 0.036625502
## 38  -0.7514112 0.11430610 0.005477099
## 114  2.4288202 0.09081611 0.142481145
## 154  1.8325554 0.11430610 0.060572236
## 206        NaN 1.00000000        NaN
```