



Assignment 2 - Vote Choice in Germany
Statistical Inference and Modelling - SIM
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Ander Barrio Campos, Odysseas Kyparissis

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1 Explanatory Data Analysis - EDA

1.1 Loading Voting Data

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

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

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

1.2 Data Types

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

1.3 Checking for Missing Data

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

1.4 Checking for Duplicates

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

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

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

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

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

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

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

1.5 Creating Factors for Qualitative Variables

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

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

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

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

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

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

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

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(quantData, sd)
```

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

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

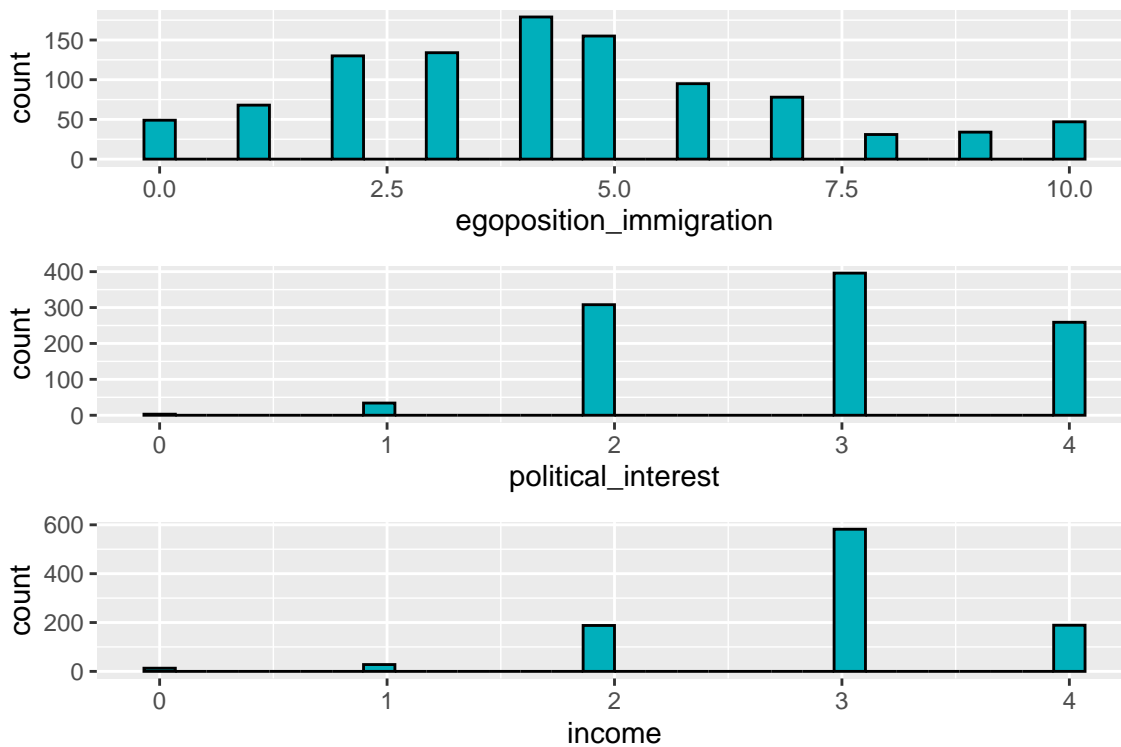
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.000   3.000   4.000   4.361   6.000   10.000
```

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

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

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

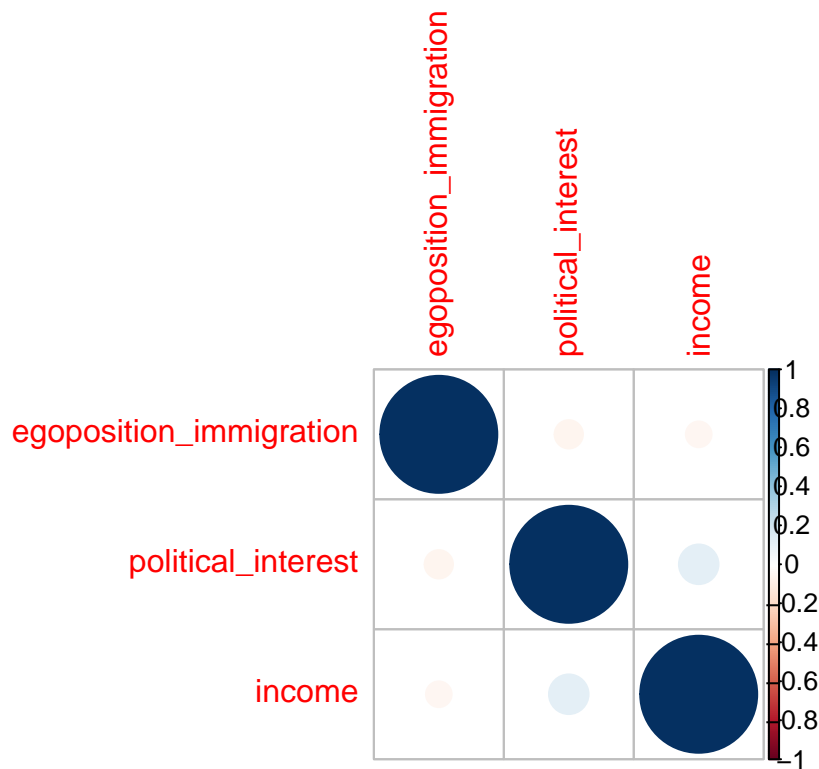
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.000   3.000   3.000   2.906   3.000   4.000
```



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

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

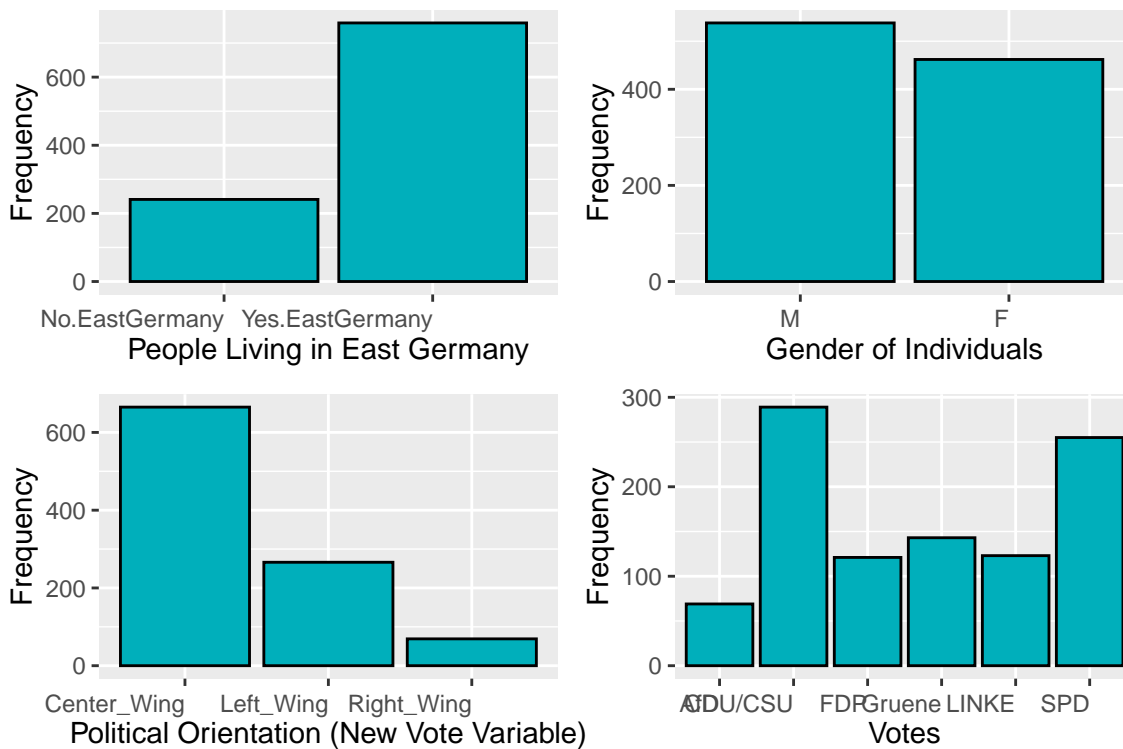
```
##               egoposition_immigration political_interest      income
## egoposition_immigration      1.00000000      -0.05861542 -0.04823165
## political_interest          -0.05861542       1.00000000  0.11449194
## income                     -0.04823165       0.11449194  1.00000000
```



1.7.3 Descriptive Analysis for Categorical Variables

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

1.7.4 Bar Plots



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

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

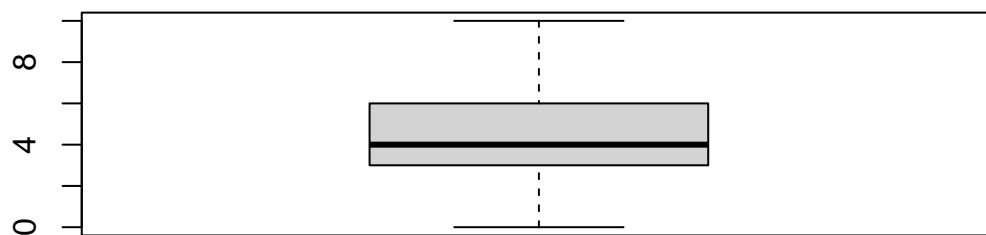
1.8 Outliers Detection

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

1.8.1 Uni-variate Outliers

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

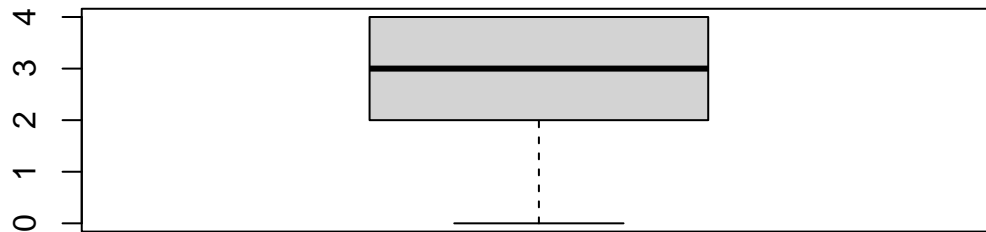
Boxplot of Variable Egoposition Immigration



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

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

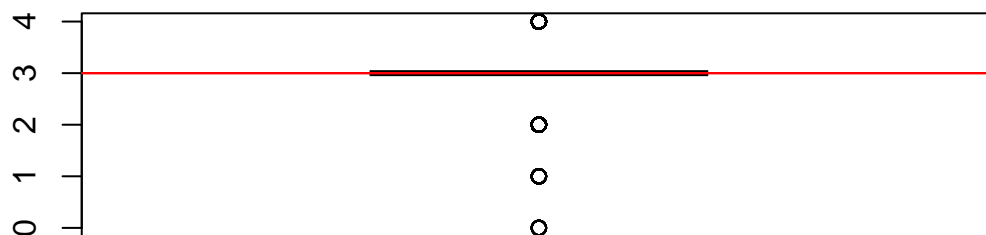
Boxplot of Variable Political Interest



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

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

Boxplot of Variable Income



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

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

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

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

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

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

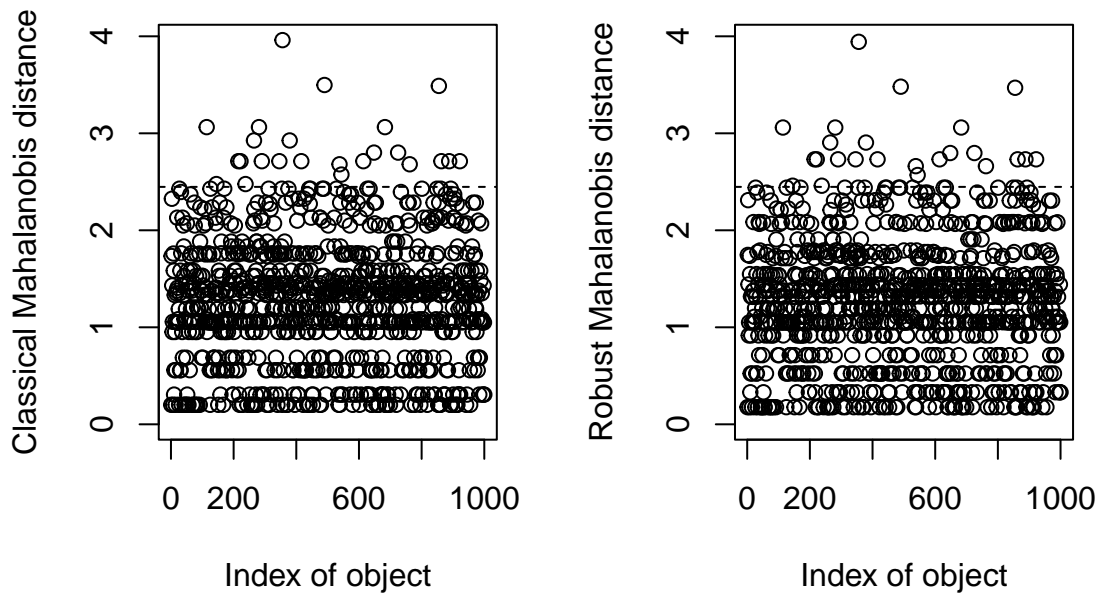
table(gles$income)

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

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

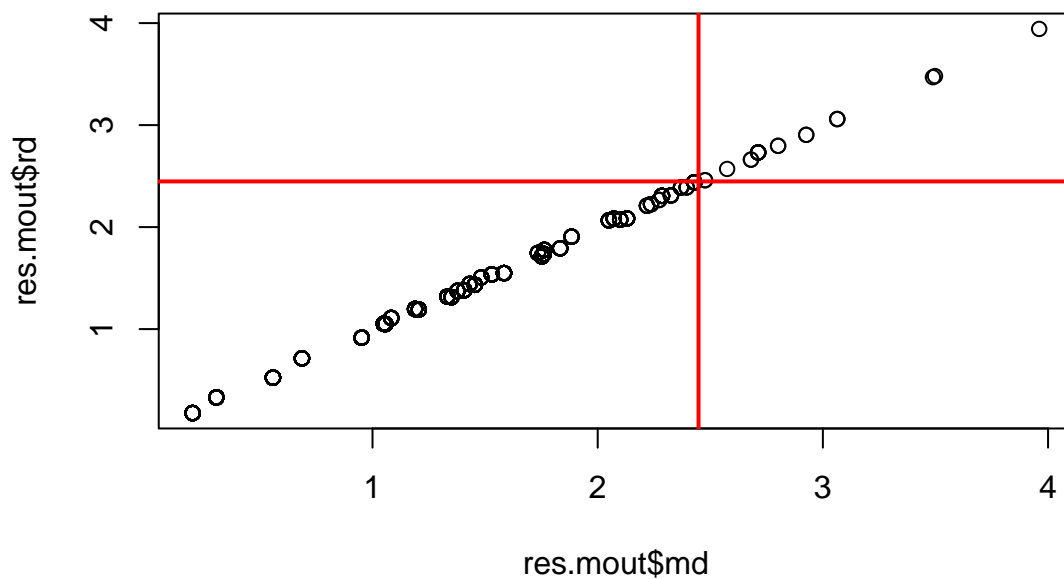
1.8.2 Multivariate Outliers

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



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

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



f.mout

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

1.9 Profiling of Target Variable(s)

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

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

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

- Party **AfD** (*right wing*) is strongly correlated with citizens who have high values for variable *egoposition_imigration* (8-10) meaning they have more far-right beliefs, they are mainly *males* with *low_political_interest* and *low_to_medium* salary satisfaction.
- Party **CDU/CSU** (*center-right*) has strong relationship with people who 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_immigration* (far-right beliefs). Also, those observations are strongly connected with observations of *males*, with value No.EastGermany for *f.eastGermany* variable, with *low political interest* and *low to medium salary satisfaction*.

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

2 Polytomous Modelling

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

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

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

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

2.1 Nominal Polytomous Modeling

2.1.1 Comparison of Variables' Numerical and Categorical Representation

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

1. Train a nominal polytomous target model containing only one of those variables in a continuous representation.
2. Train a nominal polytomous target model containing only one of those variables in a continuous representation, including second, cube and quadratic exponent of the variable.
3. Train a nominal polytomous target model containing only one of those variables in a categorical representation.
4. 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.

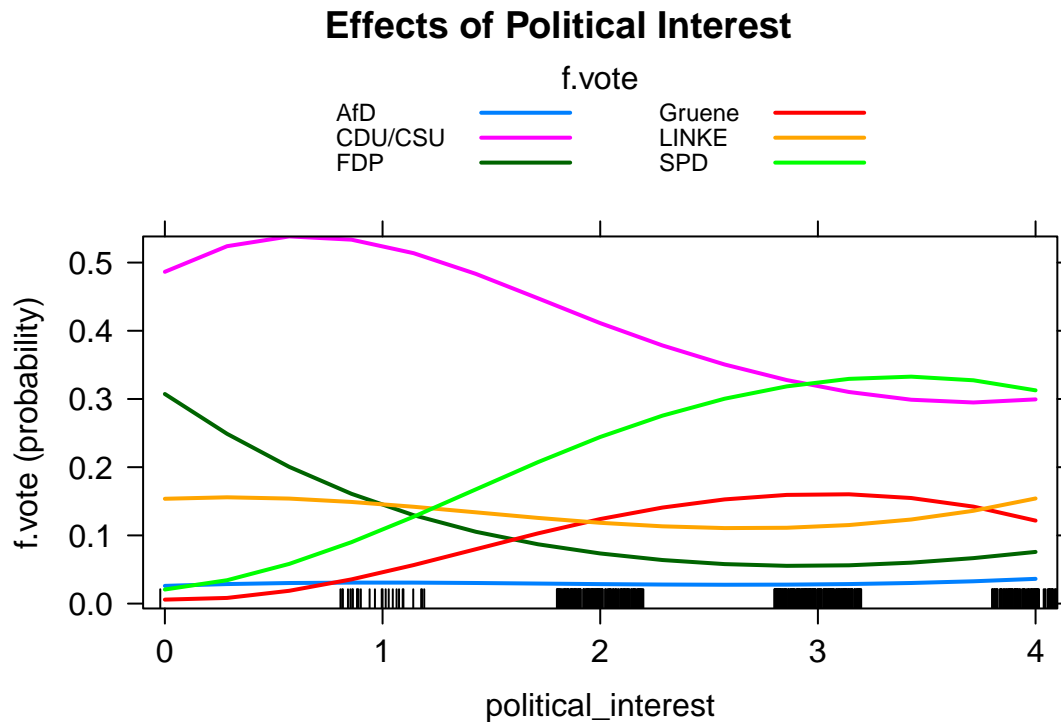
```
summary(nm_final)
```

```
## 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
```

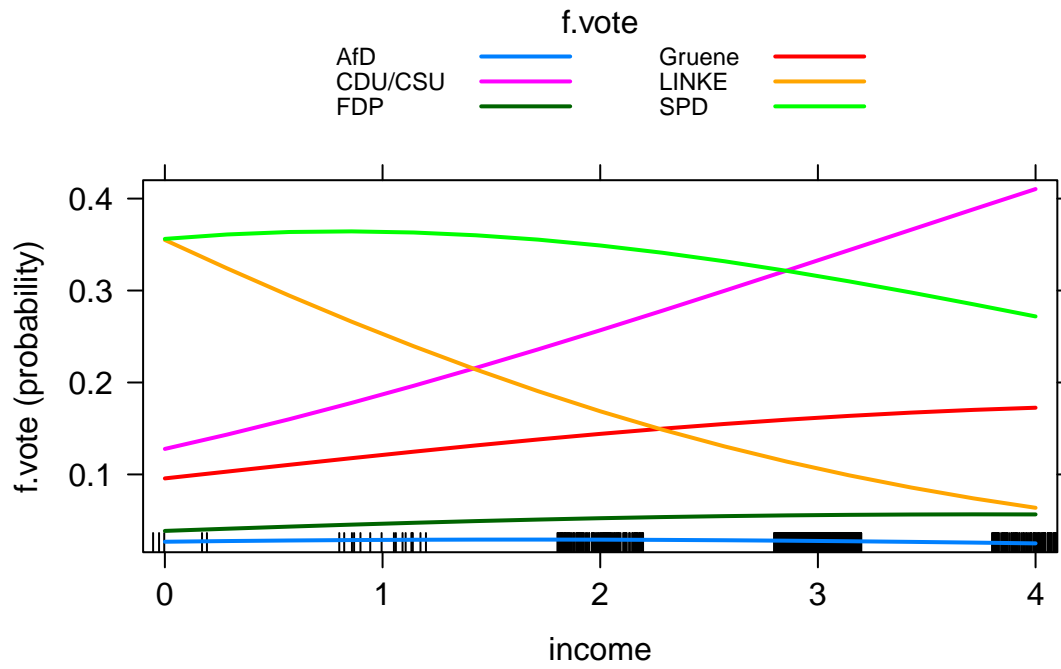


```
## FDP 0.4389828 0.4618531
## Gruene 0.4317185 0.4633330
## LINKE 0.4172363 0.4637351
## SPD 0.3919844 0.4346765
##
## Residual Deviance: 2119.625
## AIC: 2219.625
```

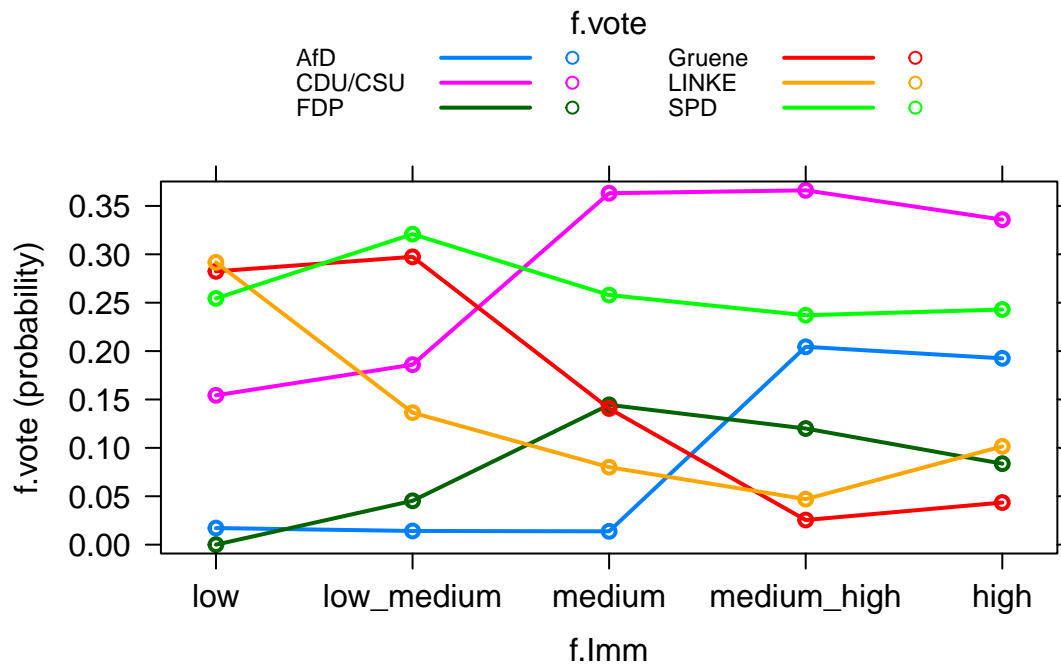
From the summary of the final nominal model, after executing the step function on the model containing all main effects and interactions of the factors and the numerical variables it can be concluded that the formula contains only the main effects of factors *f.Imm*, *f.eastGermany*, *f.gender*, the 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 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 voting preferences of the German citizens.

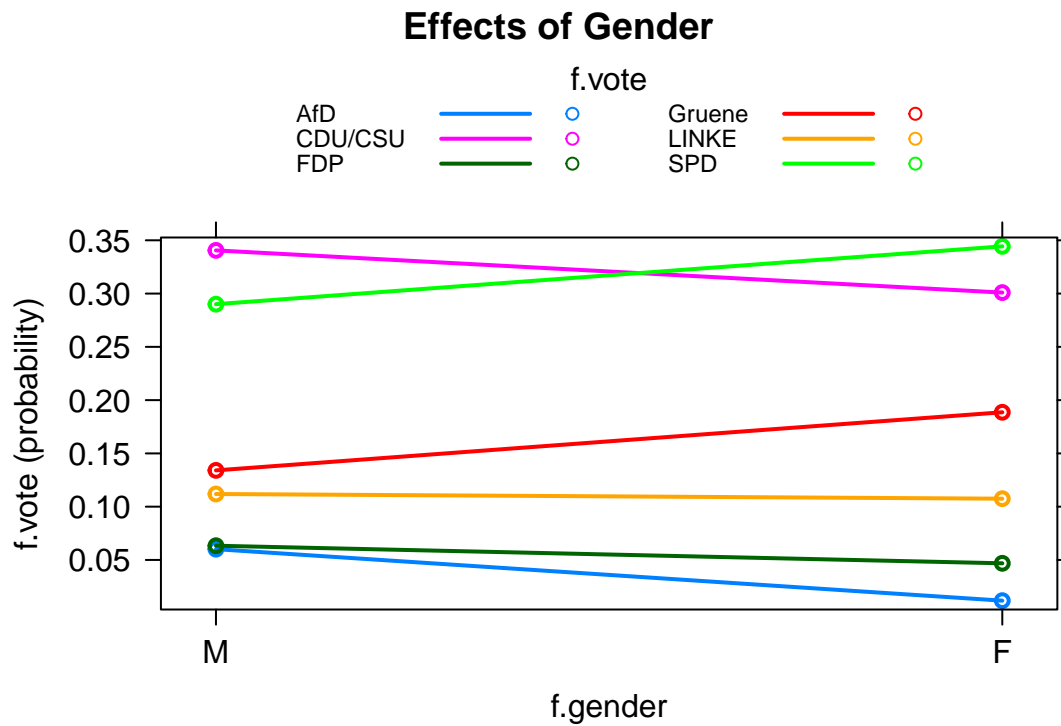
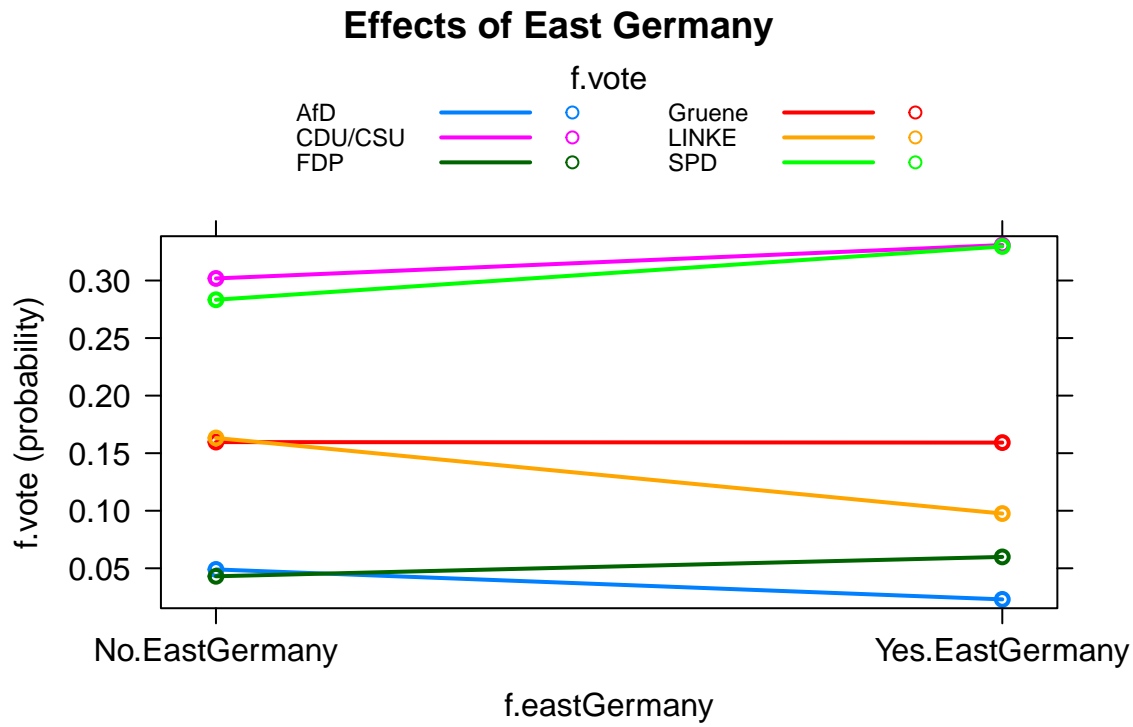


Effects of Income



Effects of Egoposition Immigration





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.

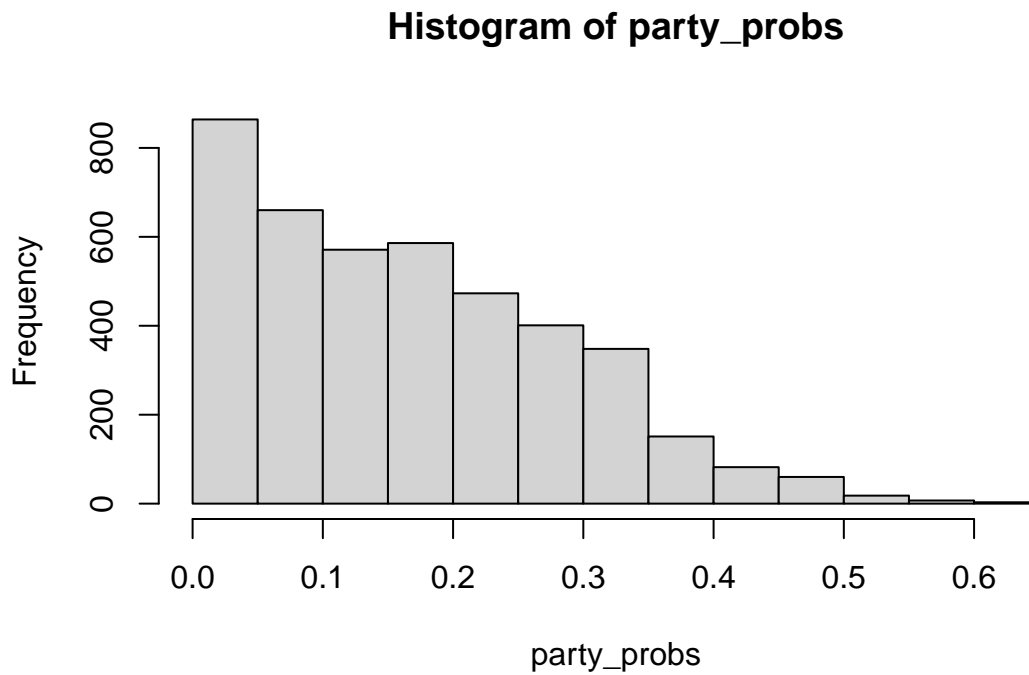
```
##
##           AfD CDU/CSU FDP Gruene LINKE SPD
## AfD      15    11   6    0    4   6
## CDU/CSU  25   144  57   36   32  79
## FDP       1    0   0    0    0   0
## Gruene    0    12   3   22    8  20
## LINKE     1    8   3   11   17  12
## SPD       6    36  13   37   27  52

## [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.



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
```

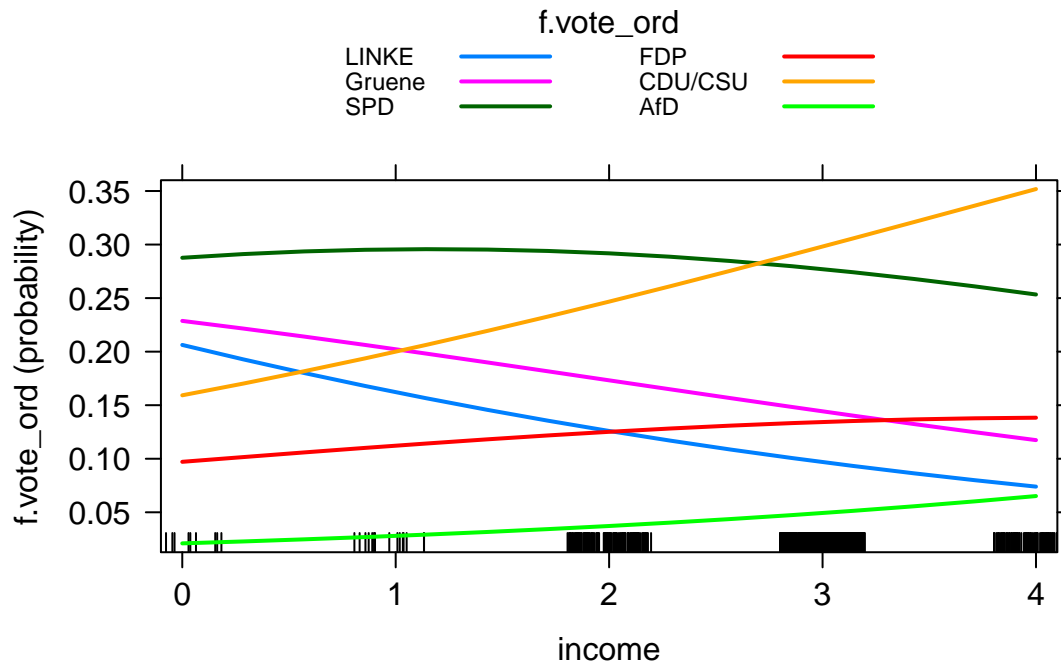
```
## Call:
```

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

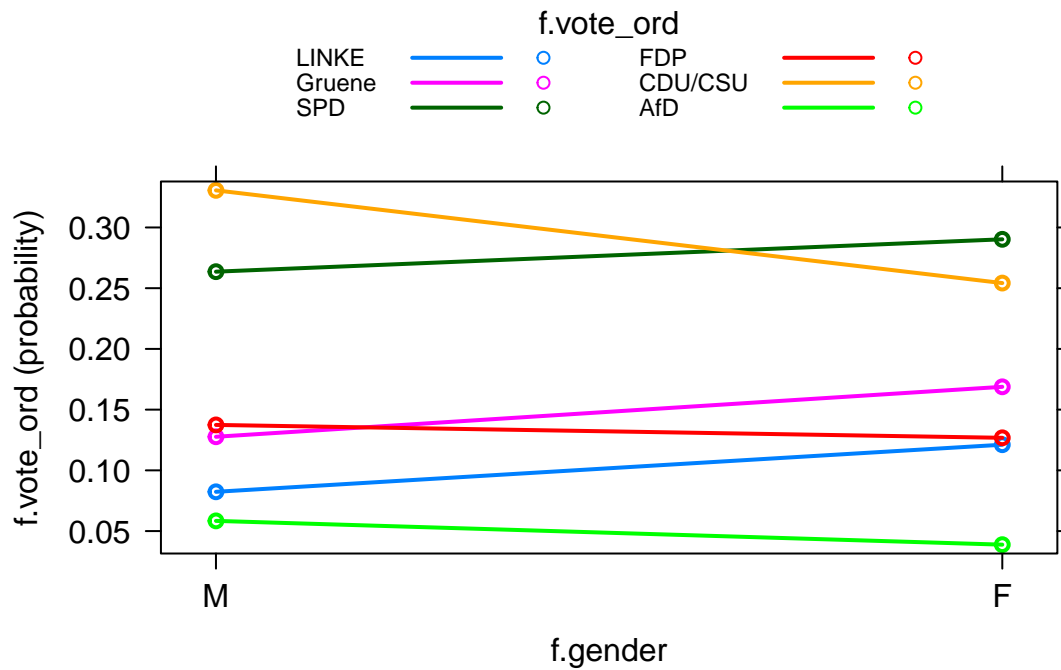
```
##      f.Imm + f.gender + poly(political_interest, 2):f.Imm, data = train)
##
## Coefficients:
##                                     Value Std. Error t value
## poly(political_interest, 2)1      -18.0008    9.07021 -1.9846
## poly(political_interest, 2)2         7.4740    9.04420  0.8264
## income                             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.

