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

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Contents

1 Explanatory Data Analysis - EDA

1.1 Loading Voting Data

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

```
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(quantiData, sd)
```

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

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

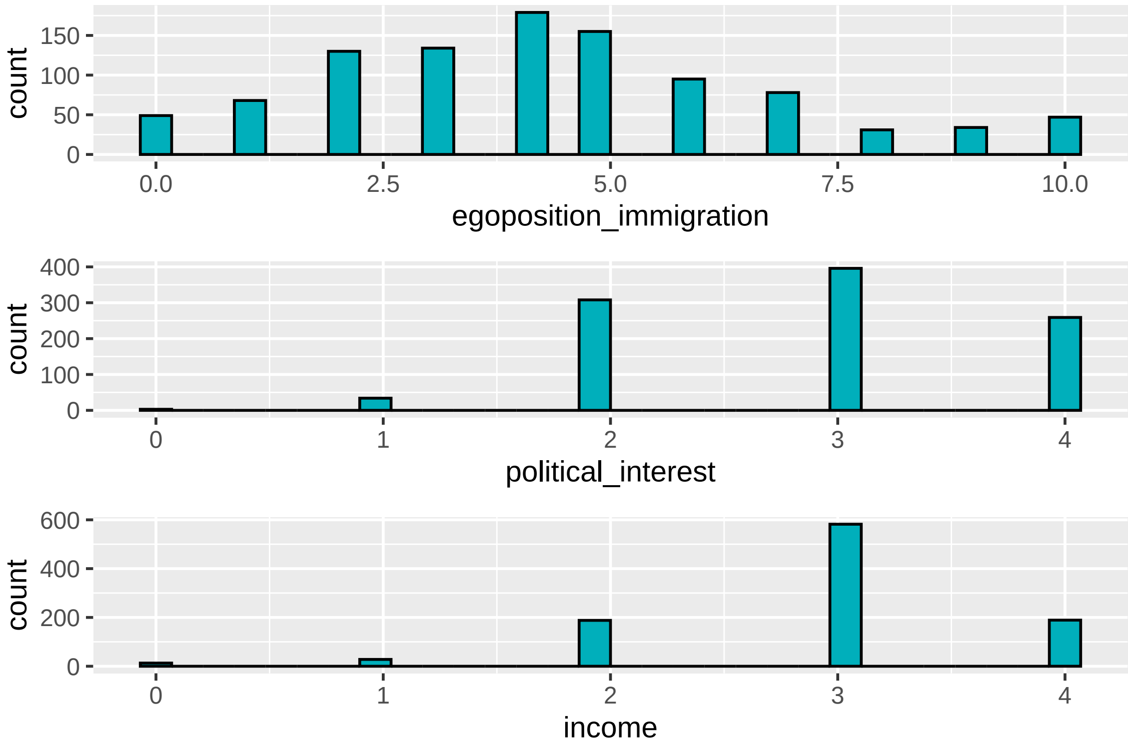
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   3.000   4.000   4.361   6.000  10.000
```

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

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

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

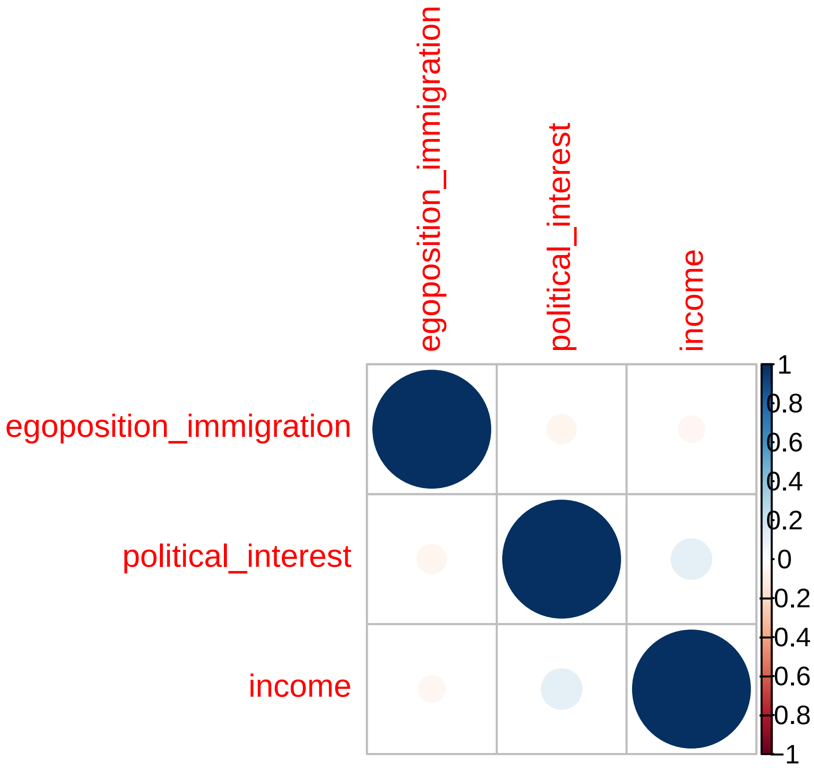
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   3.000   3.000   2.906   3.000   4.000
```



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

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

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



1.7.3 Descriptive Analysis for Categorial Variables

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

1.7.4 Bar Plots

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

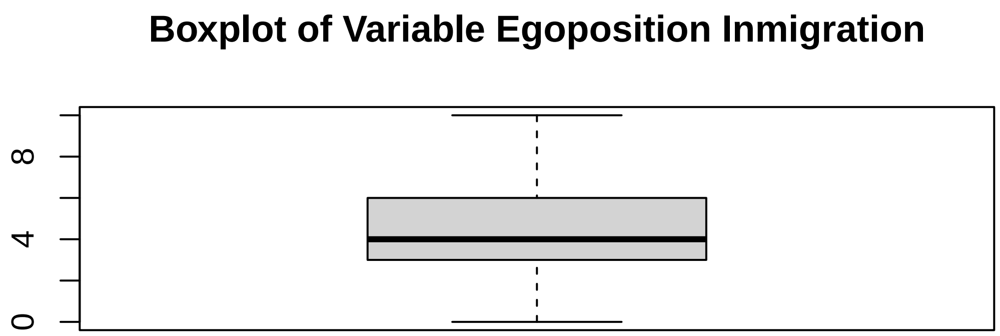
Gemany, while the gender of them are balanced. In addition, there is a huge difference in the numbers of citizens voting for parties in the *center political wing* while a smaller number of them vote for the *left wing* and finally the *right* one. Finally, party wise, the one with the most votes is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

1.8 Outliers Detection

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

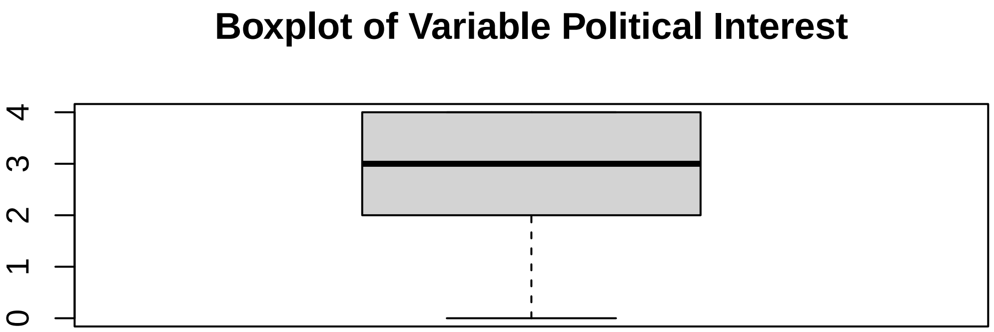
1.8.1 Uni-variate Outliers

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



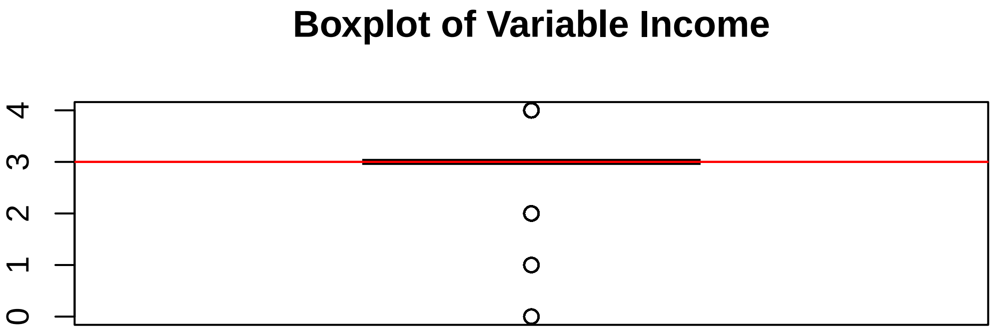

```
## [1] 0
```

Following by, the same approach is used for 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.




```
## [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
```

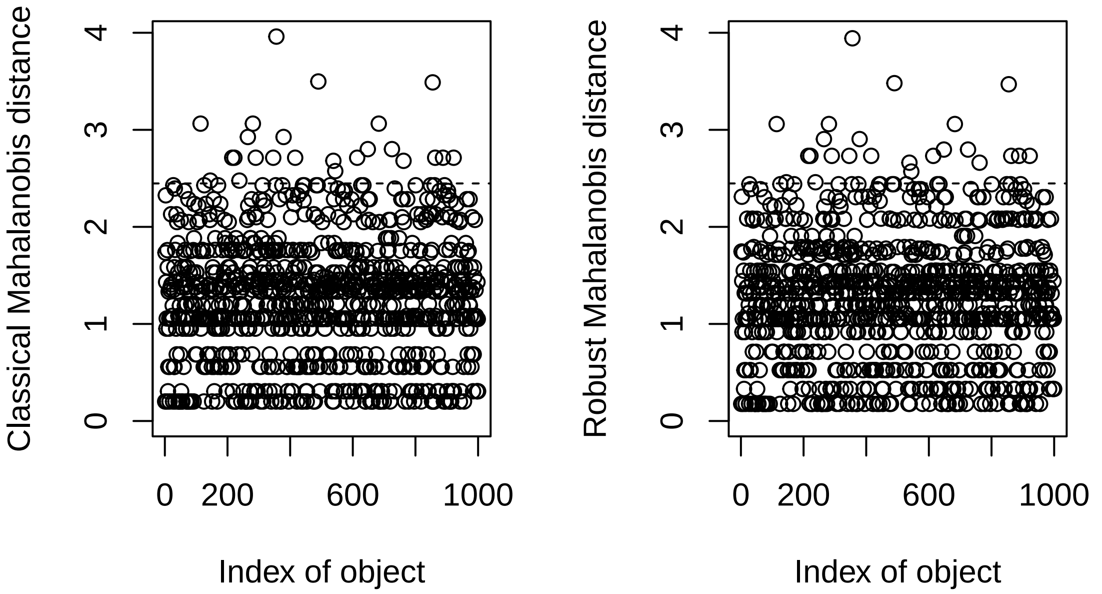
```
table(gles$income)
```

```
##
##   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.

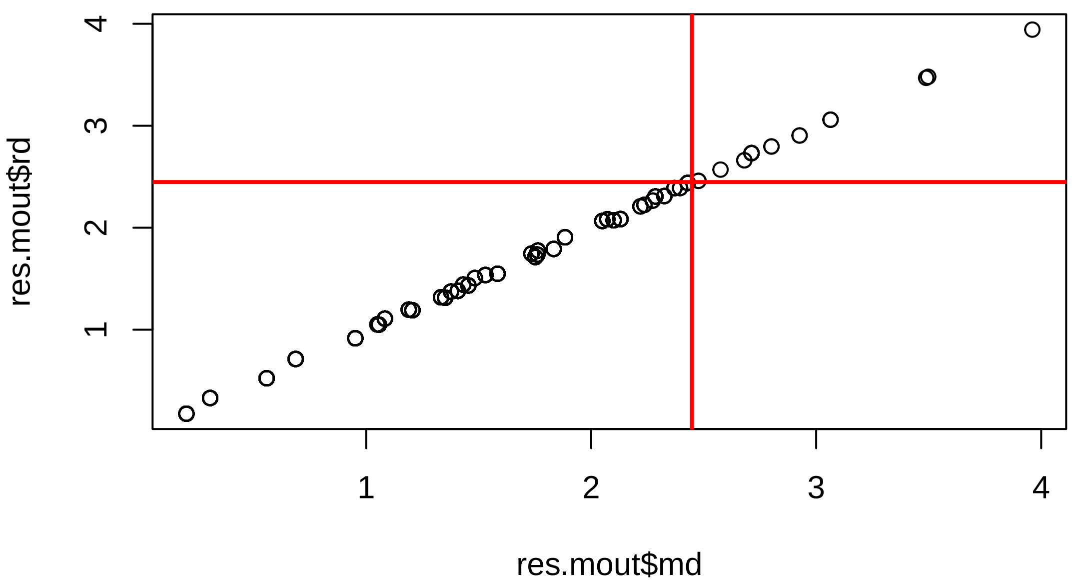
1.8.2 Multivariate Outliers

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_imigration (*far-right beliefs). Also, those observations are strongly connected with observations of *males,* with value No.EastGermany for *f.eastGermany* variable, with *low political interest* and *low to medium salary satisfaction.*

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

2 Polytomous Modelling

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

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

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

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

2.1 Nominal Polytomous Modeling

2.1.1 Comparison of Variables' Numerical and Categorical Representation

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

1. Train a nominal polytomous target model containing only one of those variables in a continuous representation.
2. Train a nominal polytomous target model containing only one of those variables in a continuous representation, including second, cube and quadratic exponent of the variable.
3. Train a nominal polytomous target model containing only one of those variables in a categorical representation.
4. Derive new factor for each variable by combining some levels of the already existed factors, and train a new model with it. The new levels are chosen below, based on the allEffects plots.

5. Compare those 6 models and the NULL model for each variable by using anova for nested models reduction of deviance, Anova and AIC.
6. Keep each variable's representation that provide the best results in each case.

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

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

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

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

```
##                 df      AIC
## nm0              5 2378.556
## nm1_imm_con     10 2256.832
## nm1_imm_con_sq  15 2253.027
## nm1_imm_con_cb  20 2246.187
## nm1_imm_con_qd  25 2247.456
## nm1_imm_cat     55 2254.358
## nm1_imm_cat_new 25 2246.546
```

- ***political_interest***: poly(political_interest,2), even if the squared form of this variable does not provide significant explanatory power (null model had pretty much the same predictability). For picking this representation of this variable the same approach as before has been followed. AIC values for the 5 models are presented here, the remaining analysis can be found in Appendix. The only reason for using this variable in the squared form is that function Anova, indicates that the squared form of *political_interest* has a p-value smaller of 0.05, thus null hypothesis can be rejected.

```
##                    df      AIC
## nm0                 5 2378.556
## nm1_polint_con     10 2381.750
## nm1_polint_con_sq  15 2377.448
## nm1_polint_con_cb  20 2378.197
## nm1_polint_con_qd  25 2385.561
## nm1_polint_cat     25 2385.557
## nm1_polint_cat_new 15 2388.672
```

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

```
##                 df      AIC
## nm0              5 2378.556
## nm1_inc_con     10 2370.628
## nm1_inc_con_sq  15 2374.321
```

```
## nm1_inc_con_cb  20 2377.178
## nm1_inc_con_qd  25 2386.675
## nm1_inc_cat     25 2386.663
## nm1_inc_cat_new 20 2386.946
```

2.1.2 Final Nominal Model

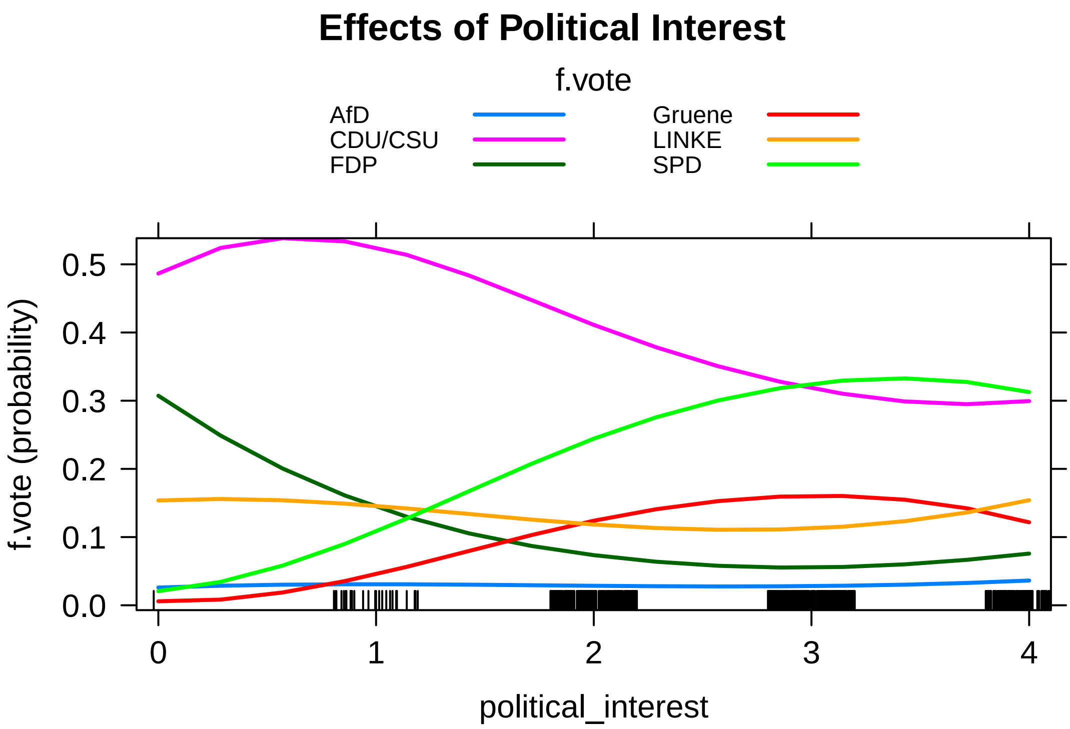
Once multiple different combinations of main effects and interactions of factors and the squared form of the numerical variable have been tested, the final model is presented below.

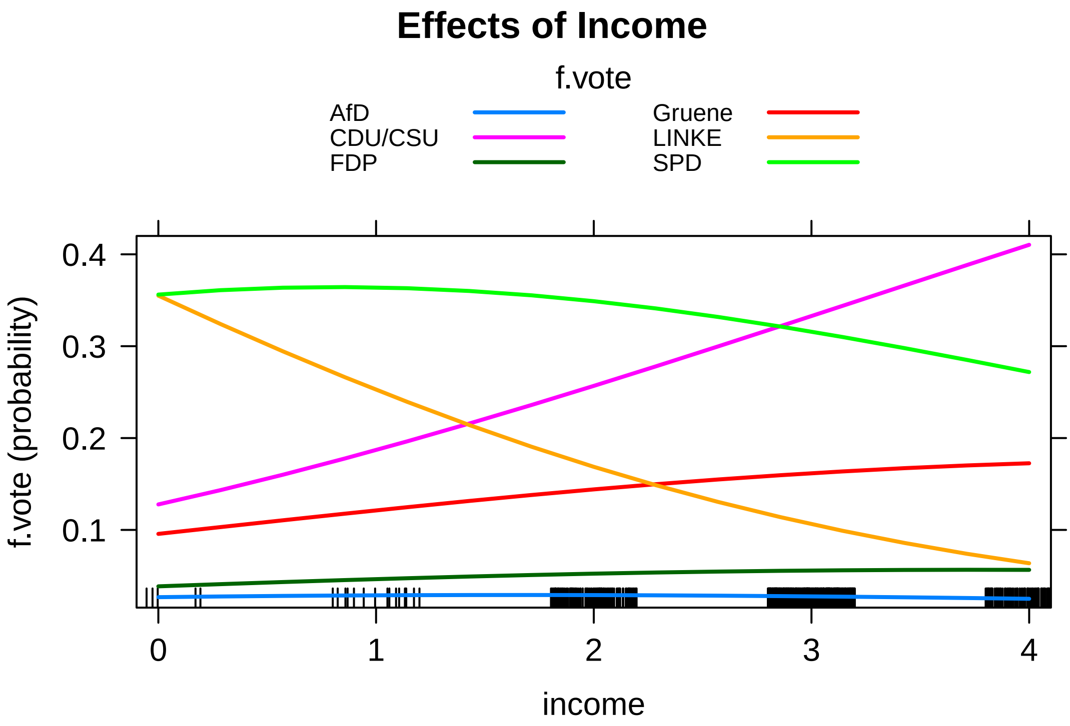
```
summary(nm_final)
```

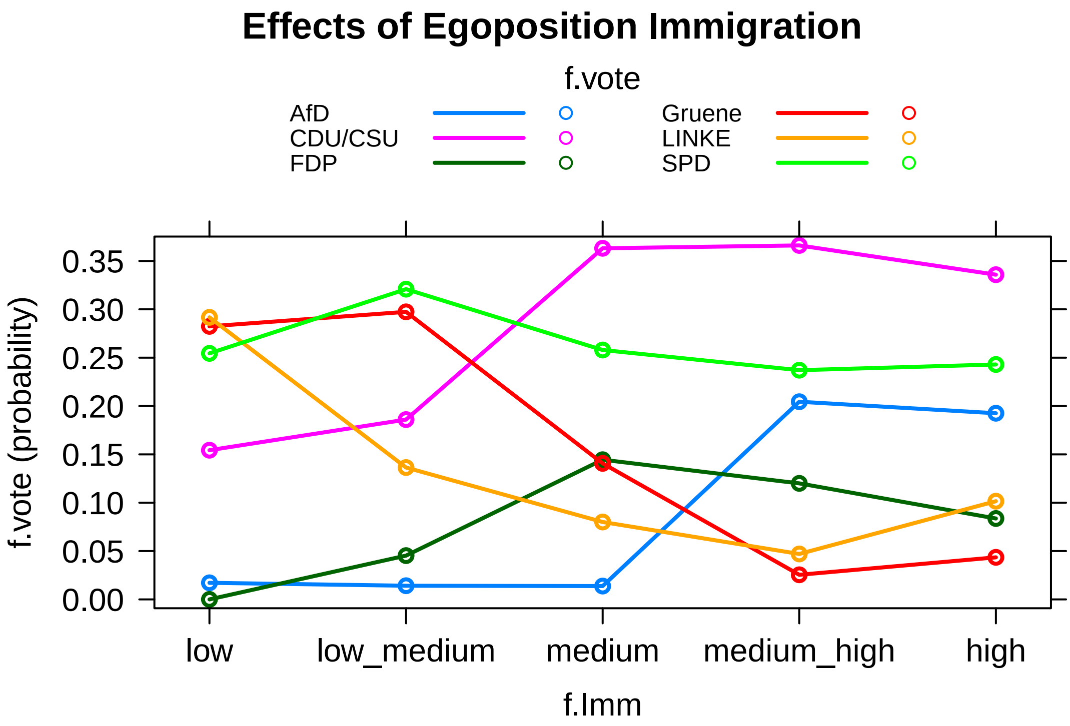
```
## Call:
## multinom(formula = f.vote ~ poly(political_interest, 2) + income +
##     f.Imm + f.eastGermany + f.gender, data = train)
##
## Coefficients:
##          (Intercept) poly(political_interest, 2)1 poly(political_interest, 2)2
## CDU/CSU  -0.09257836                    -5.941845        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

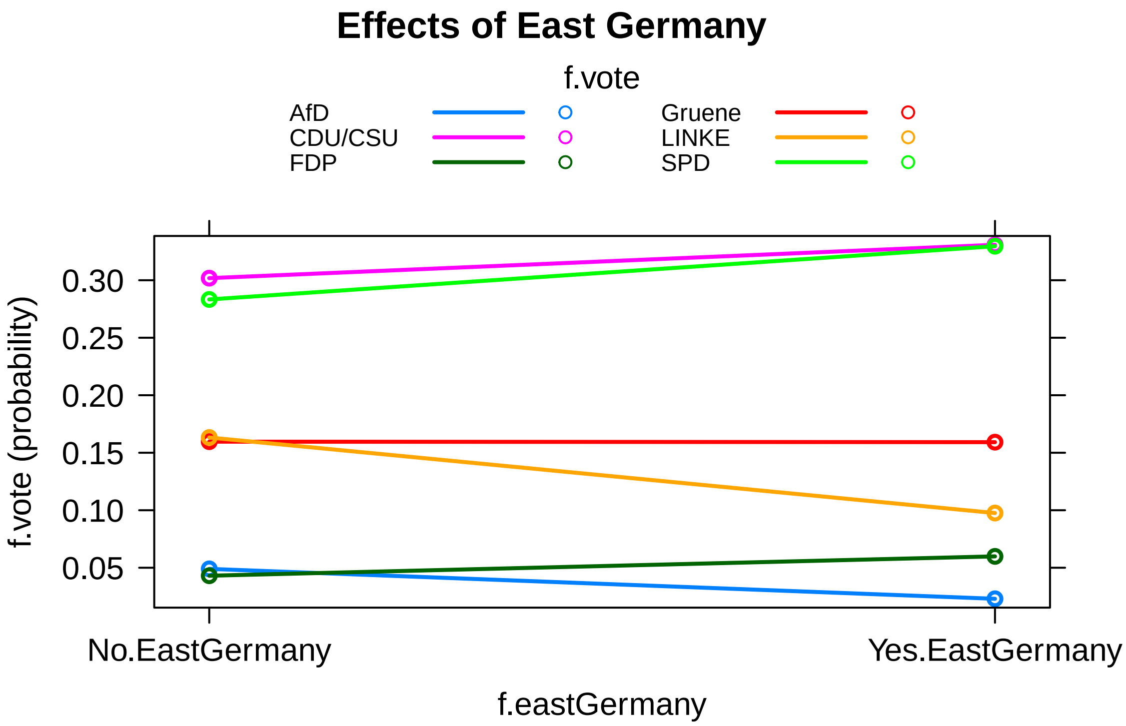
```
## FDP                           0.4389828 0.4618531
## Gruene                        0.4317185 0.4633330
## LINKE                         0.4172363 0.4637351
## SPD                           0.3919844 0.4346765
##
## Residual Deviance: 2119.625
## AIC: 2219.625
```