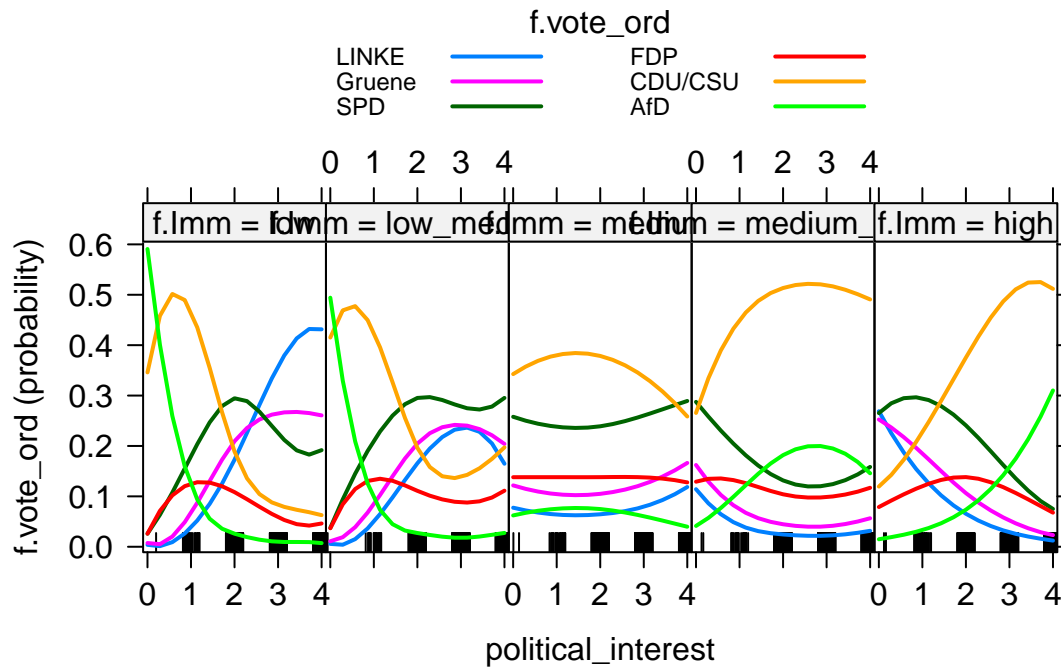
Effects of Income



Effects of Gender



Effects of Interactions (Imm – Pollnt)



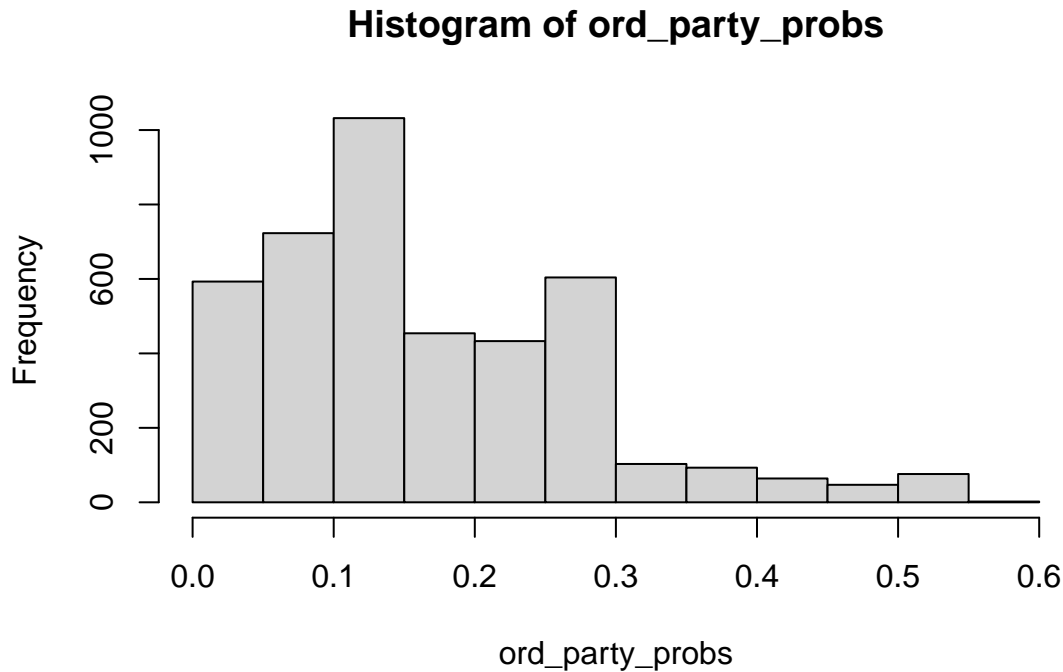
2.2.2.1 Confusion Matrix and Metrics for Training Set Here the confusion matrix and the appropriate metrics are presented for the training set.

```
##
##          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.



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*.

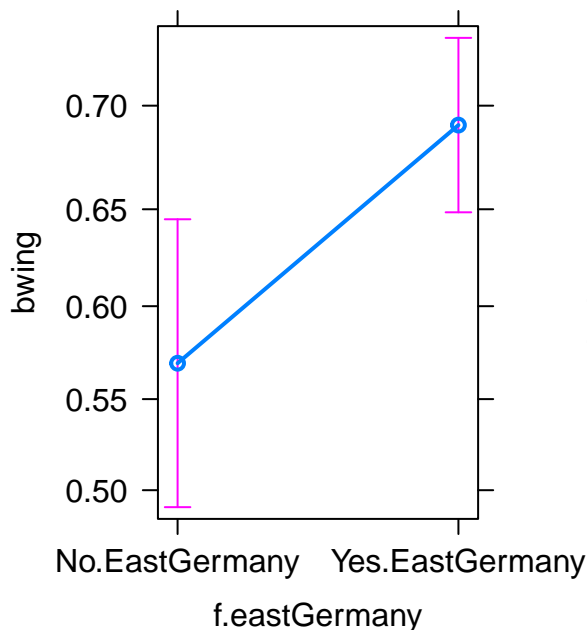
```
##
## Call:
## glm(formula = bwing ~ income + f.Imm + f.eastGermany + income:f.Imm,
##      family = binomial, data = train)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.8258  -1.1463   0.6878   0.8629   1.5708
##
## Coefficients:
##              Estimate Std. Error 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.

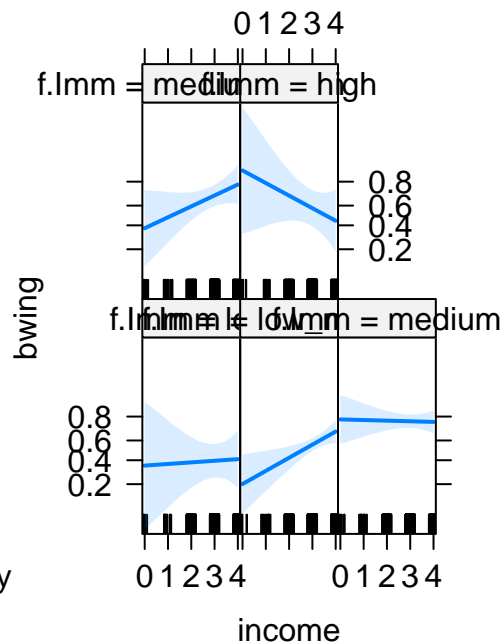
```
## Analysis of Deviance Table (Type II tests)
##
```

```
## 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

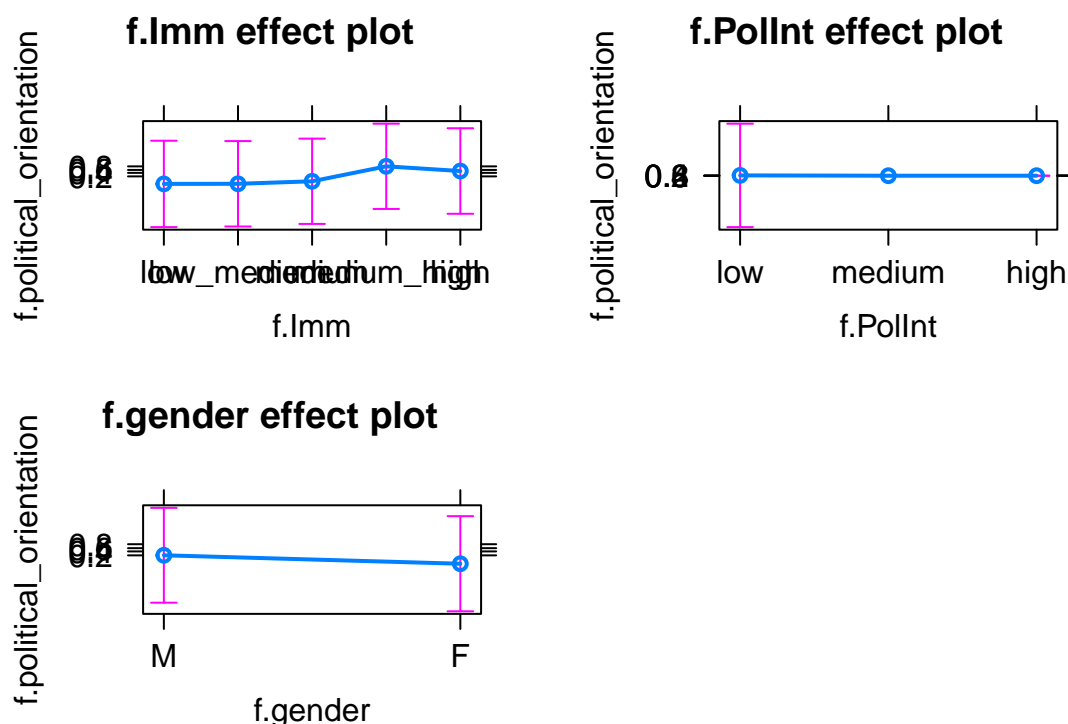


2.3.2 Second Layer of Hierarchical Approach

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 done 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.

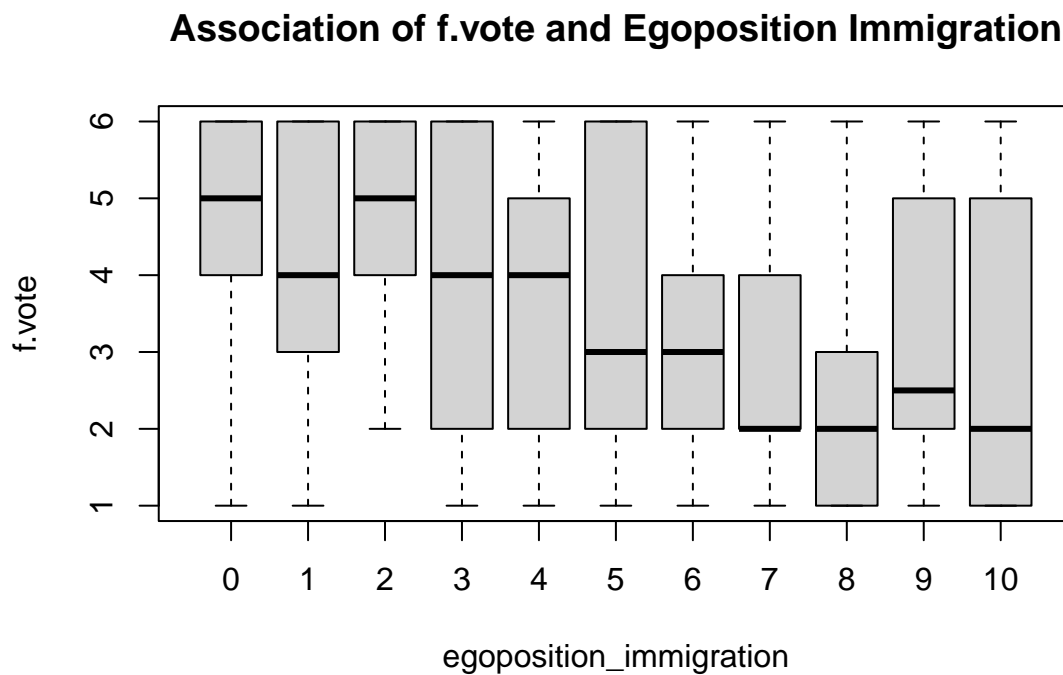
4 Appendix

4.1 EDA

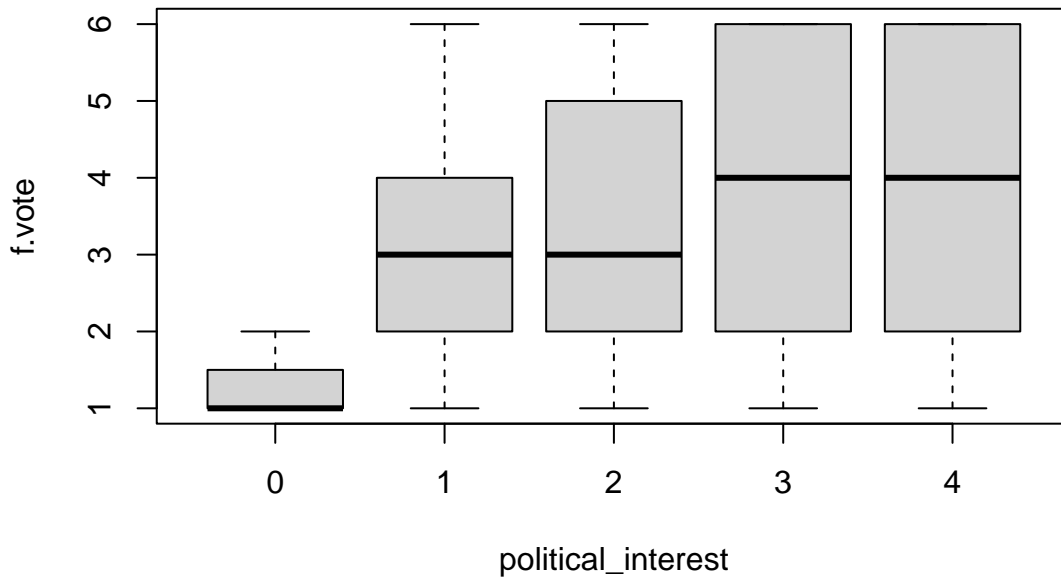
4.2 Profiling of Target Variable(s)

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

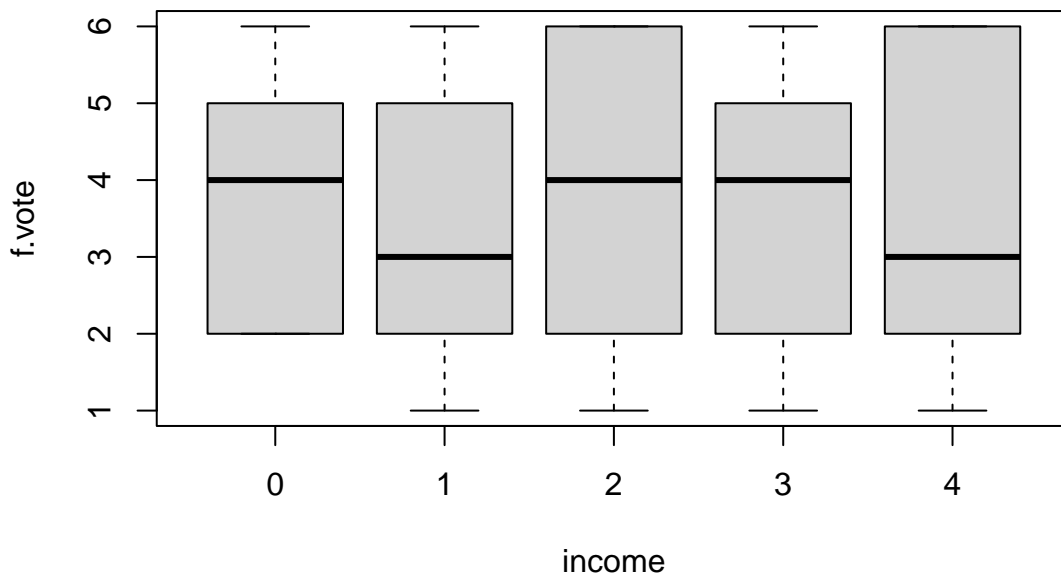
```
## [1] "Parties:"
## [1] 1 2 3 4 5 6
## [1] "AfD"      "CDU/CSU" "FDP"      "Gruene"   "LINKE"    "SPD"
## [1] "Political Wings:"
## [1] 1 2 3
## [1] "Center_Wing" "Left_Wing"  "Right_Wing"
```



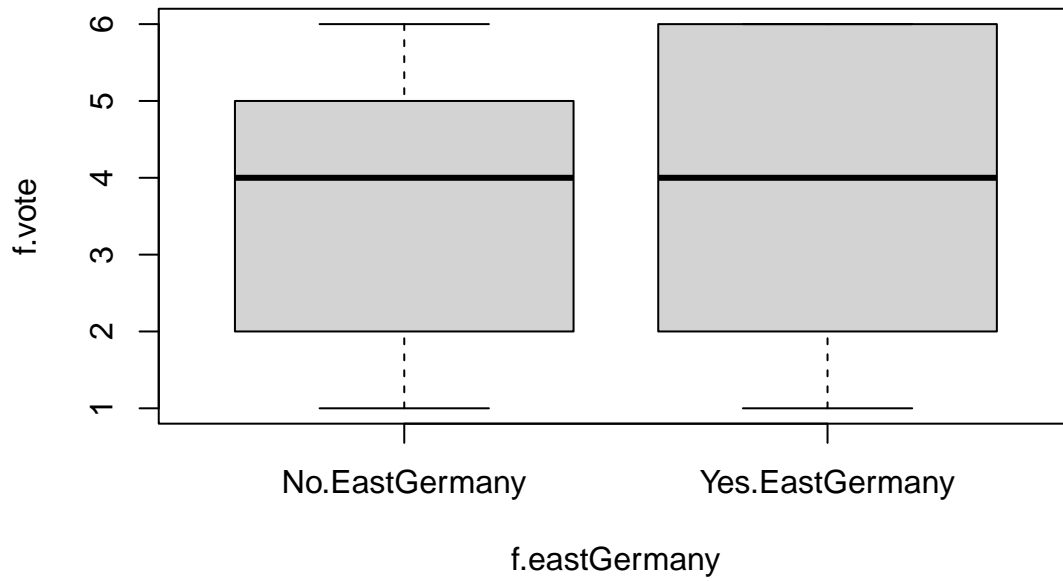
Association of f.vote and Political Interest



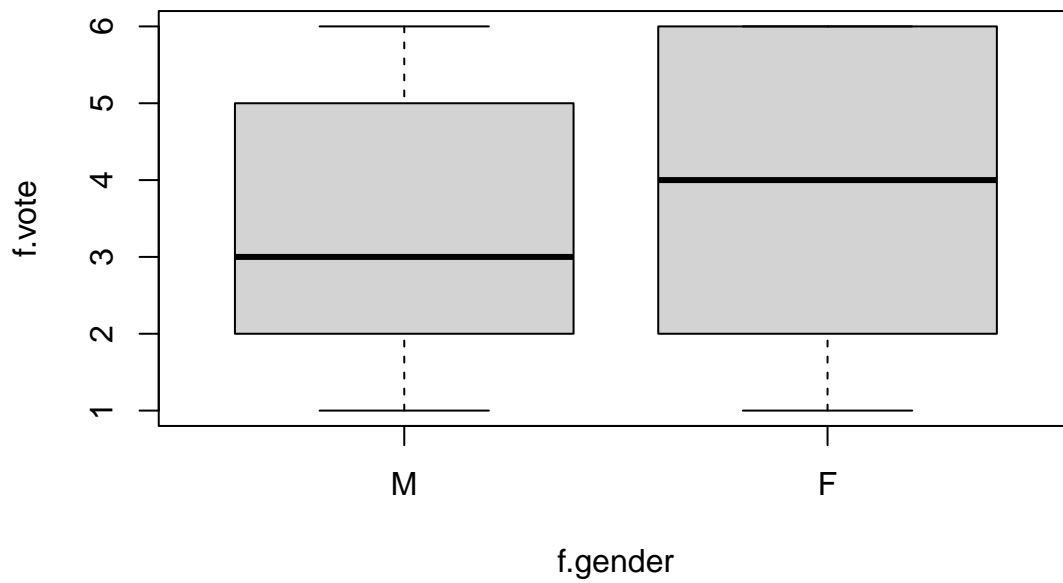
Association of f.vote and Income Satisfaction



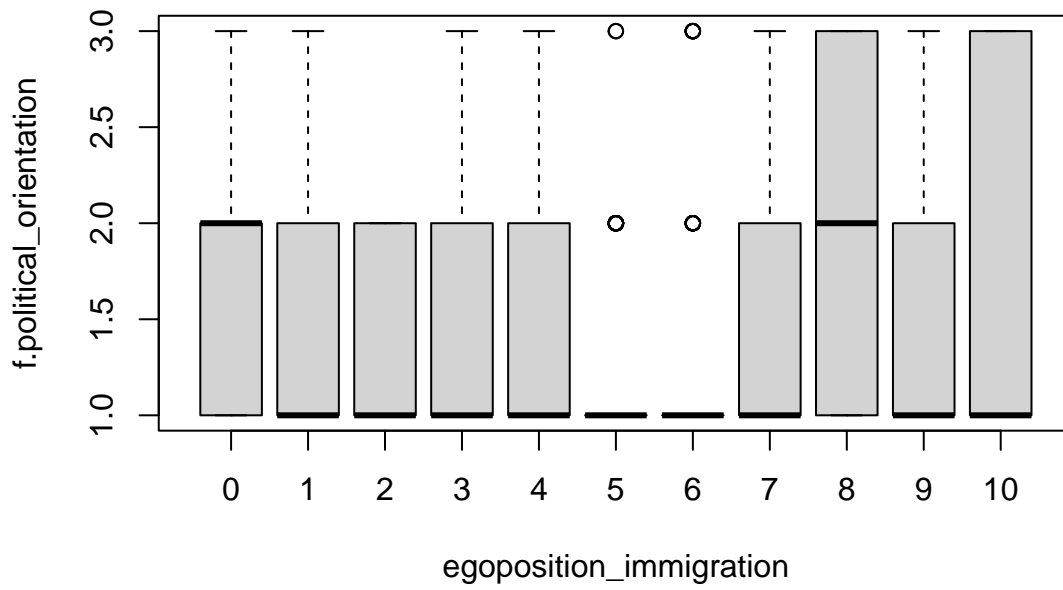
Association of f.vote and East Germany



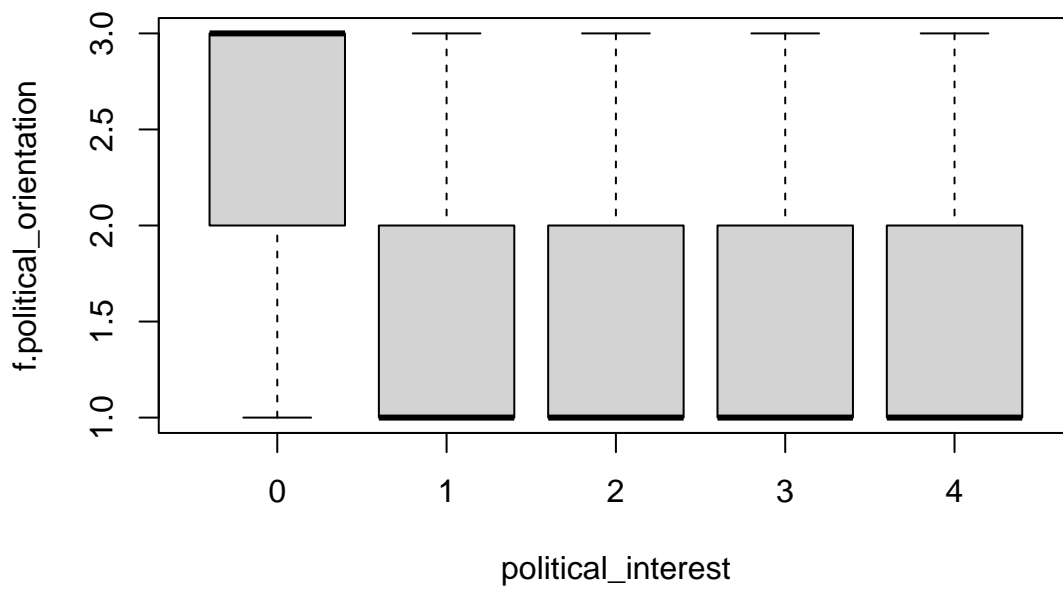
Association of f.vote and Gender



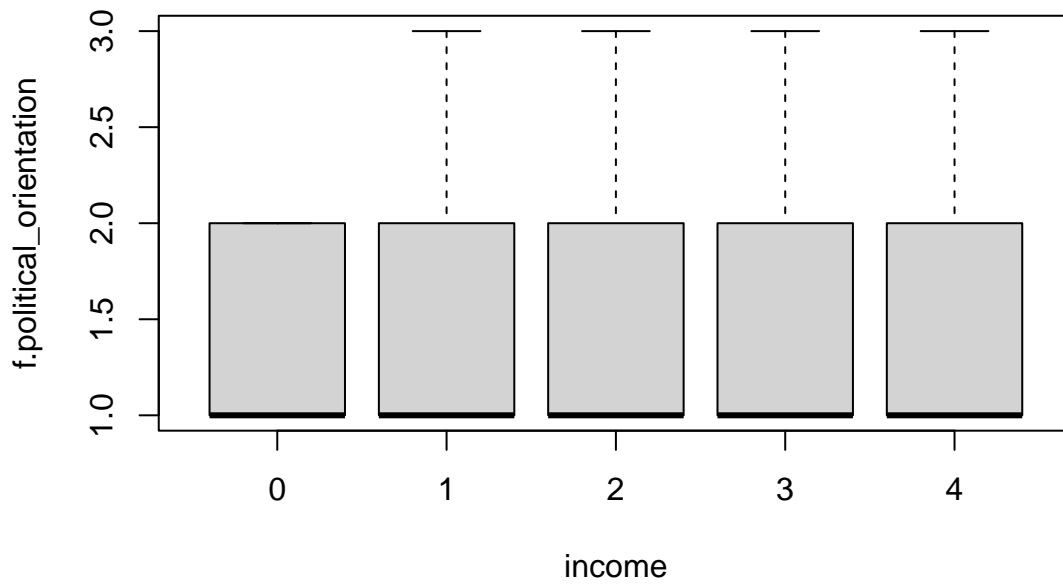
Association of Political Wings and Egoposition Immigration



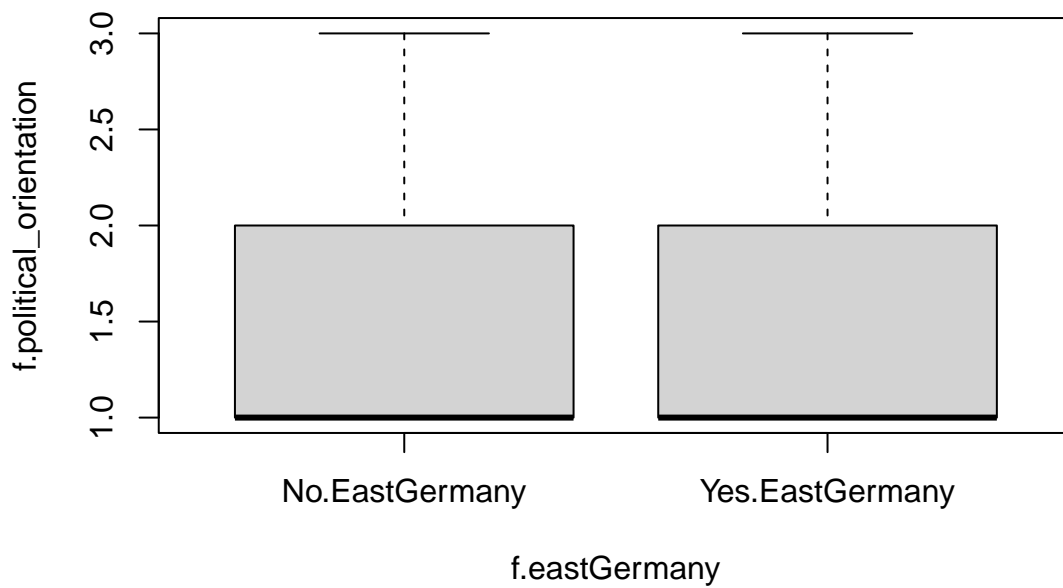
Association of Political Wings and Political Interest



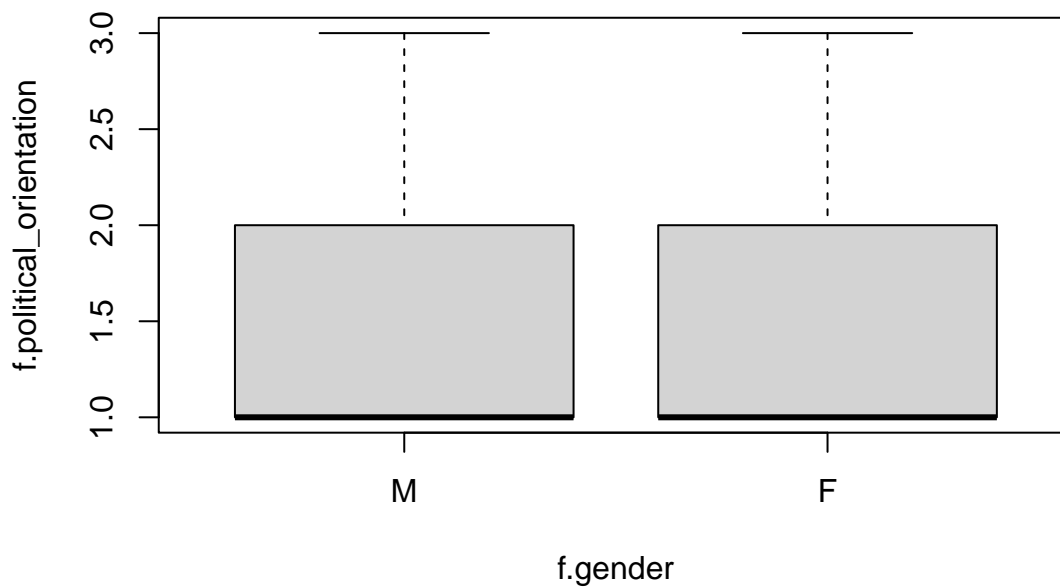
Association of Political Wings and Income Satisfaction



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

## 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	100.000000	
## f.political_orientation=Left_Wing	53.759398	100.000000	
## bwing=Left_Right_Wings	42.686567	100.000000	
## 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	0.000000	
## 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	0.000000	
## f.gender=M	11.338290	42.6573427	
## f.egoposition_immigration=7_Level.Imm	2.564103	1.3986014	
## f.vote_ord=AfD	0.000000	0.000000	
## f.political_orientation=Right_Wing	0.000000	0.000000	
## f.Imm=medium_high	1.398601	1.3986014	
## f.vote_ord=FDP	0.000000	0.000000	
## f.vote_ord=LINKE	0.000000	0.000000	
## f.vote_ord=SPD	0.000000	0.000000	
## f.vote_ord=CDU/CSU	0.000000	0.000000	
## bwing=Center_Wing	0.000000	0.000000	
## f.political_orientation=Center_Wing	0.000000	0.000000	
##	Global	p.value	
## f.vote_ord=Gruene	14.3	1.663892e-177	

## f.political_orientation=Left_Wing	26.6	4.555935e-99
## 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

```

```

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

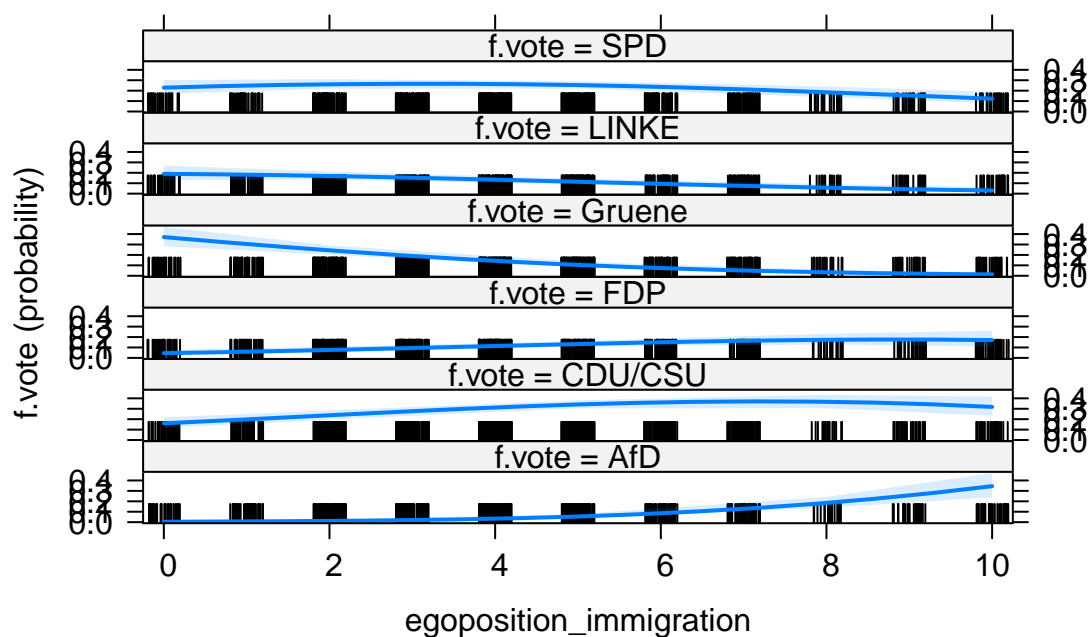
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##                                LR Chisq Df Pr(>Chisq)
## f.egoposition_immigration    224.2 50 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Anova(nm1_imm_cat_new, test="Chisq")

## # 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")

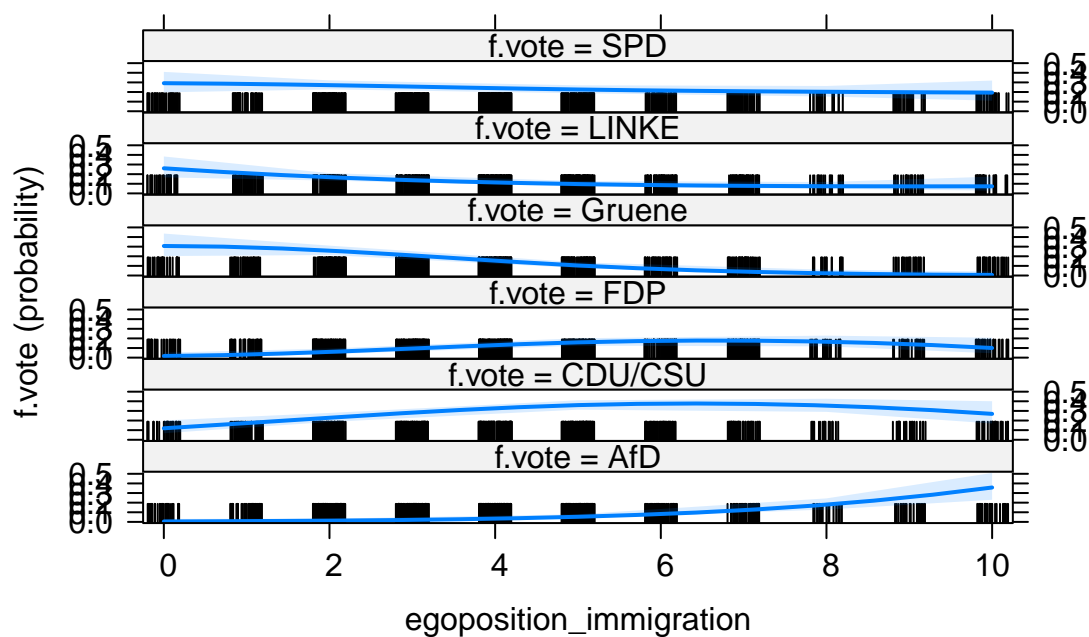
```

Effects Imm Continuous



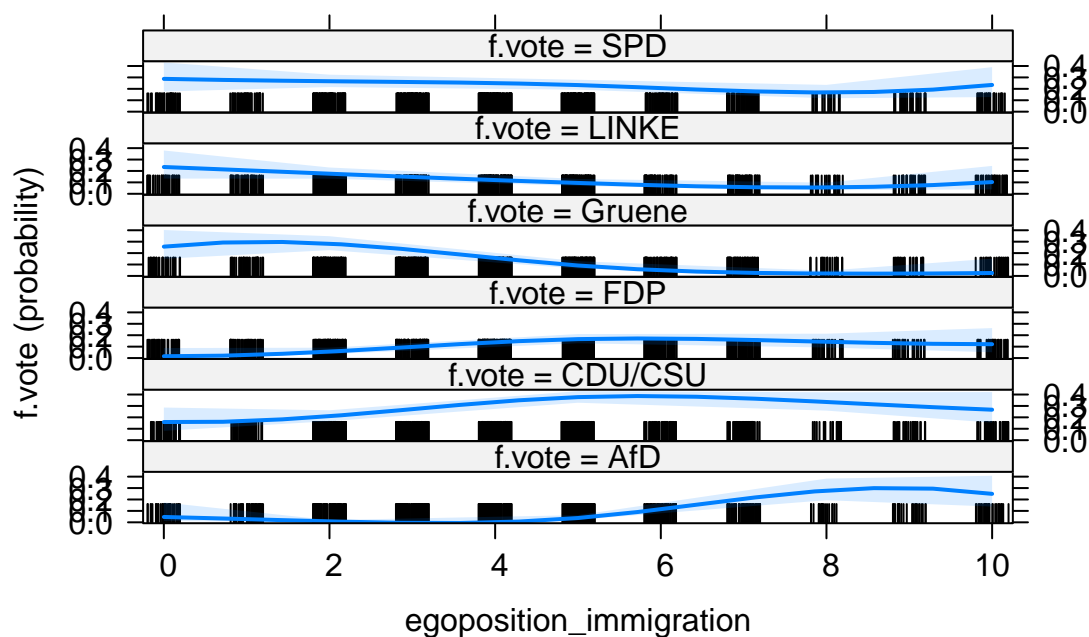
```
plot(allEffects(nm1_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```

Effects Imm Continuous Squared



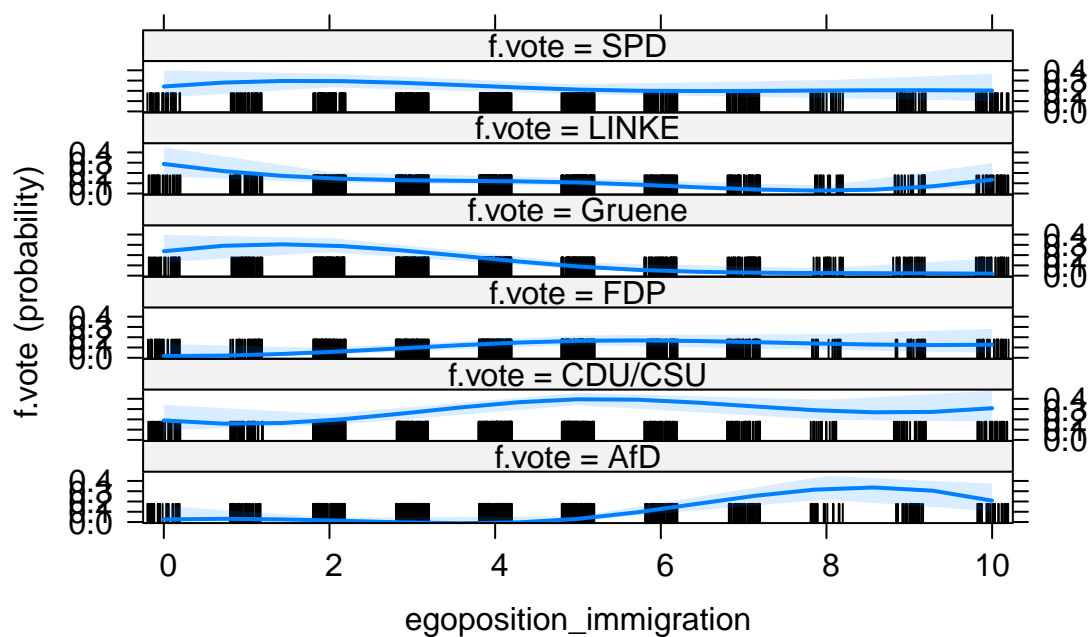
```
plot(allEffects(nm1_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```

Effects Imm Continuous Cubed



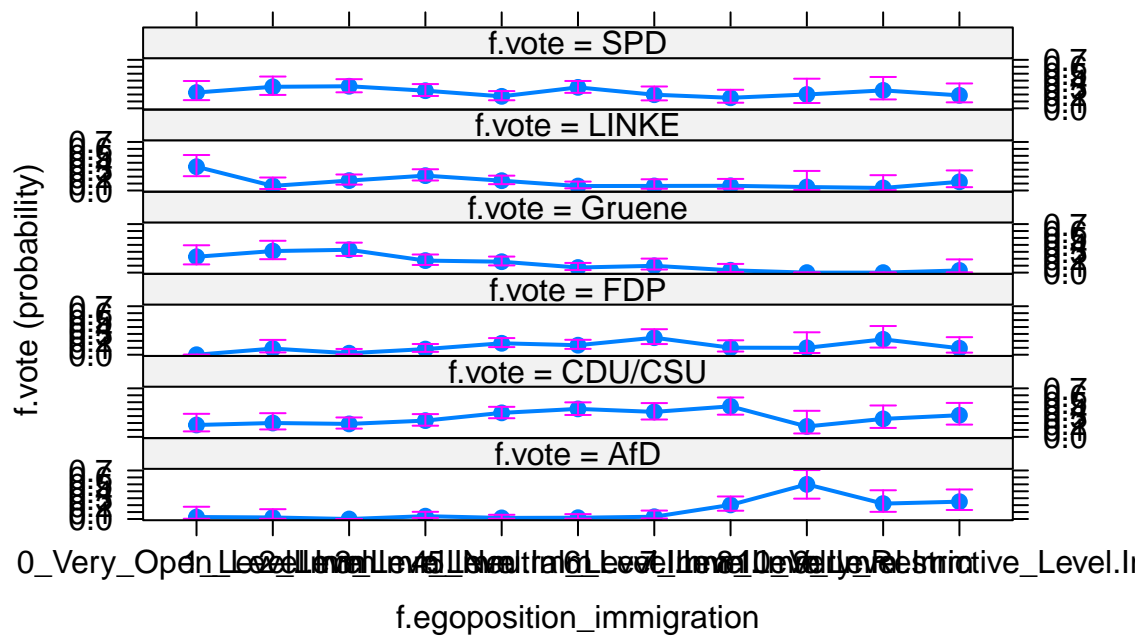
```
plot(allEffects(nm1_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```

Effects Imm Continuous Quadratic



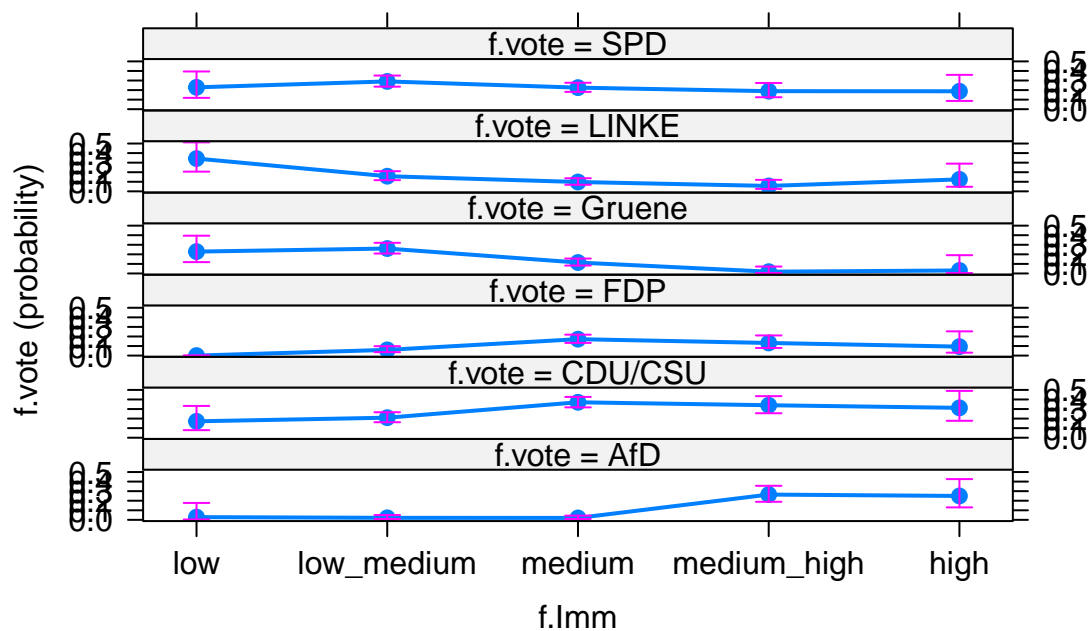
```
plot(allEffects(nm1_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

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")

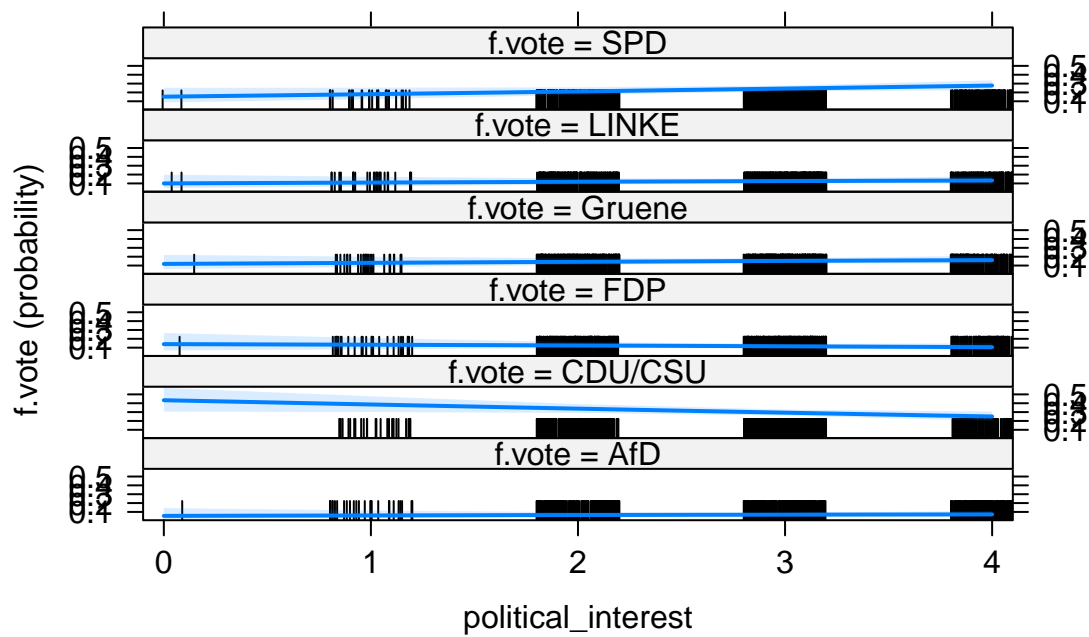
## # weights:  12 (5 variable)
## initial value 1261.398666
## iter  10 value 1184.278222
## final value 1184.278203
## converged

## 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")

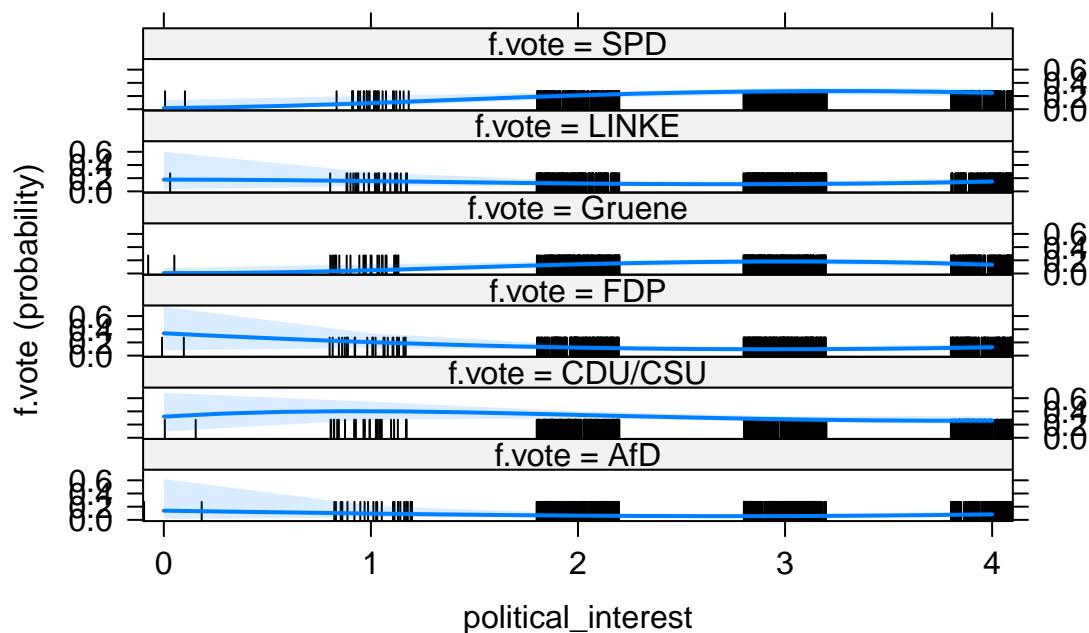
```

Effects Pol Int Continuous



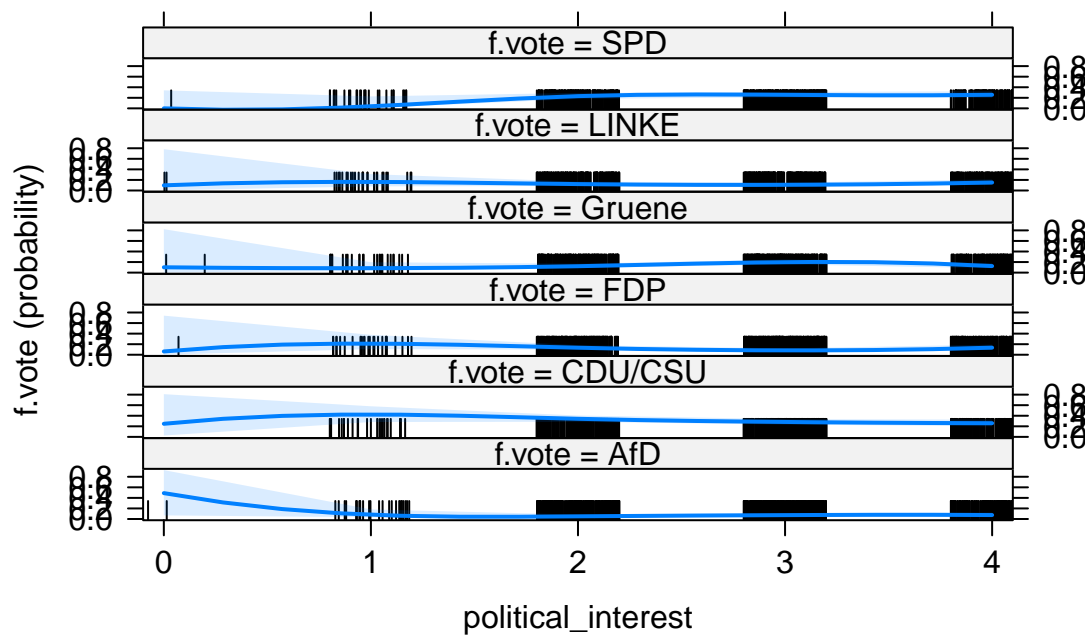
```
plot(allEffects(nm1_polint_con_sq),ask=FALSE,main="Effects Pol Int Continuous Squared")
```

Effects Pol Int Continuous Squared



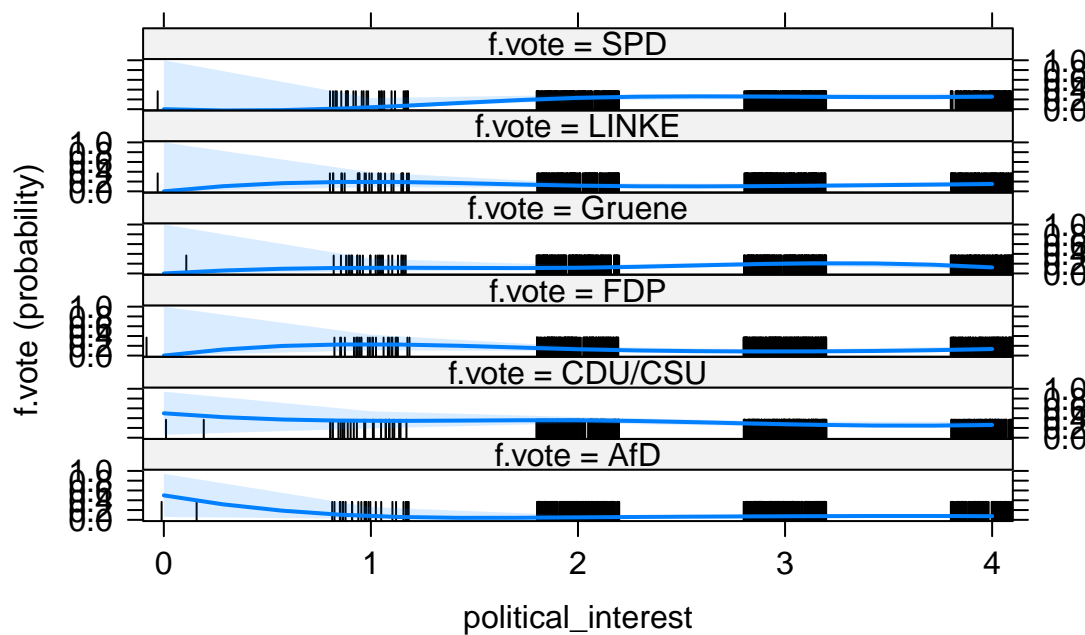
```
plot(allEffects(nm1_polint_con_cb),ask=FALSE, main="Effects Pol Int Continuous Cubed")
```

Effects Pol Int Continuous Cubed



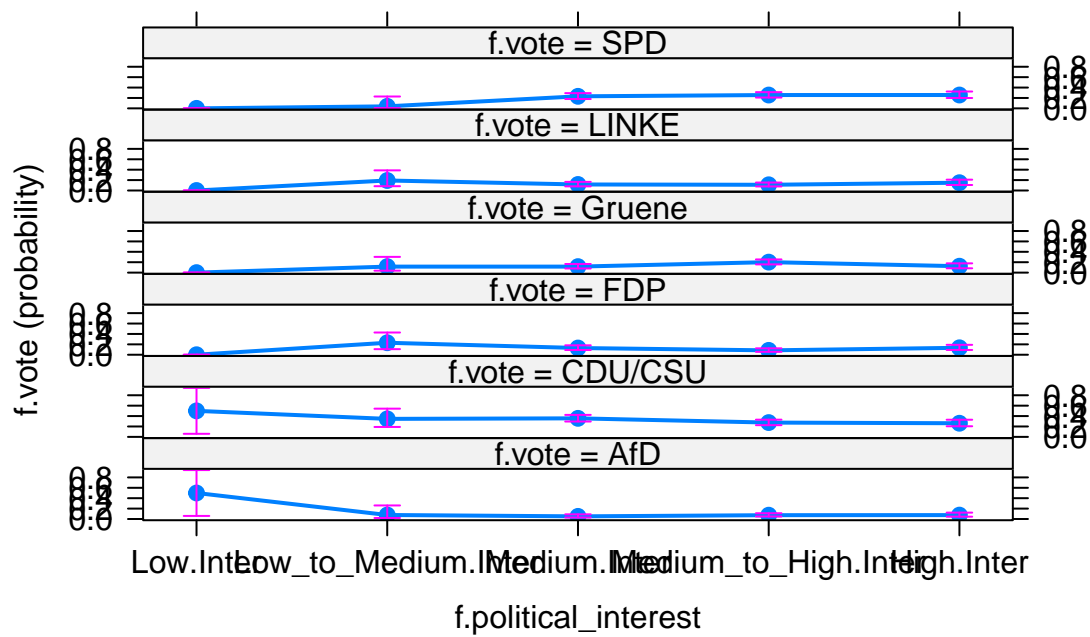
```
plot(allEffects(nm1_polint_con_qd),ask=FALSE, main="Effects Pol Int Continuous Quadratic")
```

Effects Pol Int Continuous Quadratic



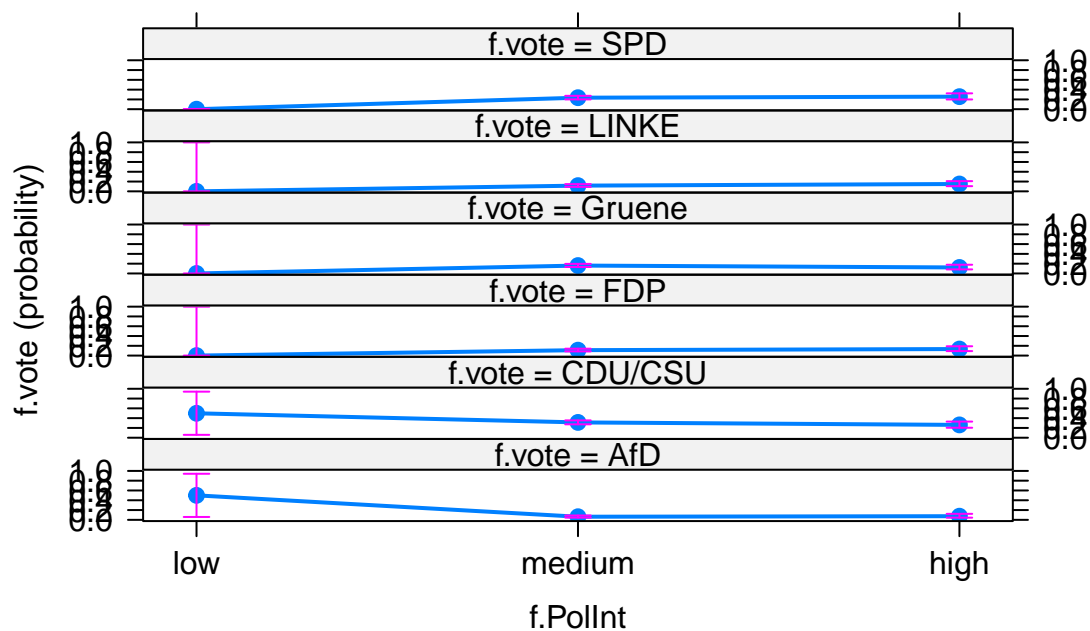
```
plot(allEffects(nm1_polint_cat),ask=FALSE, main="Effects Pol Int Categorical")
```

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

Anova(nm1_inc_con_sq, test="Chisq")

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

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##           LR Chisq Df Pr(>Chisq)
## poly(income, 2)   24.235 10      0.007 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Anova(nm1_inc_con_cb, test="Chisq")

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

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

Anova(nm1_inc_con_qd, test="Chisq")

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

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