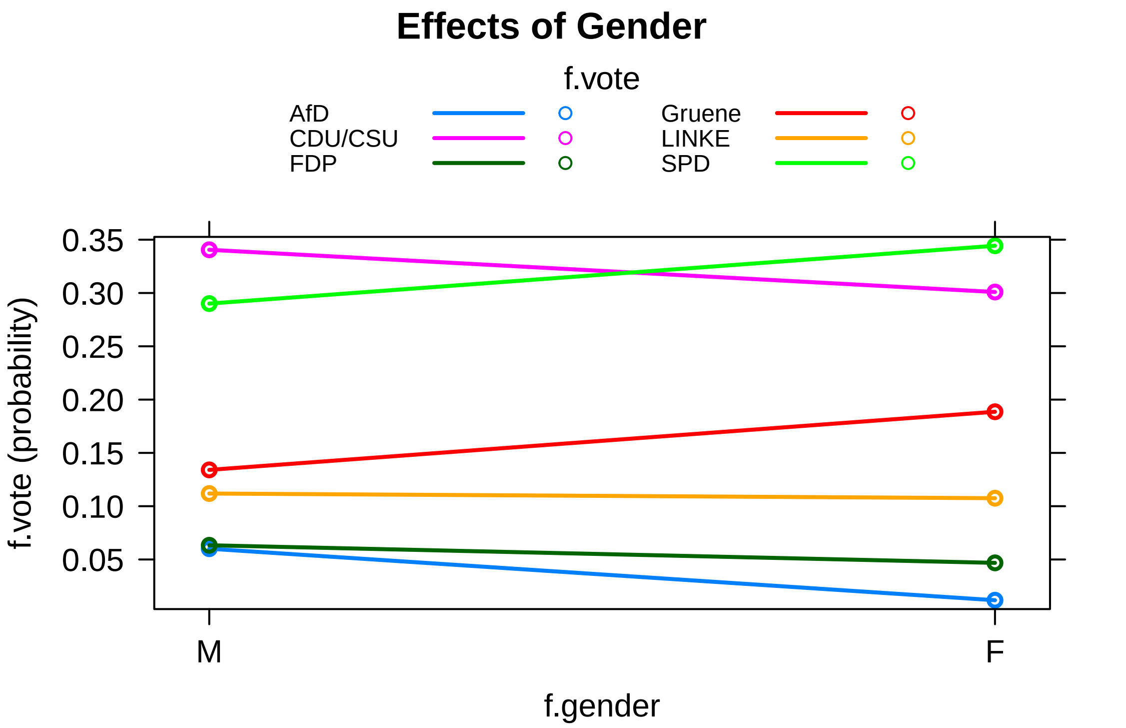
From the summary of the final nominal model, after executing the step function on the model containing all main effects and interactions of the factors and the numerical variables it can be concluded that the formula contains only the main effects of factors *f.Imm*, *f.eastGermany*, *f.gender*, the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




Effects of Income
f.vote
AfD
CDU/CSU
FDP
Gruene
LINKE
SPD
f.vote (probability)
0.1
0.2
0.3
0.4
0
1
2
3
4
income


Effects of Egoposition Immigration
f.vote
AfD
CDU/CSU
FDP
Gruene
LINKE
SPD
f.vote (probability)
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
low
low_medium
medium
medium_high
high
f.Imm





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
```

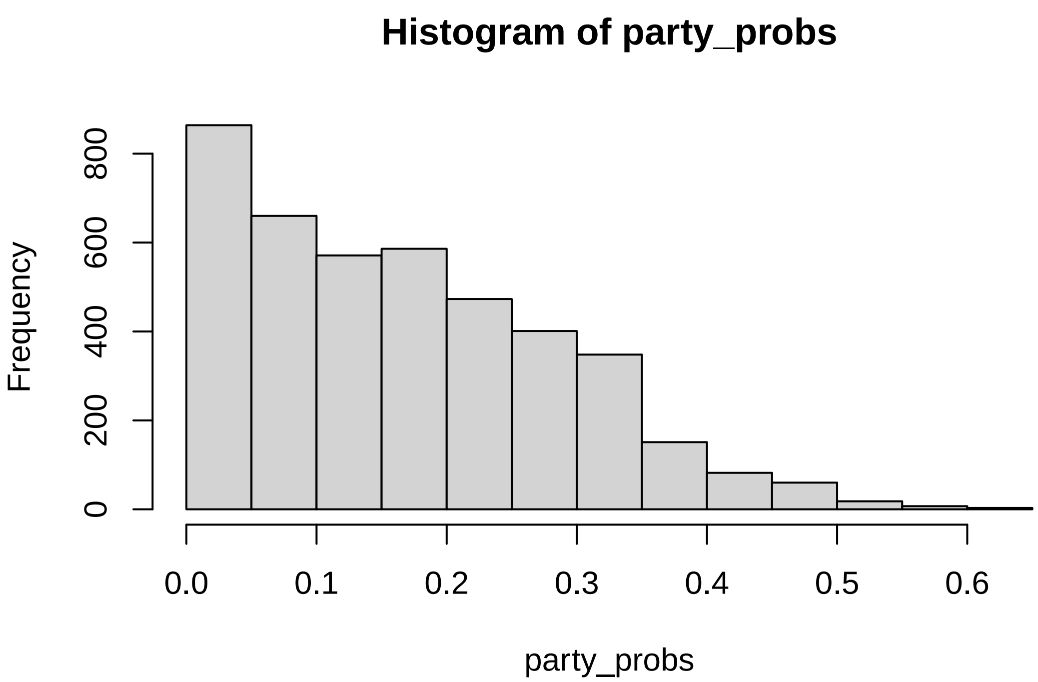
```
## [1] "Precision:"
```

```
##       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

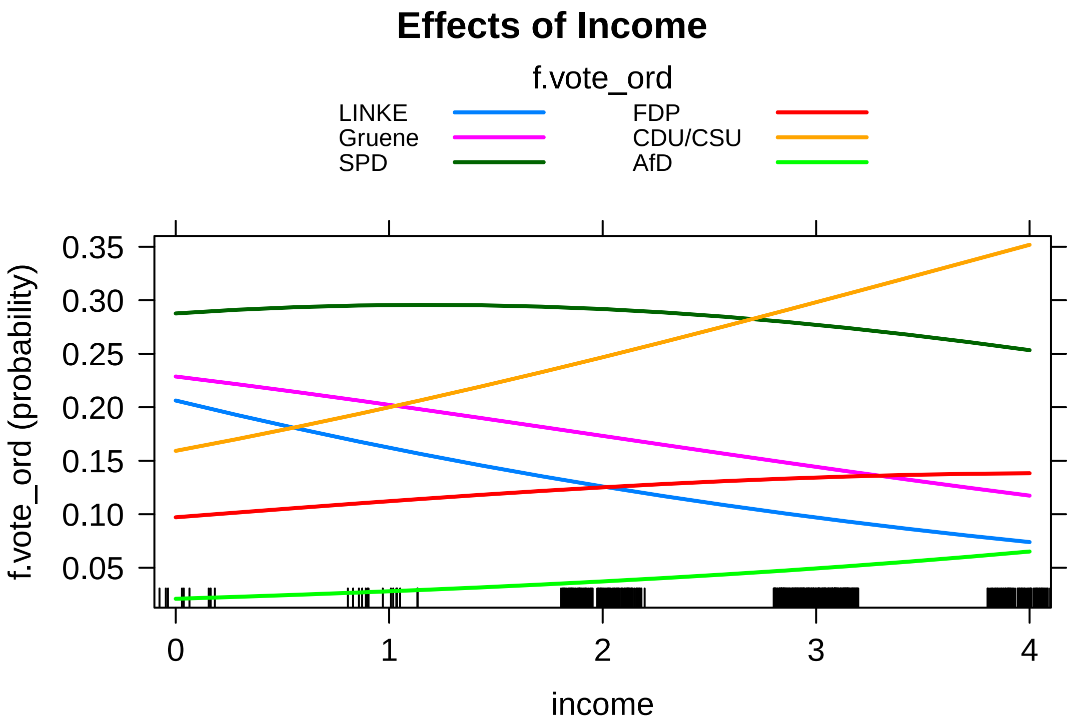
Once multiple different combinations of main effects and interactions of factors and the squared form of the numerical variable have been tested, the final model is presented below.

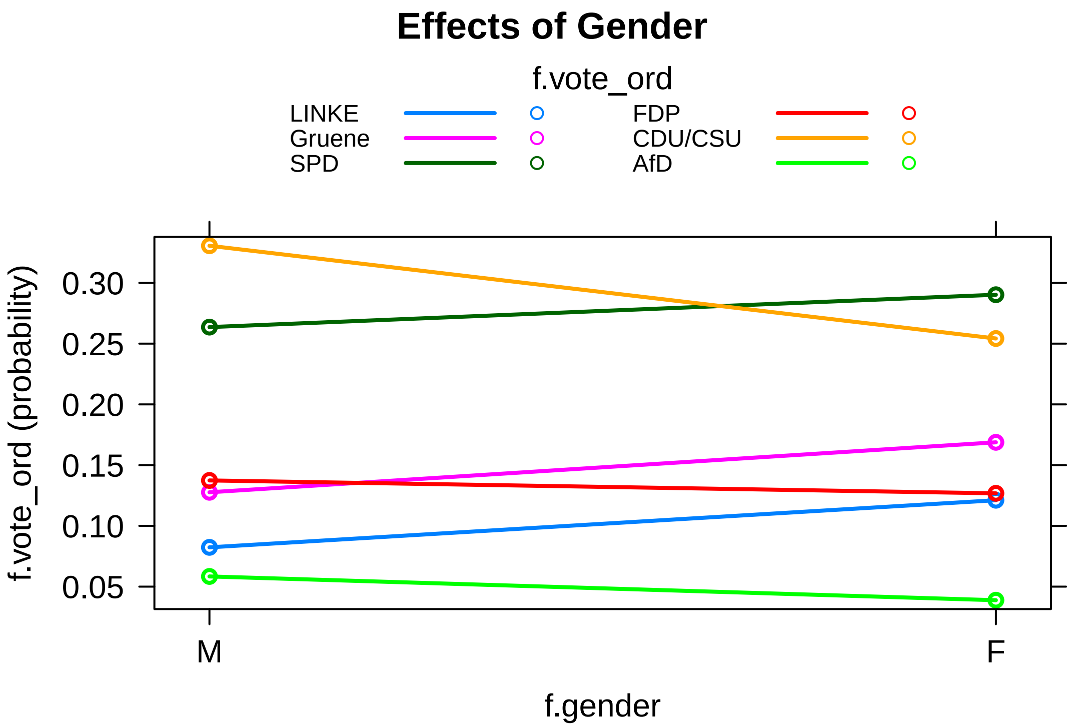
```
##
## Re-fitting to get Hessian
```

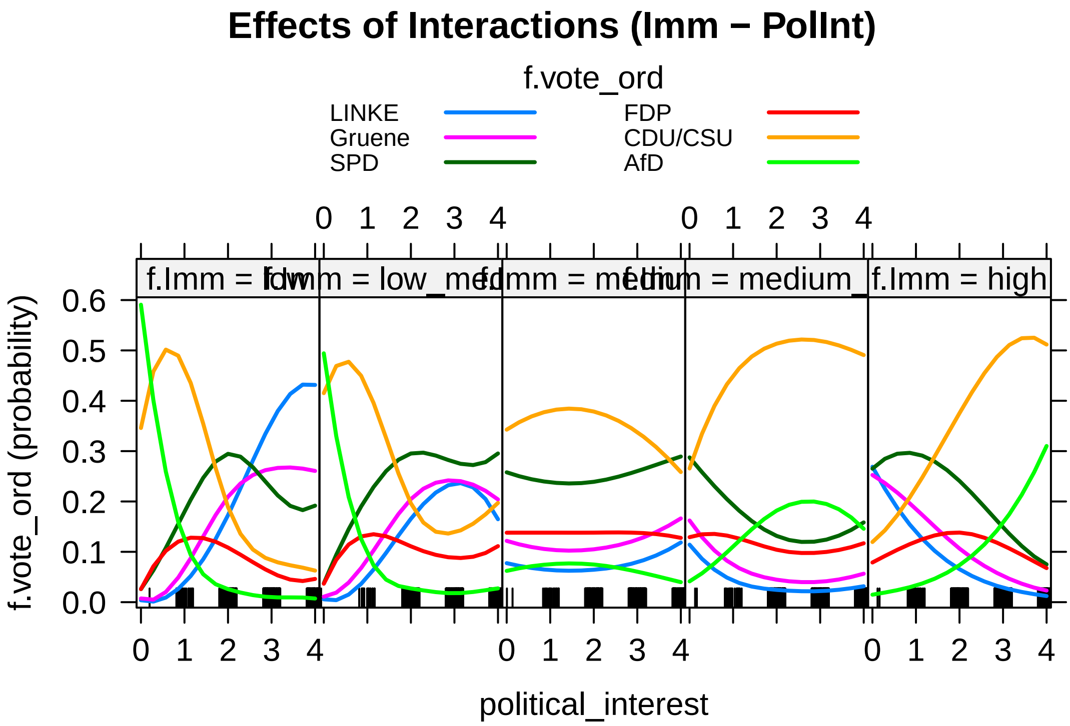
```
## Call:
## polr(formula = f.vote_ord ~ poly(political_interest, 2) + income +
```

```
##     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
f.vote_ord
LINKE
Gruene
SPD
FDP
CDU/CSU
AfD
f.vote_ord (probability)
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0
1
2
3
4
income


Effects of Gender
f.vote_ord
LINKE
Gruene
SPD
FDP
CDU/CSU
AfD
f.vote_ord (probability)
0.30
0.25
0.20
0.15
0.10
0.05
M
F
f.gender



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
```

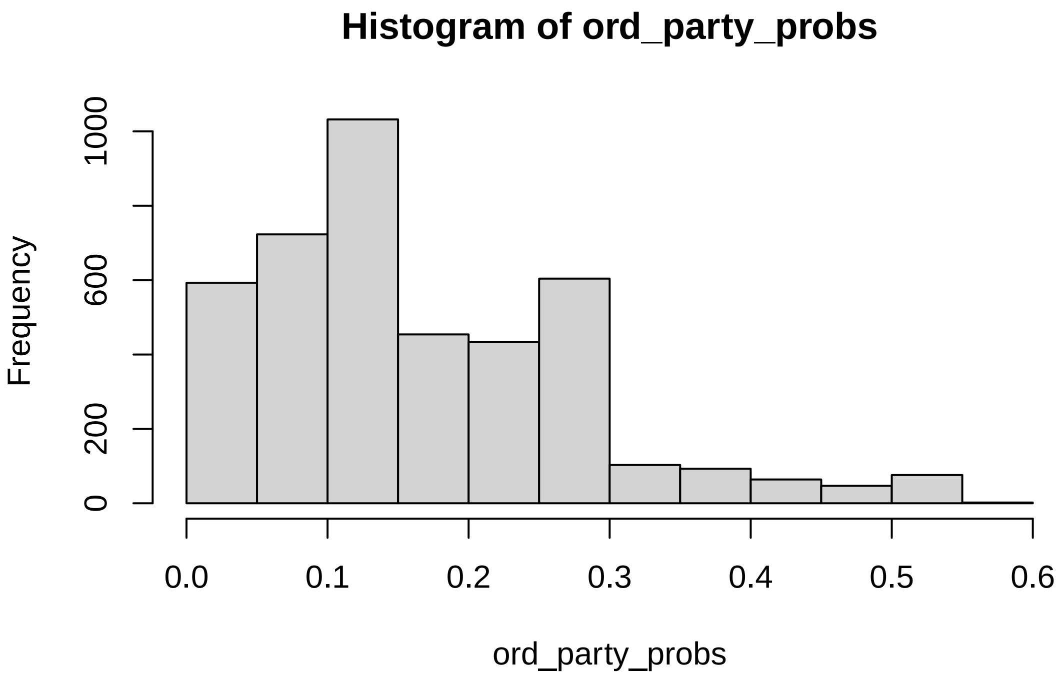
```
## [1] "Precision:"
```

```
##     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

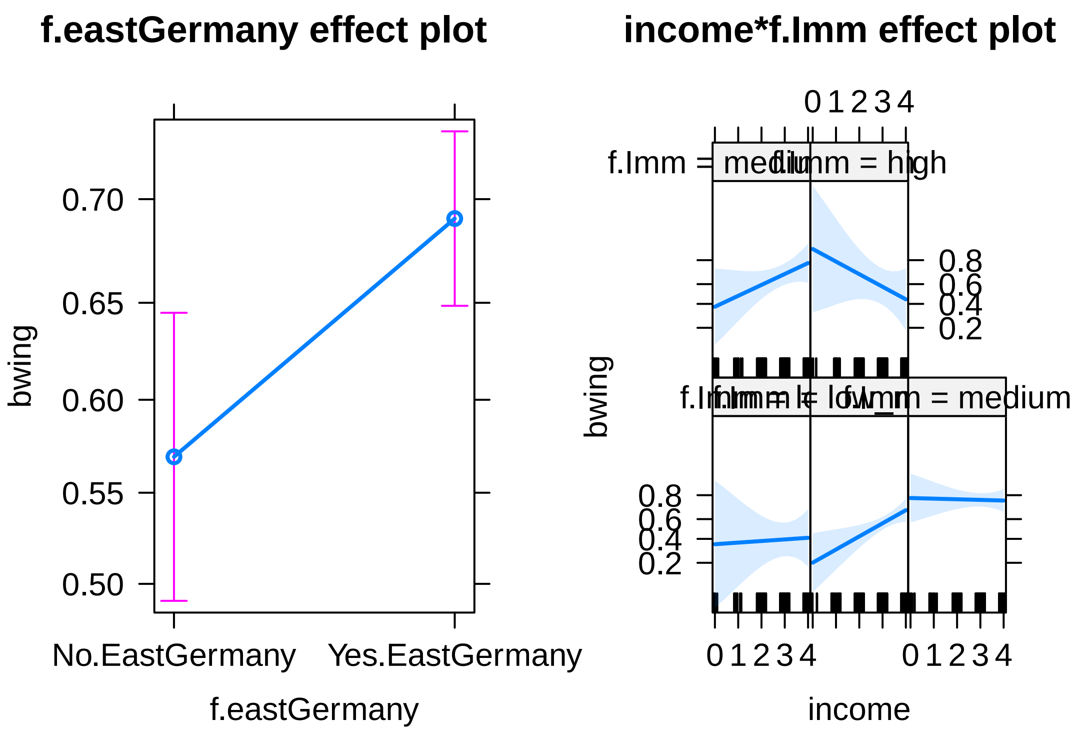
The format of the variables being used for training the first layer of the hierarchical approach is the following: *f.Imm, poly(political_interest,3), income.*

```
##
## 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
```



2.3.2 Second Layer of Hierarchical Approach

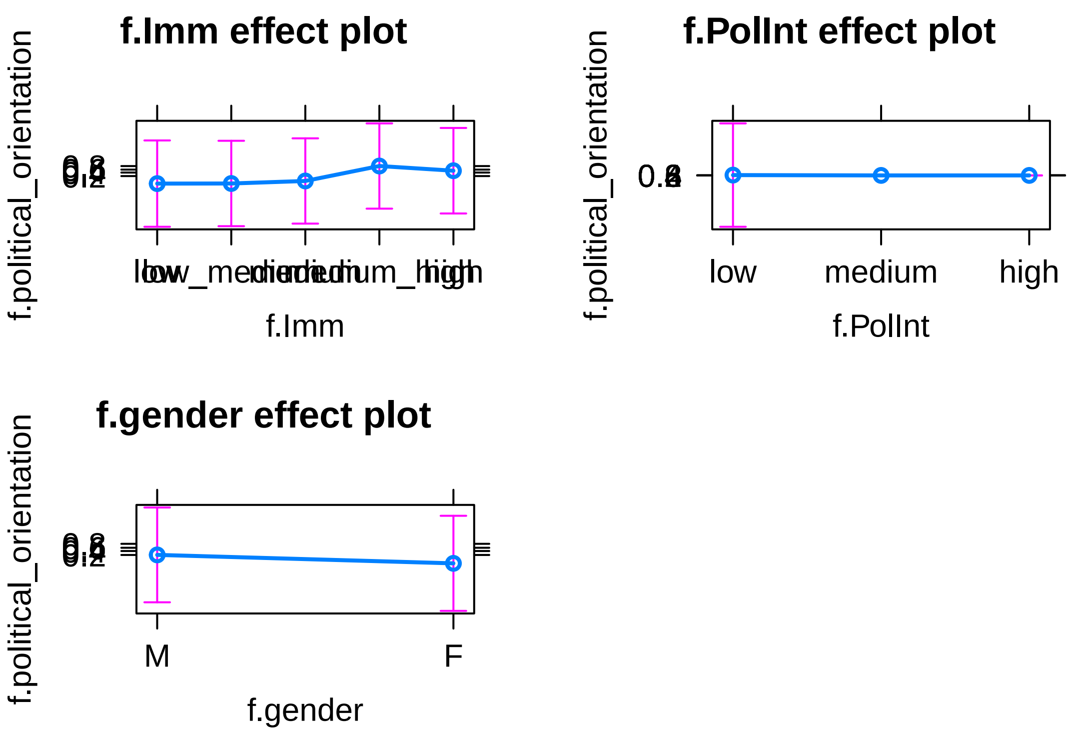
For the second layer of the hierarchical approach the separation between right and left parties is necessary. The representations of the variables after the analysis for this step is: *poly(egoposition_immigration,4), f.PolInt (null model is better), poly(income,3) (null model is better).*

```
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 influential data analysis and by checking in more detail the interactions between all the variables.

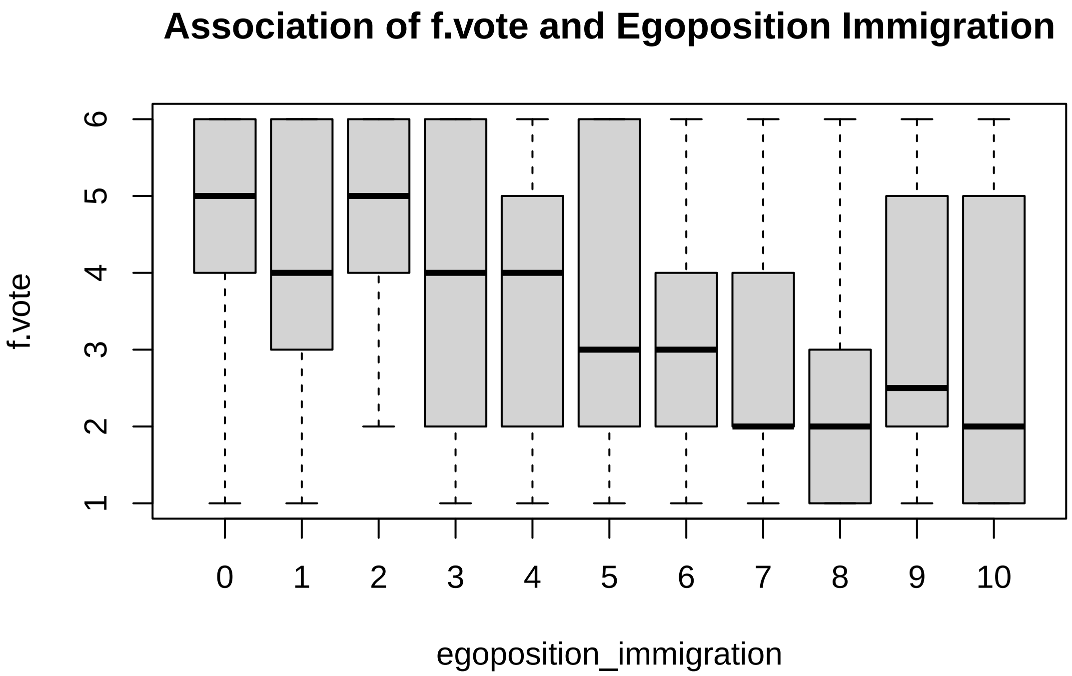
4 Appendix

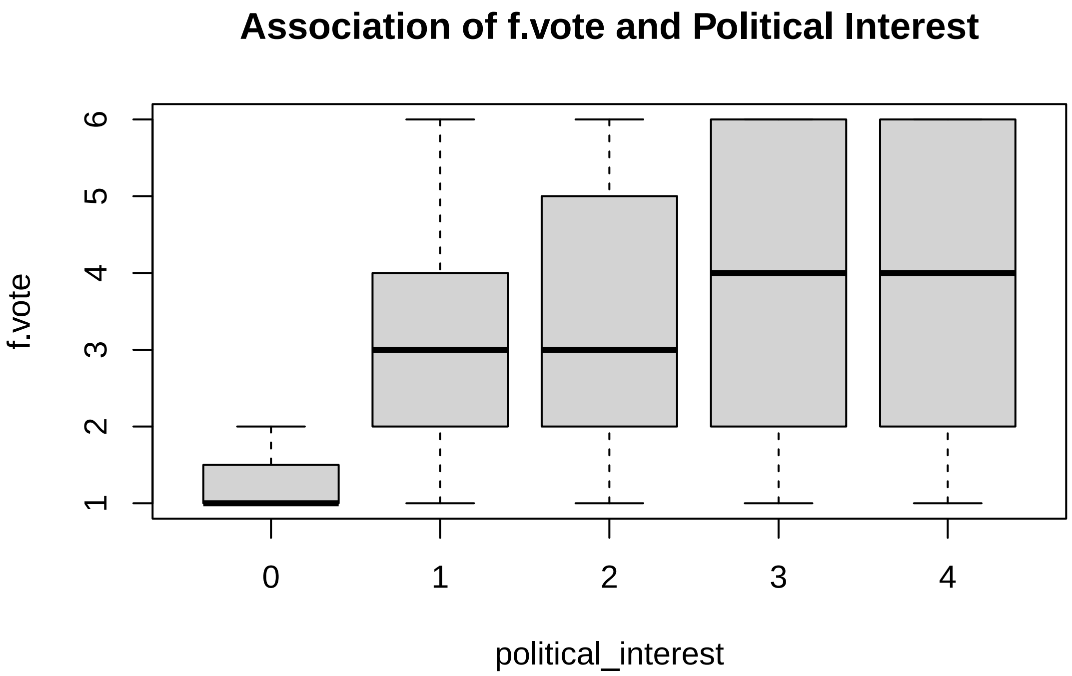
4.1 EDA

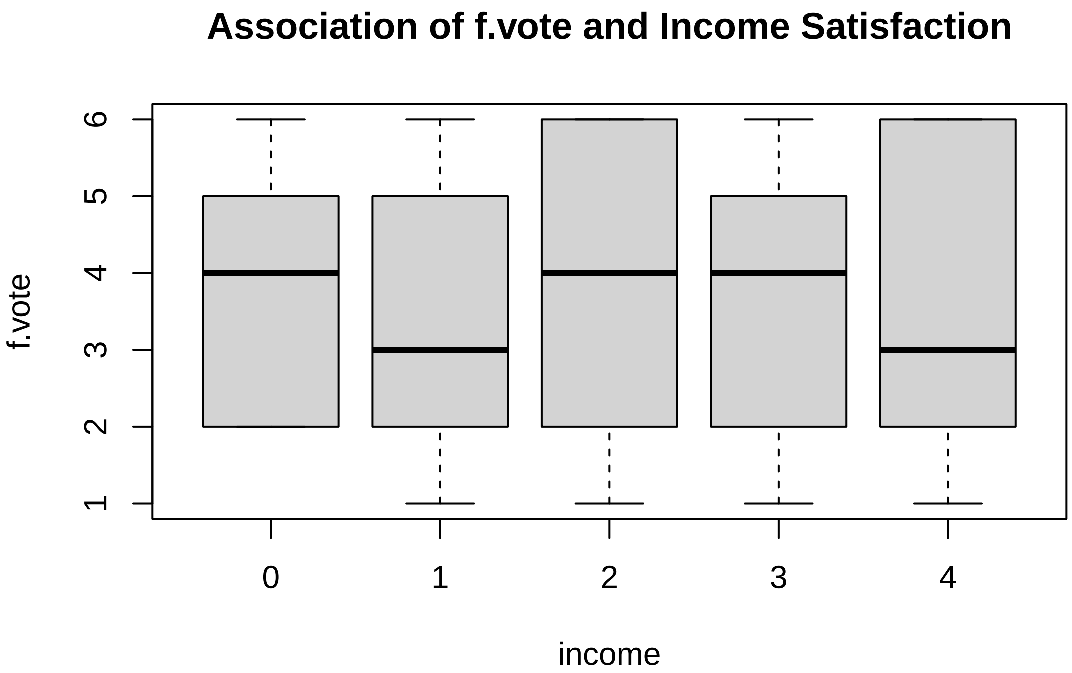
4.2 Profiling of Target Variable(s)