```

```
Anova(nm1_inc_cat, test="Chisq")
```

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

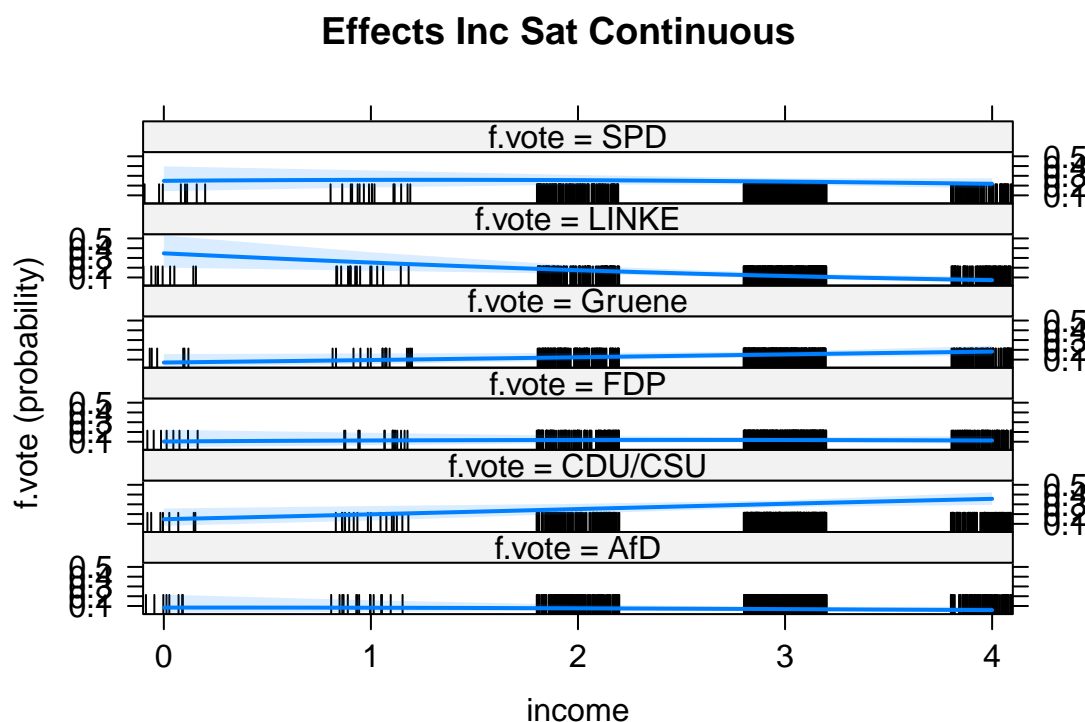
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##          LR Chisq Df Pr(>Chisq)
## f.income  31.893 20   0.04445 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(nm1_inc_cat_new, test="Chisq")
```

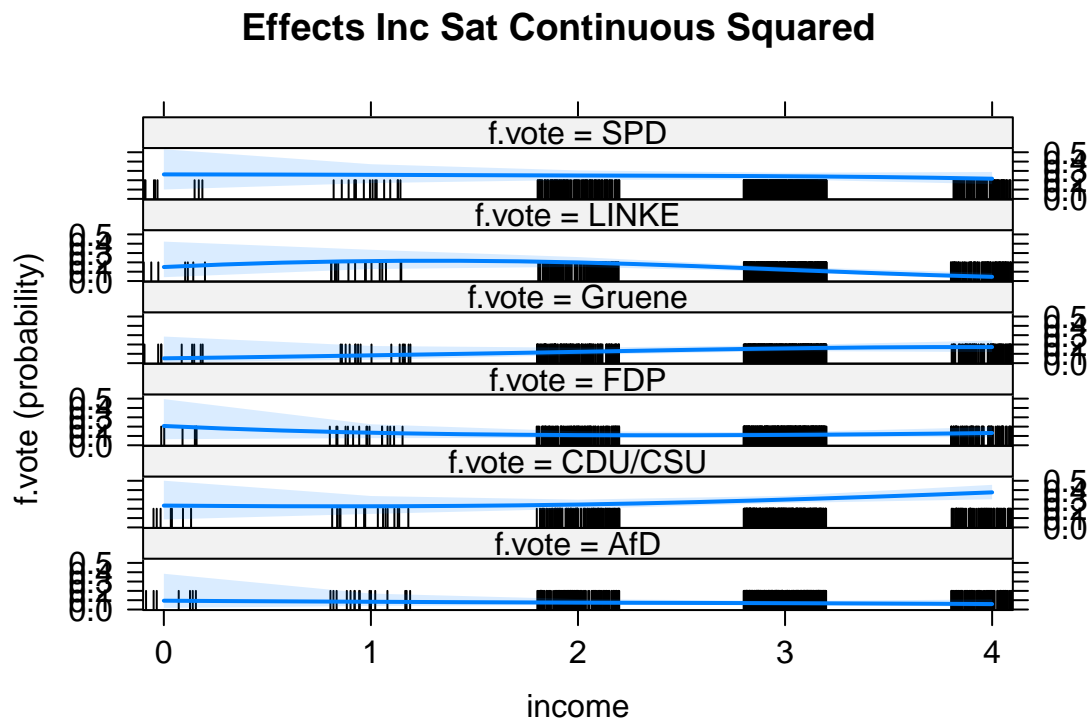
```
## # weights: 12 (5 variable)
## initial value 1261.398666
## iter 10 value 1184.278222
## final value 1184.278203
## converged

## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##          LR Chisq Df Pr(>Chisq)
## f.IncSat   21.61 15   0.1184
```

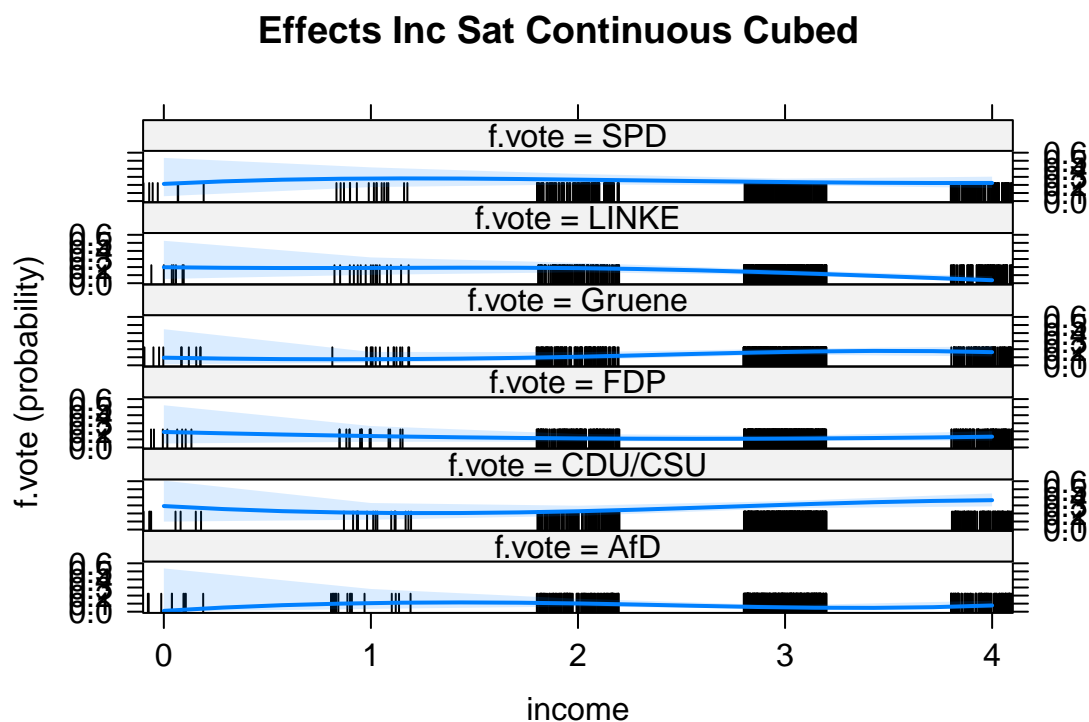
```
plot(allEffects(nm1_inc_con), ask=FALSE, main="Effects Inc Sat Continuous")
```




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

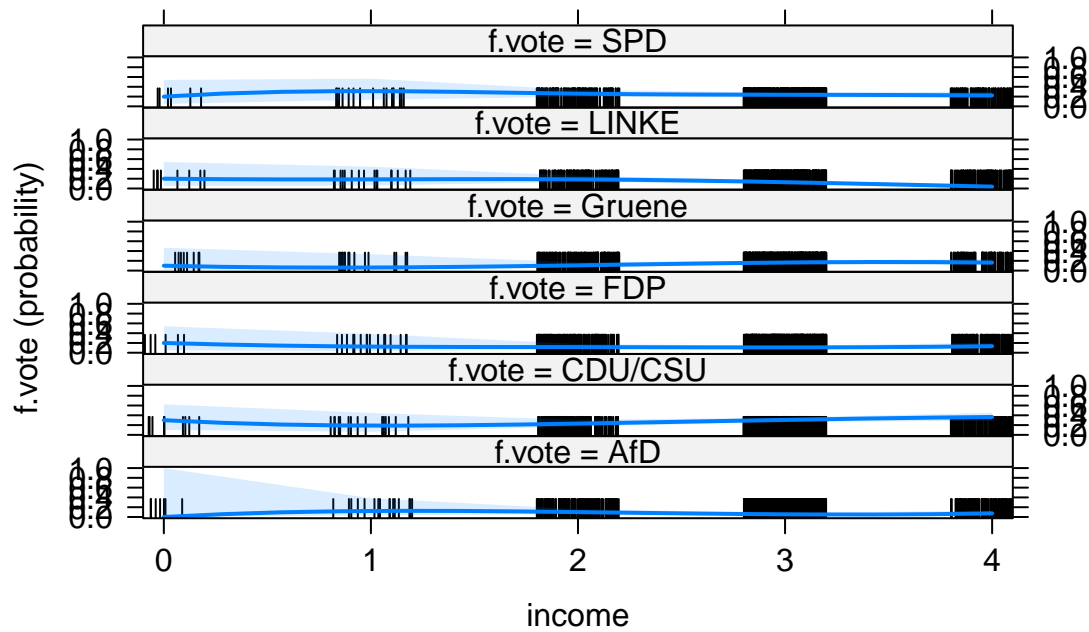


```
plot(allEffects(nm1_inc_con_cb),ask=FALSE, main="Effects Inc Sat Continuous Cubed")
```



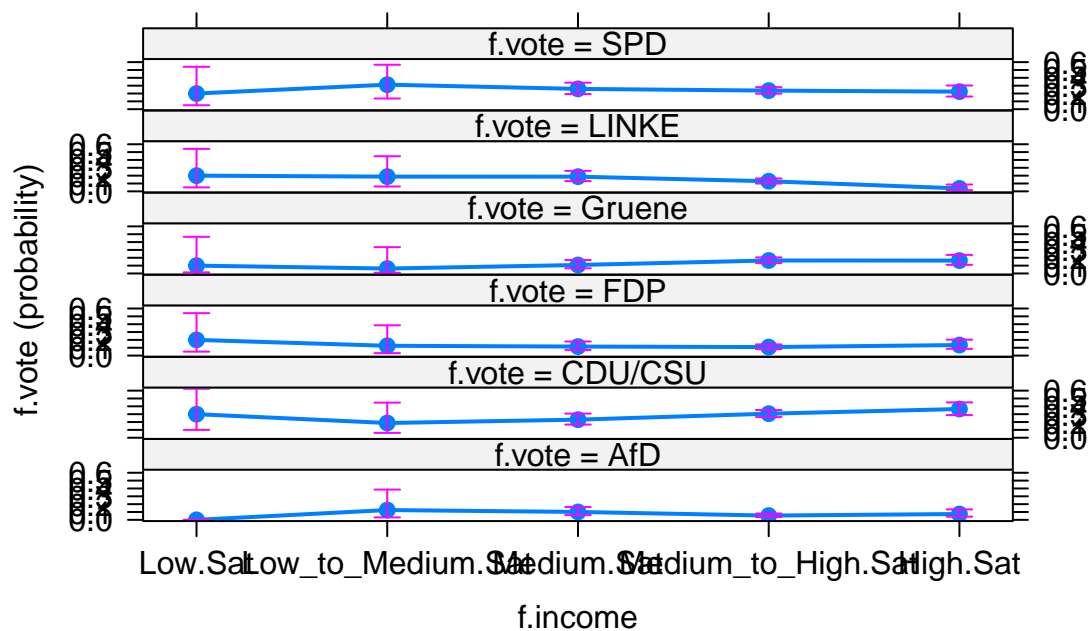
```
plot(allEffects(nm1_inc_con_qd),ask=FALSE, main="Effects Inc Sat Continuous Quadratic")
```

Effects Inc Sat Continuous Quadratic



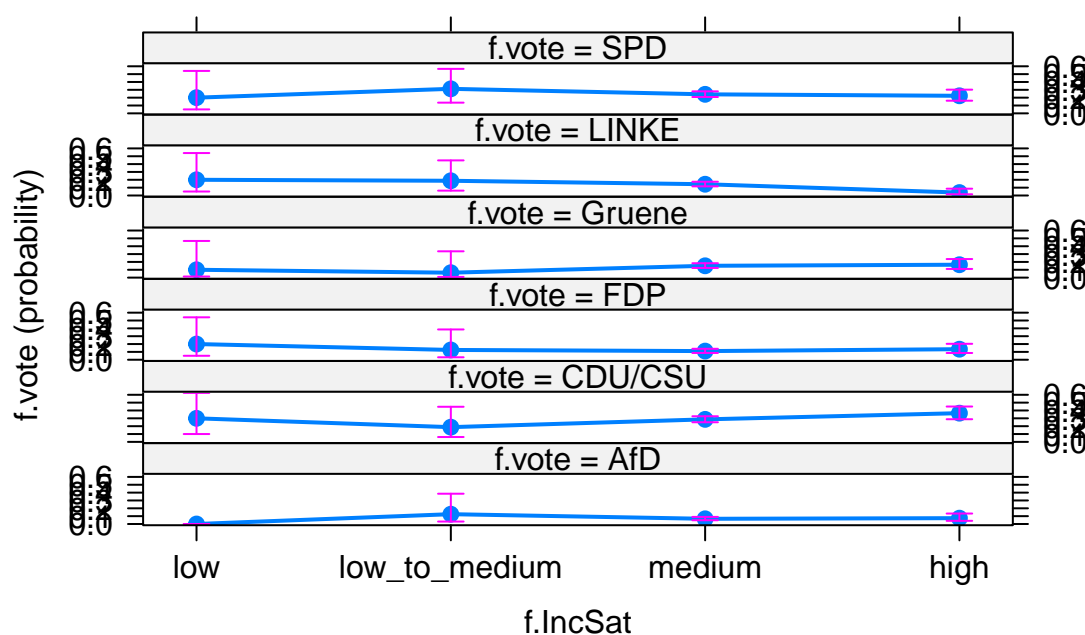
```
plot(allEffects(nm1_inc_cat),ask=FALSE, main="Effects Inc Sat Categorical")
```

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						

```

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")

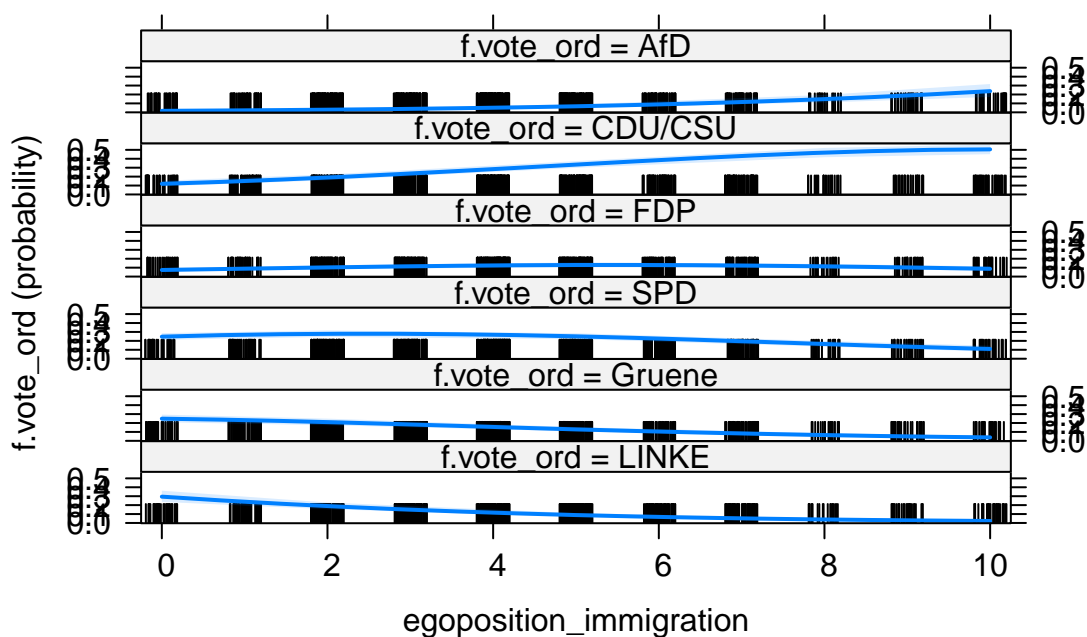
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##
##          LR Chisq Df Pr(>Chisq)
## f.Imm 111.29 4 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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

##
## Re-fitting to get Hessian

```

Effects Imm Continuous

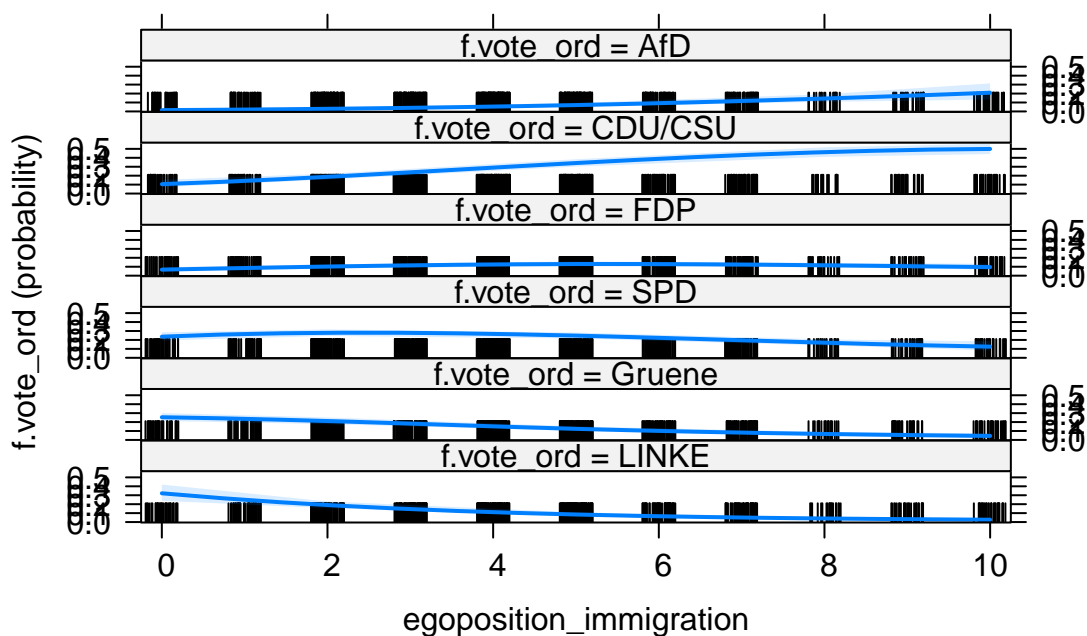


```
plot(allEffects(om1_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```

```
##
```

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

Effects Imm Continuous Squared

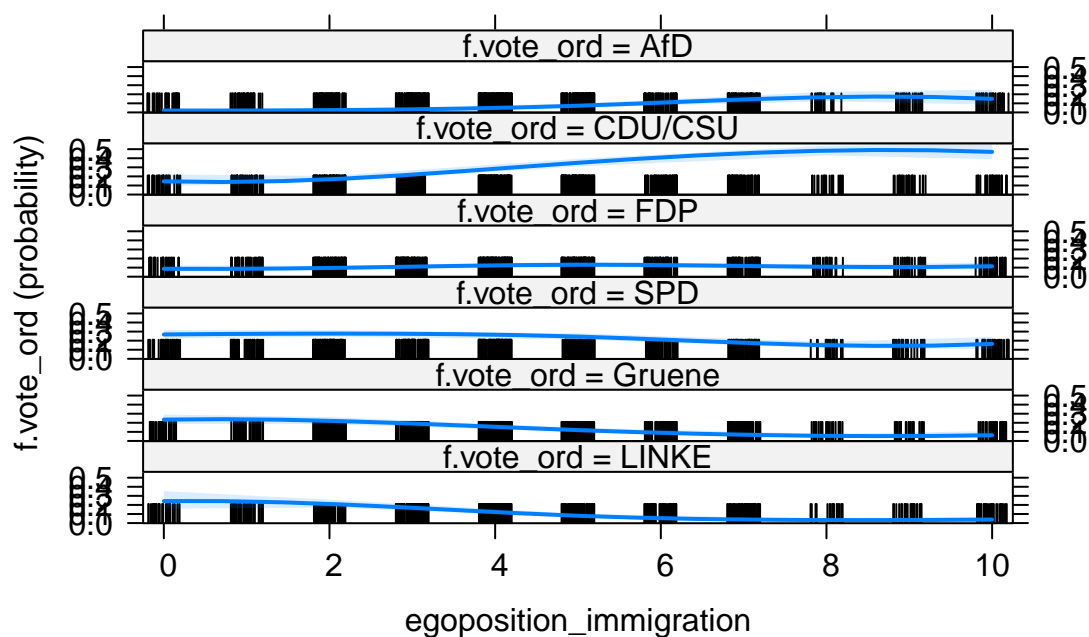


```
plot(allEffects(om1_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```

```
##
```

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

Effects Imm Continuous Cubed

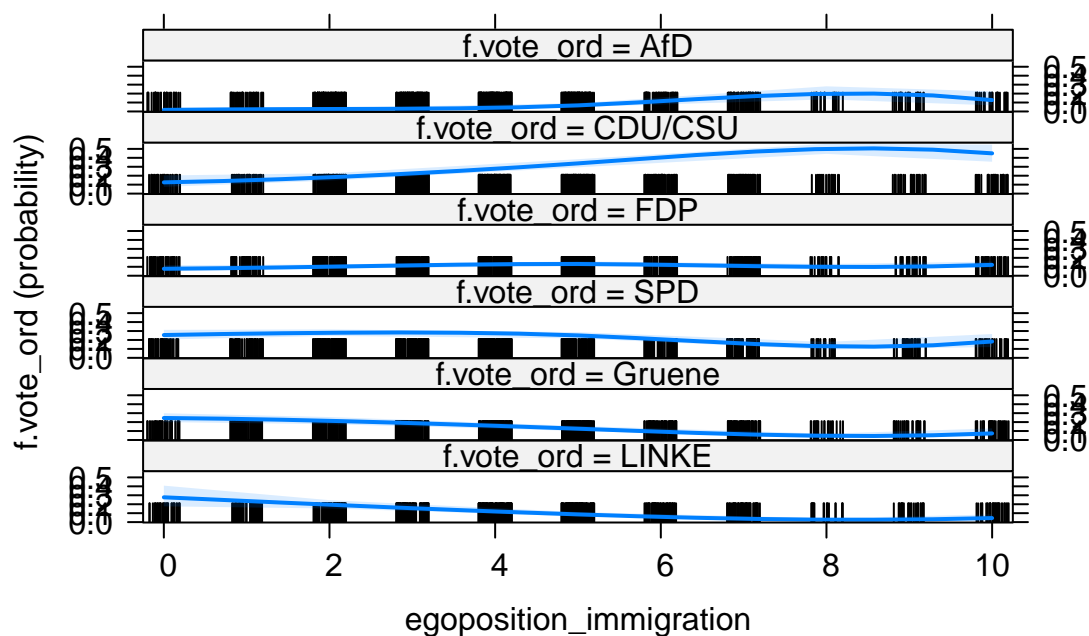


```
plot(allEffects(om1_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```

```
##
```

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

Effects Imm Continuous Quadratic

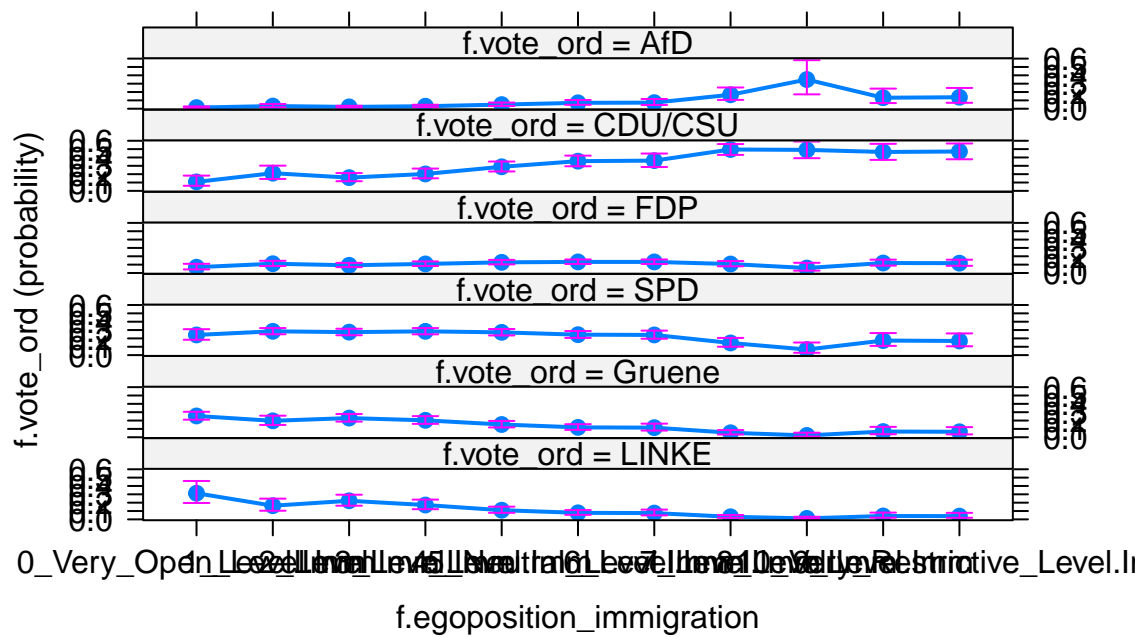


```
plot(allEffects(om1_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

```
##
```

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

Effects Imm Categorical

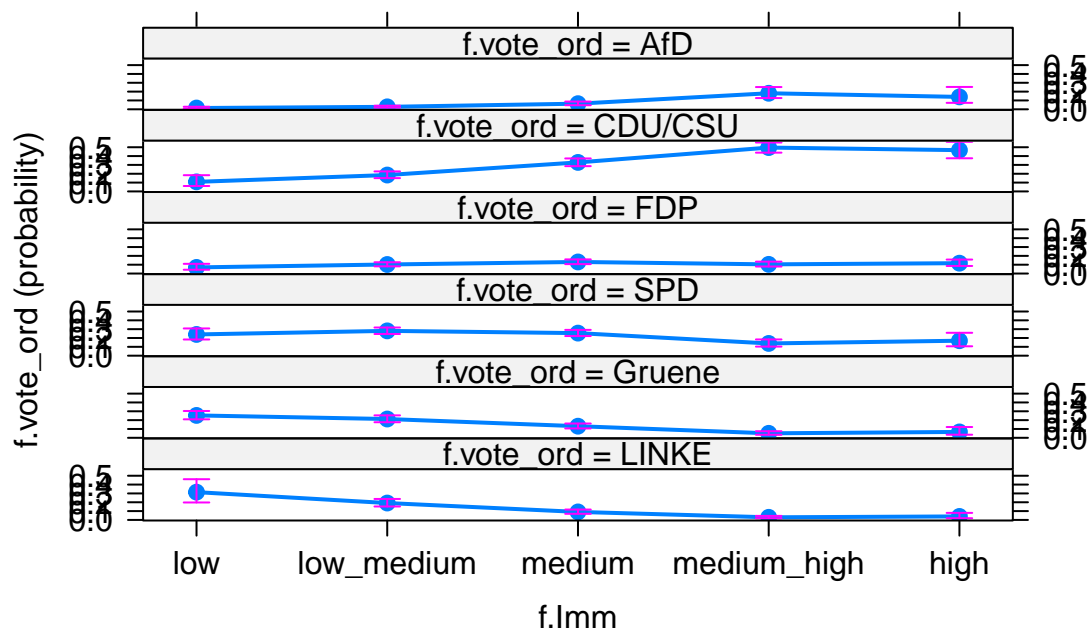


```
plot(allEffects(om1_imm_cat_new),ask=FALSE, main="Effects Imm Categorical")
```

```
##
```

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

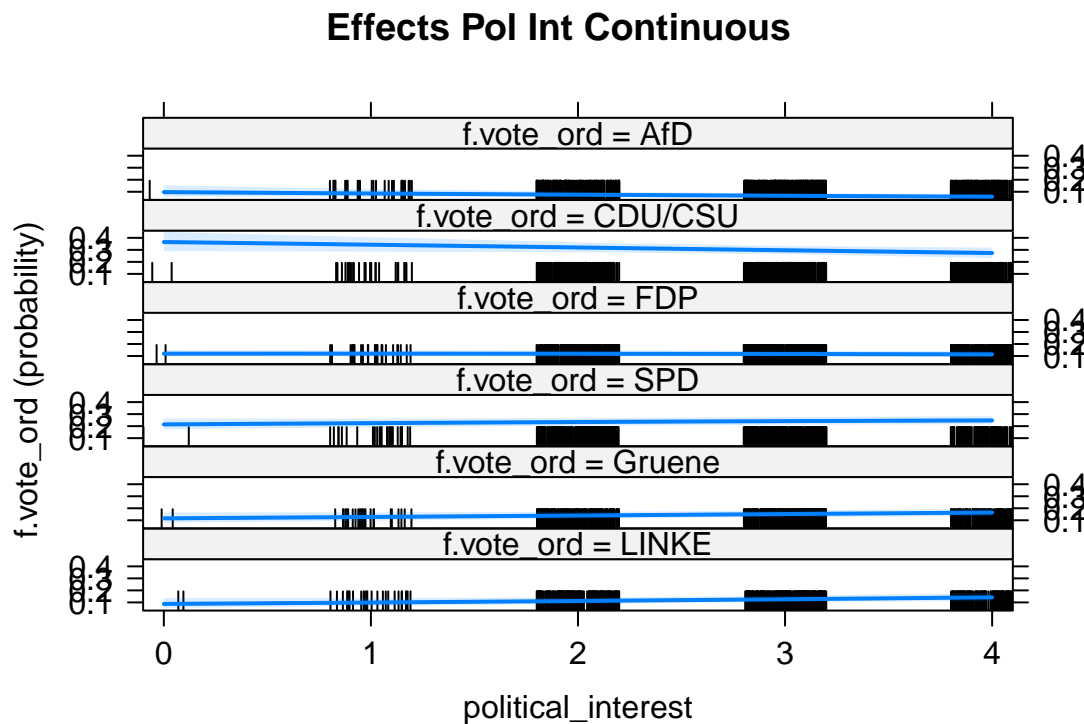
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##              LR Chisq Df Pr(>Chisq)
## f.political_interest  7.7343  4      0.1018
Anova(om1_polint_cat_new, test="Chisq")

## 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")

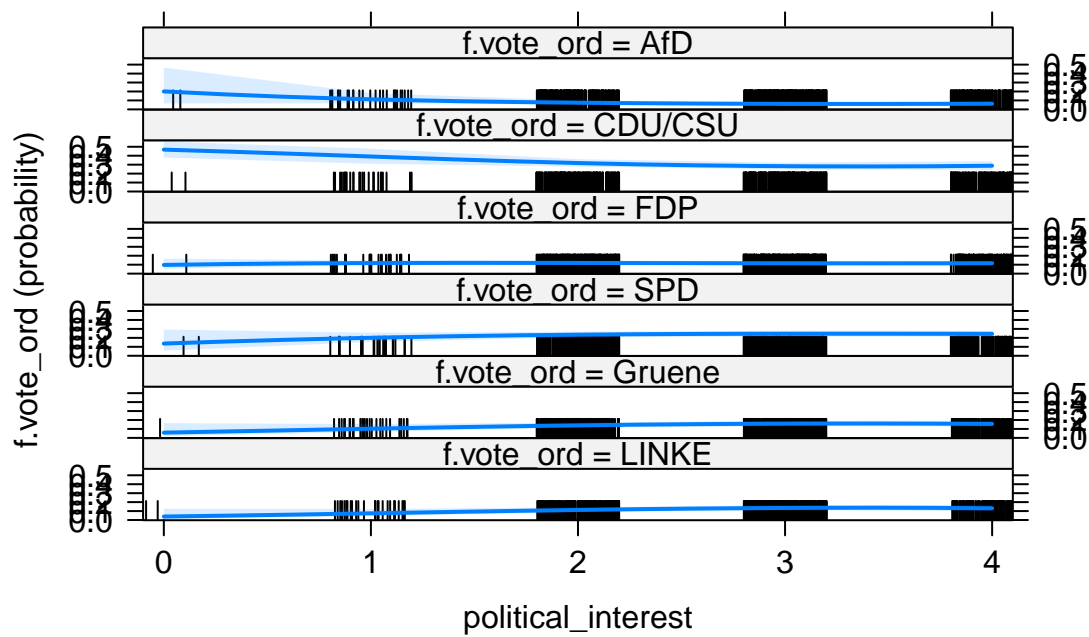
##
## Re-fitting to get Hessian
```