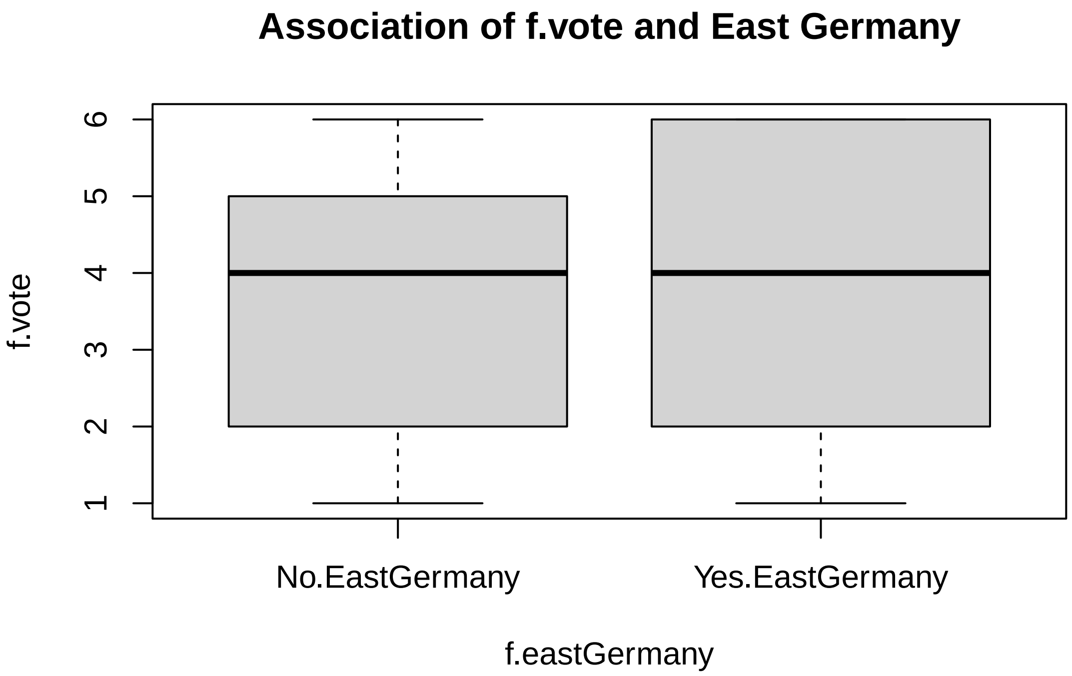
In the following plots the levels of variable *f.vote* and *f.political_orientation* follow the structure presented below.

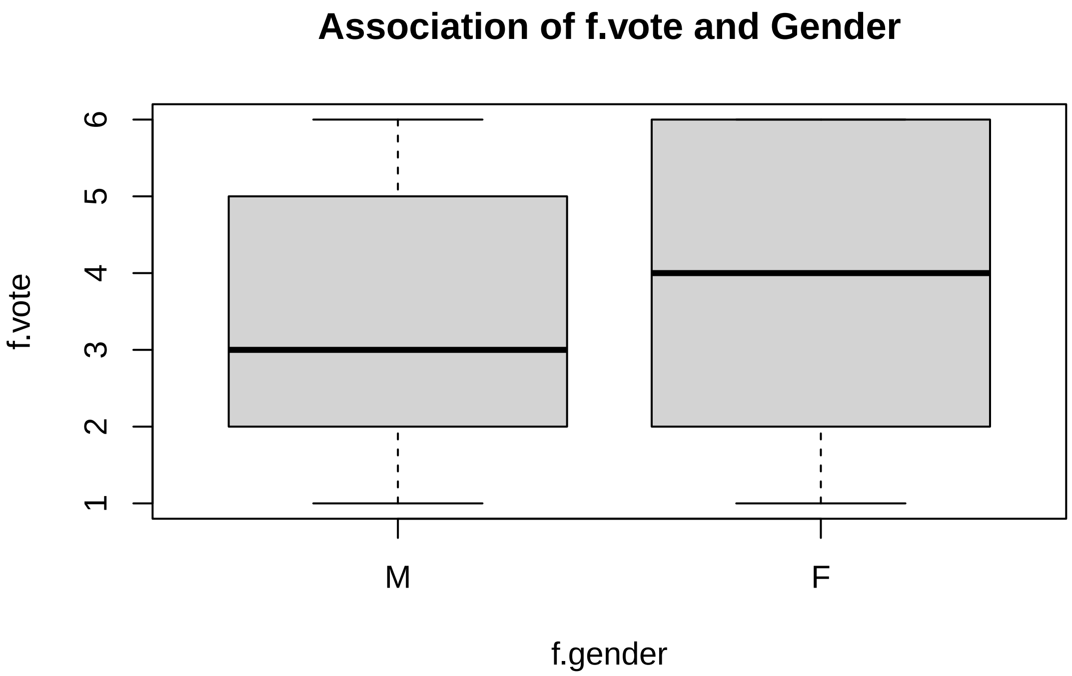
```
## [1] "Parties:"

## [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"
```

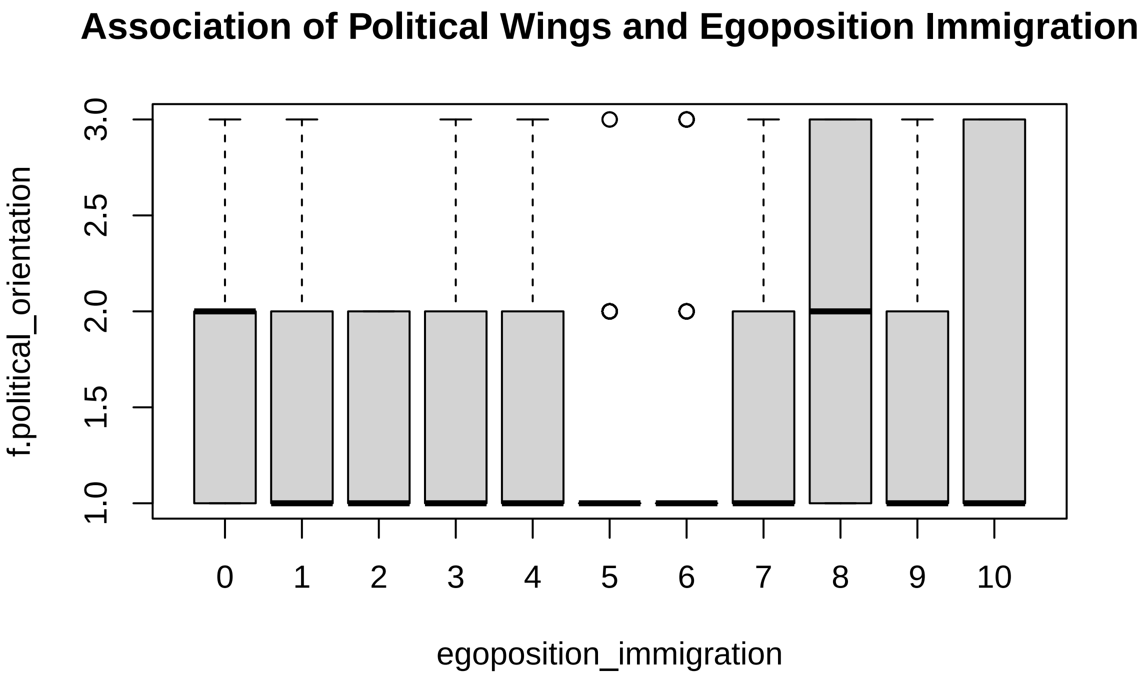


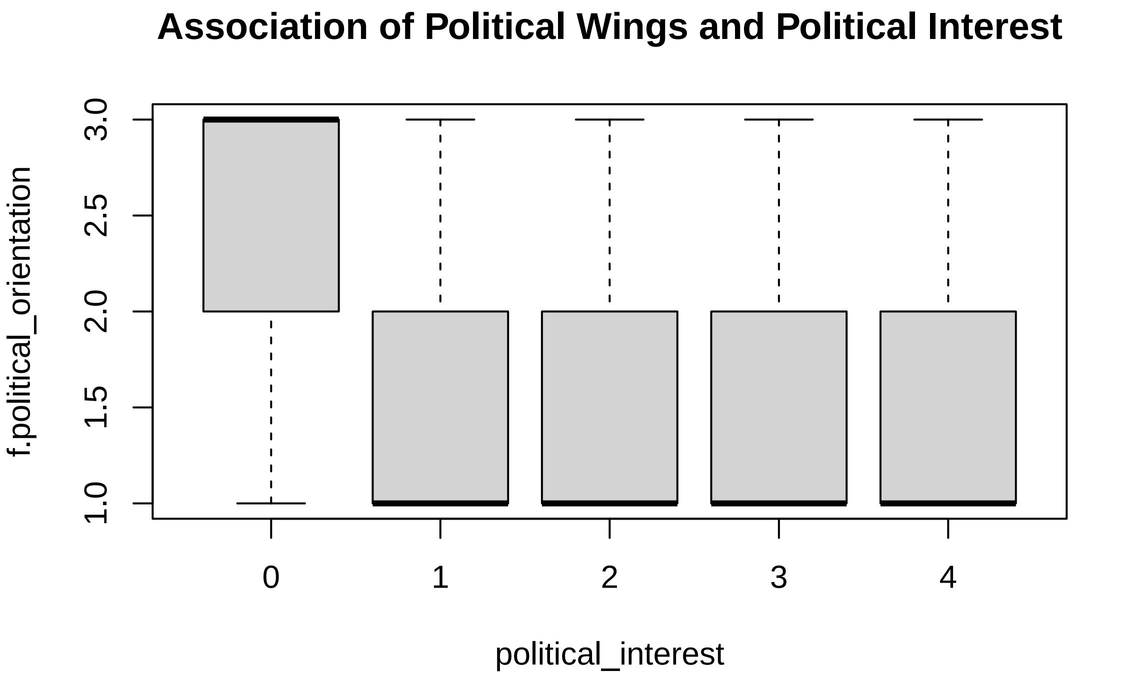

Association of f.vote and Political Interest
f.vote
1
2
3
4
5
6
0
1
2
3
4
political_interest

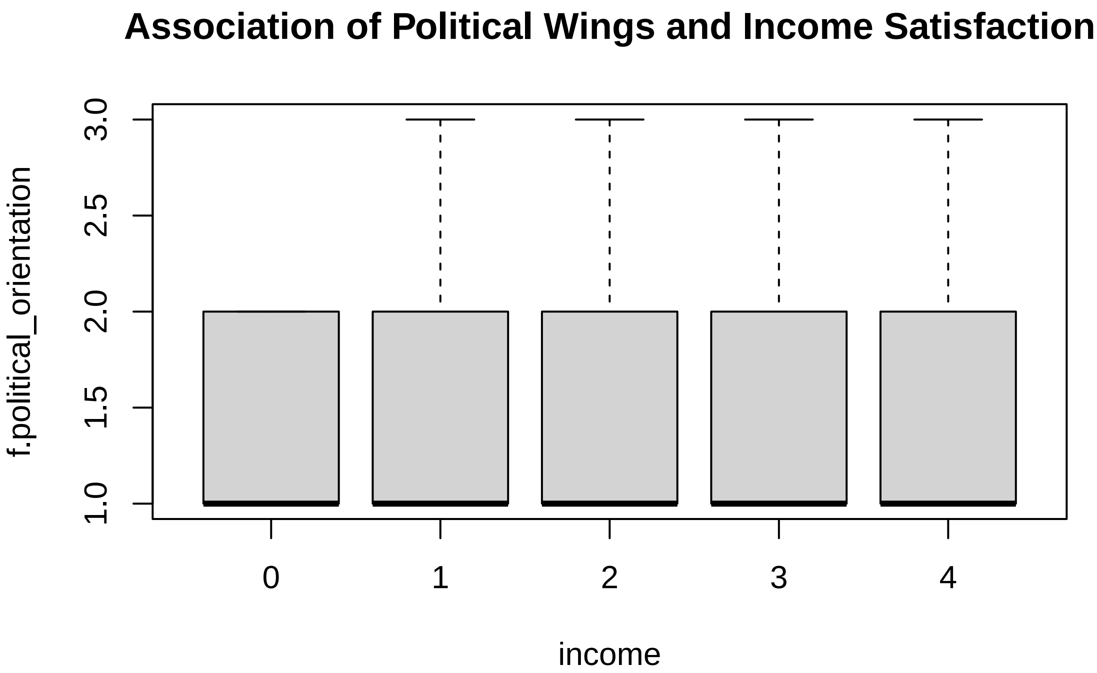

Association of f.vote and Income Satisfaction
f.vote
1
2
3
4
5
6
0
1
2
3
4
income

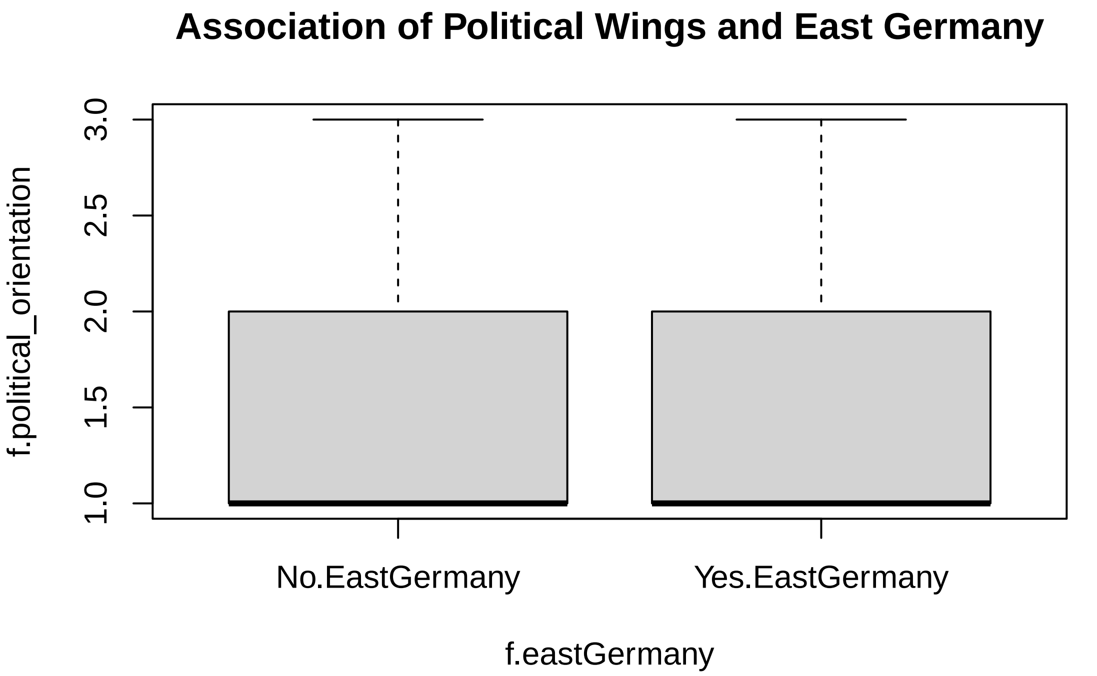

Association of f.vote and East Germany
f.vote
1
2
3
4
5
6
No.EastGermany
Yes.EastGermany
f.eastGermany

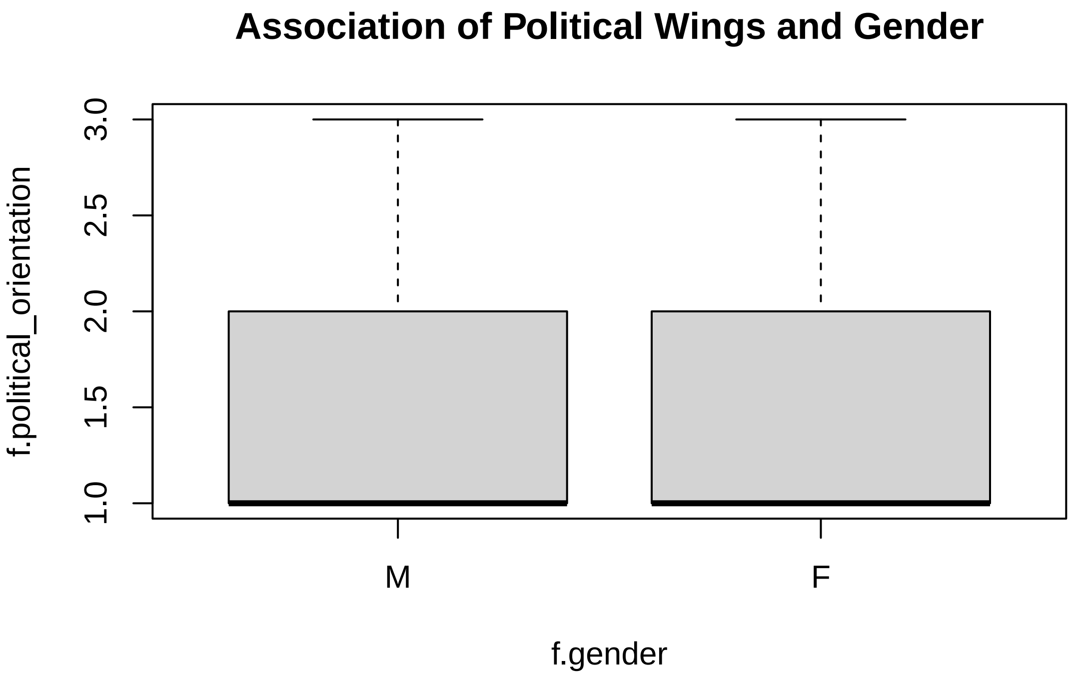

Association of f.vote and Gender
f.vote
1
2
3
4
5
6
M
F
f.gender


Association of Political Wings and Egoposition Immigration
f.political_orientation
1.0
1.5
2.0
2.5
3.0
0
1
2
3
4
5
6
7
8
9
10
egoposition_immigration


Association of Political Wings and Political Interest
f.political_orientation
1.0
1.5
2.0
2.5
3.0
0
1
2
3
4
political_interest


Association of Political Wings and Income Satisfaction
f.political_orientation
1.0
1.5
2.0
2.5
3.0
0
1
2
3
4
income


Association of Political Wings and East Germany
f.political_orientation
1.0
1.5
2.0
2.5
3.0
No.EastGermany
Yes.EastGermany
f.eastGermany




```r
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 100.0000000
## f.political_orientation=Left_Wing                     53.759398 100.0000000
## bwing=Left_Right_Wings                                42.686567 100.0000000
## f.Imm=low_medium                                      23.795181  55.2447552
## f.egoposition_immigration=2_Level.Imm                 28.461538  25.8741259
## f.gender=F                                            17.748918  57.3426573
## f.political_interest=Medium_to_High.Inter             17.676768  48.9510490
## f.egoposition_immigration=1_Level.Imm                 25.000000  11.8881119
## f.egoposition_immigration=6_Level.Imm                  7.368421   4.8951049
## f.egoposition_immigration=8_Level.Imm                  0.000000   0.0000000
## f.Imm=high                                             2.127660   0.6993007
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm  2.127660   0.6993007
## f.egoposition_immigration=9_Level.Imm                  0.000000   0.0000000
## f.gender=M                                            11.338290  42.6573427
## f.egoposition_immigration=7_Level.Imm                  2.564103   1.3986014
## f.vote_ord=AfD                                         0.000000   0.0000000
## f.political_orientation=Right_Wing                     0.000000   0.0000000
## f.Imm=medium_high                                      1.398601   1.3986014
## f.vote_ord=FDP                                         0.000000   0.0000000
## f.vote_ord=LINKE                                       0.000000   0.0000000
## f.vote_ord=SPD                                         0.000000   0.0000000
## f.vote_ord=CDU/CSU                                     0.000000   0.0000000
## bwing=Center_Wing                                      0.000000   0.0000000
## f.political_orientation=Center_Wing                    0.000000   0.0000000
##                                                      Global       p.value
## f.vote_ord=Gruene                                      14.3 1.663892e-177
```

```
## f.political_orientation=Left_Wing                               26.6  4.555935e-99
## bwing=Left_Right_Wings                                          33.5  1.406134e-79
## f.Imm=low_medium                                                33.2  4.705371e-09
## f.egoposition_immigration=2_Level.Imm                           13.0  5.773018e-06
## f.gender=F                                                      46.2  4.072838e-03
## f.political_interest=Medium_to_High.Inter                       39.6  1.459058e-02
## f.egoposition_immigration=1_Level.Imm                            6.8  1.540367e-02
## f.egoposition_immigration=6_Level.Imm                            9.5  3.395532e-02
## f.egoposition_immigration=8_Level.Imm                            3.1  7.725865e-03
## f.Imm=high                                                       4.7  6.044056e-03
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm          4.7  6.044056e-03
## f.egoposition_immigration=9_Level.Imm                            3.4  4.782805e-03
## f.gender=M                                                      53.8  4.072838e-03
## f.egoposition_immigration=7_Level.Imm                            7.8  4.551511e-04
## f.vote_ord=AfD                                                   6.9  1.573110e-05
## f.political_orientation=Right_Wing                               6.9  1.573110e-05
## f.Imm=medium_high                                               14.3  1.816764e-08
## f.vote_ord=FDP                                                  12.1  2.059483e-09
## f.vote_ord=LINKE                                                12.3  1.443577e-09
## f.vote_ord=SPD                                                  25.5  1.039117e-20
## f.vote_ord=CDU/CSU                                              28.9  6.155171e-24
## bwing=Center_Wing                                               66.5  1.406134e-79
## f.political_orientation=Center_Wing                             66.5  1.406134e-79
##                                                                     v.test
## f.vote_ord=Gruene                                                28.406856
## f.political_orientation=Left_Wing                                21.126332
## bwing=Left_Right_Wings                                           18.888951
## f.Imm=low_medium                                                  5.857270
## f.egoposition_immigration=2_Level.Imm                             4.534536
## f.gender=F                                                        2.872465
## f.political_interest=Medium_to_High.Inter                         2.442385
## f.egoposition_immigration=1_Level.Imm                             2.422746
## f.egoposition_immigration=6_Level.Imm                            -2.120602
## f.egoposition_immigration=8_Level.Imm                            -2.663821
## f.Imm=high                                                       -2.745382
## f.egoposition_immigration=10_Very_Restrictive_Level.Imm          -2.745382
## f.egoposition_immigration=9_Level.Imm                            -2.821309
## f.gender=M                                                       -2.872465
## f.egoposition_immigration=7_Level.Imm                            -3.505850
## f.vote_ord=AfD                                                   -4.318194
## f.political_orientation=Right_Wing                               -4.318194
## f.Imm=medium_high                                                -5.628602
## f.vote_ord=FDP                                                   -5.993045
## f.vote_ord=LINKE                                                 -6.050544
## f.vote_ord=SPD                                                   -9.331980
## f.vote_ord=CDU/CSU                                              -10.089389
## bwing=Center_Wing                                               -18.888951
## f.political_orientation=Center_Wing                             -18.888951
##
## $LINKE
```

```
##                                                 Cla/Mod    Mod/Cla Global
## f.vote_ord=LINKE                             100.000000 100.000000   12.3
## f.political_orientation=Left_Wing             46.240602 100.000000   26.6
## bwing=Left_Right_Wings                        36.716418 100.000000   33.5
## f.eastGermany=No.EastGermany                  19.087137  37.398374   24.1
## f.Imm=low                                     28.571429  11.382114    4.9
## f.egoposition_immigration=0_Very_Open_Level.Imm  28.571429  11.382114    4.9
## f.IncSat=medium                               13.896104  86.991870   77.0
## f.Imm=low_medium                              16.566265  44.715447   33.2
## f.egoposition_immigration=3_Level.Imm         19.402985  21.138211   13.4
## f.duplicate=No.Duplicate                      14.196568  73.983740   64.1
## f.income=Medium.Sat                           17.553191  26.829268   18.8
## f.Imm=medium_high                              6.993007   8.130081   14.3
## f.duplicate=Yes.Duplicate                      8.913649  26.016260   35.9
## f.Imm=medium                                   9.324009  32.520325   42.9
## f.egoposition_immigration=6_Level.Imm          4.210526   3.252033    9.5
## f.egoposition_immigration=5_Neutral_Level.Imm    5.161290   6.504065   15.5
## f.eastGermany=Yes.EastGermany                 10.144928  62.601626   75.9
## f.IncSat=high                                  4.761905   7.317073   18.9
## f.income=High.Sat                              4.761905   7.317073   18.9
## f.vote_ord=AfD                                 0.000000   0.000000    6.9
## f.political_orientation=Right_Wing             0.000000   0.000000    6.9
## f.vote_ord=FDP                                 0.000000   0.000000   12.1
## f.vote_ord=Gruene                              0.000000   0.000000   14.3
## f.vote_ord=SPD                                 0.000000   0.000000   25.5
## f.vote_ord=CDU/CSU                             0.000000   0.000000   28.9
## bwing=Center_Wing                              0.000000   0.000000   66.5
## f.political_orientation=Center_Wing            0.000000   0.000000   66.5
##                                                     p.value     v.test
## f.vote_ord=LINKE                              3.053611e-161  27.058260
## f.political_orientation=Left_Wing              8.361150e-83  19.277115
## bwing=Left_Right_Wings                         6.141124e-67  17.284633
## f.eastGermany=No.EastGermany                   4.265885e-04   3.523064
## f.Imm=low                                      1.737035e-03   3.131859
## f.egoposition_immigration=0_Very_Open_Level.Imm   1.737035e-03   3.131859
## f.IncSat=medium                                3.395906e-03   2.929424
## f.Imm=low_medium                               4.615992e-03   2.832678
## f.egoposition_immigration=3_Level.Imm          1.099556e-02   2.542840
## f.duplicate=No.Duplicate                       1.345692e-02   2.471442
## f.income=Medium.Sat                            1.925059e-02   2.340643
## f.Imm=medium_high                              3.007057e-02  -2.169160
## f.duplicate=Yes.Duplicate                      1.345692e-02  -2.471442
## f.Imm=medium                                   1.252121e-02  -2.497104
## f.egoposition_immigration=6_Level.Imm          6.136722e-03  -2.740385
## f.egoposition_immigration=5_Neutral_Level.Imm    1.585127e-03  -3.158630
## f.eastGermany=Yes.EastGermany                  4.265885e-04  -3.523064
## f.IncSat=high                                  1.536281e-04  -3.785130
## f.income=High.Sat                              1.536281e-04  -3.785130
## f.vote_ord=AfD                                 8.254390e-05  -3.936892
## f.political_orientation=Right_Wing             8.254390e-05  -3.936892
```

```
## f.vote_ord=FDP                                 4.155458e-08  -5.484114
## f.vote_ord=Gruene                              1.443577e-09  -6.050544
## f.vote_ord=SPD                                 1.096795e-17  -8.563303
## f.vote_ord=CDU/CSU                             2.036114e-20  -9.260430
## bwing=Center_Wing                              6.141124e-67 -17.284633
## f.political_orientation=Center_Wing            6.141124e-67 -17.284633
##
## $SPD
##                                               Cla/Mod     Mod/Cla Global
## f.vote_ord=SPD                              100.000000 100.0000000   25.5
## bwing=Center_Wing                            38.345865 100.0000000   66.5
## f.political_orientation=Center_Wing          38.345865 100.0000000   66.5
## f.Imm=low_medium                             32.530120  42.3529412   33.2
## f.egoposition_immigration=2_Level.Imm        36.923077  18.8235294   13.0
## f.mout=MvOut.No                              26.024590  99.6078431   97.6
## f.egoposition_immigration=1_Level.Imm        38.235294  10.1960784    6.8
## f.political_interest=Low_to_Medium.Inter      8.823529   1.1764706    3.4
## f.mout=MvOut.Yes                              4.166667   0.3921569    2.4
## f.Imm=medium_high                            16.783217   9.4117647   14.3
## f.vote_ord=AfD                                0.000000   0.0000000    6.9
## f.political_orientation=Right_Wing            0.000000   0.0000000    6.9
## f.vote_ord=FDP                                0.000000   0.0000000   12.1
## f.vote_ord=LINKE                              0.000000   0.0000000   12.3
## f.vote_ord=Gruene                             0.000000   0.0000000   14.3
## f.political_orientation=Left_Wing             0.000000   0.0000000   26.6
## f.vote_ord=CDU/CSU                            0.000000   0.0000000   28.9
## bwing=Left_Right_Wings                        0.000000   0.0000000   33.5
##                                                   p.value      v.test
## f.vote_ord=SPD                              9.178288e-246   33.480784
## bwing=Center_Wing                            5.401466e-55   15.619038
## f.political_orientation=Center_Wing          5.401466e-55   15.619038
## f.Imm=low_medium                             3.909839e-04    3.546096
## f.egoposition_immigration=2_Level.Imm        1.985233e-03    3.092433
## f.mout=MvOut.No                              8.131457e-03    2.646562
## f.egoposition_immigration=1_Level.Imm        1.674243e-02    2.392316
## f.political_interest=Low_to_Medium.Inter     1.626155e-02   -2.402992
## f.mout=MvOut.Yes                             8.131457e-03   -2.646562
## f.Imm=medium_high                            7.988755e-03   -2.652545
## f.vote_ord=AfD                               6.459324e-10   -6.178794
## f.political_orientation=Right_Wing           6.459324e-10   -6.178794
## f.vote_ord=FDP                               2.177390e-17   -8.483916
## f.vote_ord=LINKE                             1.096795e-17   -8.563303
## f.vote_ord=Gruene                            1.039117e-20   -9.331980
## f.political_orientation=Left_Wing            2.115265e-41  -13.477726
## f.vote_ord=CDU/CSU                           9.555546e-46  -14.197047
## bwing=Left_Right_Wings                       5.401466e-55  -15.619038
```

```
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
```