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

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

Effects Pol Int Continuous Squared

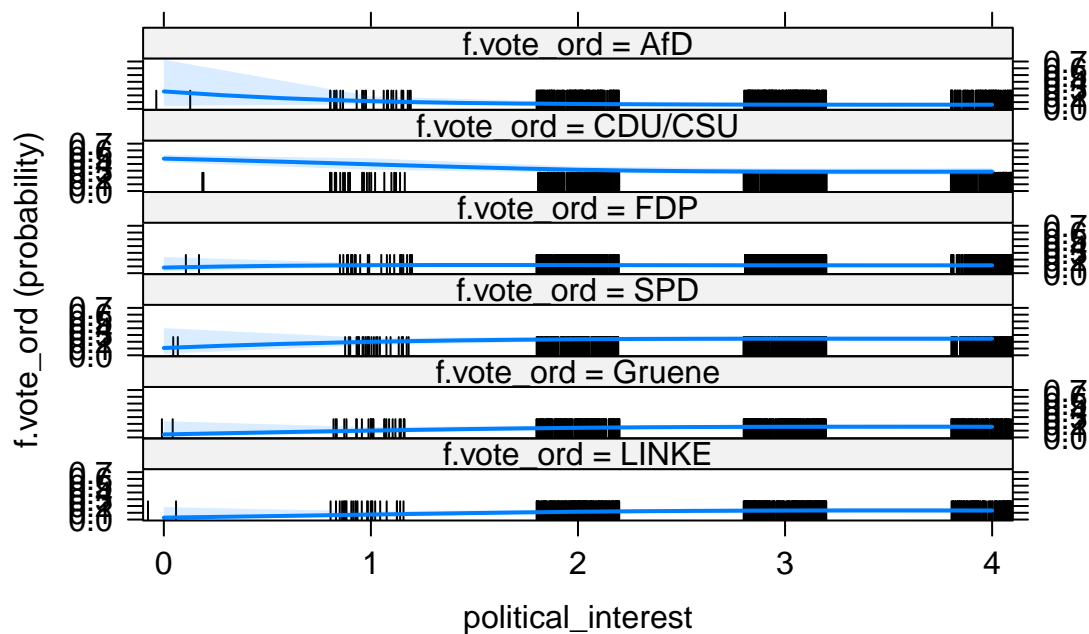


```
plot(allEffects(om1_polint_con_cb),ask=FALSE, main="Effects Pol Int Continuous Cubed")
```

```
##
```

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

Effects Pol Int Continuous Cubed

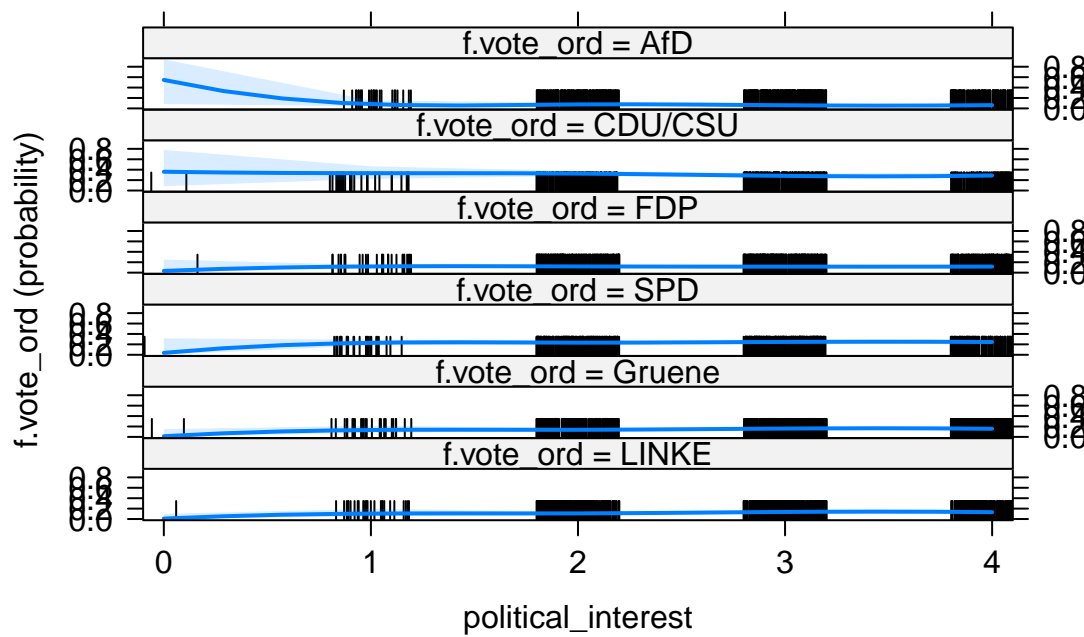


```
plot(allEffects(om1_polint_con_qd),ask=FALSE, main="Effects Pol Int Continuous Quadratic")
```

```
##
```

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

Effects Pol Int Continuous Quadratic

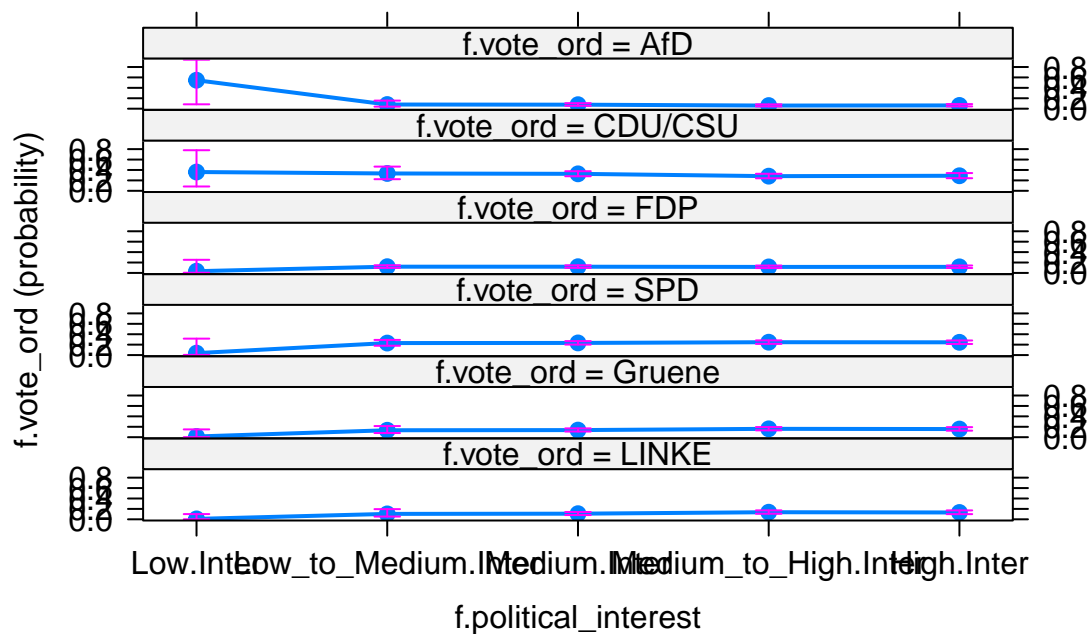


```
plot(allEffects(om1_polint_cat),ask=FALSE, main="Effects Pol Int Categorical")
```

```
##
```

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

Effects Pol Int Categorical

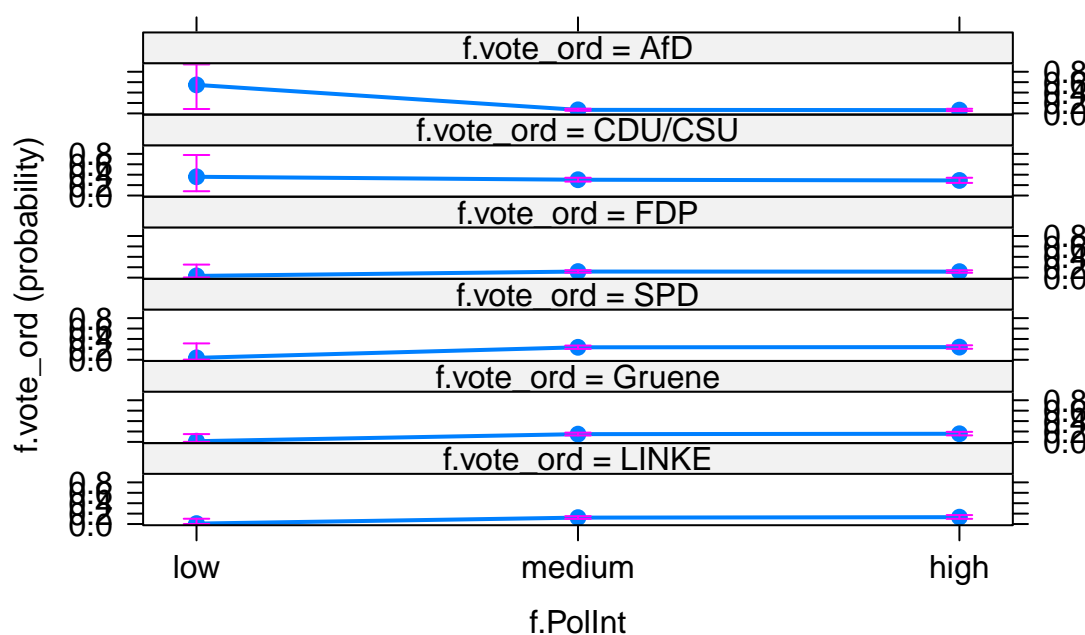


```
plot(allEffects(om1_polint_cat_new),ask=FALSE, main="Effects Pol Int Categorical")
```

```
##
```

```
## 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 .
```

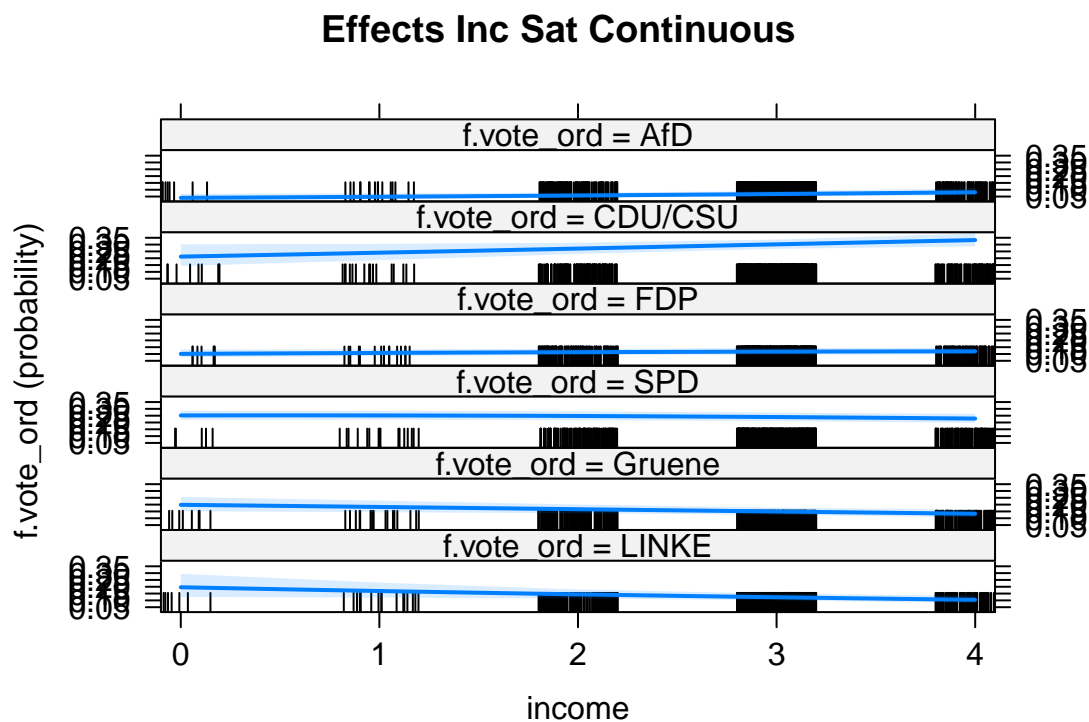
```
## ---
```

```
## 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
```

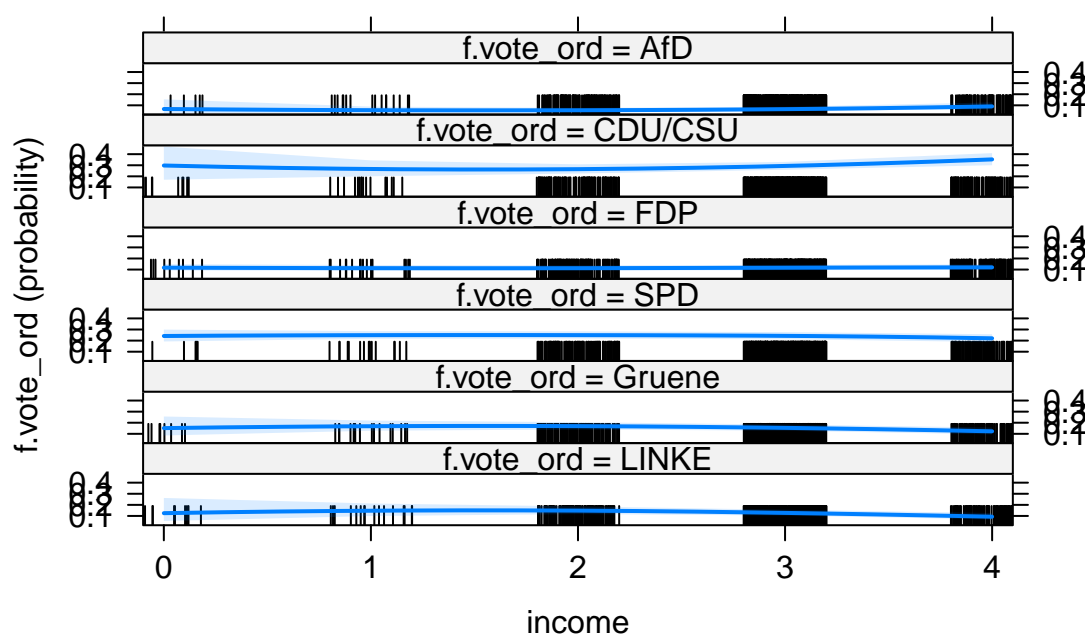


```
plot(allEffects(om1_inc_con_sq),ask=FALSE,main="Effects Inc Sat Continuous Squared")
```

```
##
```

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


Effects Inc Sat Continuous Squared

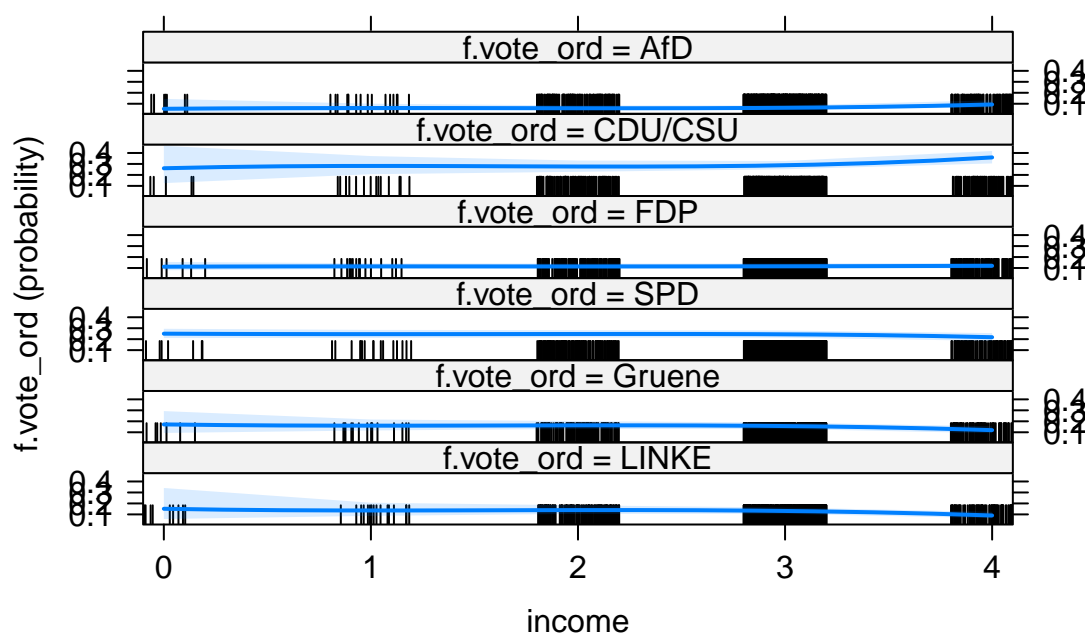


```
plot(allEffects(om1_inc_con_cb),ask=FALSE, main="Effects Inc Sat Continuous Cubed")
```

```
##
```

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

Effects Inc Sat Continuous Cubed

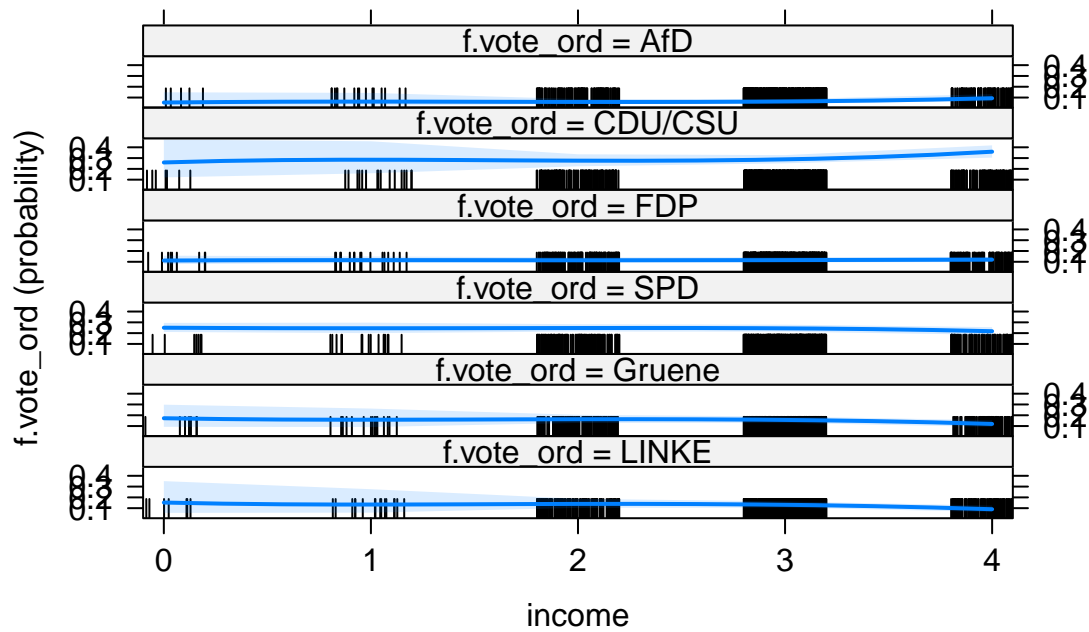


```
plot(allEffects(om1_inc_con_qd),ask=FALSE, main="Effects Inc Sat Continuous Quadratic")
```

```
##
```

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

Effects Inc Sat Continuous Quadratic

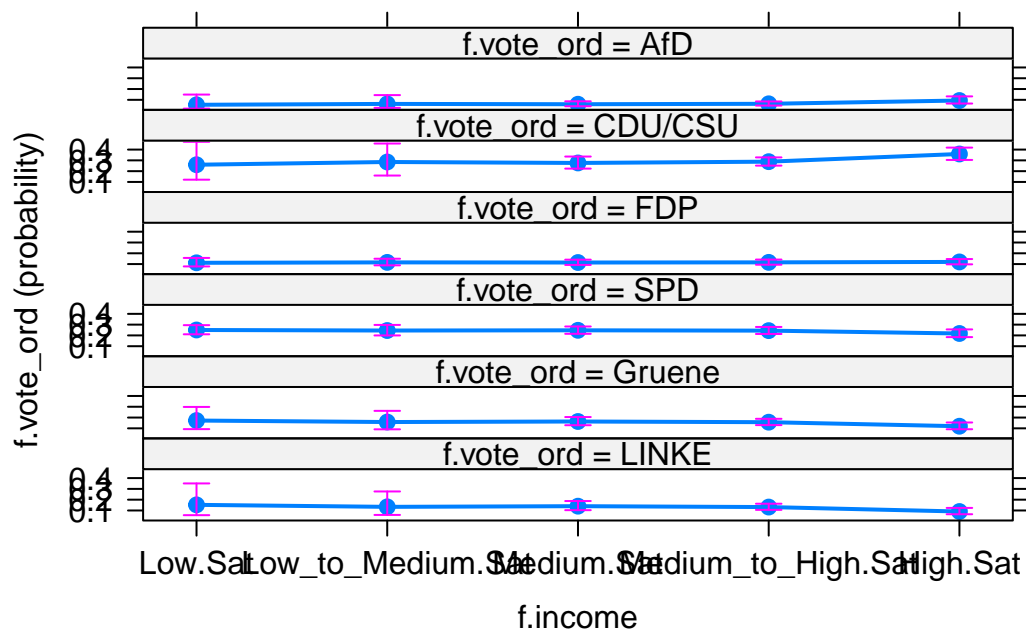


```
plot(allEffects(om1_inc_cat),ask=FALSE, main="Effects Inc Sat Categorical")
```

```
##
```

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

Effects Inc Sat Categorical

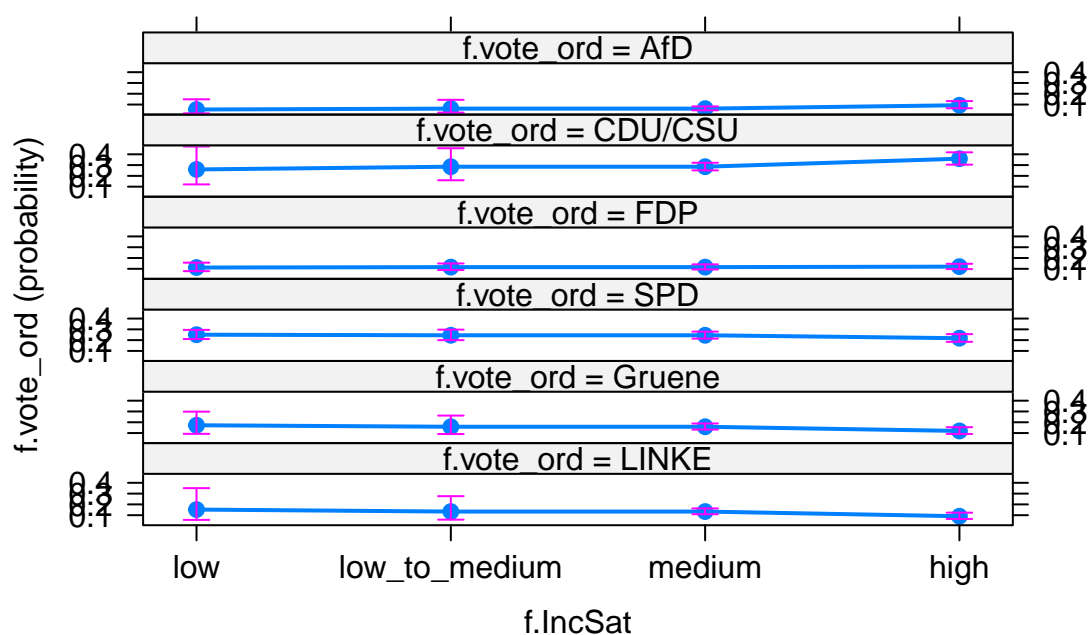


```
plot(allEffects(om1_inc_cat_new),ask=FALSE, main="Effects Inc Sat Categorical")
```

```
##
```

```
## 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

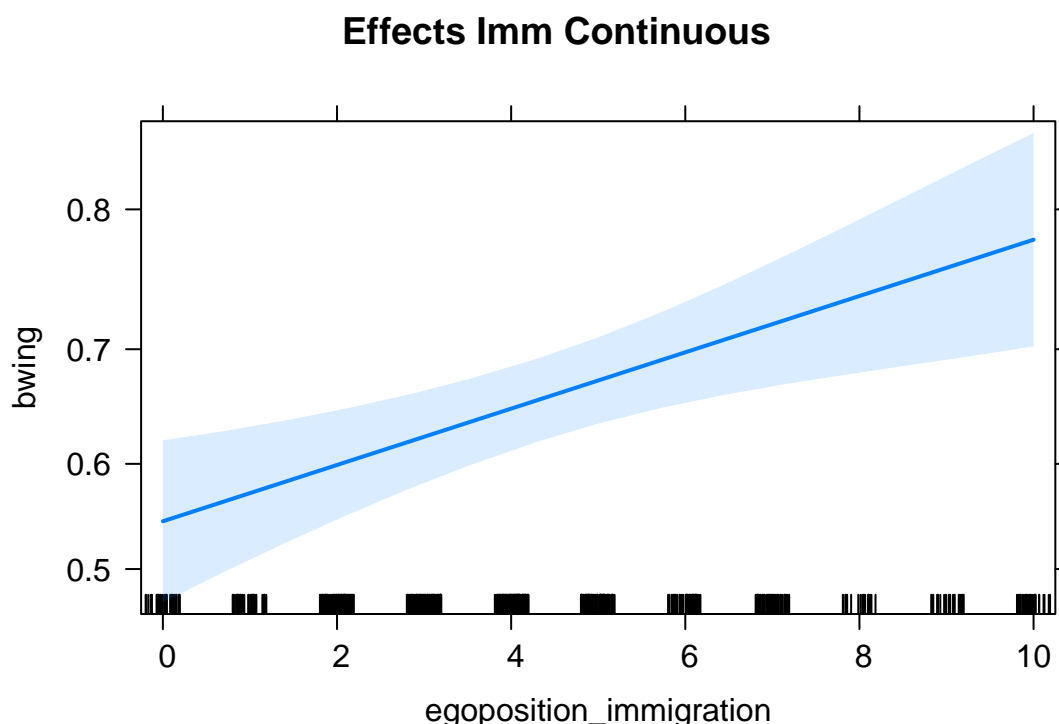
Anova(bhm1_imm_con_qd, test="Wald")

## 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")

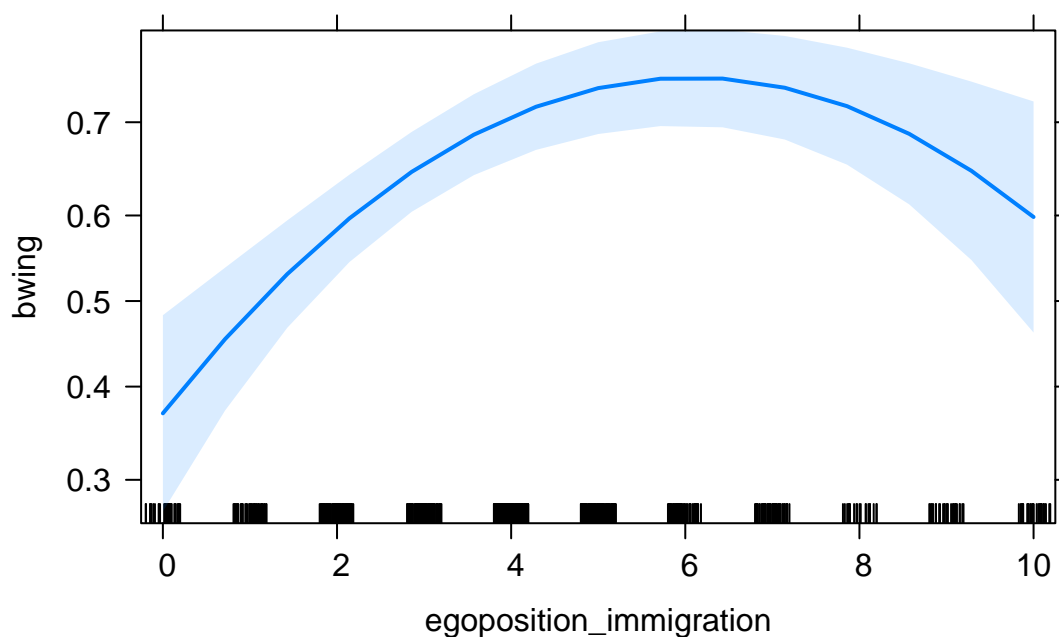
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##                                Df  Chisq Pr(>Chisq)
## f.egoposition_immigration 10 46.032  1.415e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Anova(bhm1_imm_cat_new, test="Wald")

## 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")
```



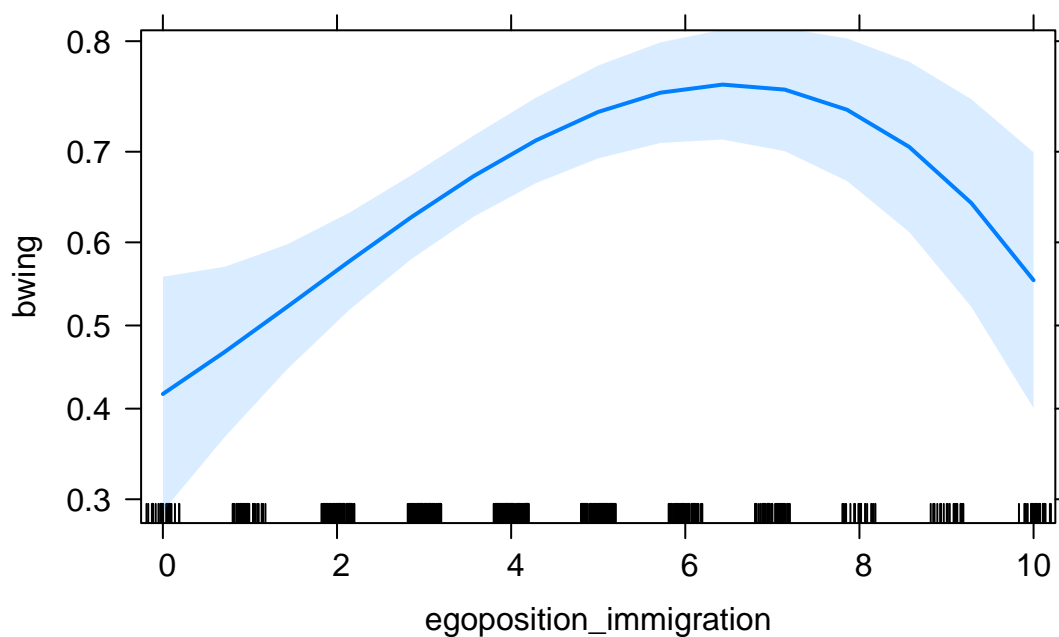
```
plot(allEffects(bhm1_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```

Effects Imm Continuous Squared



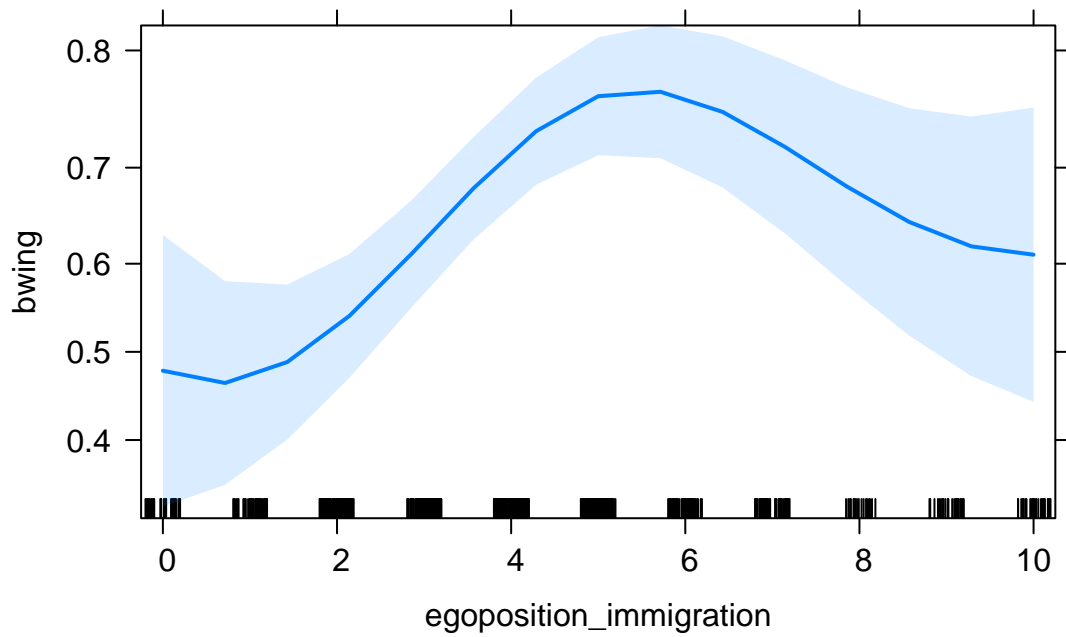
```
plot(allEffects(bhm1_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```