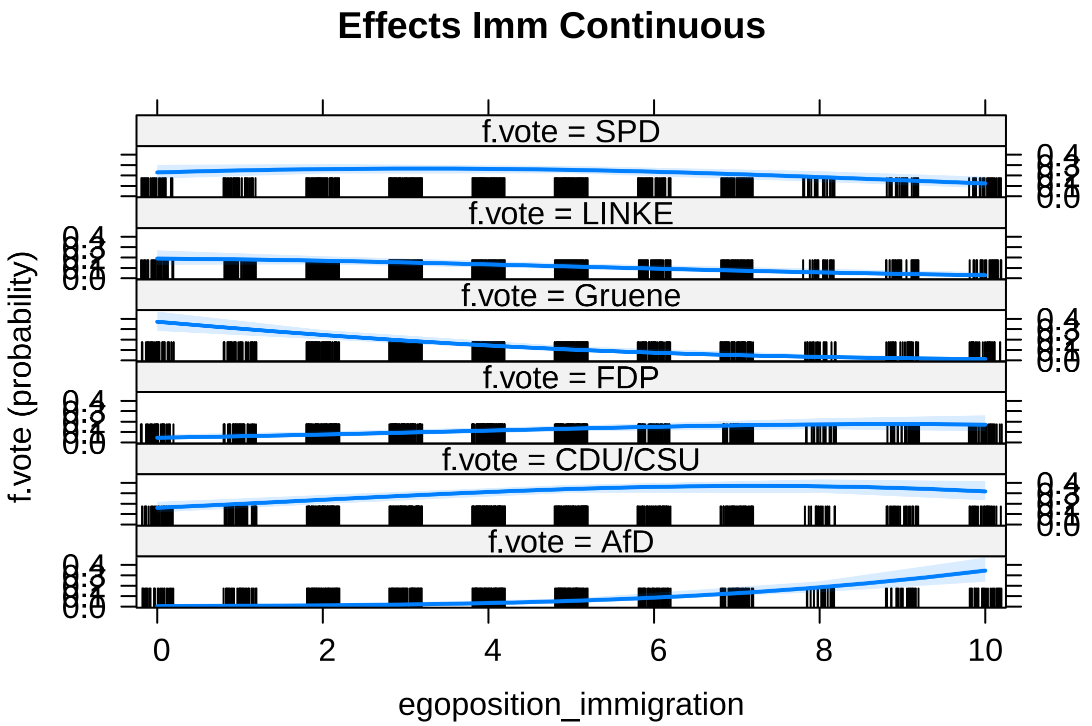
```
Anova(nm1_imm_cat, test="Chisq")
```

```
## # 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
```

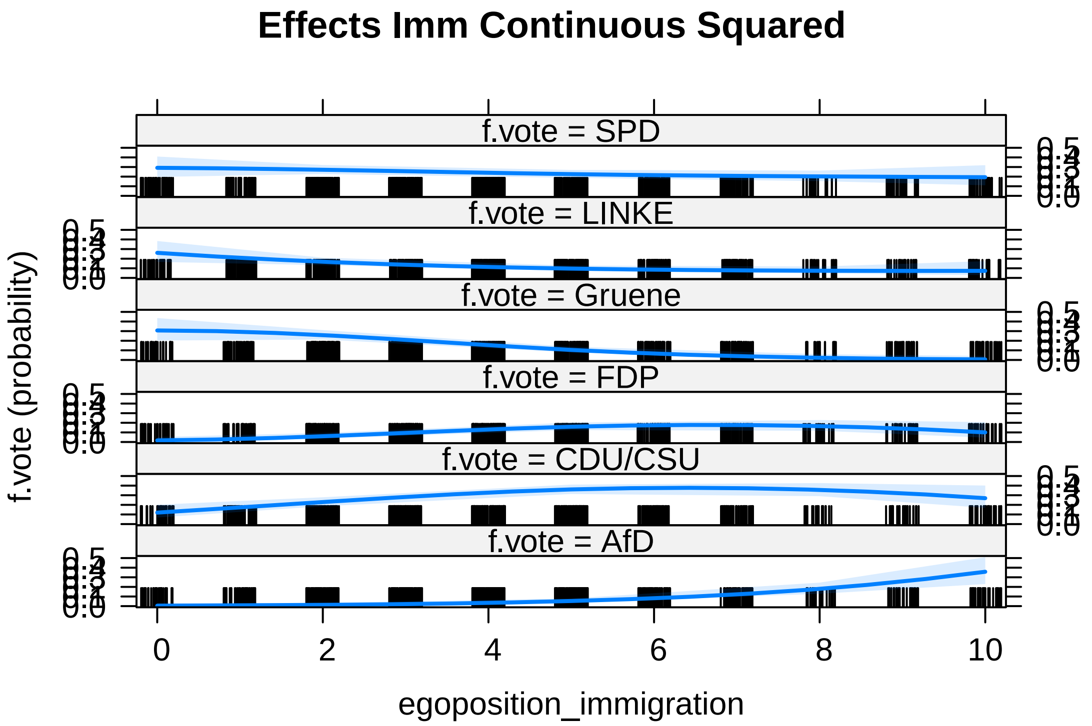
```
Anova(nm1_imm_cat_new, test="Chisq")
```

```
## # 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
```

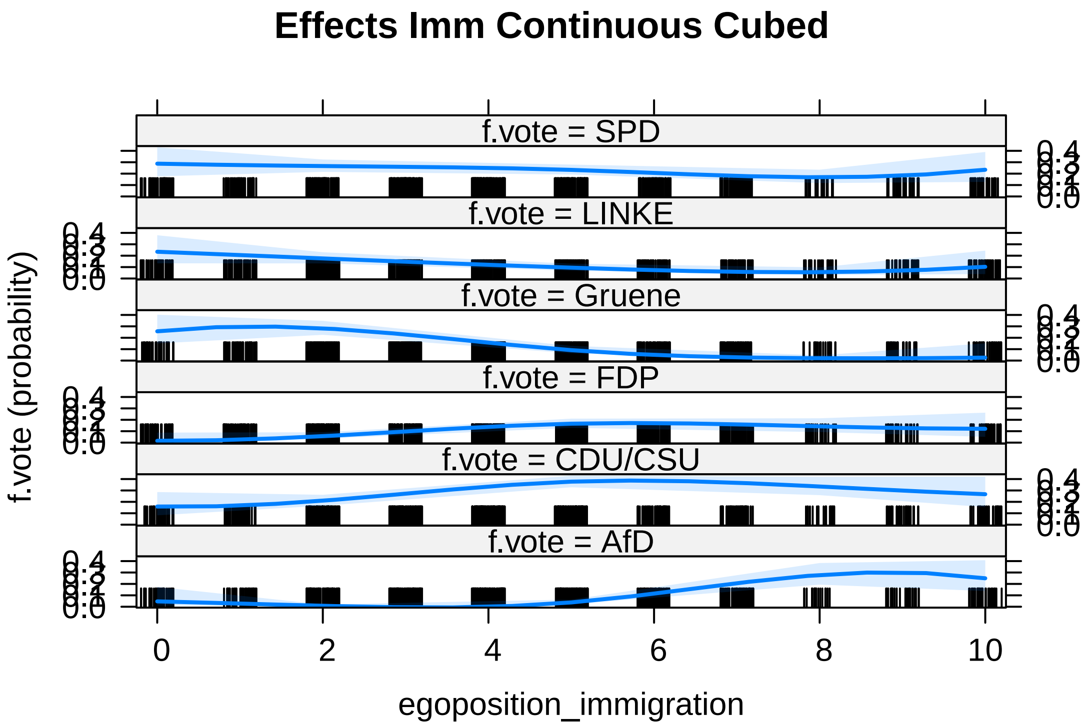
```
plot(allEffects(nm1_imm_con),ask=FALSE, main="Effects Imm Continuous")
```



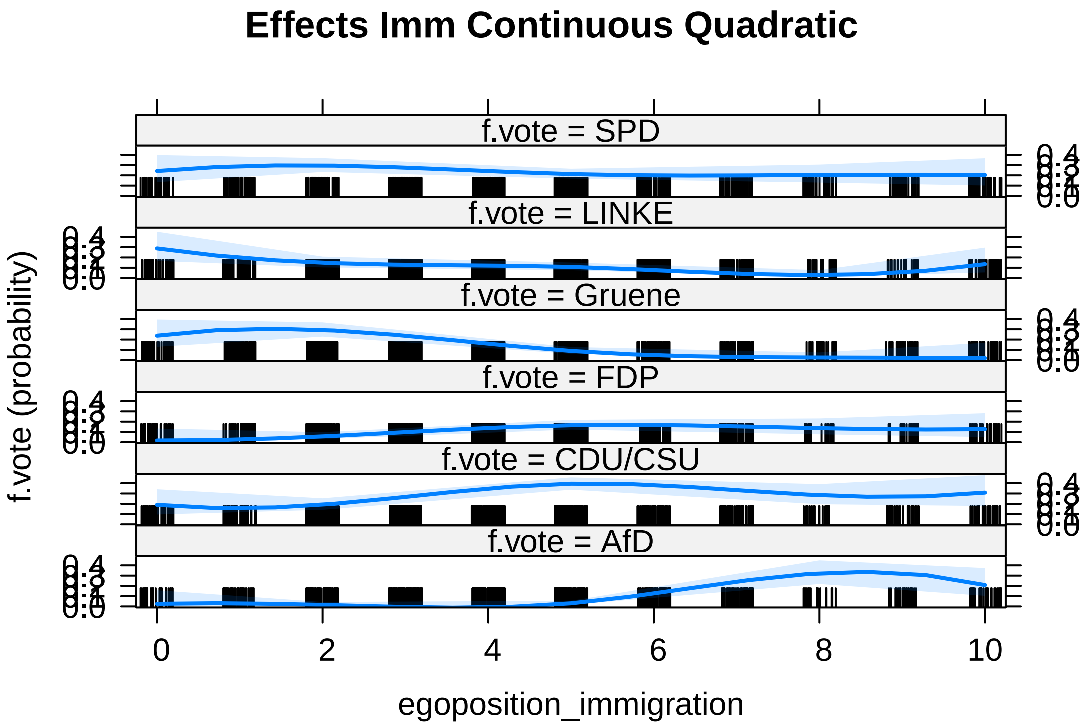

```
plot(allEffects(nm1_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```




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

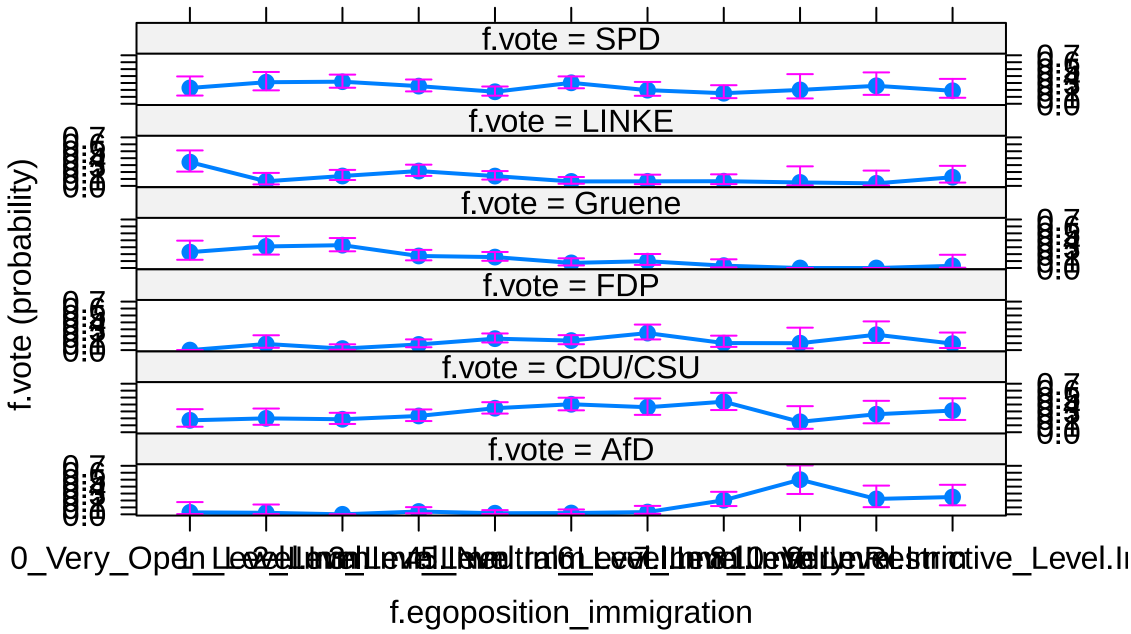



```
plot(allEffects(nm1_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```



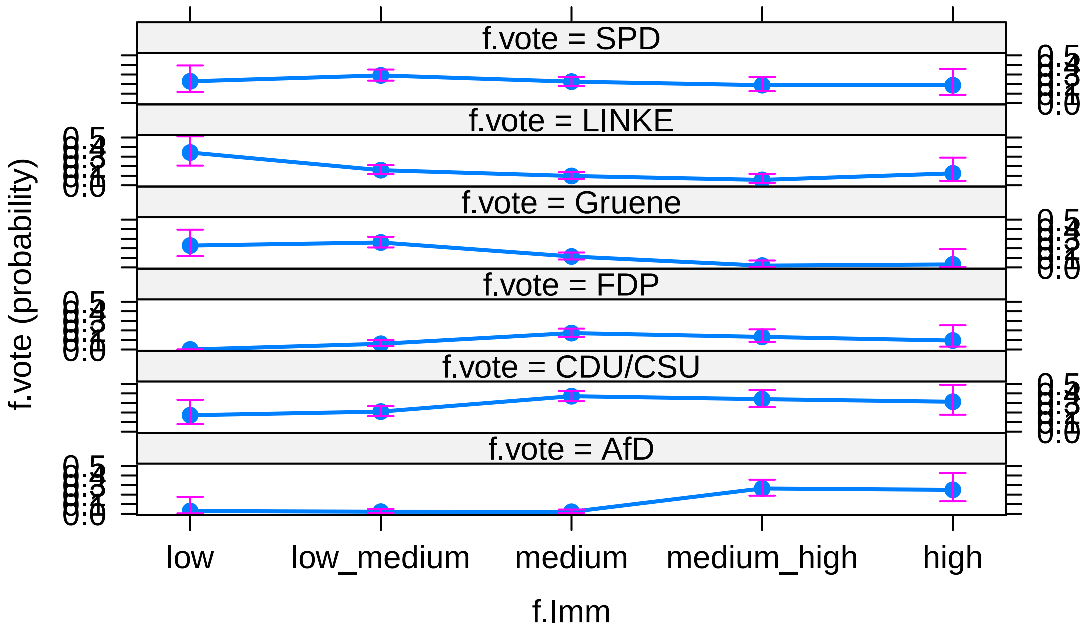

```
plot(allEffects(nm1_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

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
```

```r
nm0$dev - nm1_polint_con_sq$dev
```

```
## [1] 21.10837
```

```r
nm0$dev - nm1_polint_con_cb$dev
```

```
## [1] 30.35926
```

```r
nm0$dev - nm1_polint_con_qd$dev
```

```
## [1] 32.99533
```

```r
nm0$dev - nm1_polint_cat$dev
```

```
## [1] 32.99949
```

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

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

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

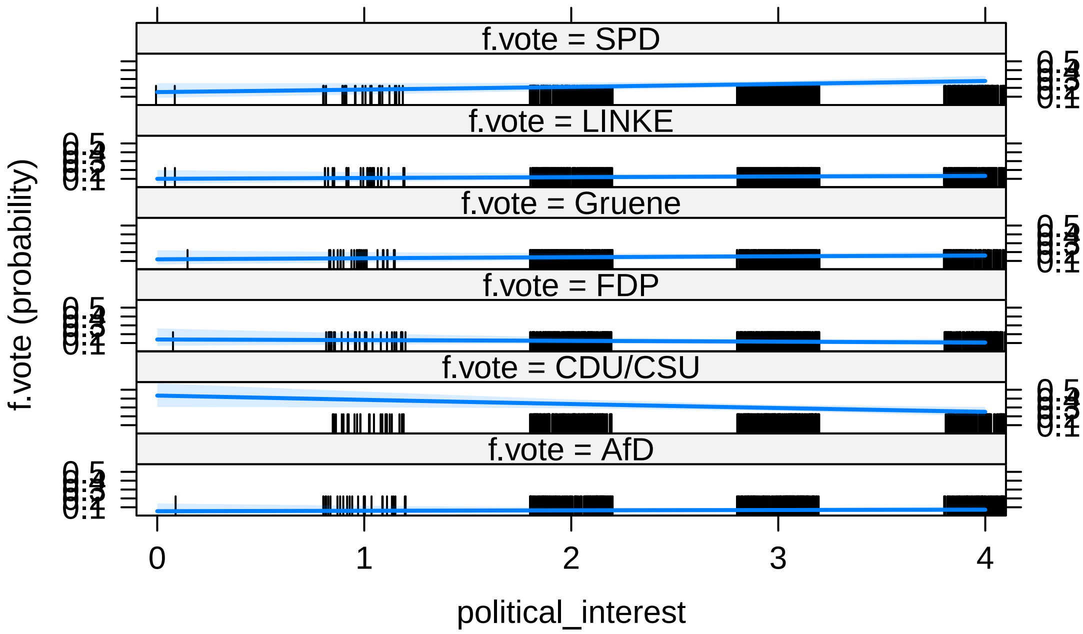
```
Anova(nm1_polint_cat_new, test="Chisq")
```

```
## # 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
```

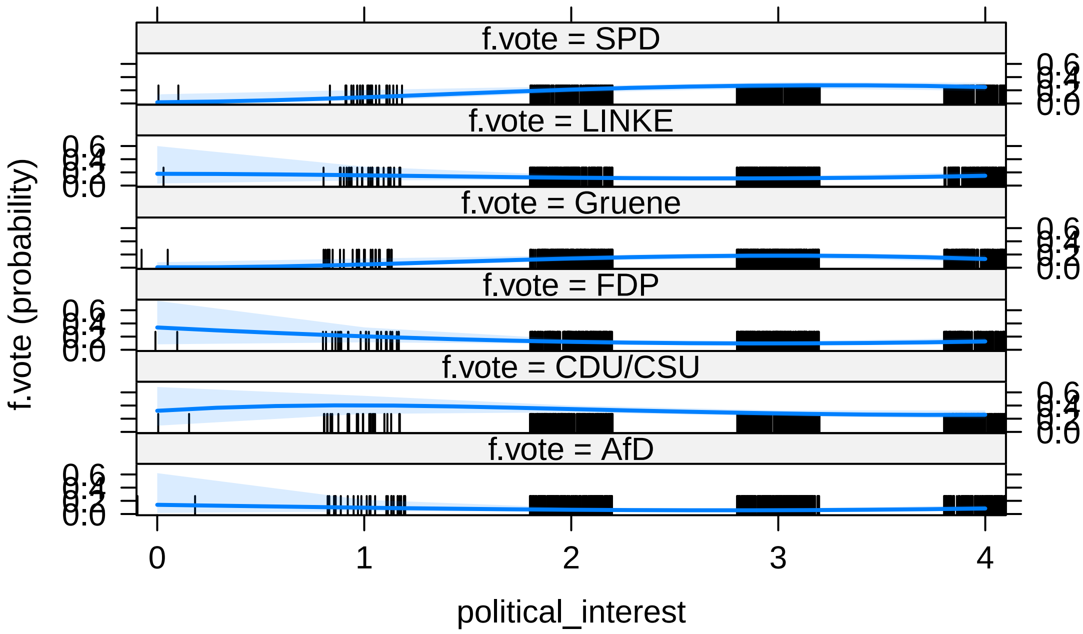
```
plot(allEffects(nm1_polint_con),ask=FALSE, main="Effects Pol Int Continuous")
```

Effects Pol Int Continuous

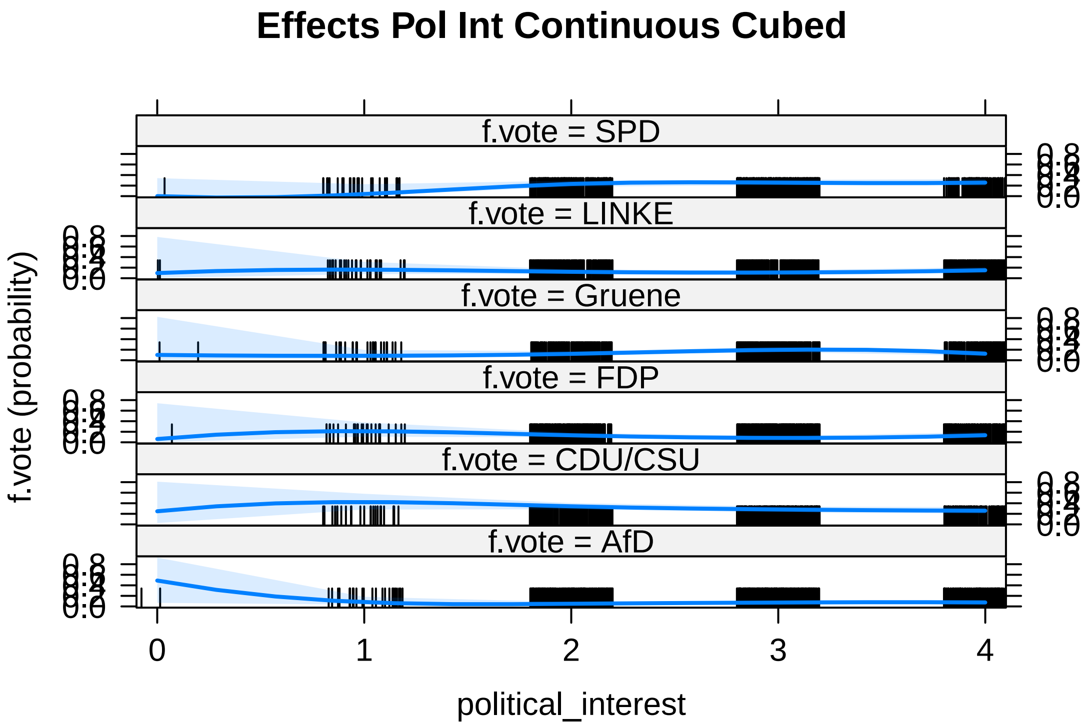



```r
plot(allEffects(nm1_polint_con_sq),ask=FALSE,main="Effects Pol Int Continuous Squared")
```