Effects Imm Continuous Cubed



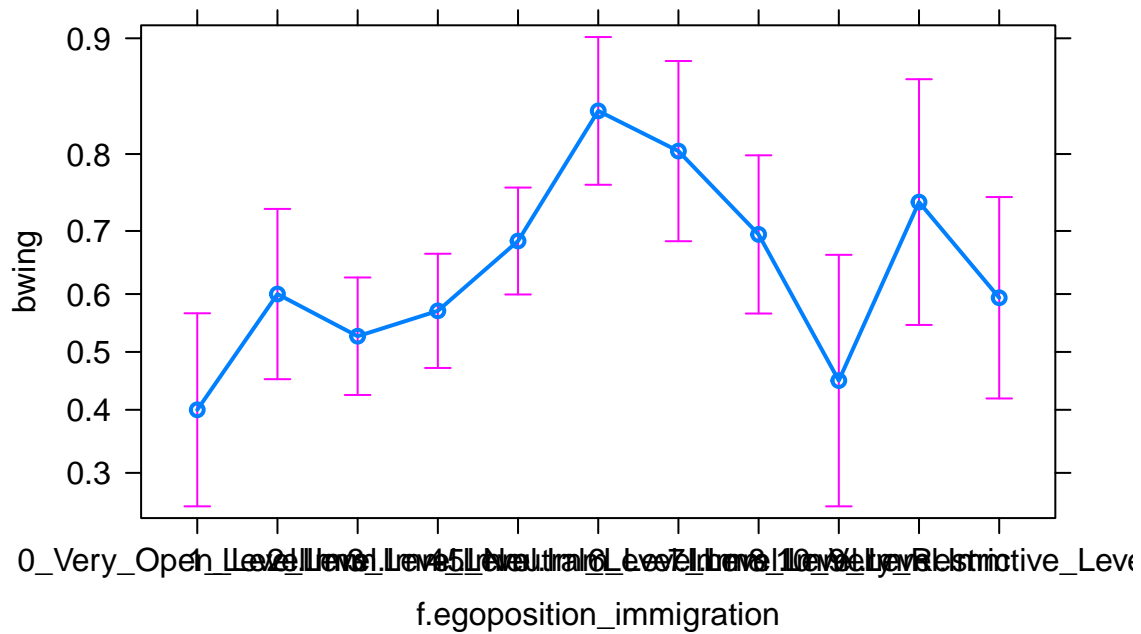
```
plot(allEffects(bhm1_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```

Effects Imm Continuous Quadratic



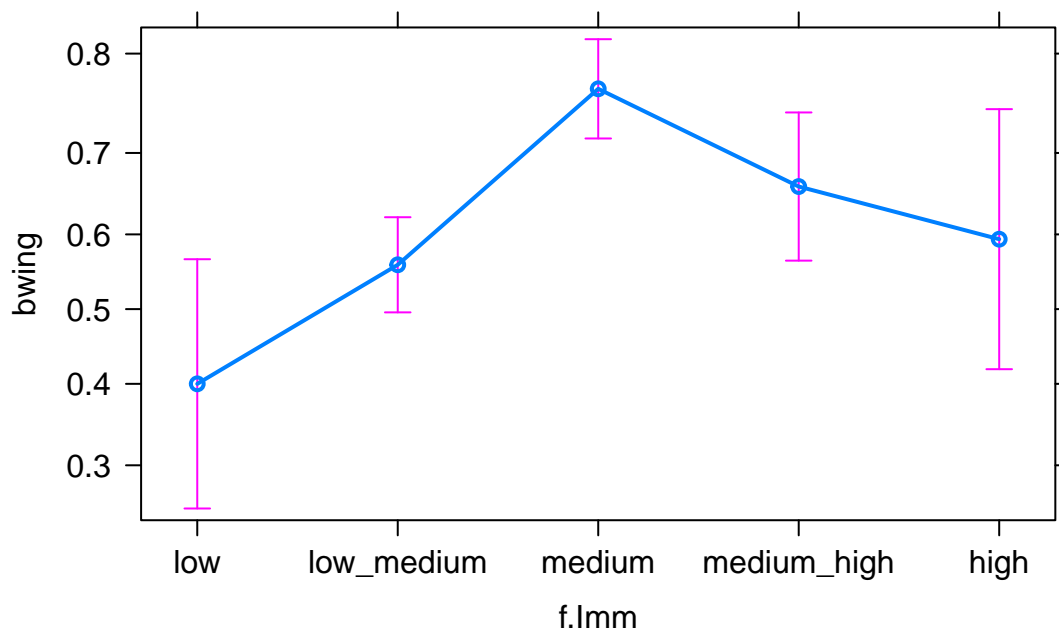
```
plot(allEffects(bhm1_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

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)
```

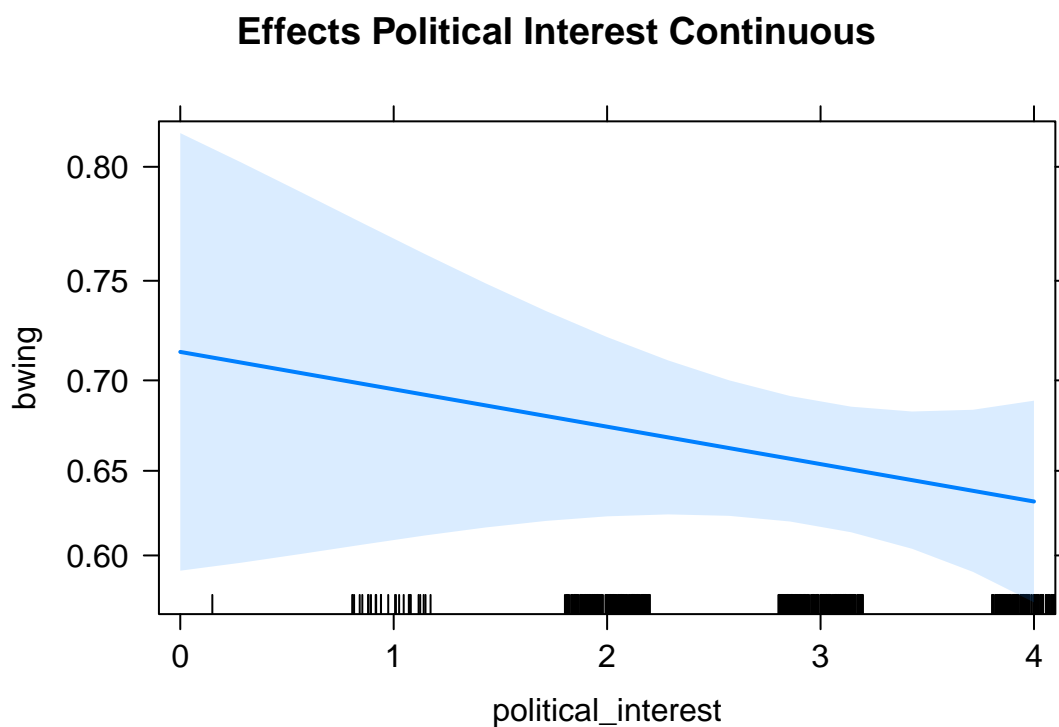
```
##
```

```
## Response: bwing
```

```
##           Df  Chisq Pr(>Chisq)
```

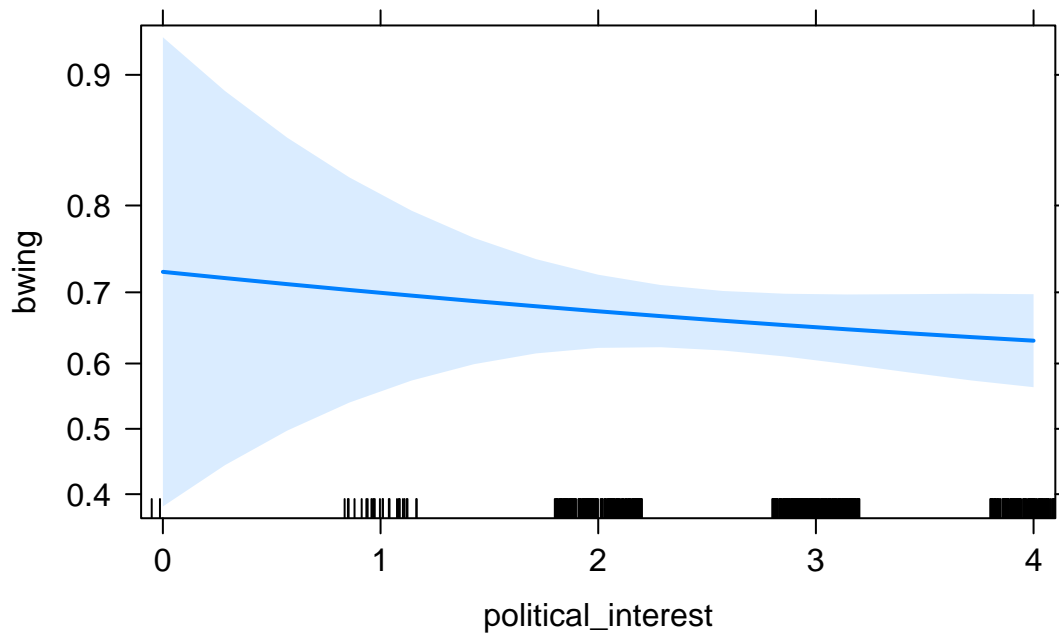
```
## f.PolInt    2 0.2305    0.8912
```

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



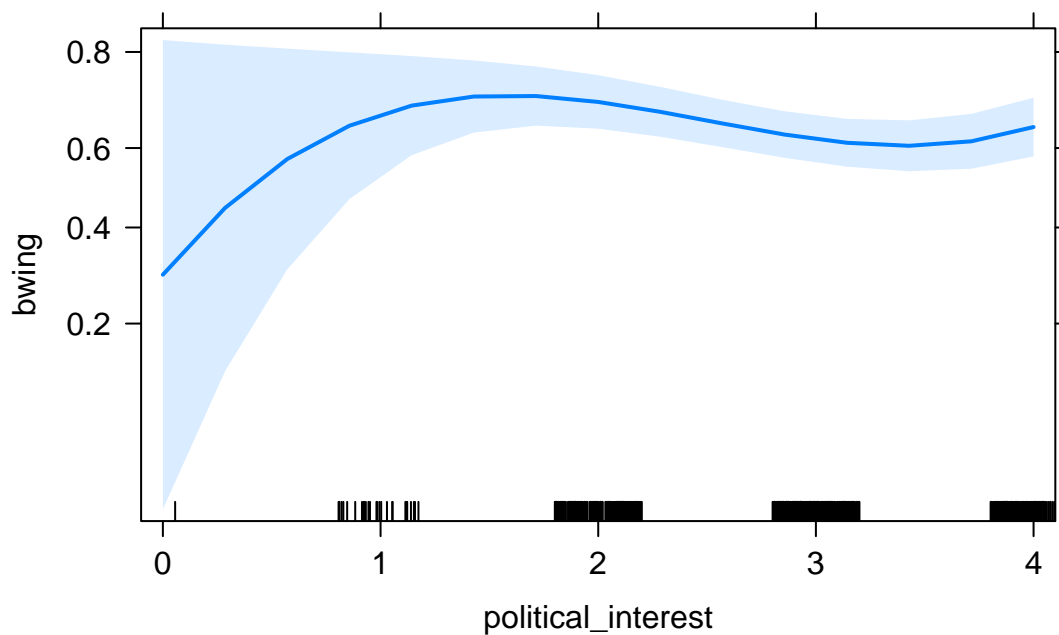
```
plot(allEffects(bhm1_polint_con_sq),ask=FALSE,main="Effects Political Interest Continuous")
```

Effects Political Interest Continuous Squared



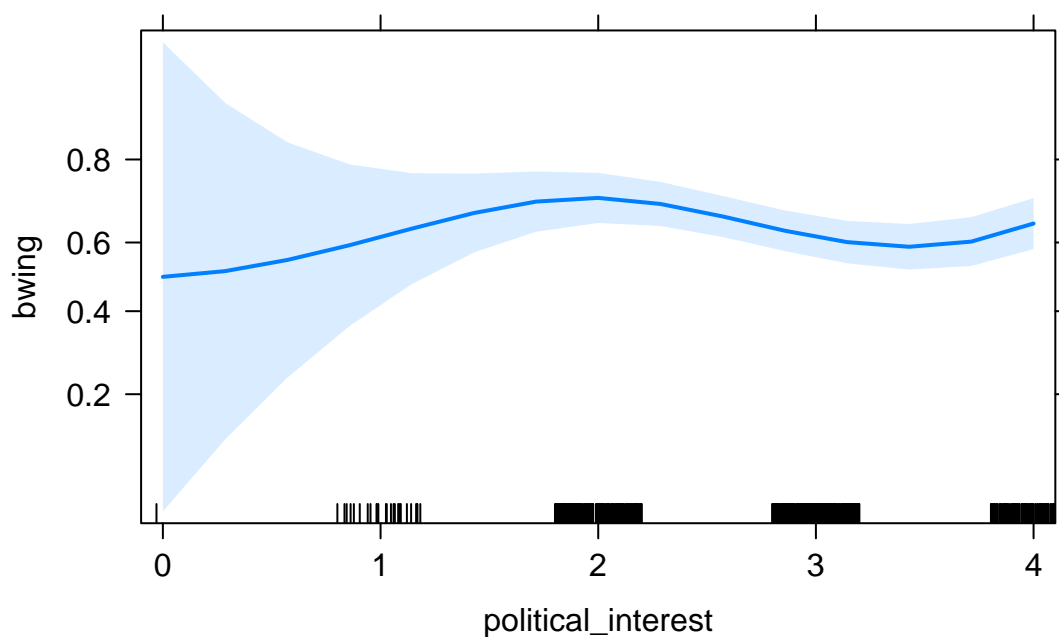
```
plot(allEffects(bhm1_polint_con_cb),ask=FALSE, main="Effects Political Interest Continuous Squared")
```

Effects Political Interest Continuous Cubed



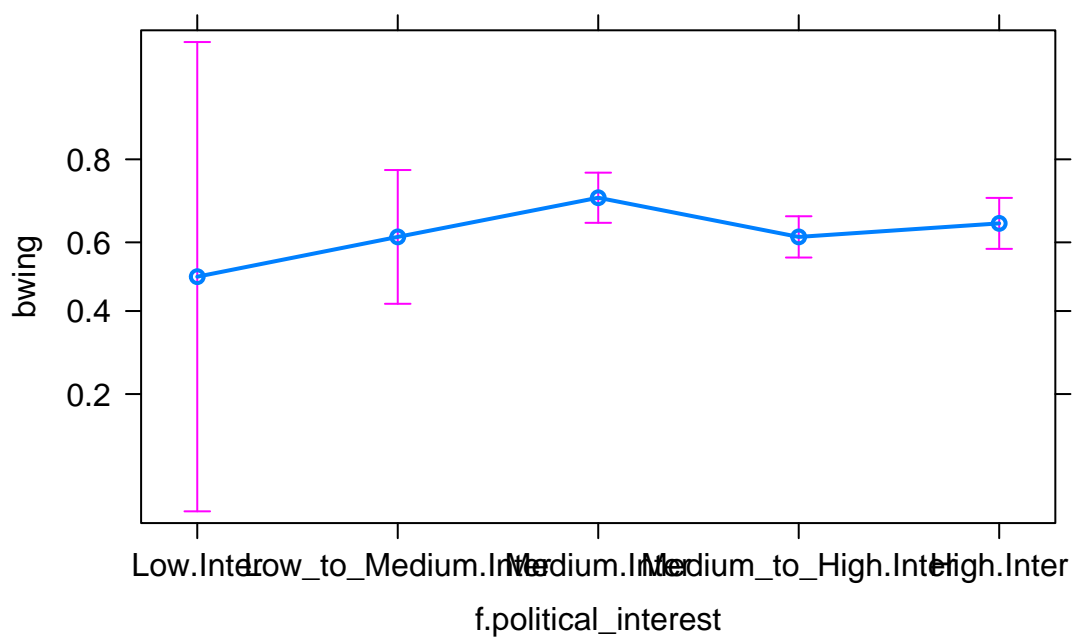
```
plot(allEffects(bhm1_polint_con_qd),ask=FALSE, main="Effects Political Interest Continuous Cubed")
```

Effects Political Interest Continuous Quadratic



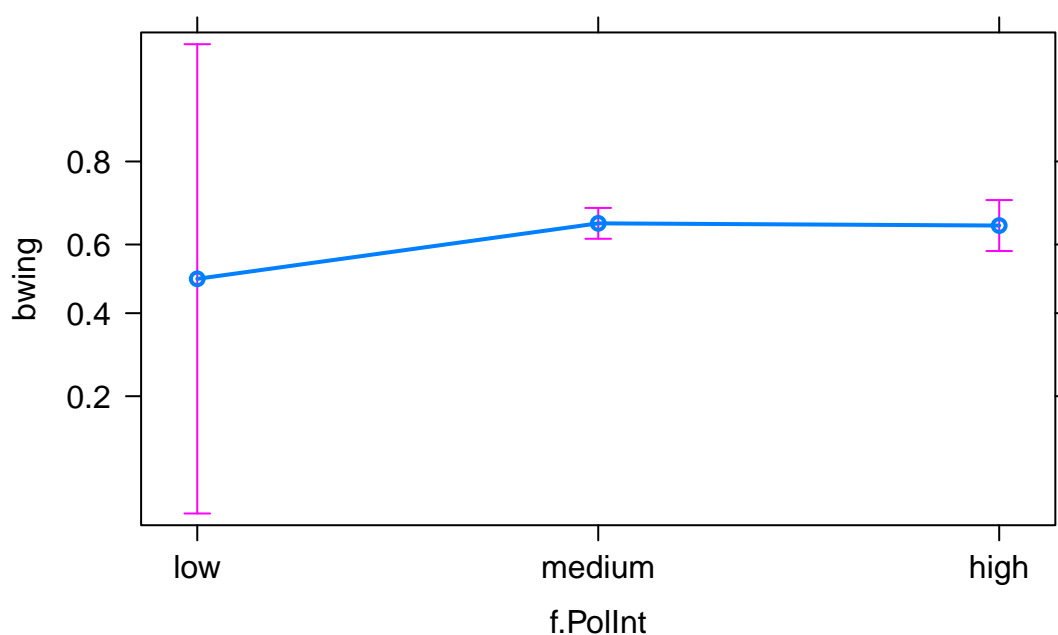
```
plot(allEffects(bhm1_polint_cat),ask=FALSE, main="Effects Political Interest Categorical")
```

Effects Political Interest Categorical



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

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")

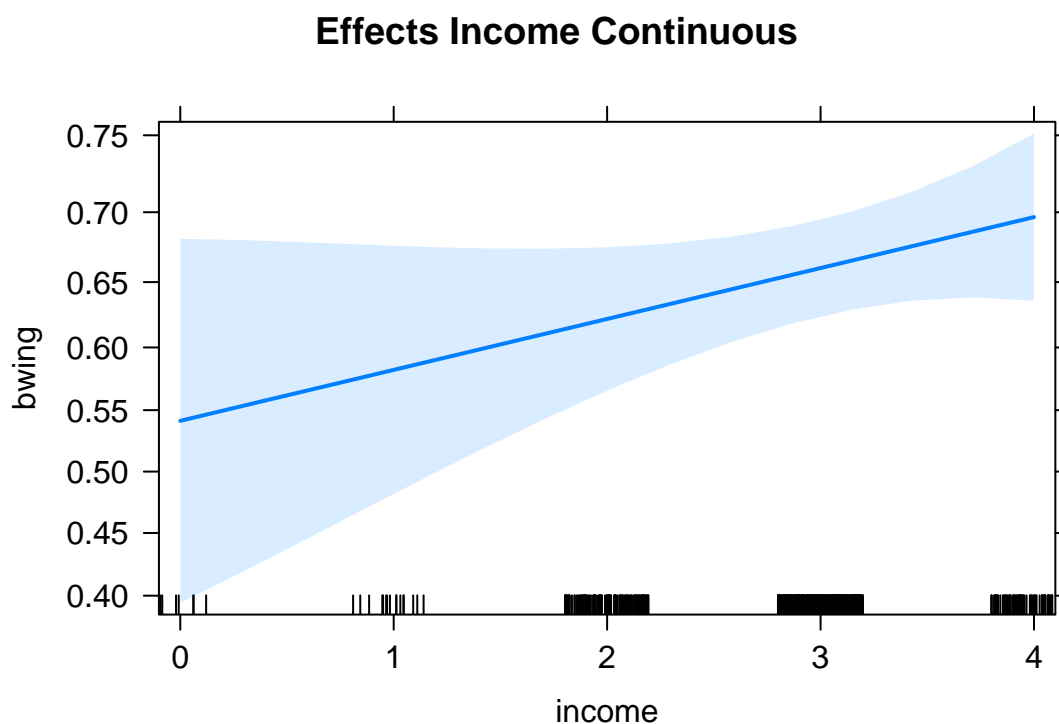
```

```
## 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")
```

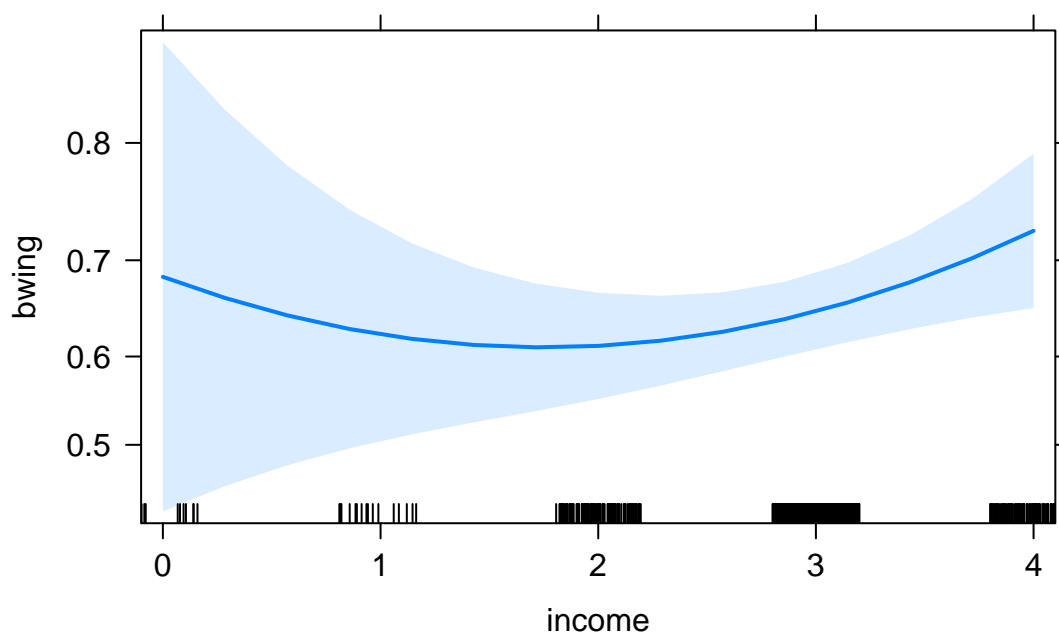
```
## Analysis of Deviance Table (Type II tests)
##
## Response: bwing
##           Df  Chisq Pr(>Chisq)
## f.IncSat    3 3.5048   0.3201
```

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



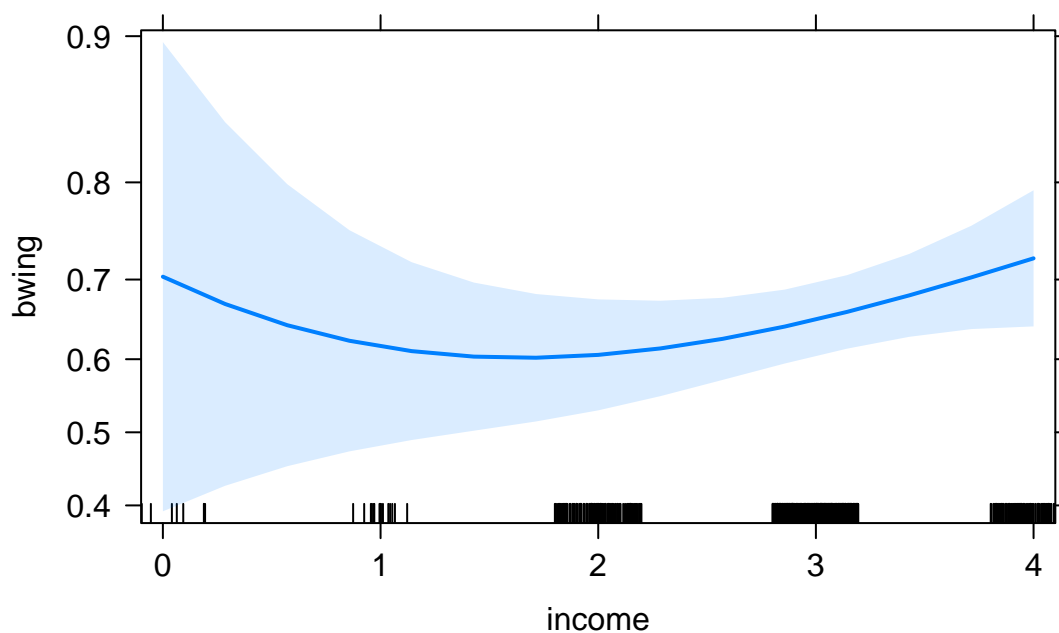
```
plot(allEffects(bhm1_inc_con_sq),ask=FALSE,main="Effects Income Continuous Squared")
```

Effects Income Continuous Squared



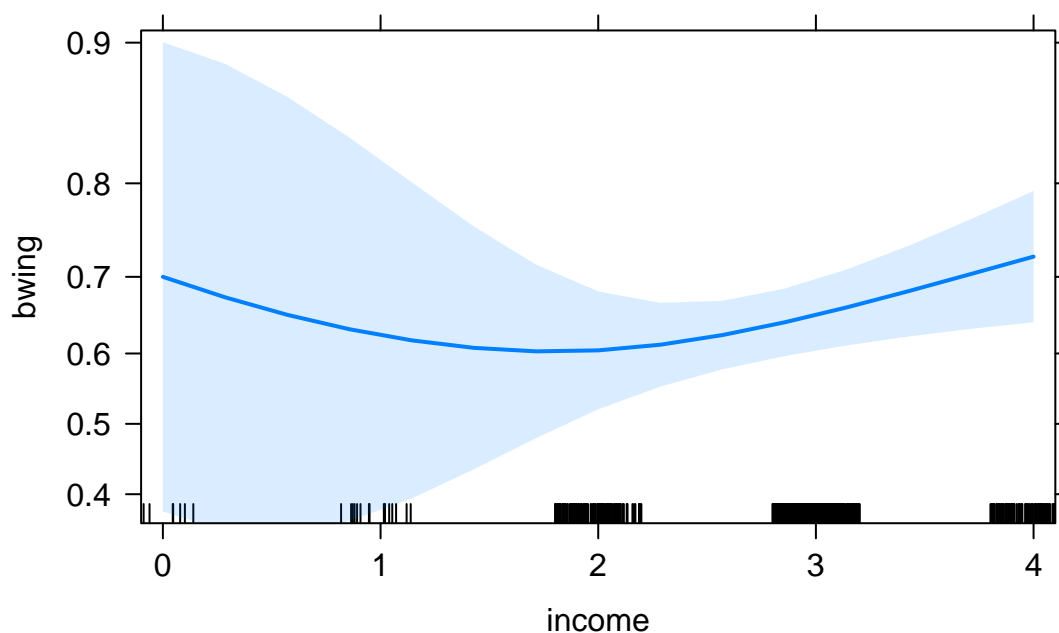
```
plot(allEffects(bhm1_inc_con_cb),ask=FALSE, main="Effects Income Continuous Cubed")
```

Effects Income Continuous Cubed



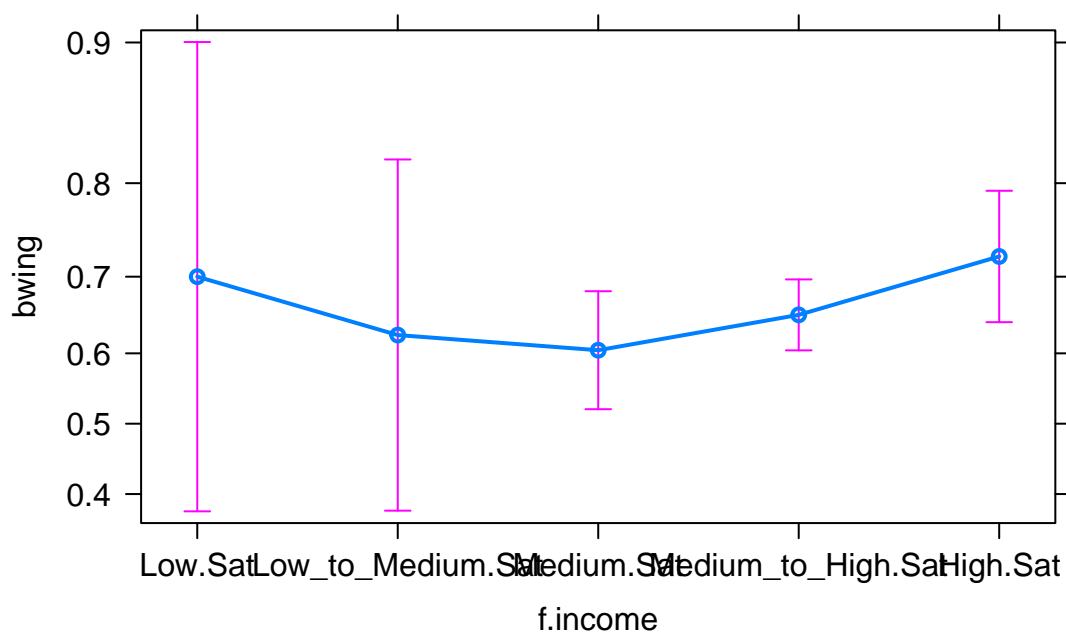
```
plot(allEffects(bhm1_inc_con_qd),ask=FALSE, main="Effects Income Interest Continuous Qua")
```


Effects Income Interest Continuous Quadratic



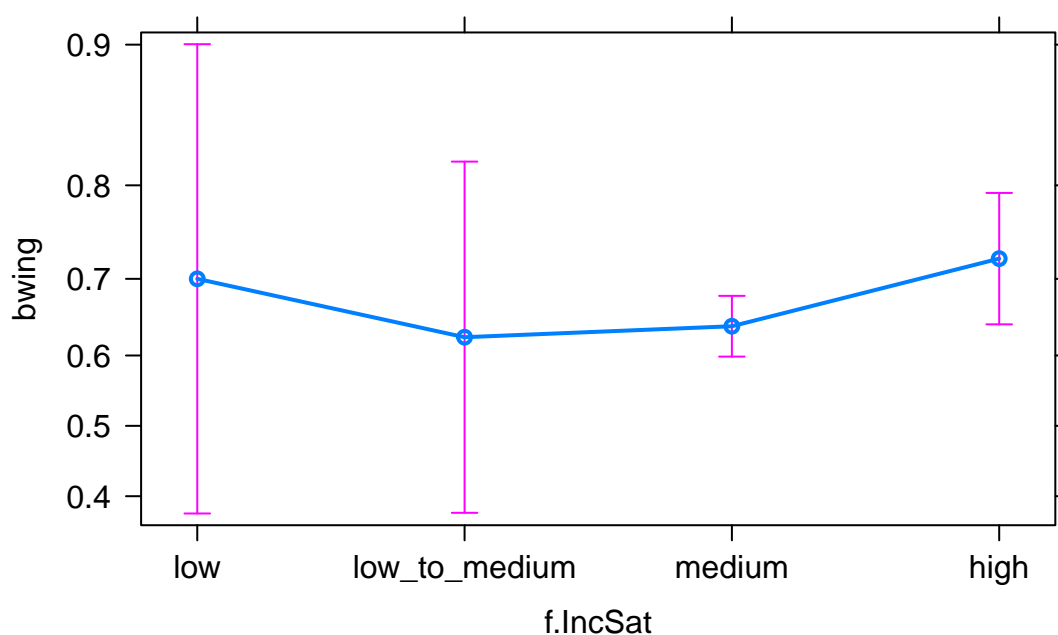
```
plot(allEffects(bhm1_inc_cat),ask=FALSE, main="Effects Income Interest Categorical")
```