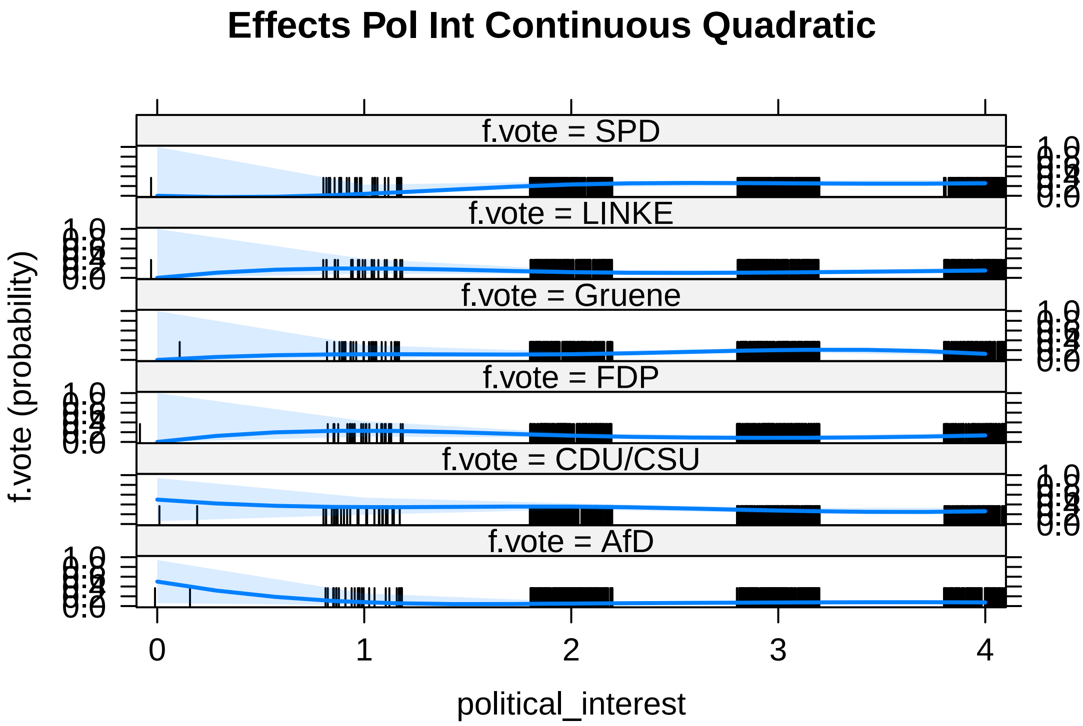
Effects Pol Int Continuous Squared



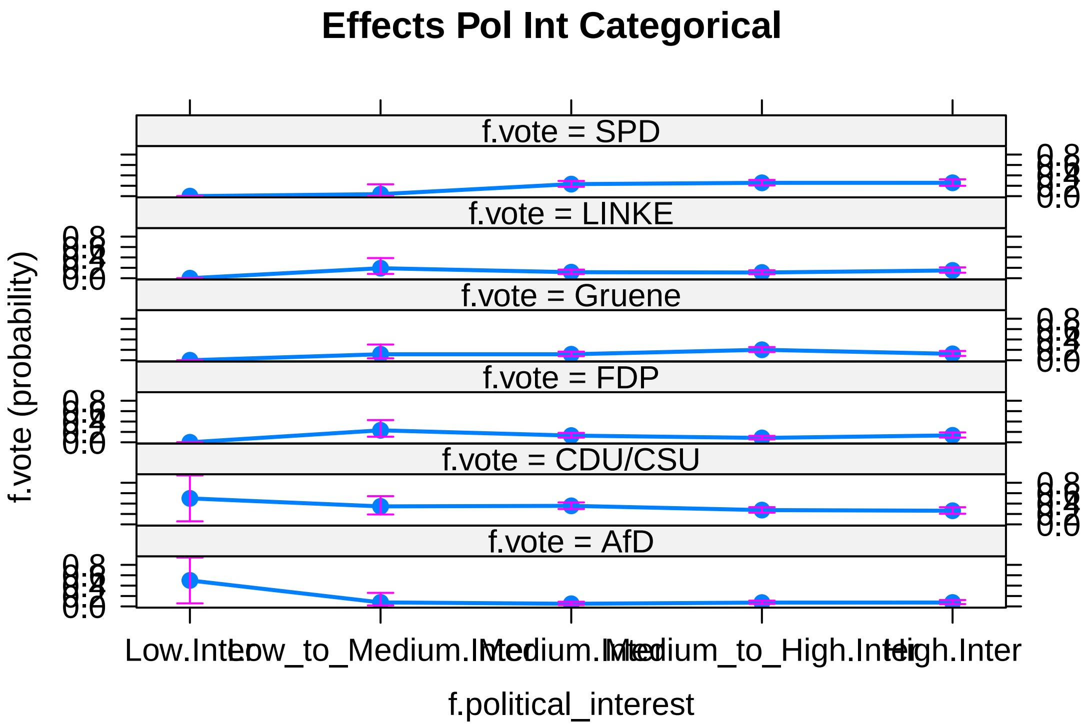

```r
plot(allEffects(nm1_polint_con_cb),ask=FALSE, main="Effects Pol Int Continuous Cubed")
```



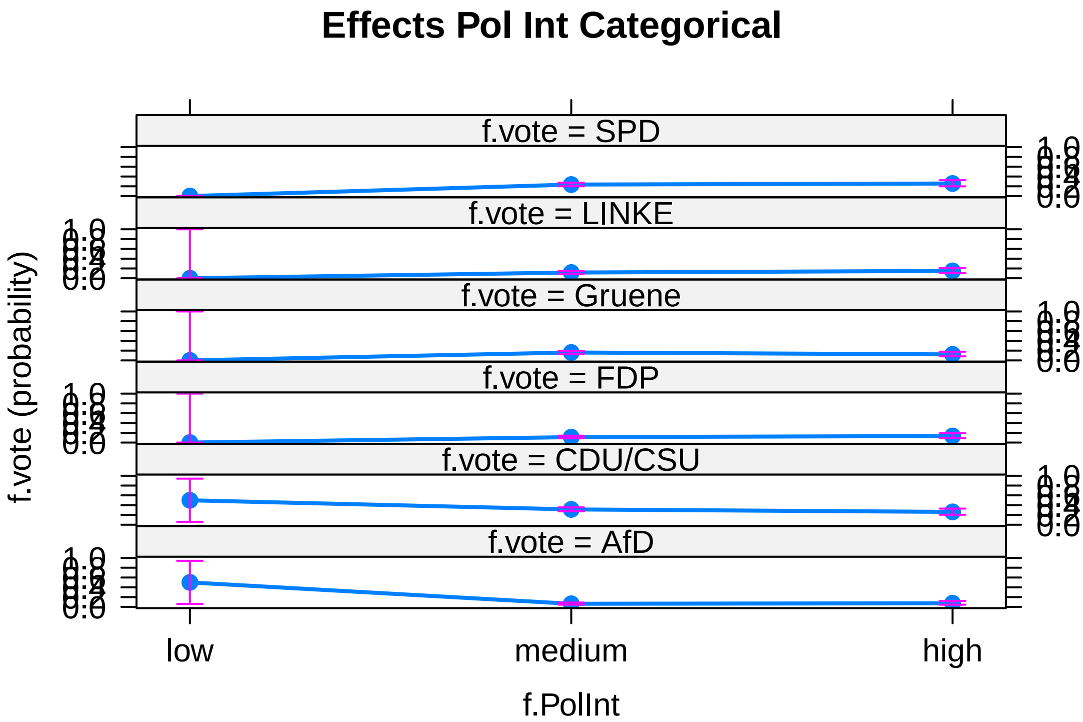

```
plot(allEffects(nm1_polint_con_qd),ask=FALSE, main="Effects Pol Int Continuous Quadratic
```




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




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




```
#step(nm1_polint_con_sq)
```

```
nm0$dev - nm1_inc_con$dev
```

```
## [1] 17.92852
```

```r
nm0$dev - nm1_inc_con_sq$dev
```

```
## [1] 24.23512
```

```r
nm0$dev - nm1_inc_con_cb$dev
```

```
## [1] 31.37888
```

```r
nm0$dev - nm1_inc_con_qd$dev
```

```
## [1] 31.88161
```

```r
nm0$dev - nm1_inc_cat$dev
```

```
## [1] 31.89324
```

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

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

```r
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
```

```r
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
```

```r
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
```

```r
Anova(nm1_inc_con, test="Chisq")
```

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

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

```
##
## Response: f.vote
##        LR Chisq Df Pr(>Chisq)
## income   17.928  5   0.003037 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
Anova(nm1_inc_con_sq, test="Chisq")
```

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

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

```r
Anova(nm1_inc_con_cb, test="Chisq")
```

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

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

```r
Anova(nm1_inc_con_qd, test="Chisq")
```

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

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

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

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

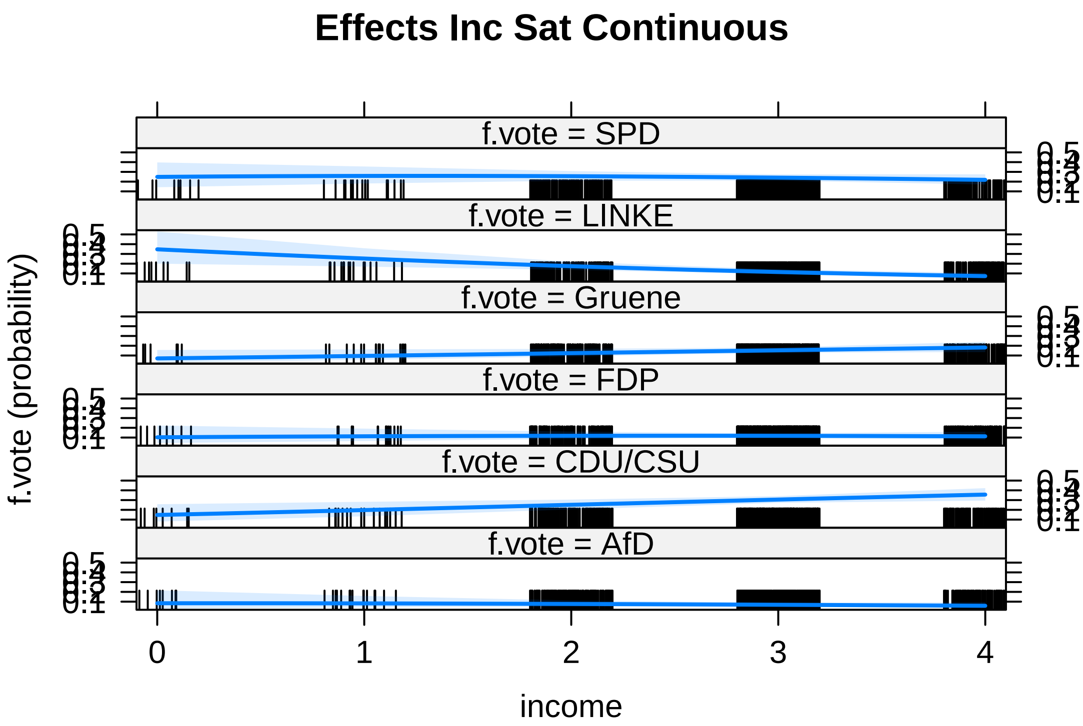
```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote
##          LR Chisq Df Pr(>Chisq)
## f.income   31.893 20    0.04445 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

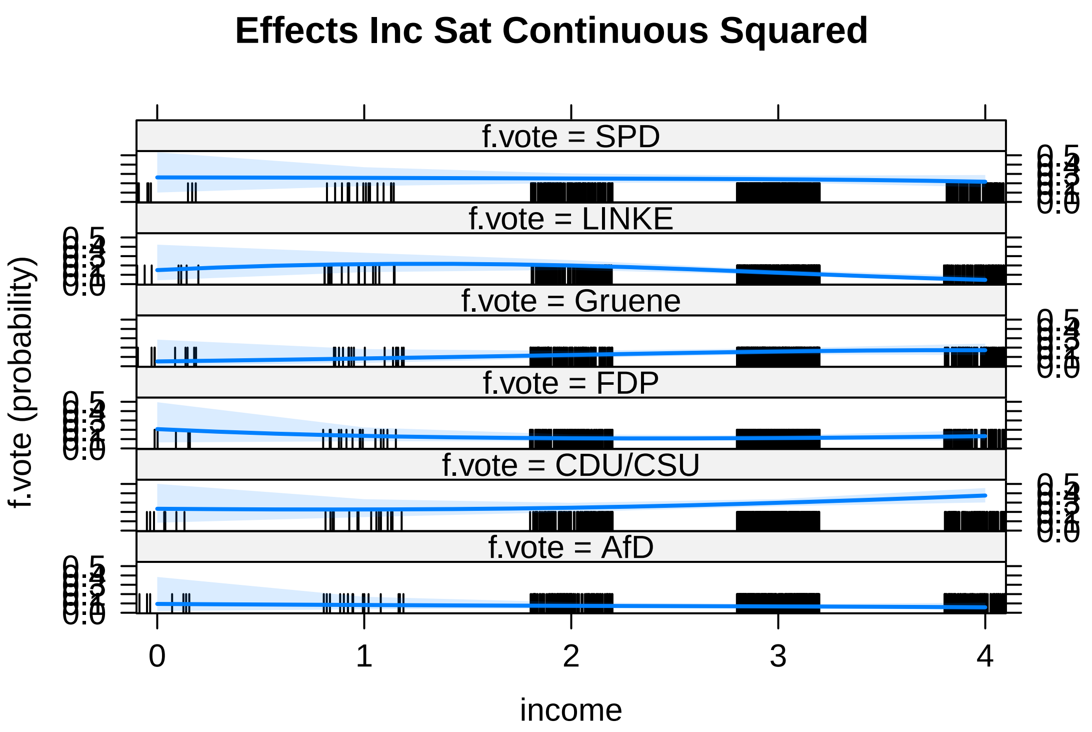
```
## # weights:  12 (5 variable)
## initial  value 1261.398666
## iter  10 value 1184.278222
## final  value 1184.278203
## converged
```

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

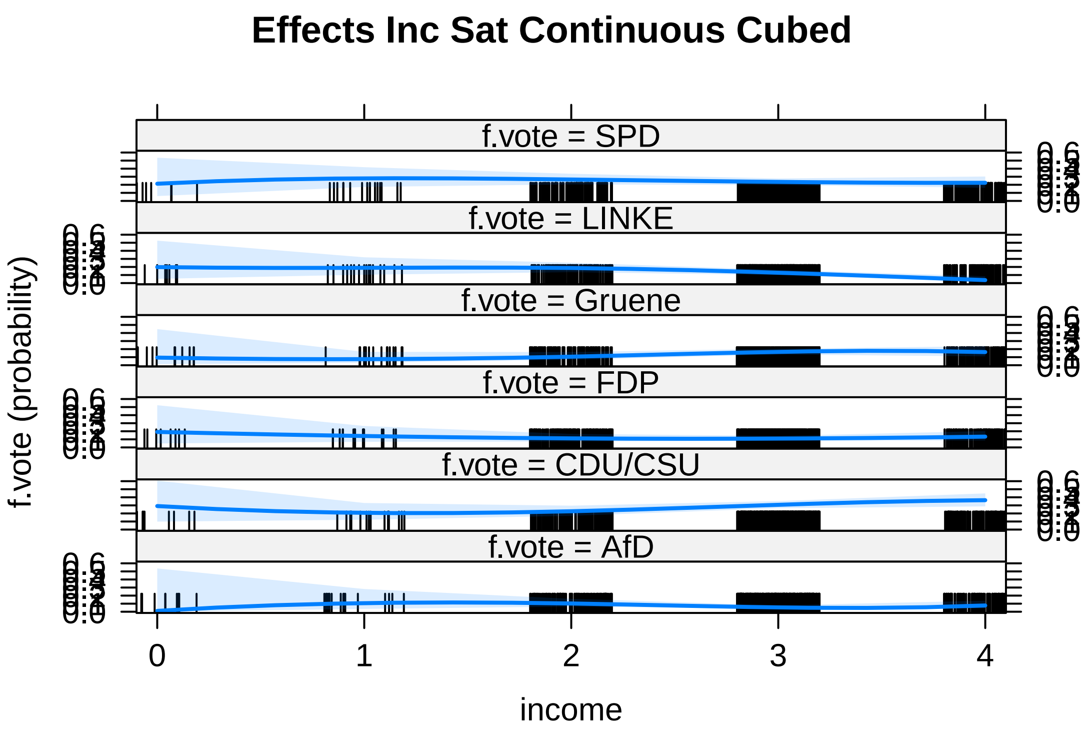
```
plot(allEffects(nm1_inc_con),ask=FALSE, main="Effects Inc Sat Continuous")
```



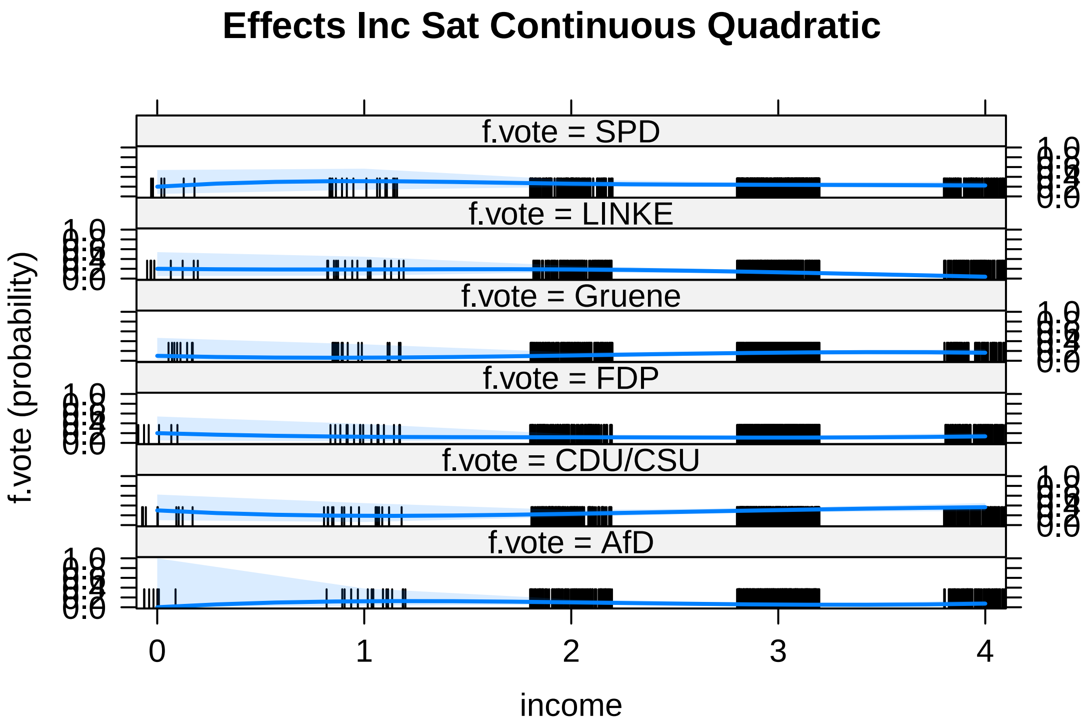
```
plot(allEffects(nm1_inc_con_sq),ask=FALSE,main="Effects Inc Sat Continuous Squared")
```



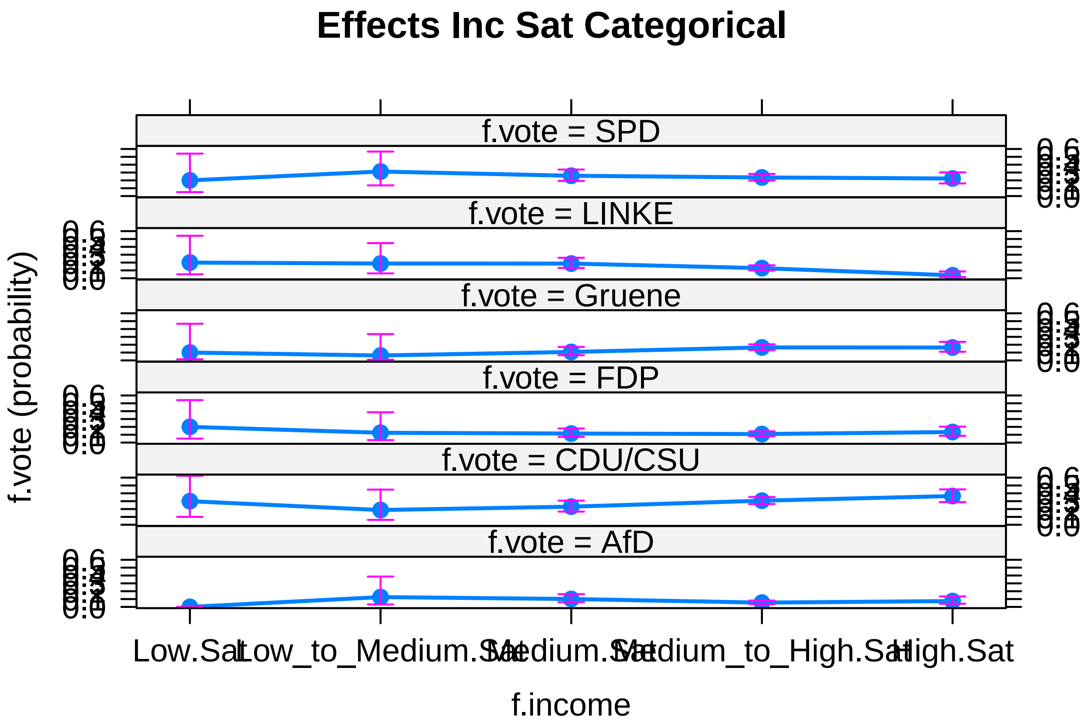

```
plot(allEffects(nm1_inc_con_cb),ask=FALSE, main="Effects Inc Sat Continuous Cubed")
```



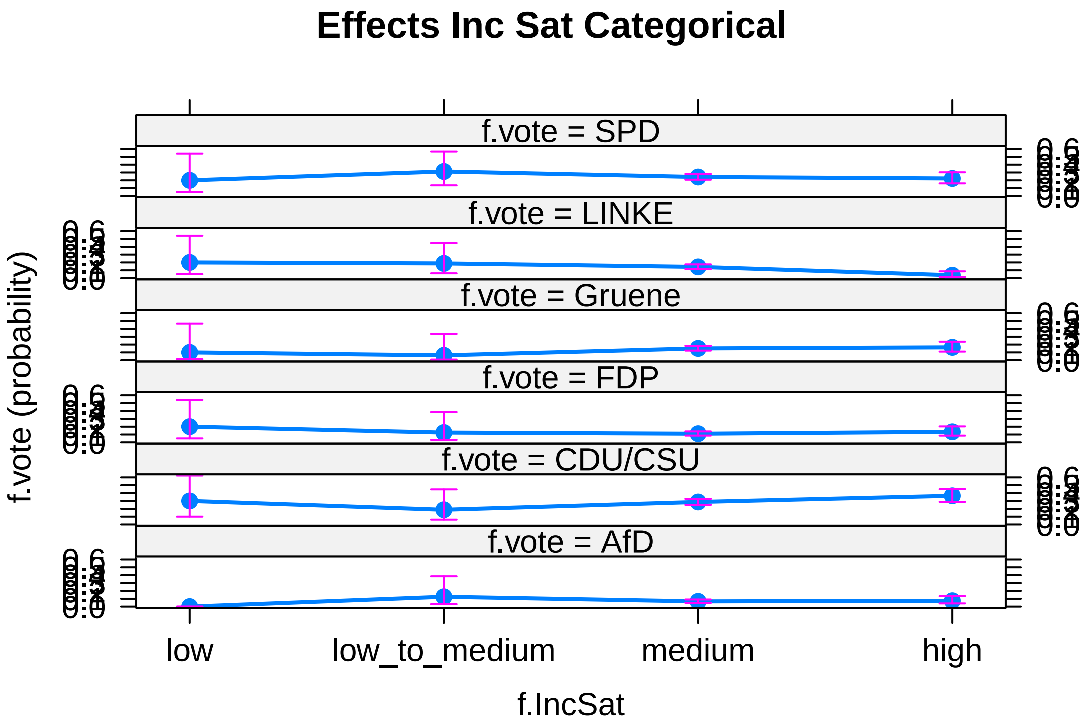

```
plot(allEffects(nm1_inc_con_qd),ask=FALSE, main="Effects Inc Sat Continuous Quadratic")
```




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




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




```
#step(nm1_imm_cat_new)
```

4.3.2 Ordinal Models

Comparison of Variables' Numerical and Categorical Representation for Ordinal Models

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

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

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

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

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

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

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

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

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

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

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

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

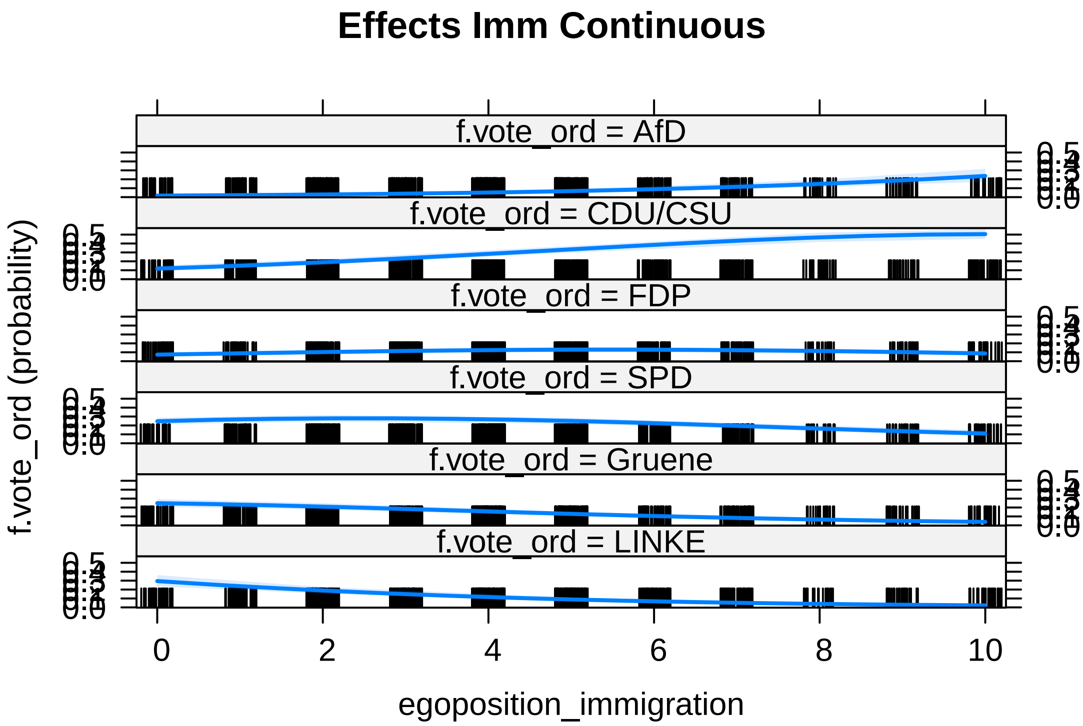
```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##                             LR Chisq Df Pr(>Chisq)
## f.egoposition_immigration   121.65 10  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
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
```

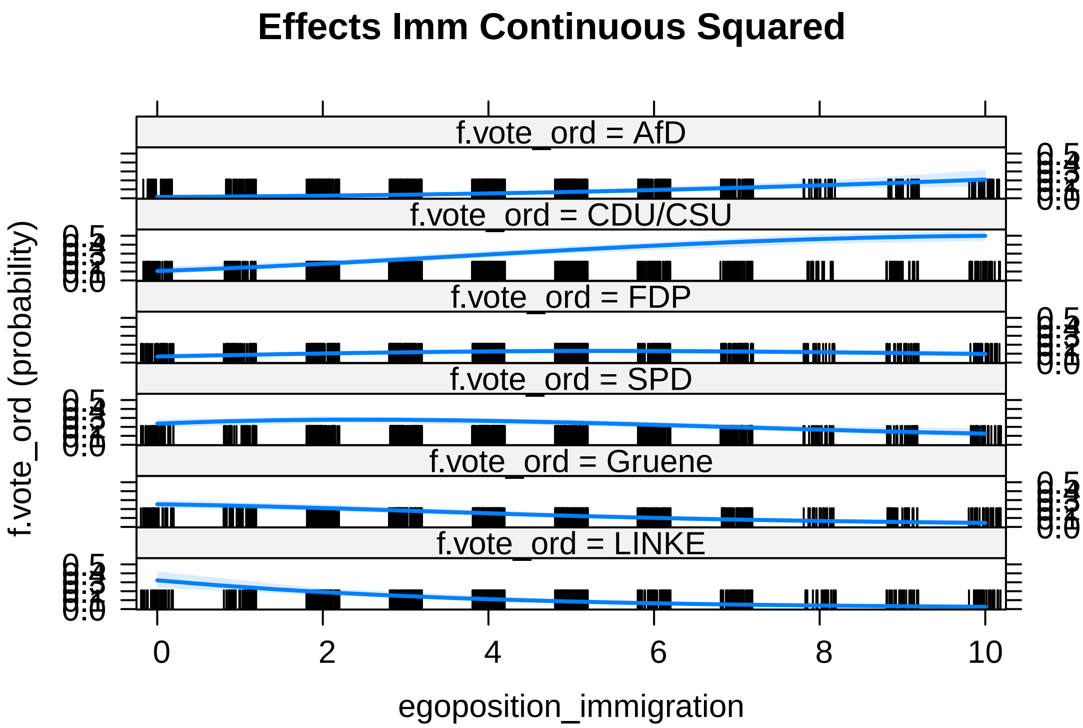
```r
plot(allEffects(om1_imm_con),ask=FALSE, main="Effects Imm Continuous")
```

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



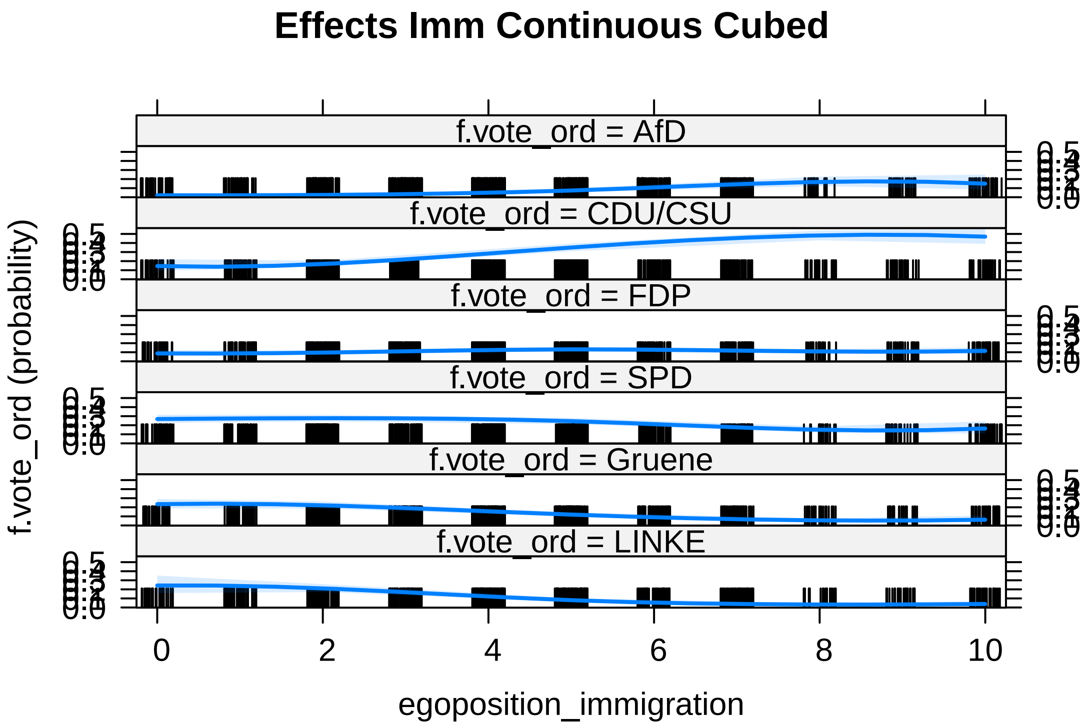

```
plot(allEffects(om1_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```

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



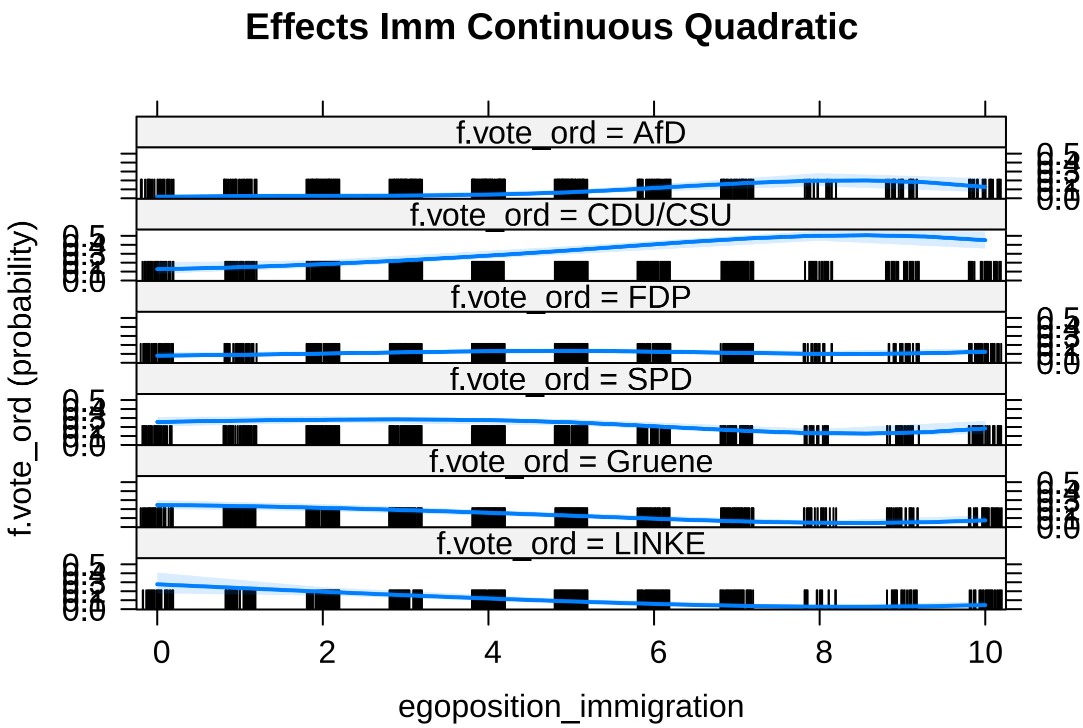

```
plot(allEffects(om1_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```

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



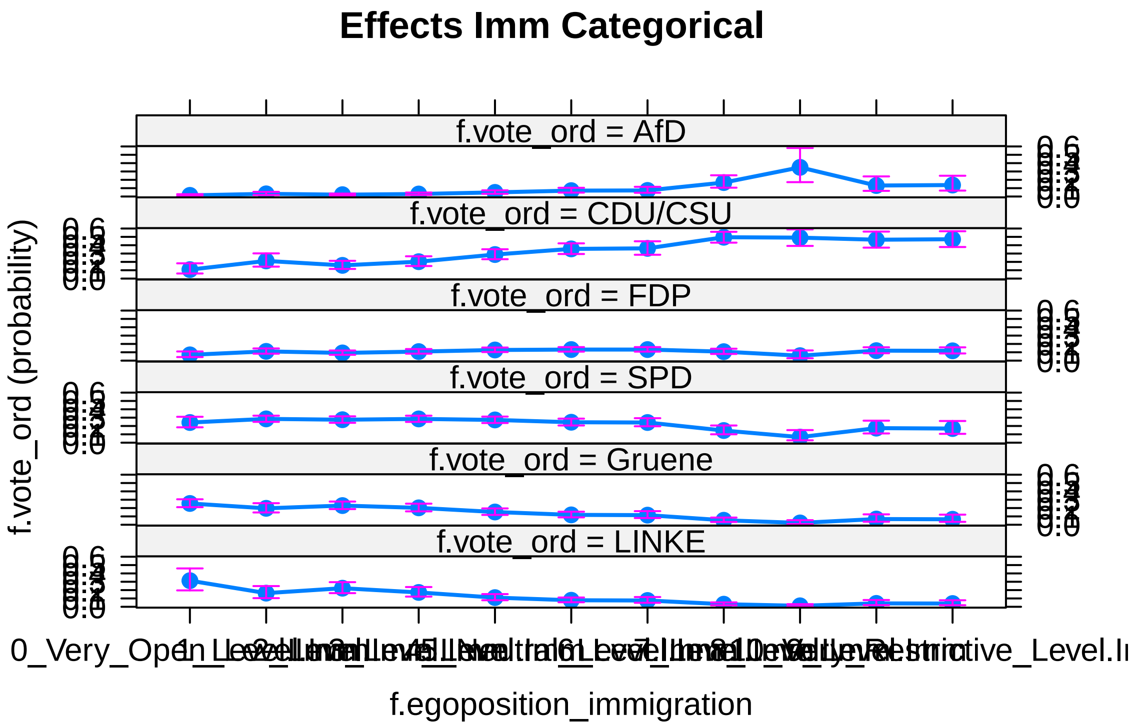

```
plot(allEffects(om1_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```

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



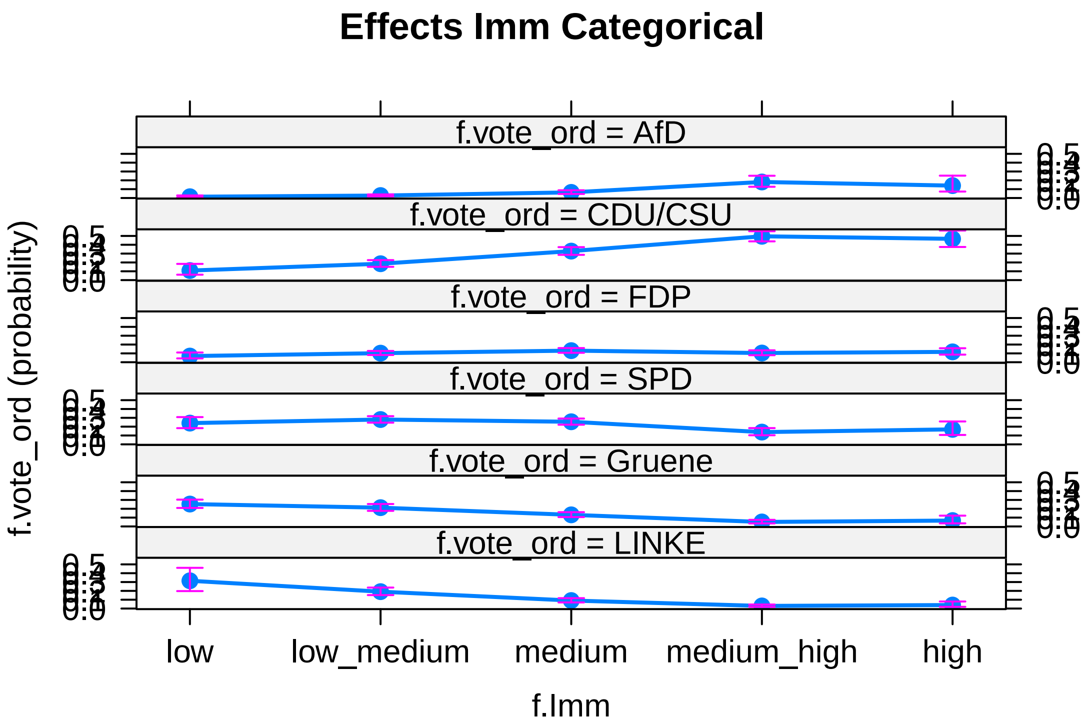

```
plot(allEffects(om1_imm_cat),ask=FALSE, main="Effects Imm Categorical")
```

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




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

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




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

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

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

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

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

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

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

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

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

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

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

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

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

```r
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
```

```r
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
```

```r
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
```

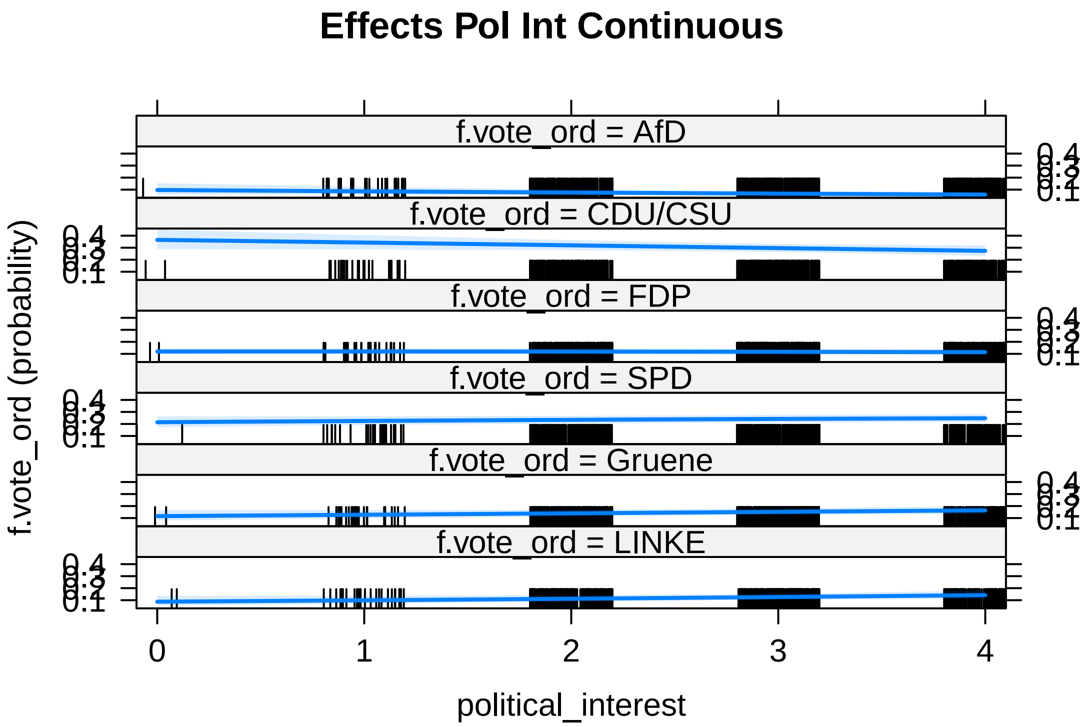
```
Anova(om1_polint_cat_new, test="Chisq")
```

```
## 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
```

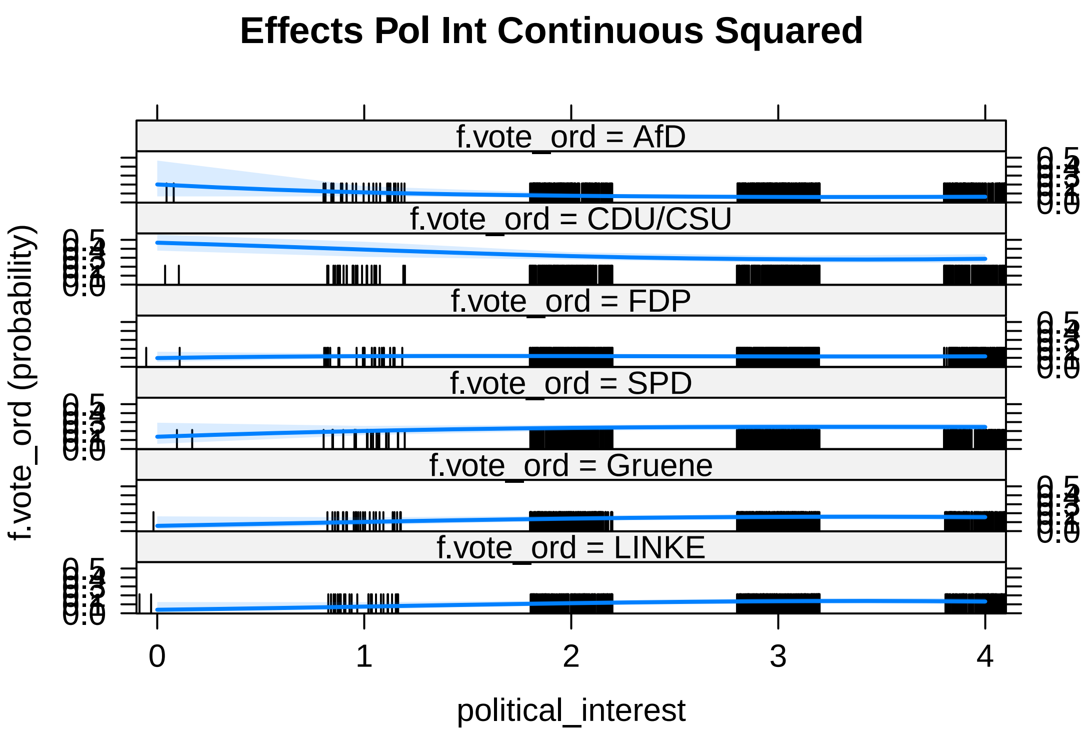
```
plot(allEffects(om1_polint_con),ask=FALSE, main="Effects Pol Int Continuous")
```

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



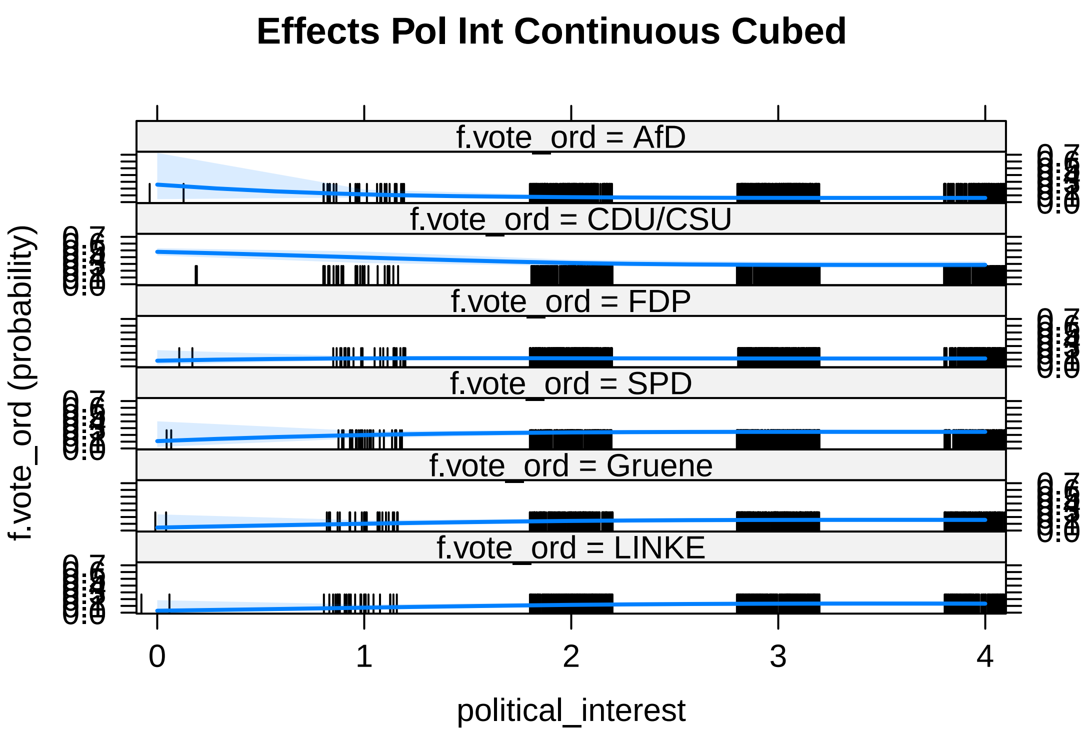

```
plot(allEffects(om1_polint_con_sq),ask=FALSE,main="Effects Pol Int Continuous Squared")
```

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



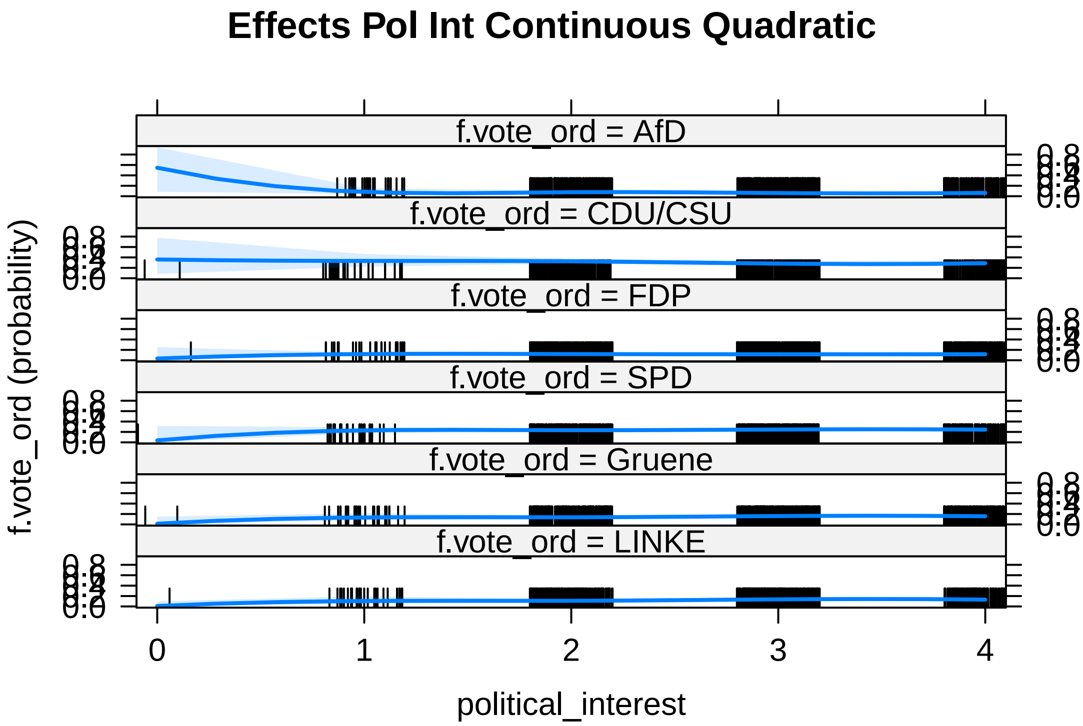

```
plot(allEffects(om1_polint_con_cb),ask=FALSE, main="Effects Pol Int Continuous Cubed")
```