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
```

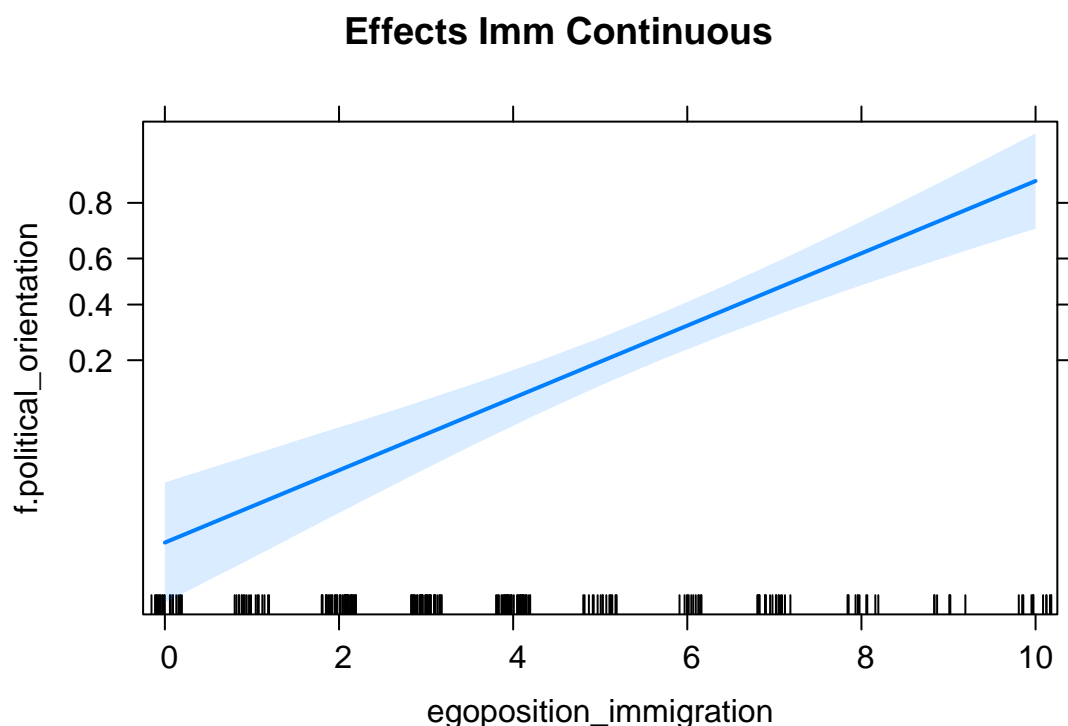
```
##           Df  Chisq Pr(>Chisq)
```

```
## f.Imm  4 70.592  1.702e-14 ***
```

```
## ---
```

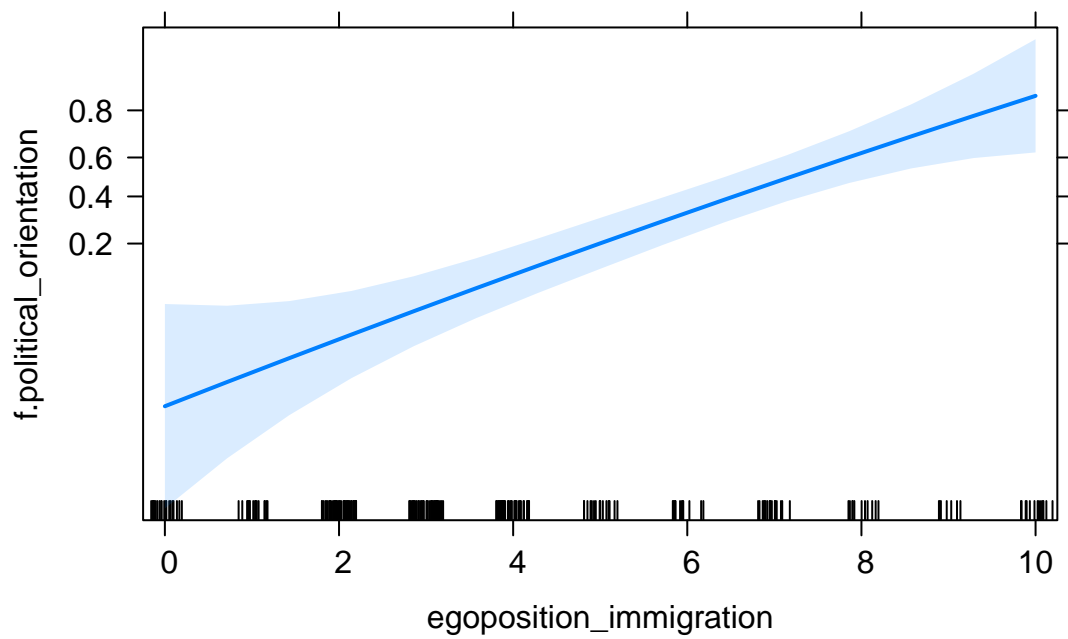
```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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



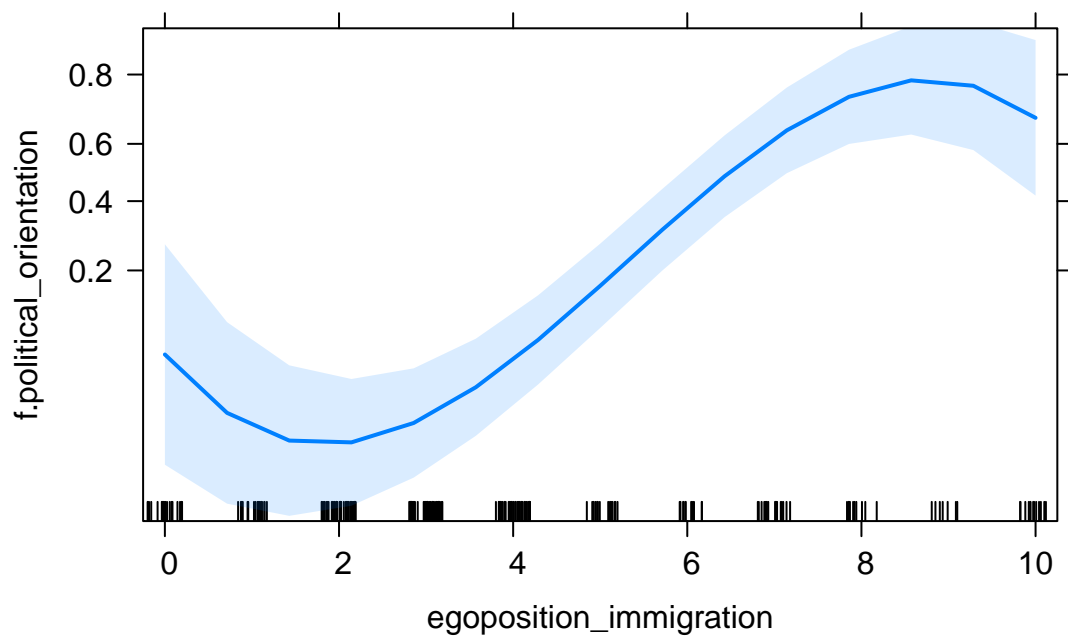
```
plot(allEffects(bhm2_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```

Effects Imm Continuous Squared



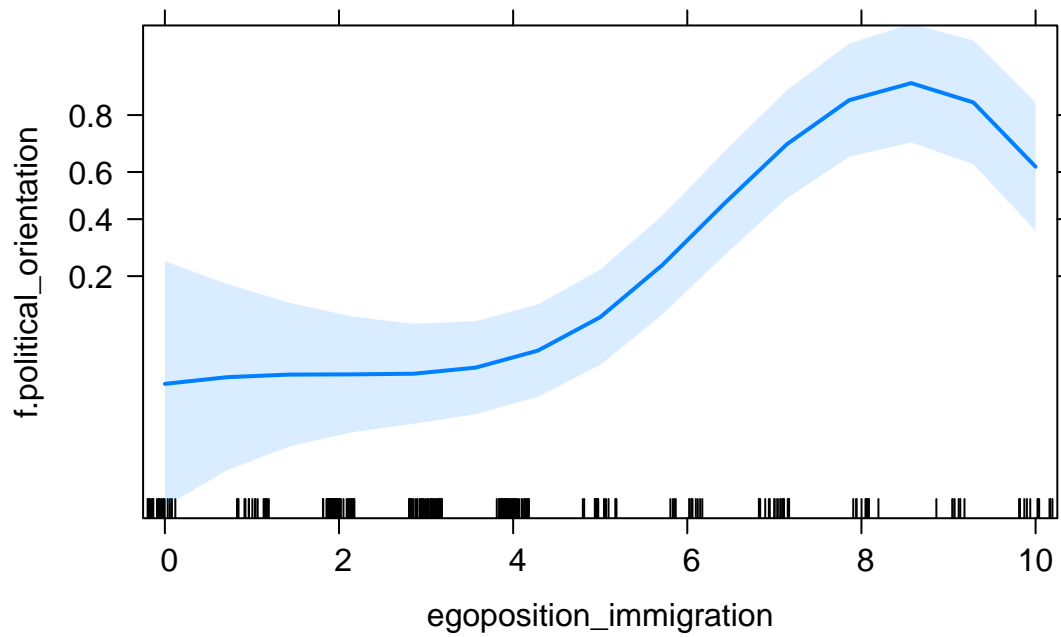
```
plot(allEffects(bhm2_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```

Effects Imm Continuous Cubed



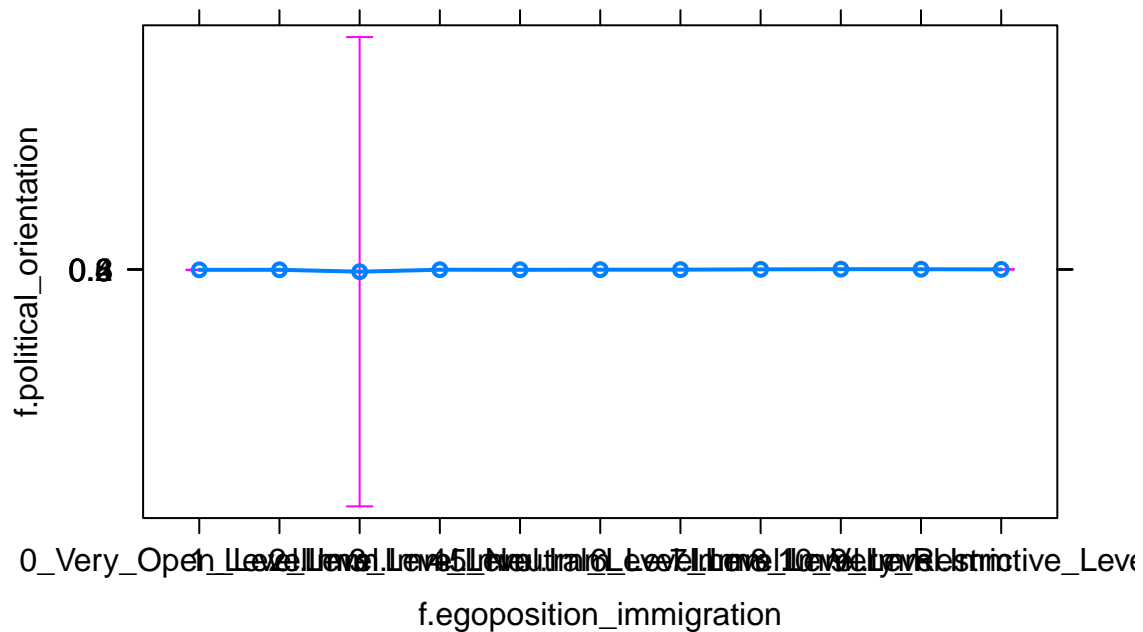
```
plot(allEffects(bhm2_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```

Effects Imm Continuous Quadratic



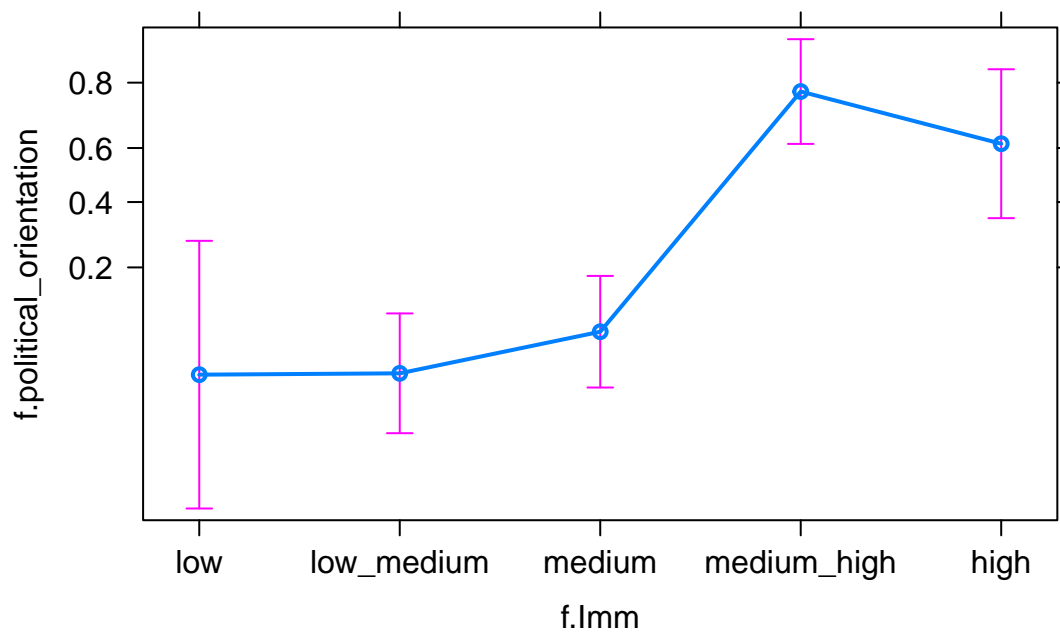
```
plot(allEffects(bhm2_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

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)
```

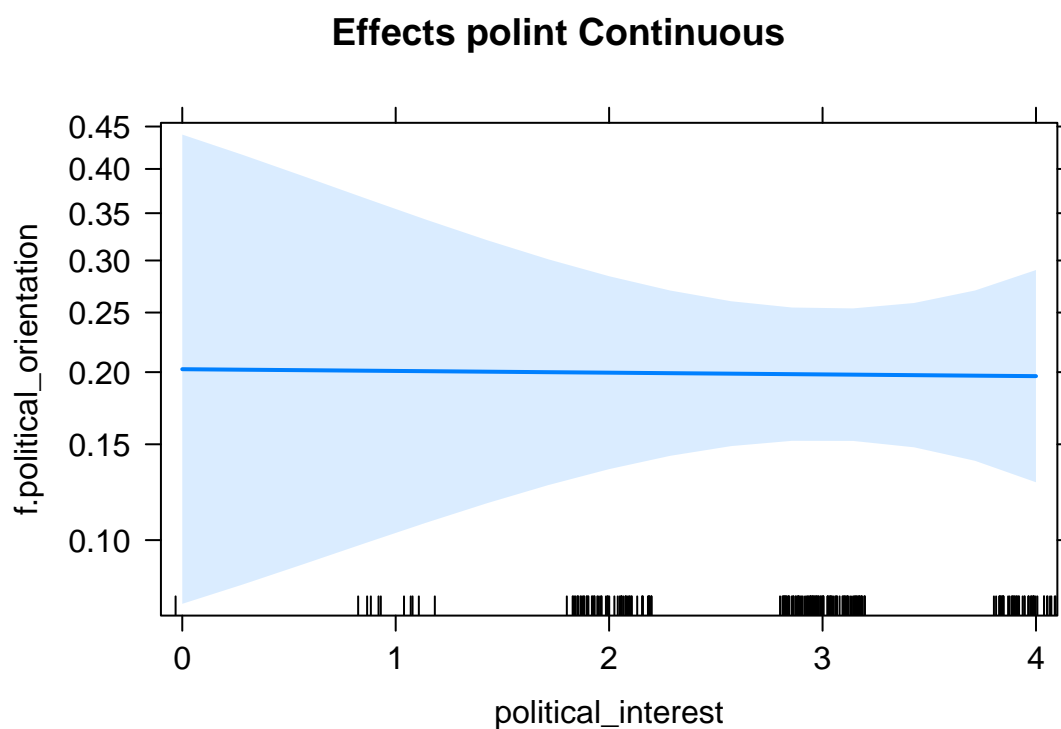
```
##
```

```
## Response: f.political_orientation
```

```
##          Df  Chisq Pr(>Chisq)
```

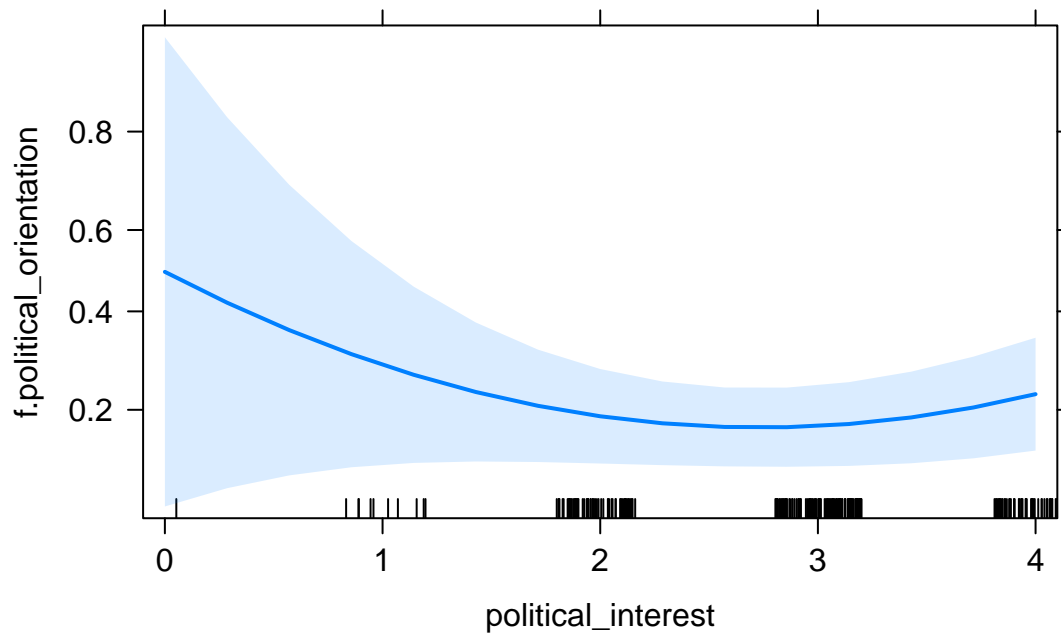
```
## f.PolInt  2  0.2351    0.8891
```

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



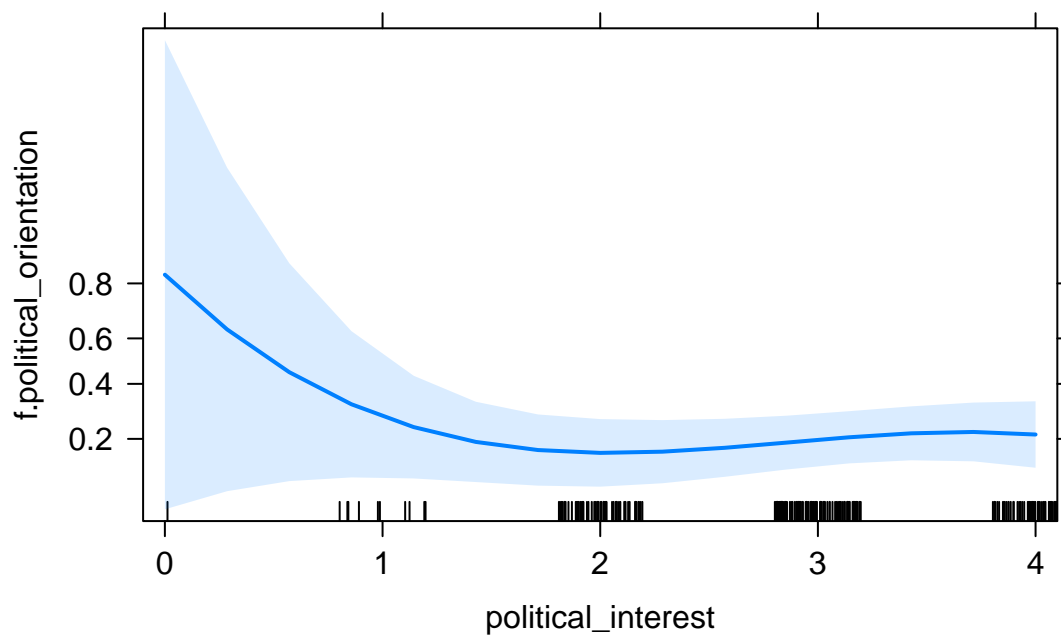
```
plot(allEffects(bhm2_polint_con_sq),ask=FALSE,main="Effects polint Continuous Squared")
```

Effects polint Continuous Squared



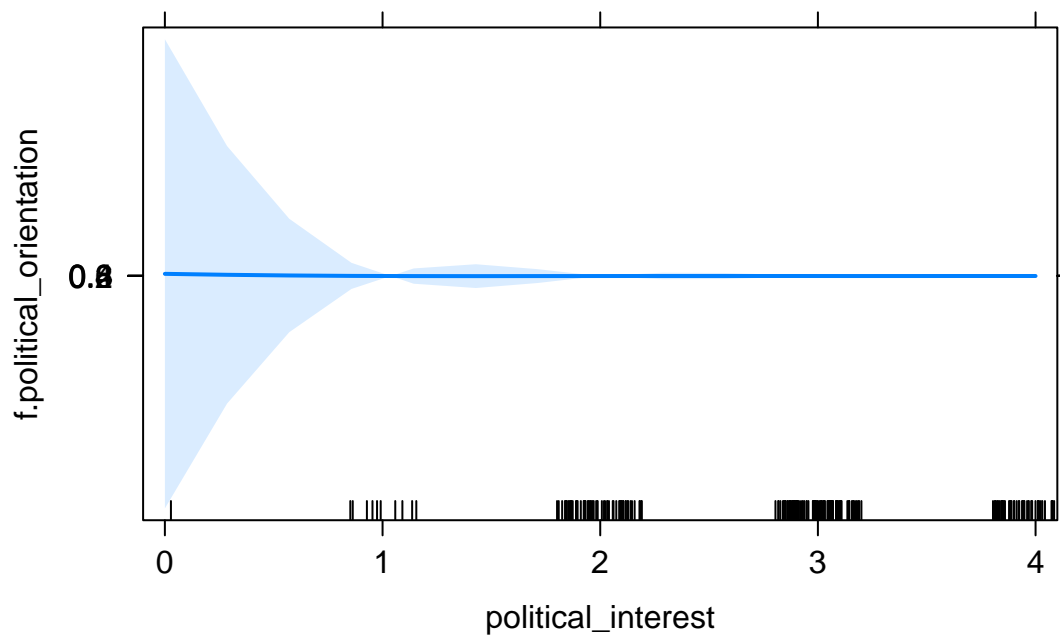
```
plot(allEffects(bhm2_polint_con_cb),ask=FALSE, main="Effects polint Continuous Cubed")
```

Effects polint Continuous Cubed



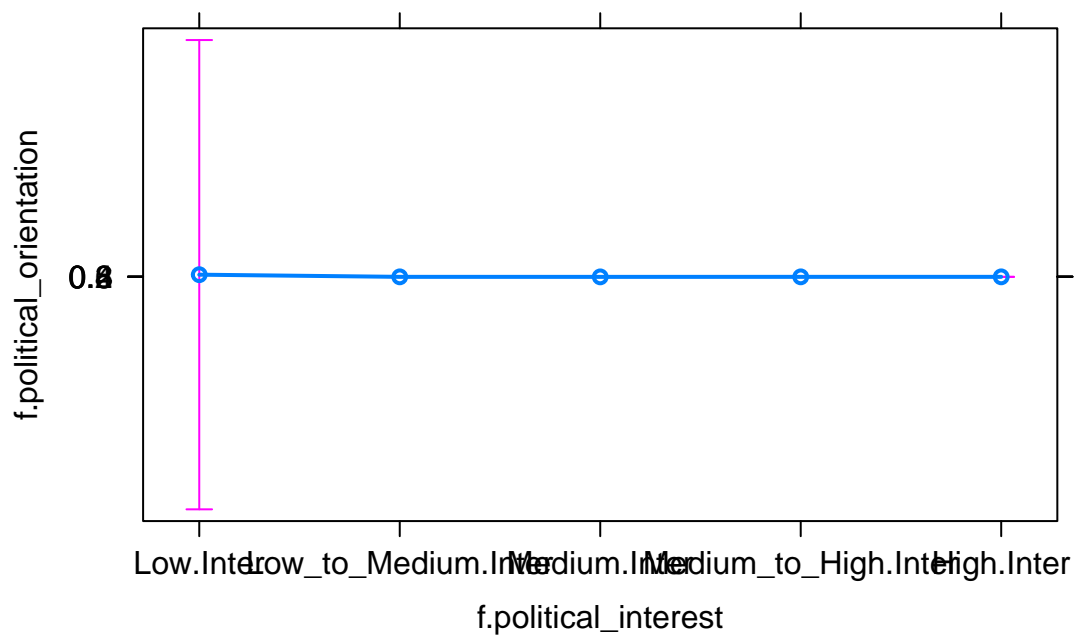
```
plot(allEffects(bhm2_polint_con_qd),ask=FALSE, main="Effects polint Continuous Quadratic")
```

Effects polint Continuous Quadratic



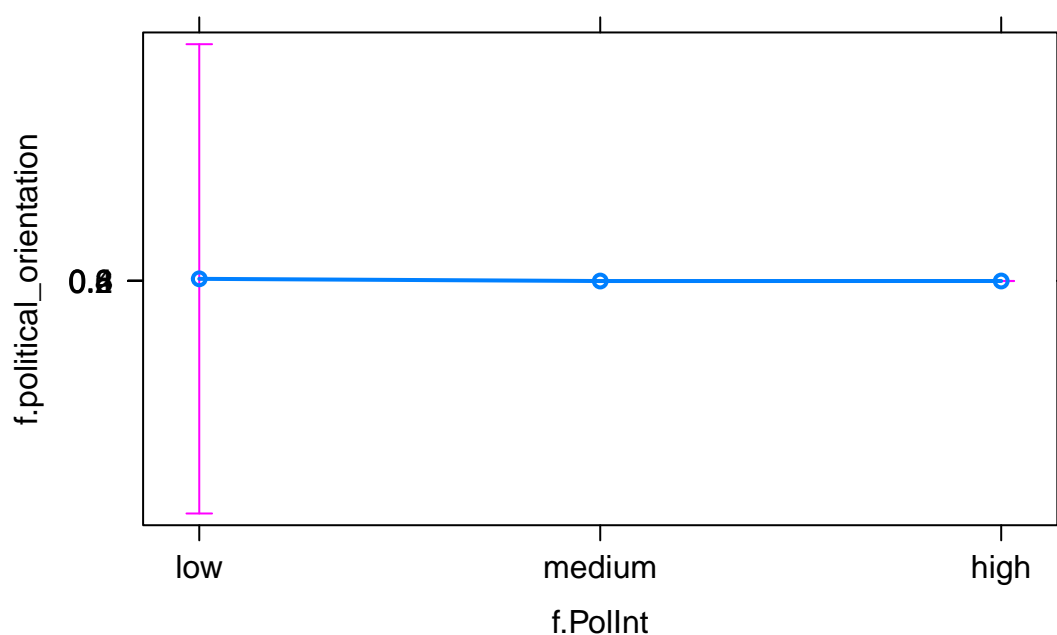
```
plot(allEffects(bhm2_polint_cat),ask=FALSE, main="Effects polint Categorical")
```

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)
```

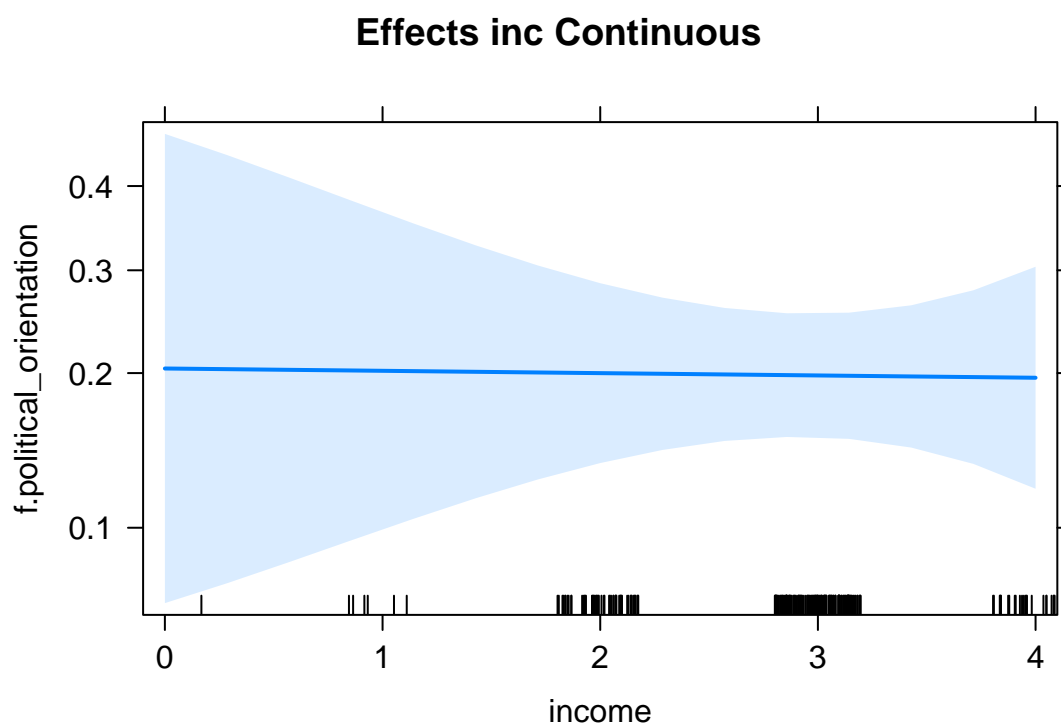
```
##
```

```
## Response: f.political_orientation
```

```
##           Df  Chisq Pr(>Chisq)
```

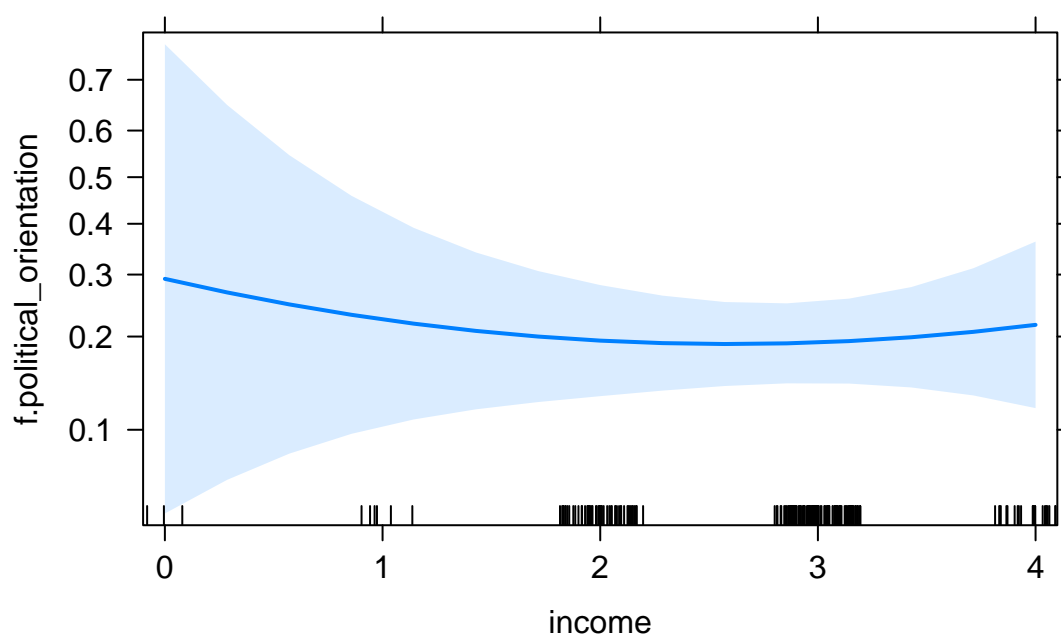
```
## f.IncSat   3  2.0817   0.5556
```