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



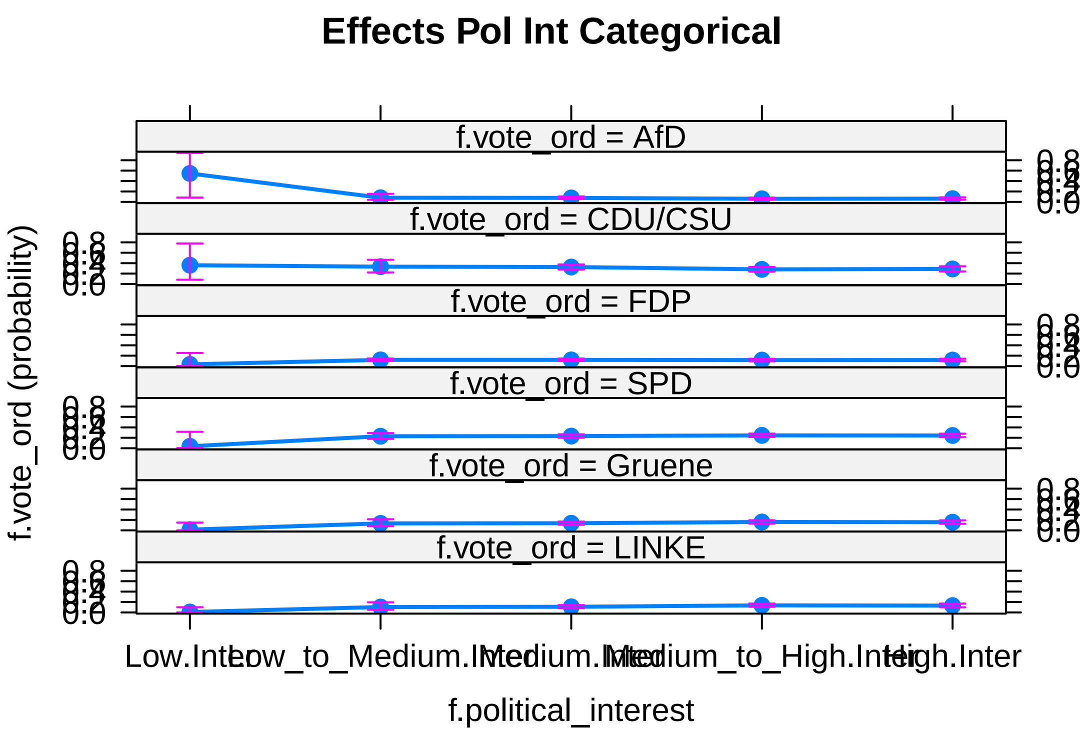

```
plot(allEffects(om1_polint_con_qd),ask=FALSE, main="Effects Pol Int Continuous Quadratic
```

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



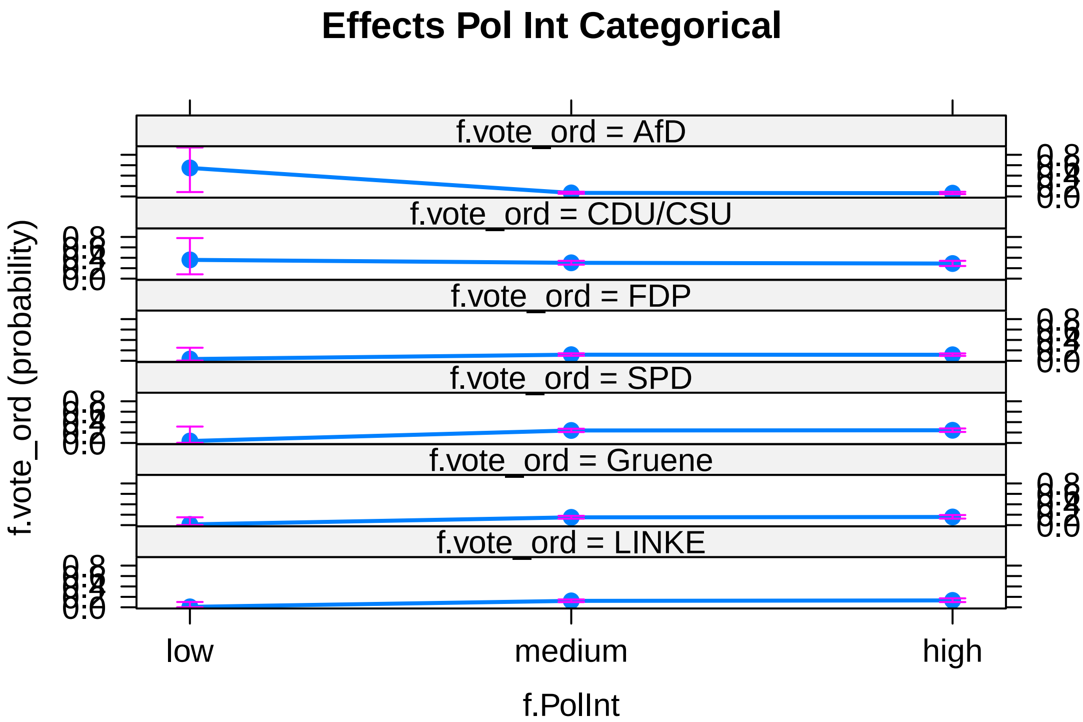

```
plot(allEffects(om1_polint_cat),ask=FALSE, main="Effects Pol Int Categorical")
```

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




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

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




```
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")
```

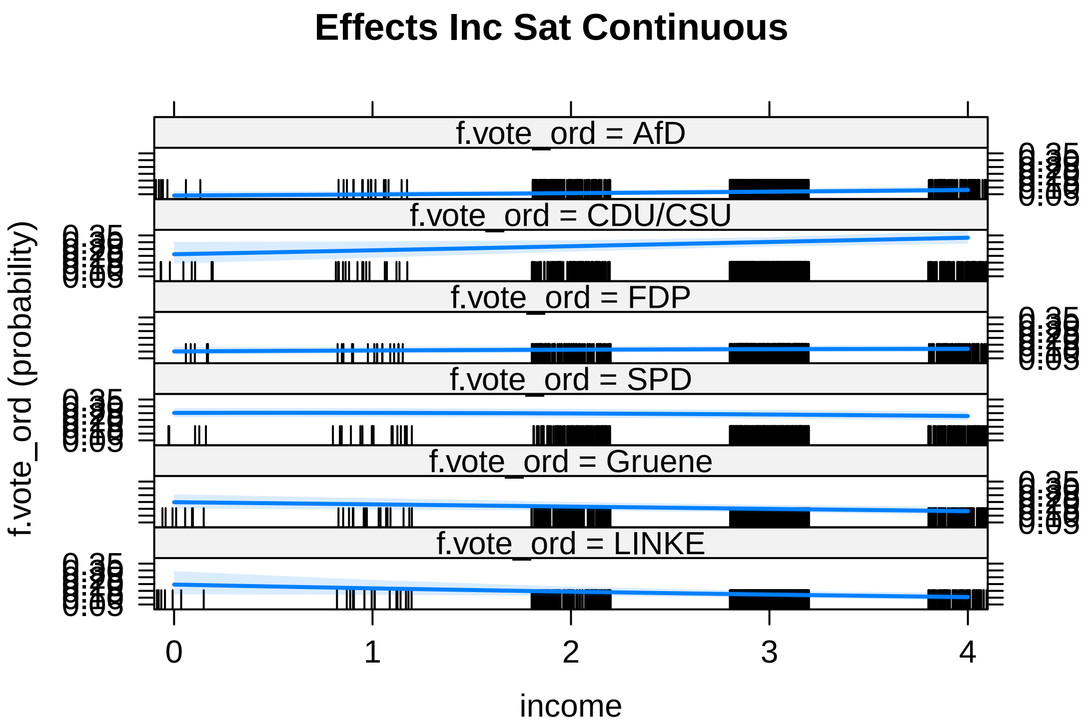
```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.vote_ord
##          LR Chisq Df Pr(>Chisq)
## f.income    7.227  4     0.1244
```

```r
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
```

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

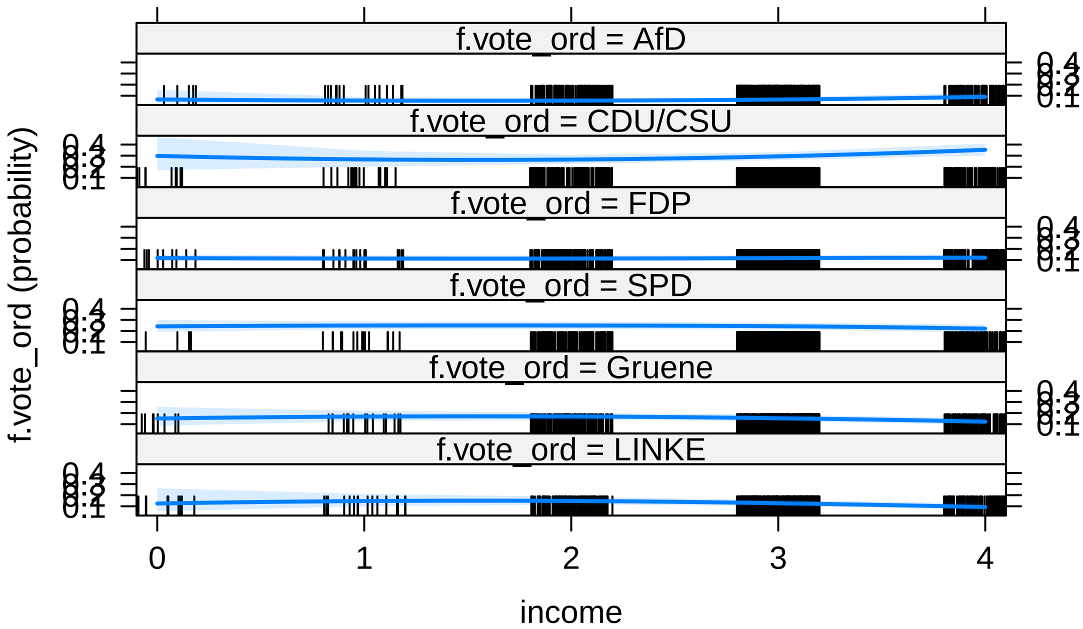
```
##
## Re-fitting to get Hessian
```




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

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

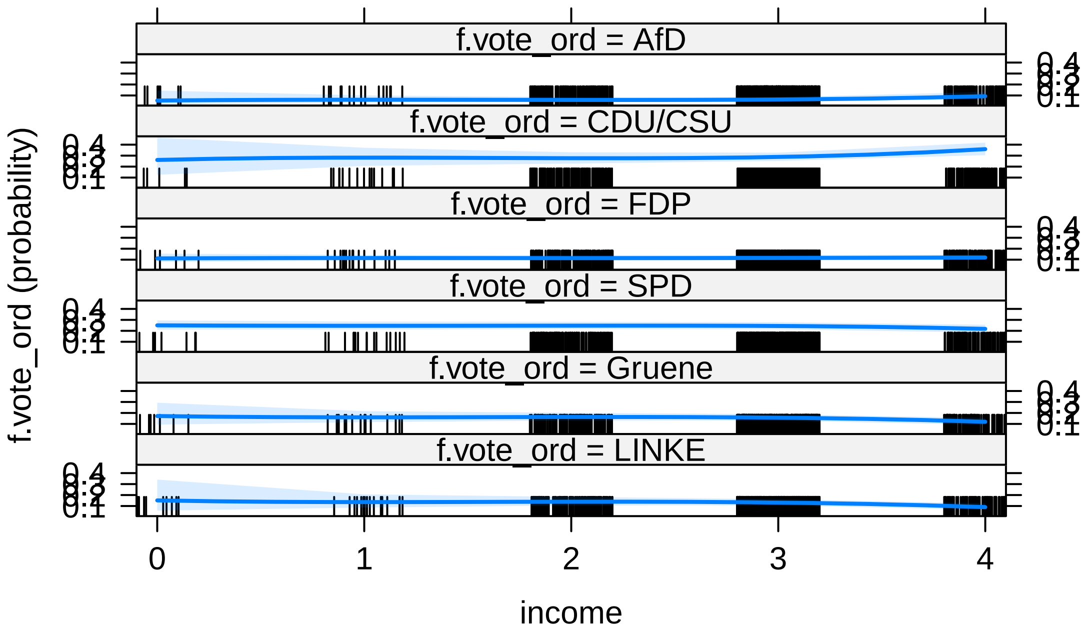
Effects Inc Sat Continuous Squared




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

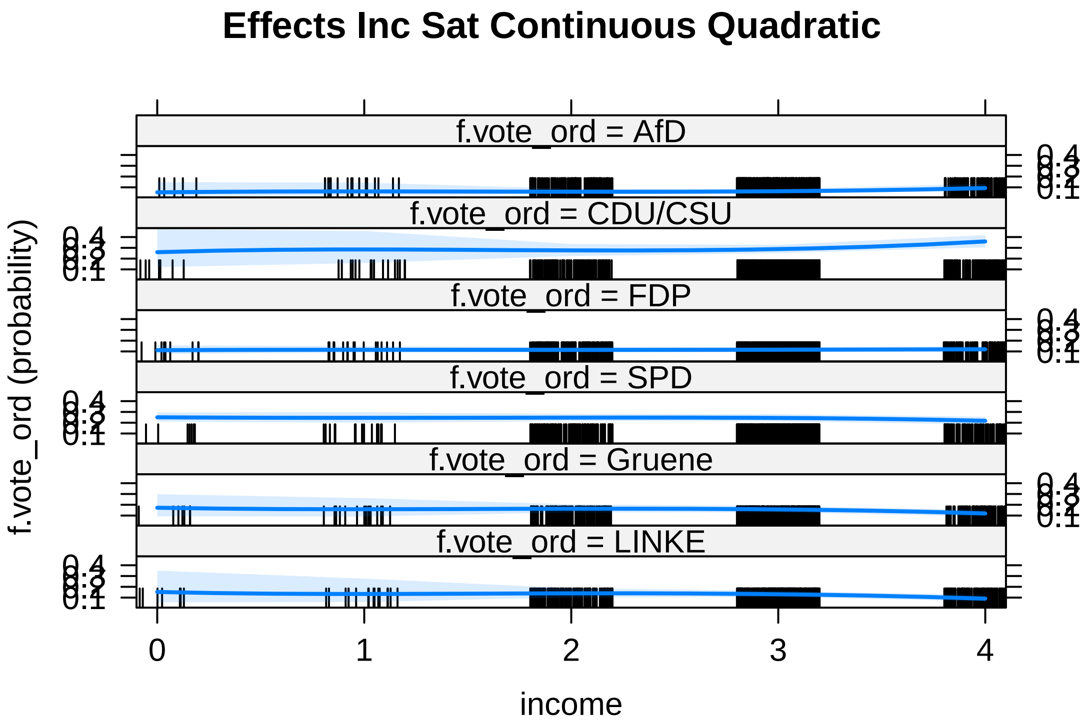
```
##
## Re-fitting to get Hessian
```

Effects Inc Sat Continuous Cubed



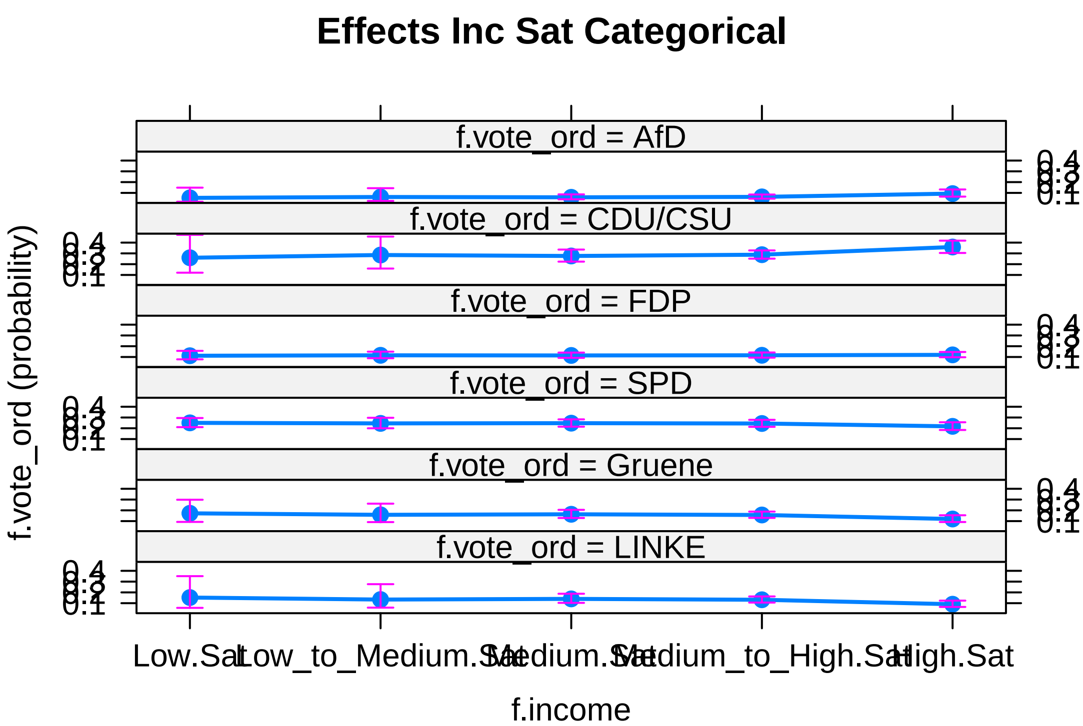

```r
plot(allEffects(om1_inc_con_qd),ask=FALSE, main="Effects Inc Sat Continuous Quadratic")
```

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



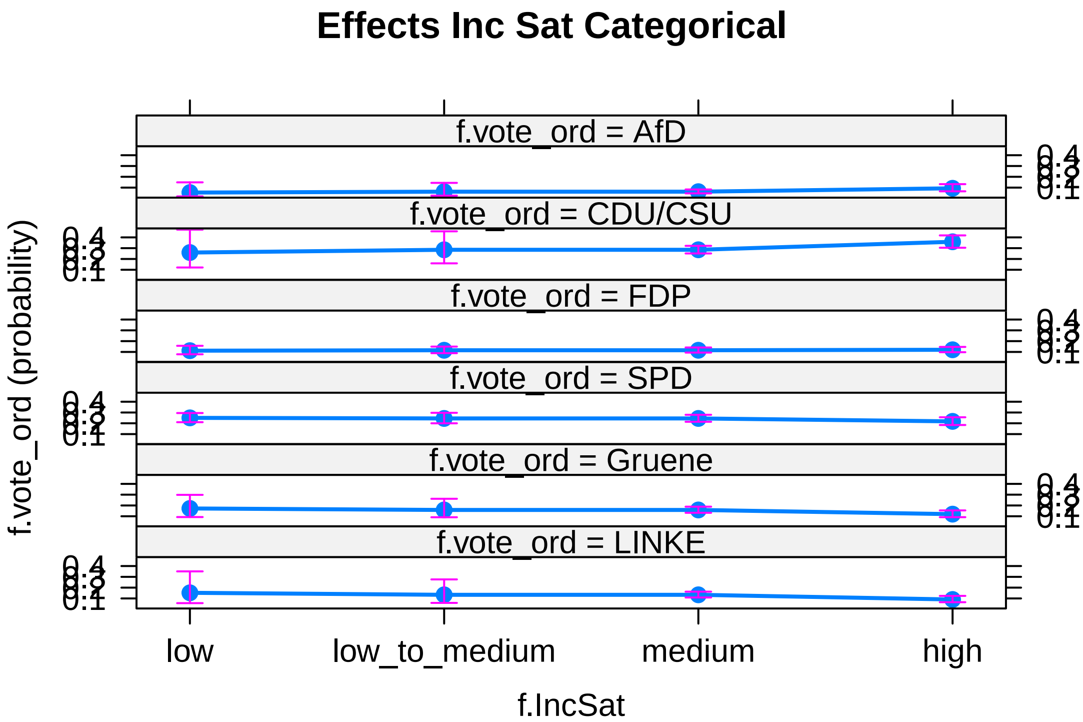

```
plot(allEffects(om1_inc_cat),ask=FALSE, main="Effects Inc Sat Categorical")
```

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




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

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



4.3.3 Hierarchical Models

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

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

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

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

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

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

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

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

```r
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
```

```r
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
```

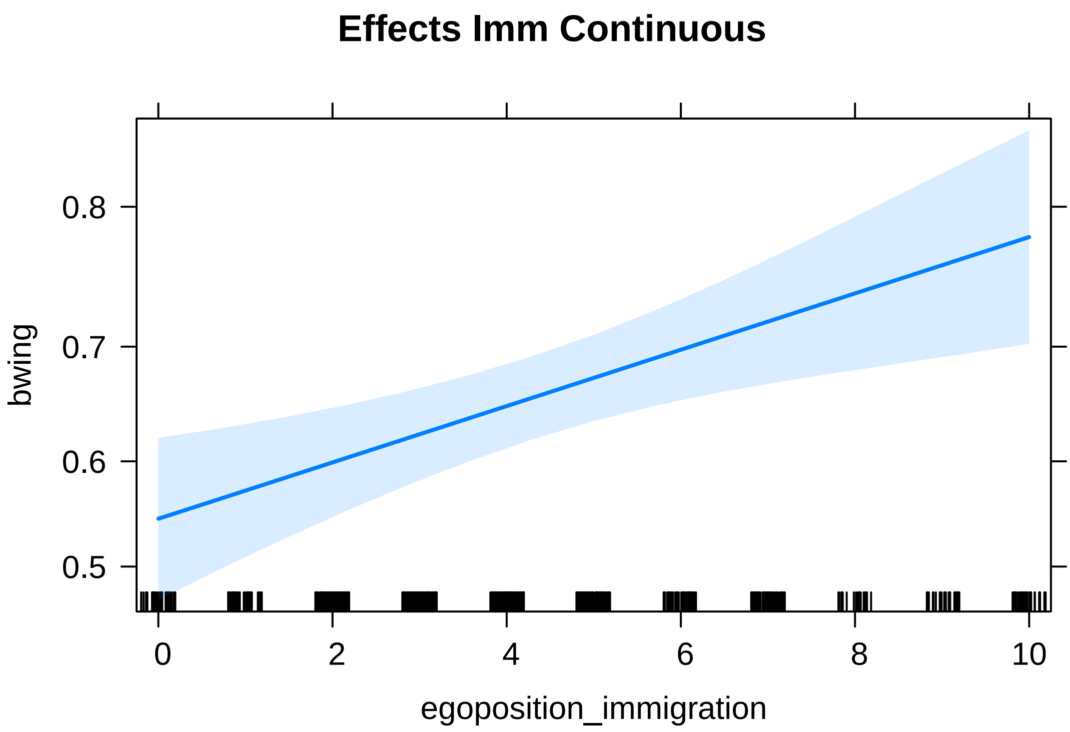
```
Anova(bhm1_imm_cat, test="Wald")
```

```
## 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
```

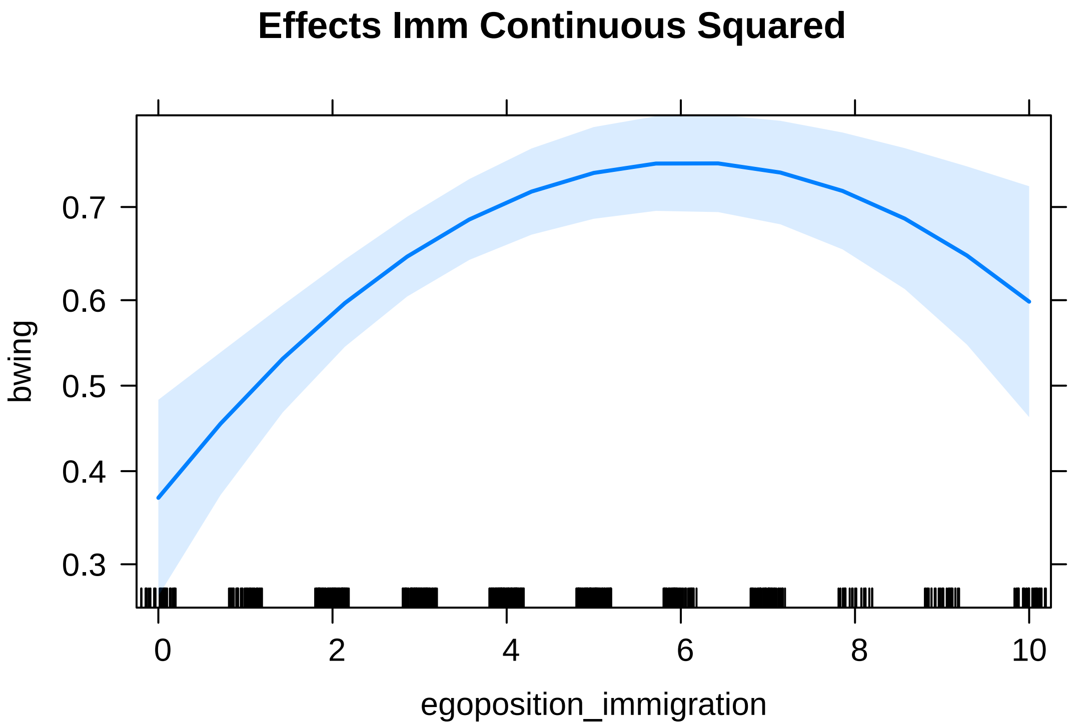
```
Anova(bhm1_imm_cat_new, test="Wald")
```

```
## 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
```

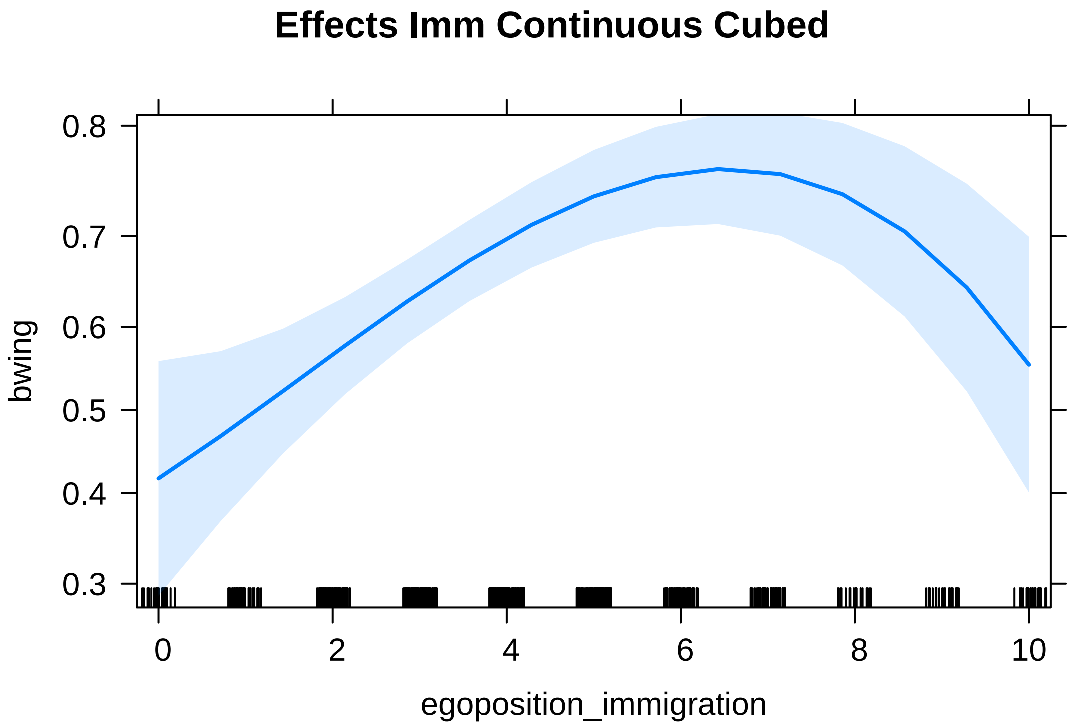
```
plot(allEffects(bhm1_imm_con),ask=FALSE, main="Effects Imm Continuous")
```