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



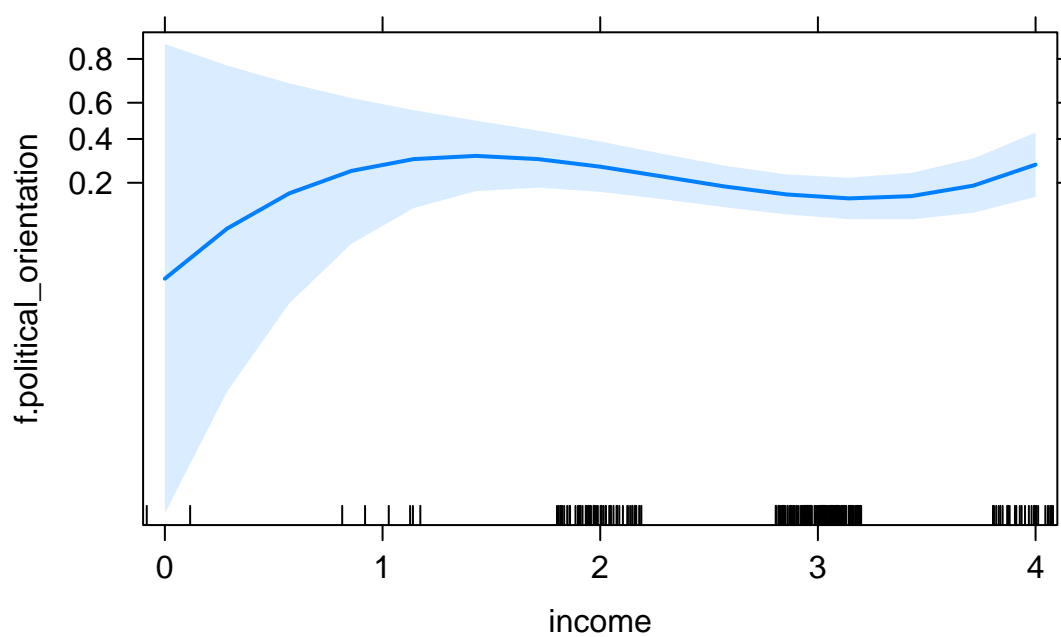
```
plot(allEffects(bhm2_inc_con_sq),ask=FALSE,main="Effects inc Continuous Squared")
```

Effects inc Continuous Squared



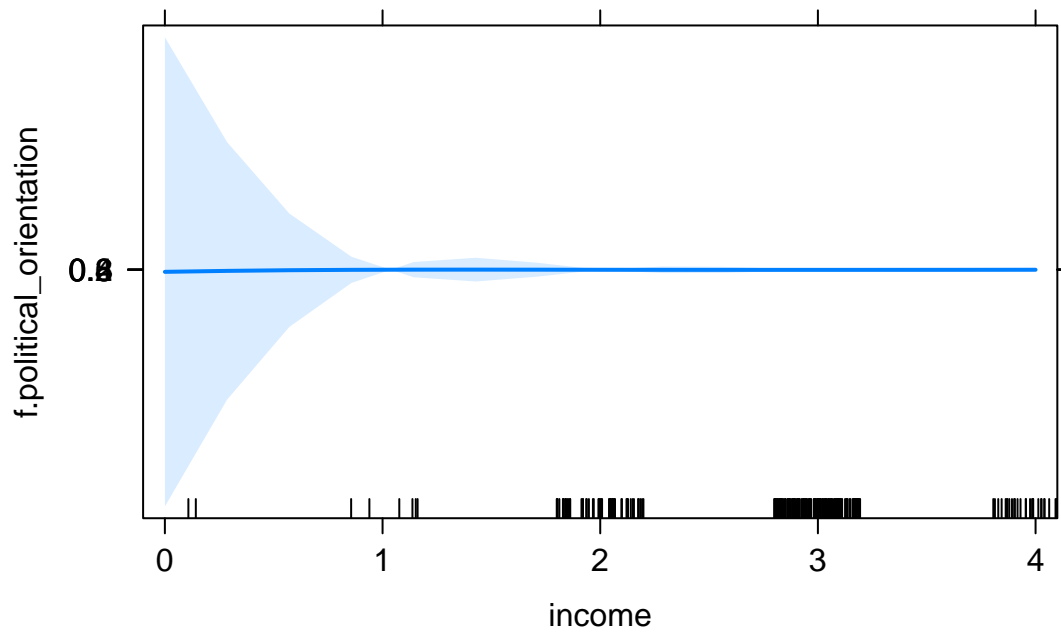
```
plot(allEffects(bhm2_inc_con_cb),ask=FALSE, main="Effects inc Continuous Cubed")
```

Effects inc Continuous Cubed



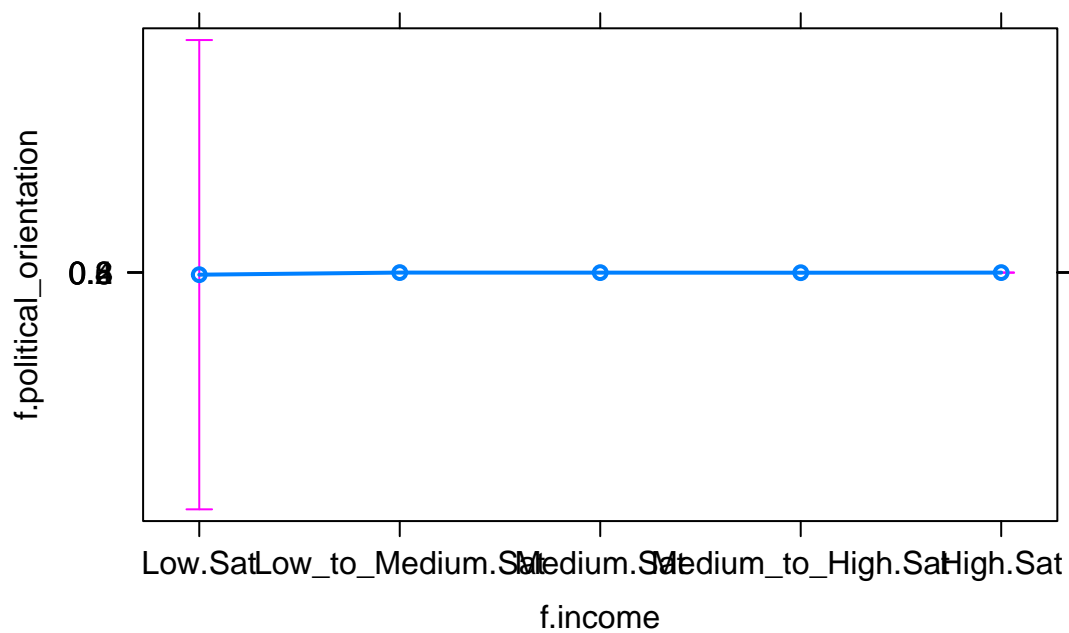
```
plot(allEffects(bhm2_inc_con_qd),ask=FALSE, main="Effects inc Continuous Quadratic")
```

Effects inc Continuous Quadratic



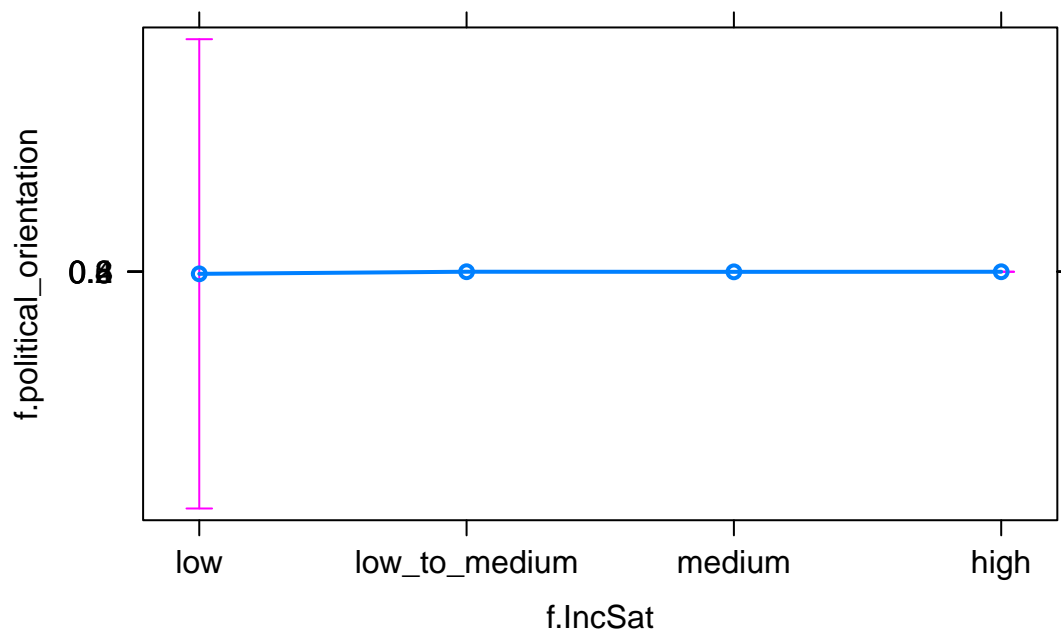
```
plot(allEffects(bhm2_inc_cat),ask=FALSE, main="Effects inc Categorical")
```

Effects inc Categorical



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

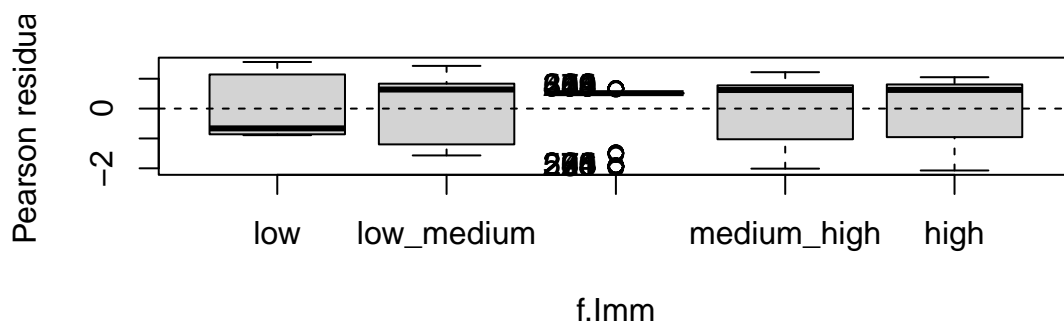
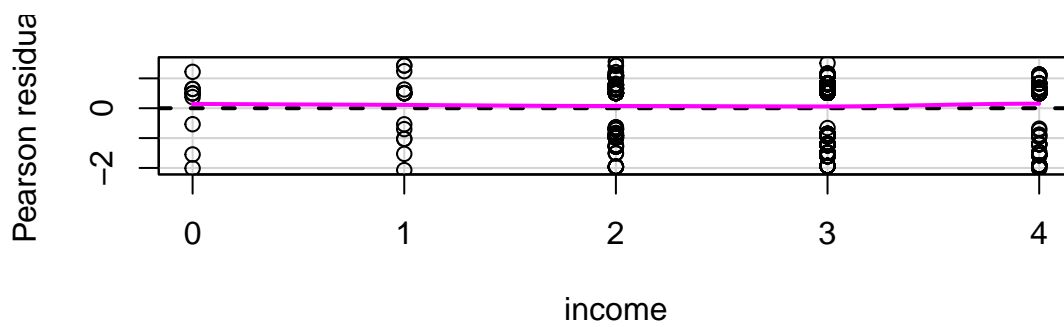

Effects inc Categorical



4.3.4 Influential Data

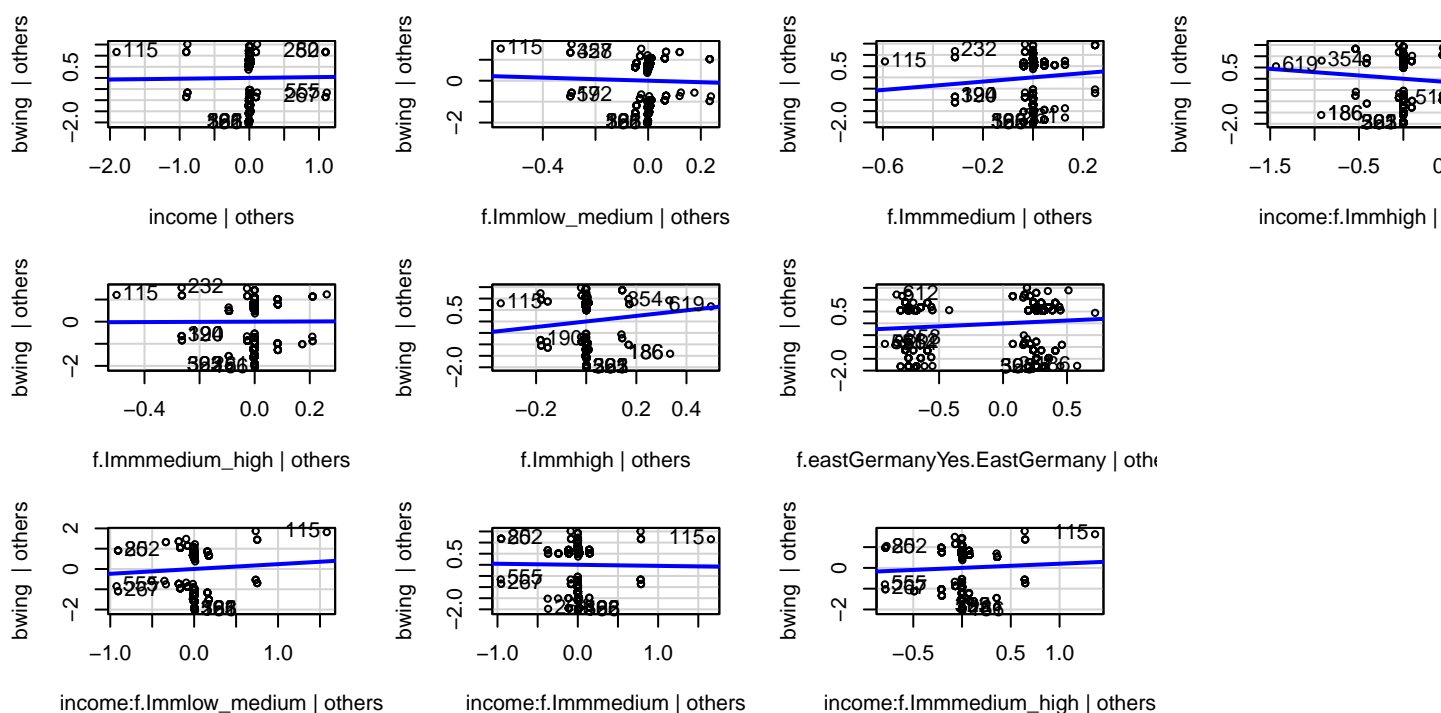
LAYER 1

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



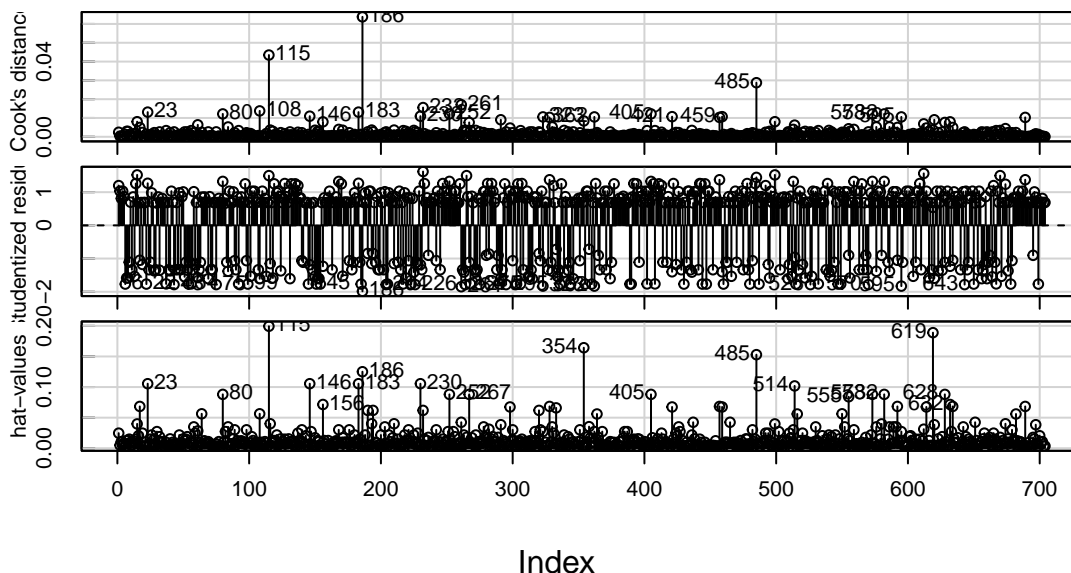
```
##               Test stat Pr(>|Test stat|)
## income          0.3272      0.5673
## f.Imm
## f.eastGermany
```

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

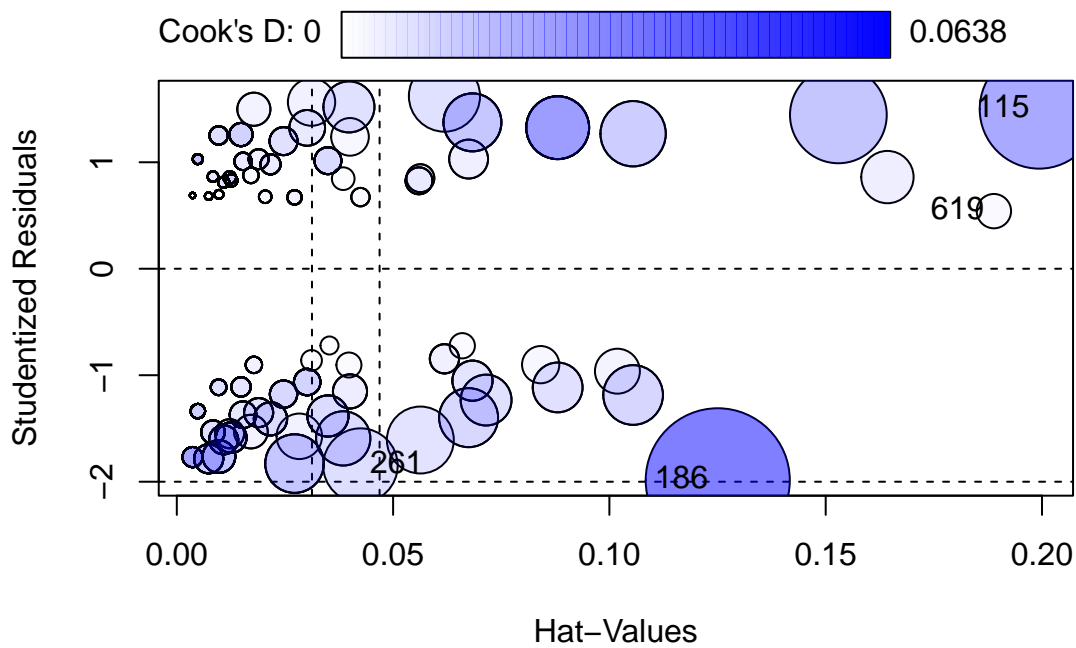


```
influenceIndexPlot(layer1,id=list(n=20),vars=c("Cook", "Student", "hat"))
```

Diagnostic Plots



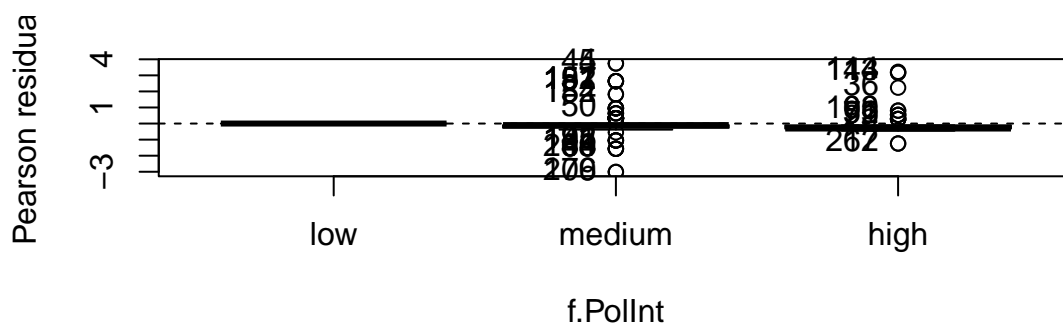
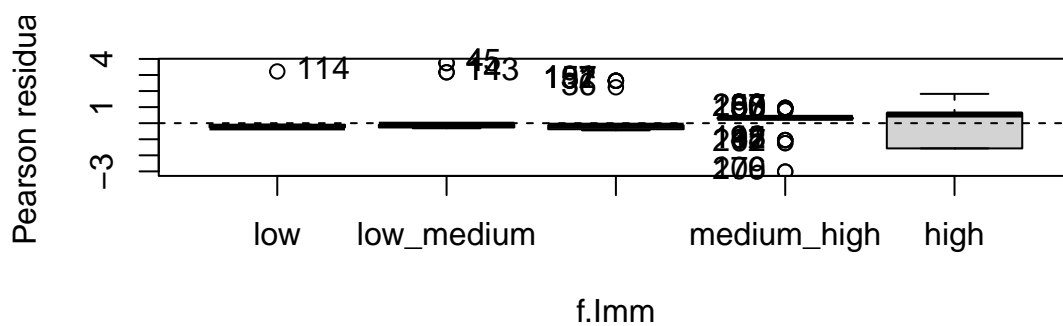
```
influencePlot(layer1,id=list(method="noteworthy"))
```



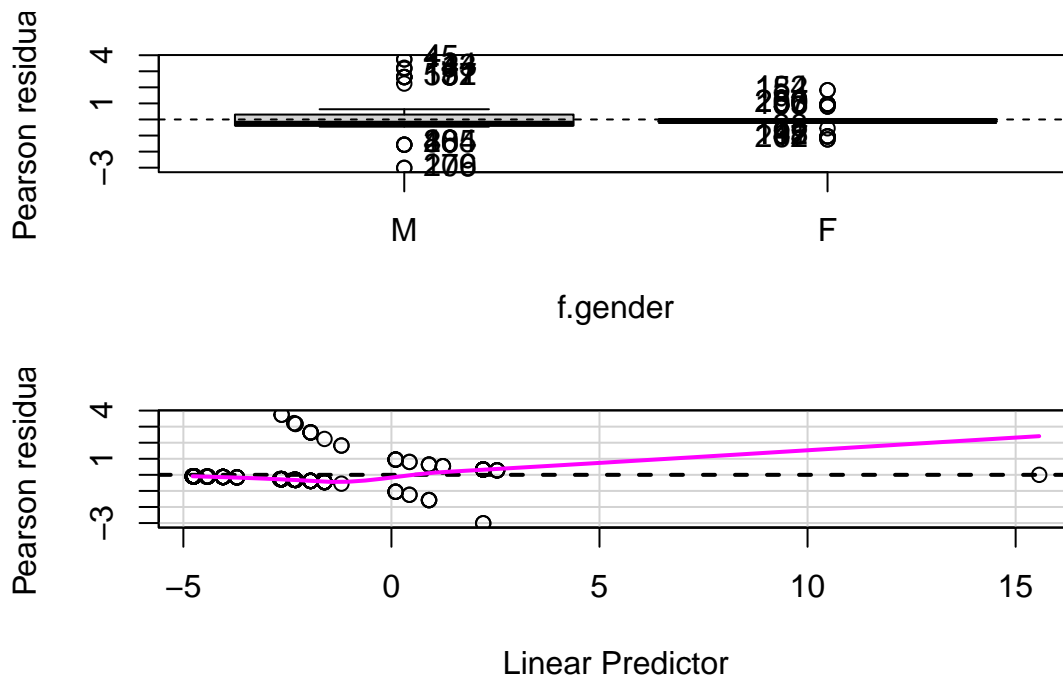
##	StudRes	Hat	CookD
## 115	1.4984544	0.19935318	0.043472427
## 186	-1.9868059	0.12504695	0.063779519
## 261	-1.8485185	0.04245303	0.017034566
## 619	0.5409559	0.18888395	0.003627381

LAYER 2

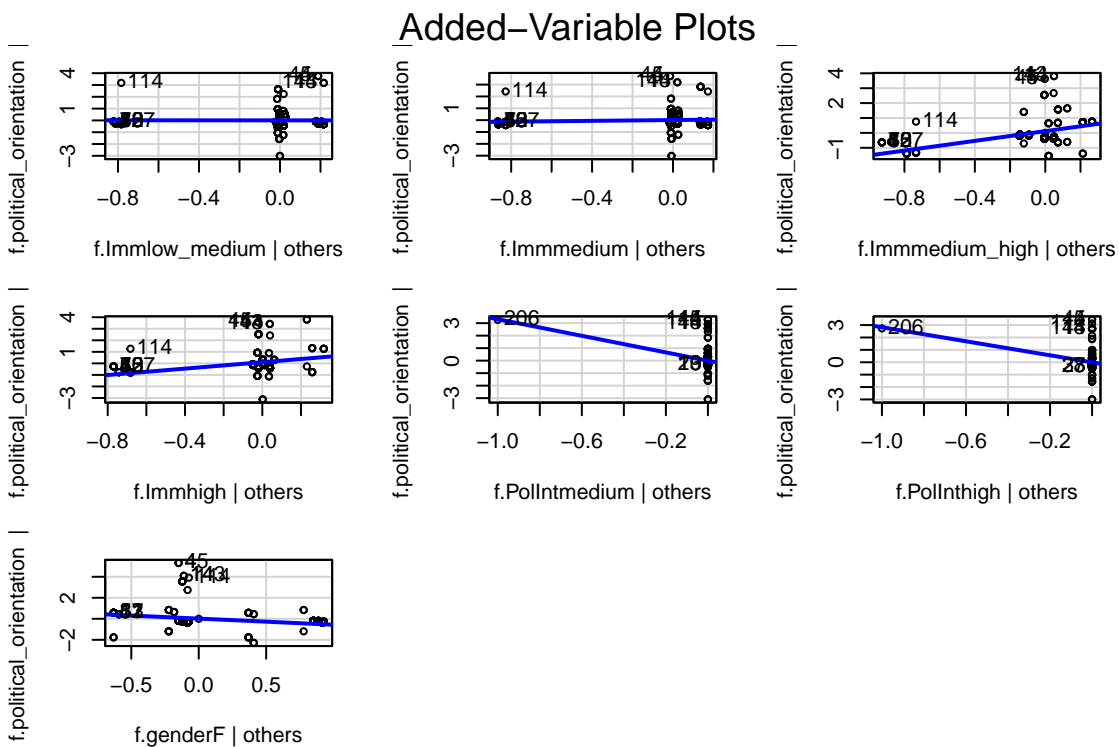
```
residualPlots(layer2, layout=c(2, 1))
```



```
## Warning in residualPlots.default(model, ...): No possible lack-of-fit tests
```

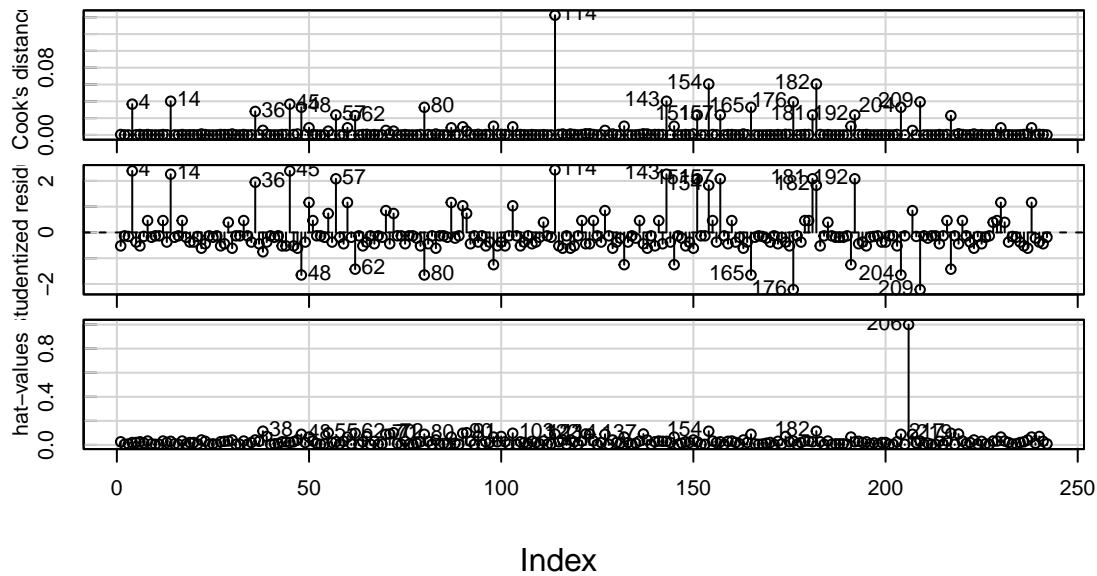


```
avPlots(layer2,id=list(n=5))
```

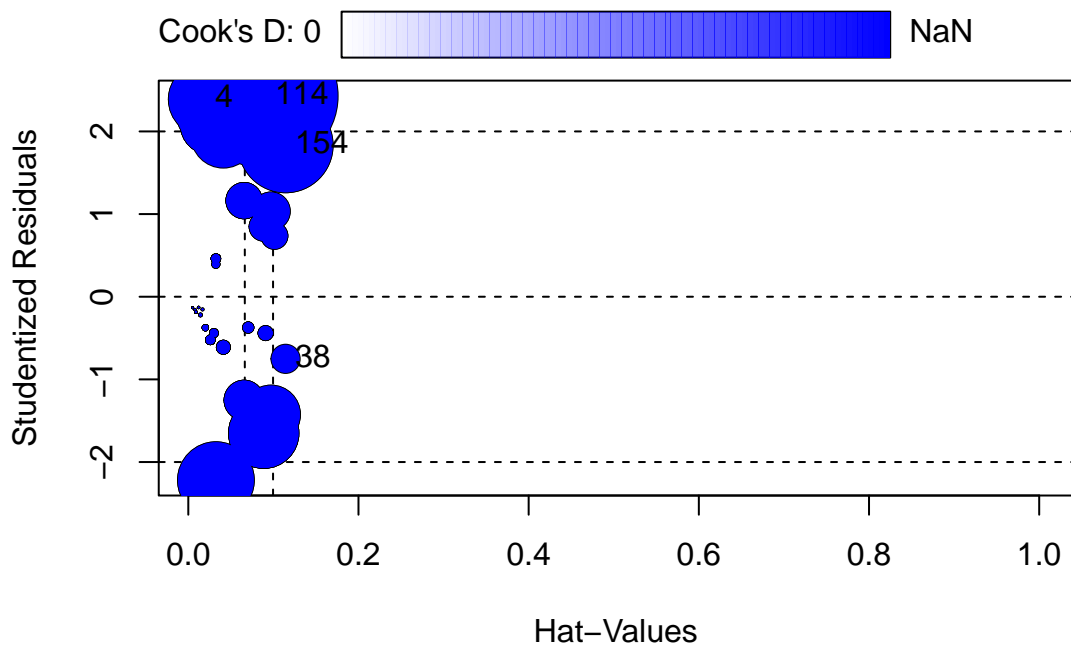


```
influenceIndexPlot(layer2,id=list(n=20),vars=c("Cook", "Student", "hat"))
```

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