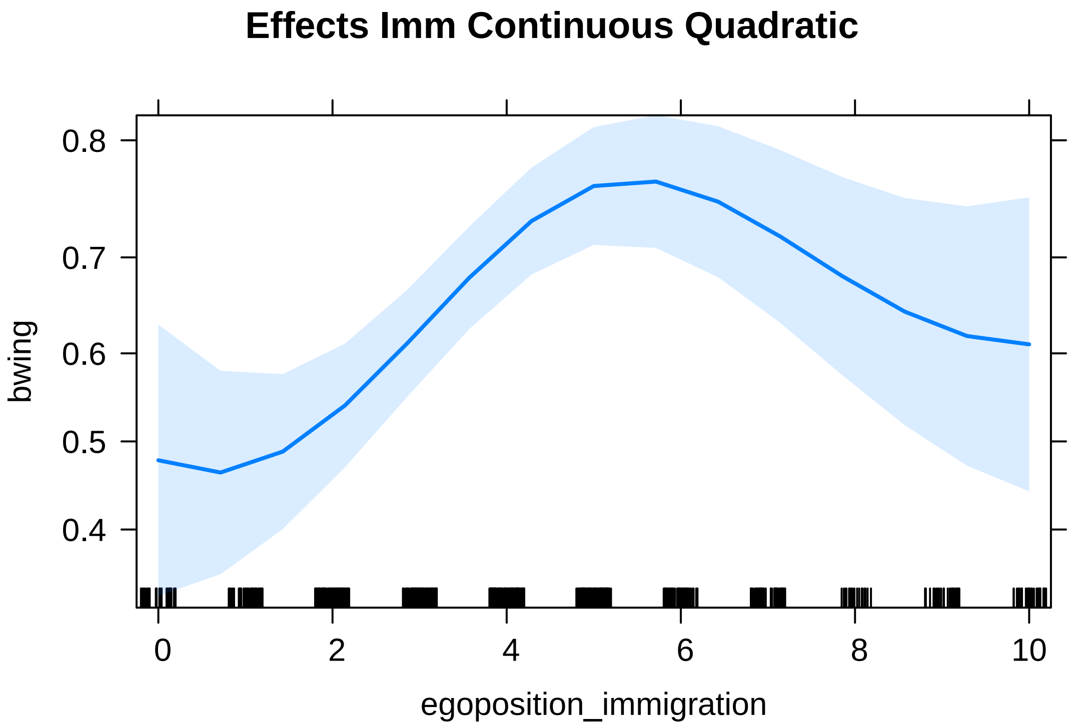

```
plot(allEffects(bhm1_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```



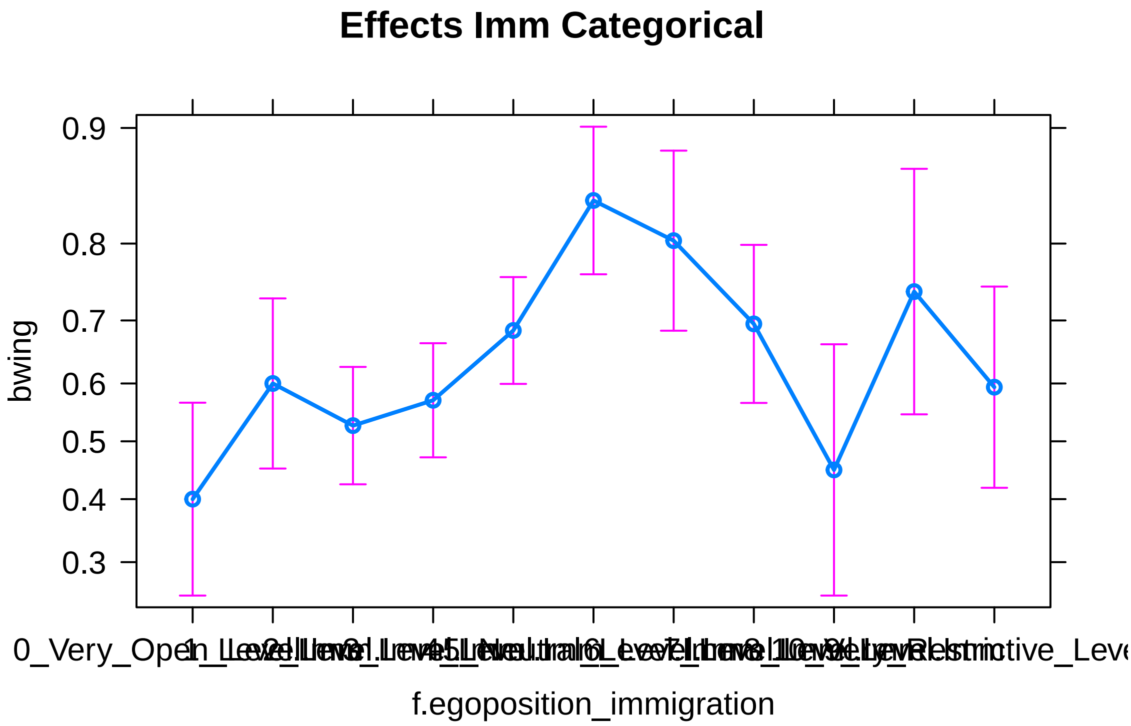

```
plot(allEffects(bhm1_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```



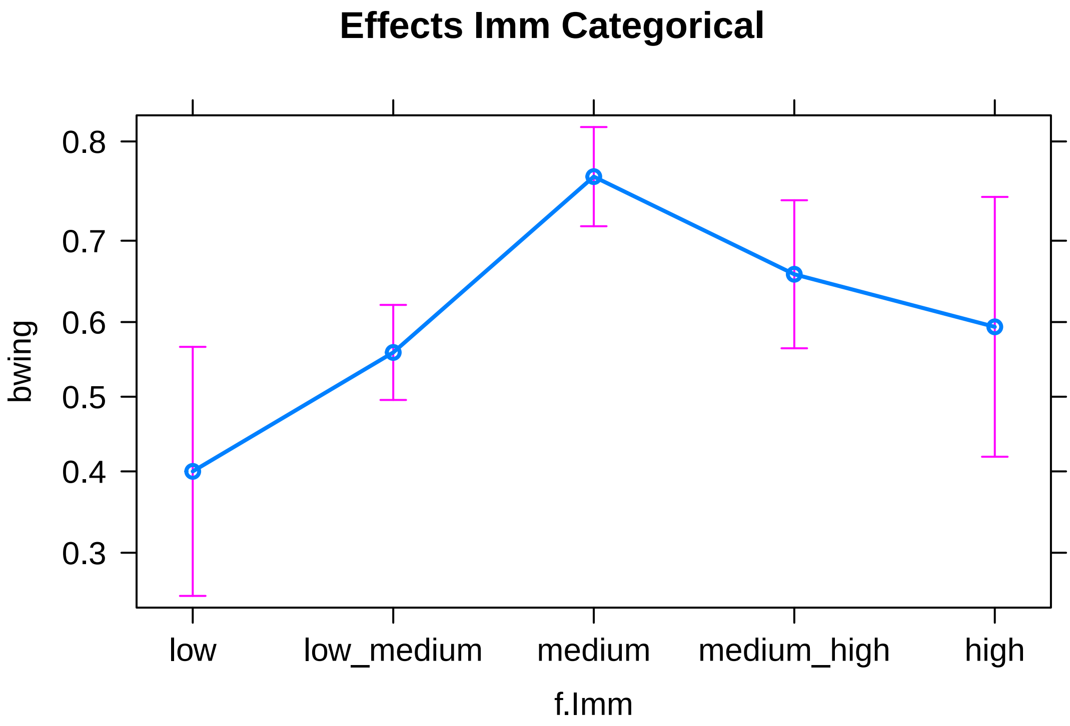

```
plot(allEffects(bhm1_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```




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




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

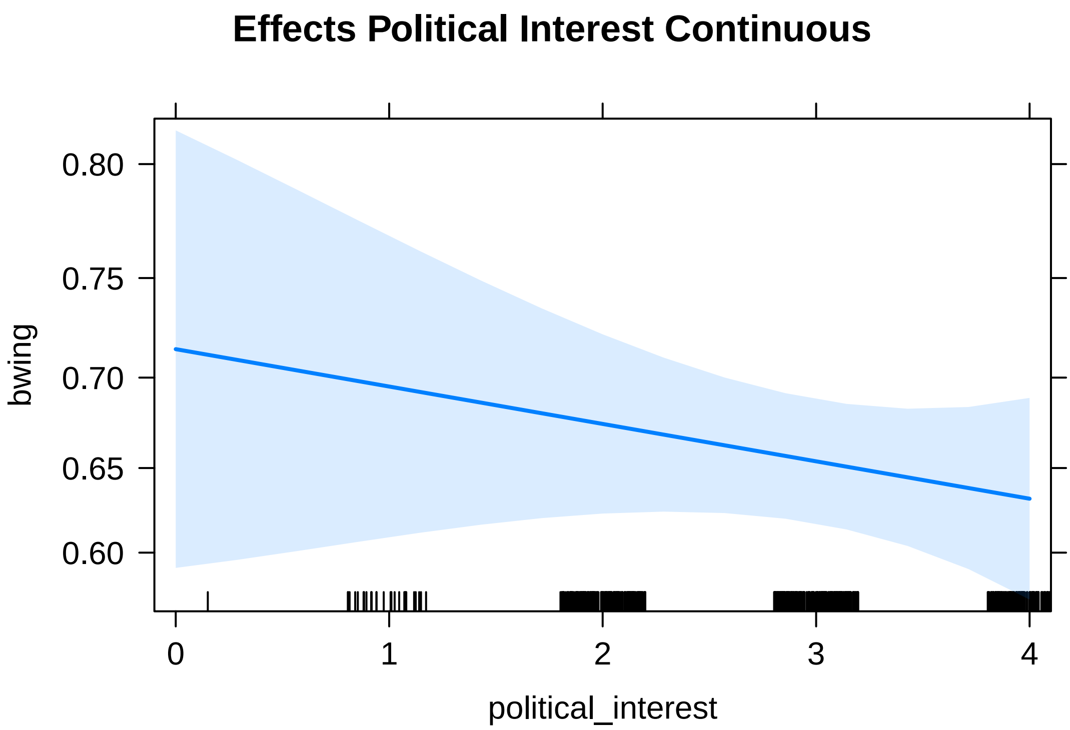
```r
Anova(bhm1_polint_cat, test="Wald")
```

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

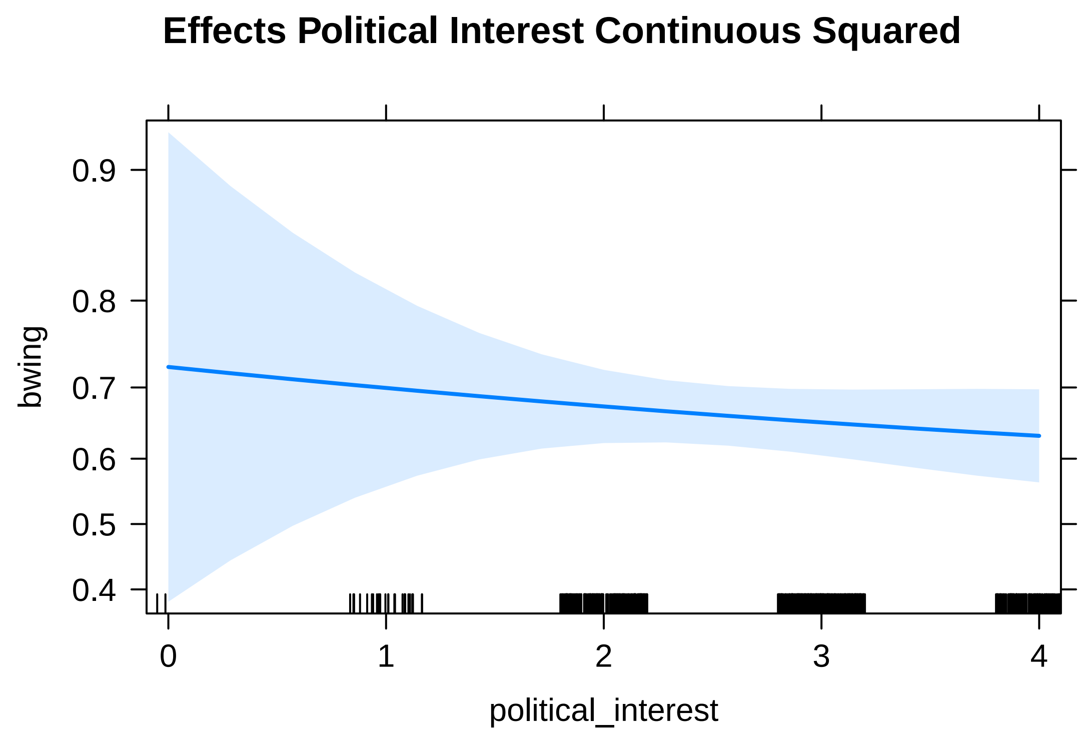
```r
Anova(bhm1_polint_cat_new, test="Wald")
```

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

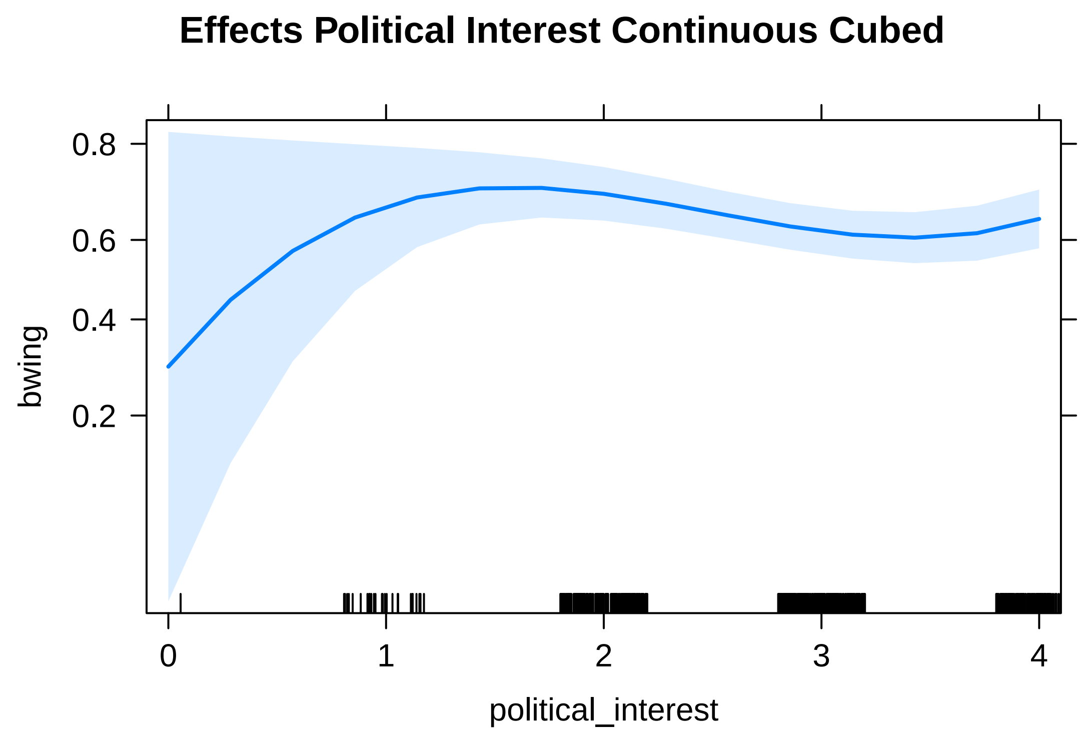
```r
plot(allEffects(bhm1_polint_con),ask=FALSE, main="Effects Political Interest Continuous"
```



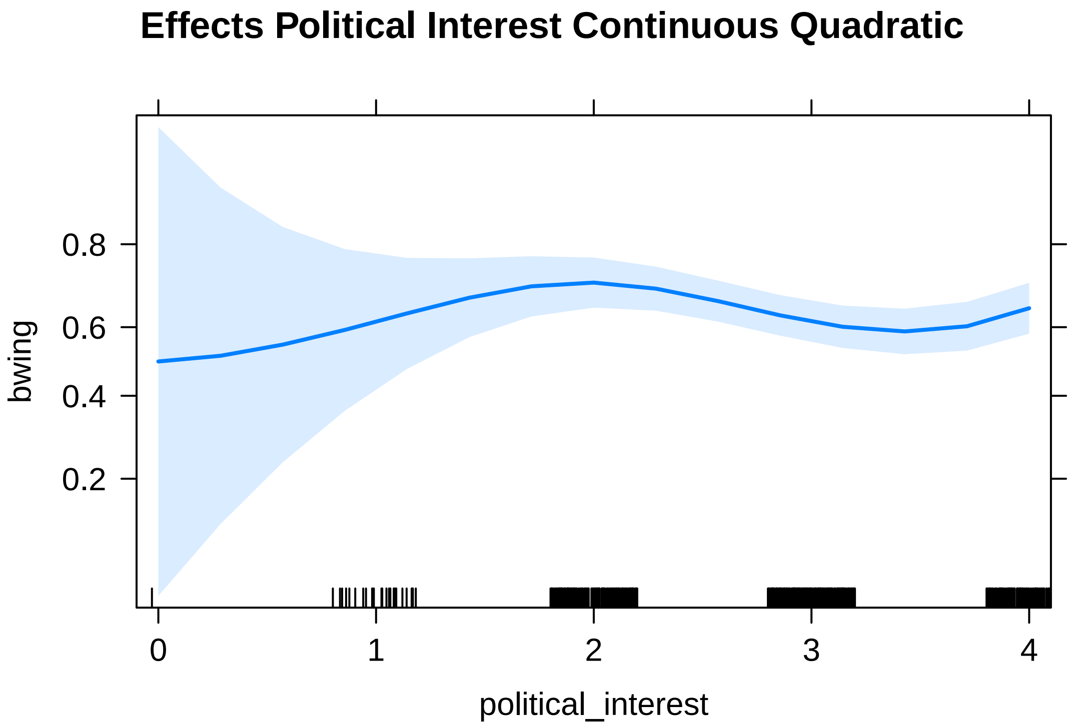

```r
plot(allEffects(bhm1_polint_con_sq),ask=FALSE,main="Effects Political Interest Continuou
```



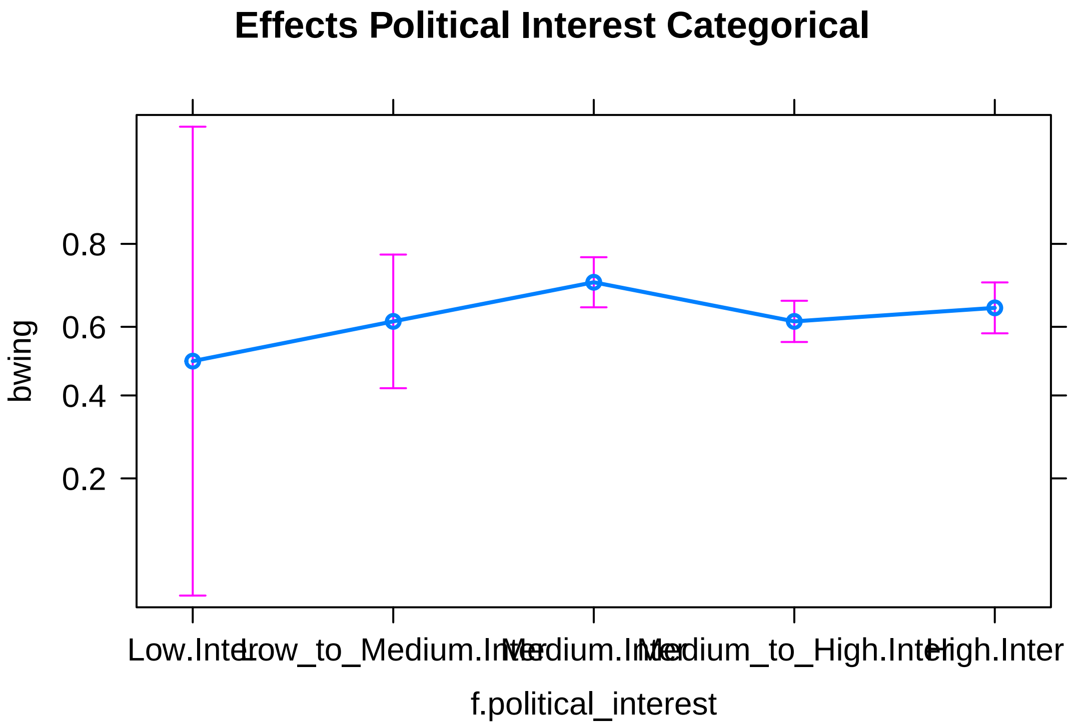

```
plot(allEffects(bhm1_polint_con_cb),ask=FALSE, main="Effects Political Interest Continuo
```



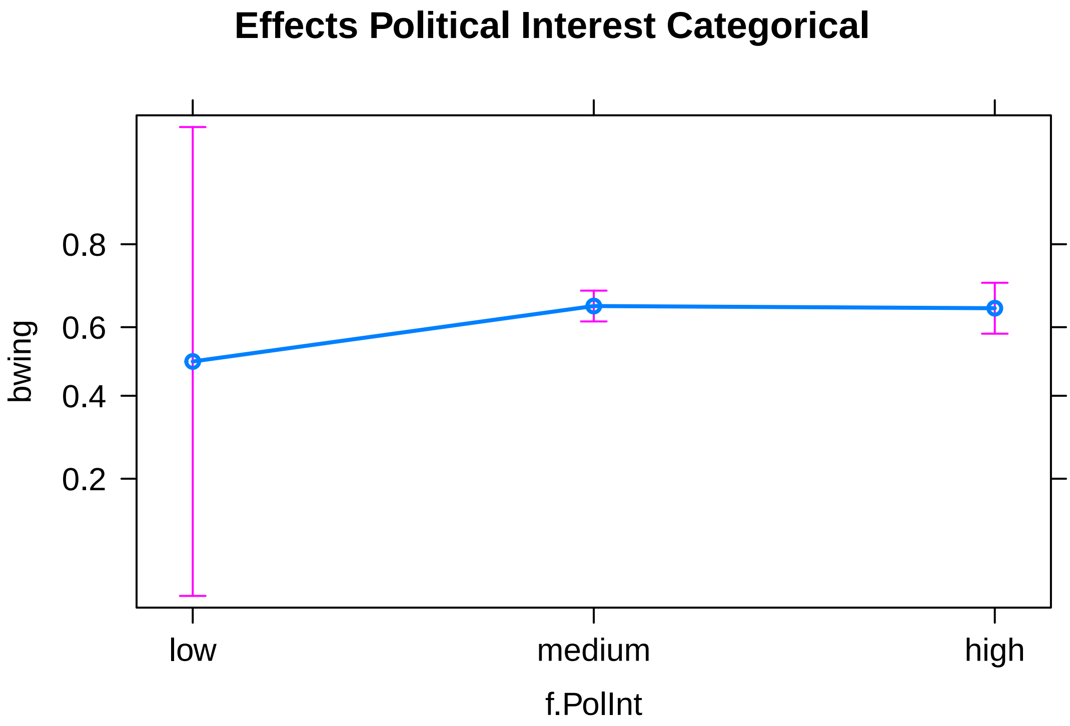

```
plot(allEffects(bhm1_polint_con_qd),ask=FALSE, main="Effects Political Interest Continuo
```




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




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




```
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

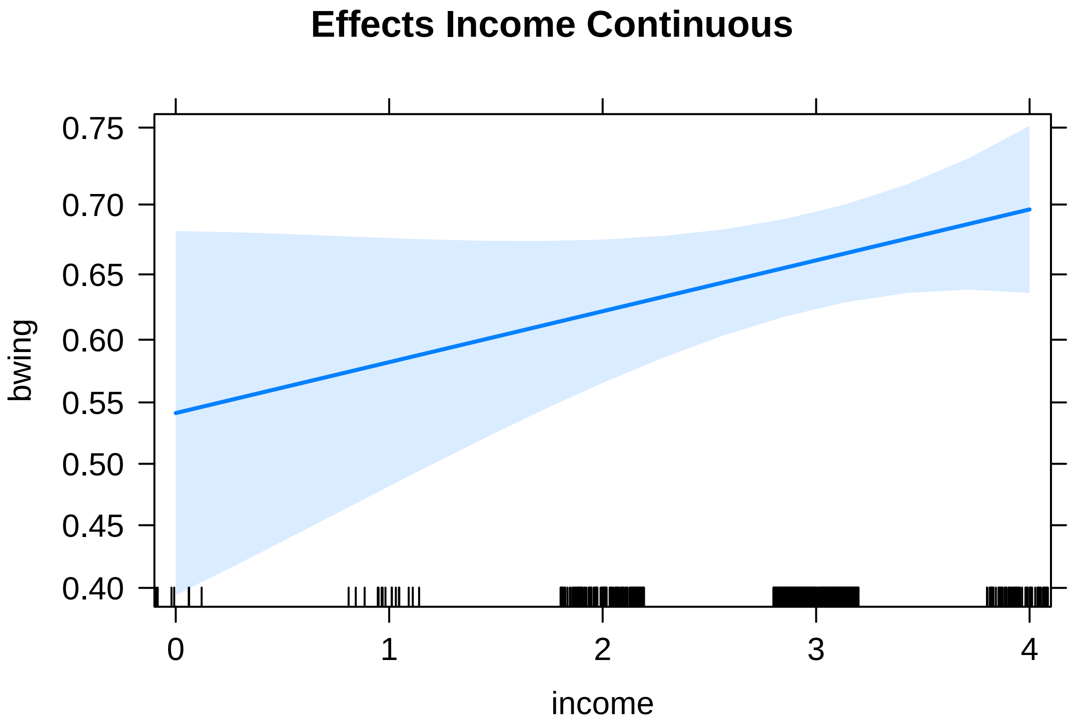
```r
Anova(bhm1_inc_cat, test="Wald")
```

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

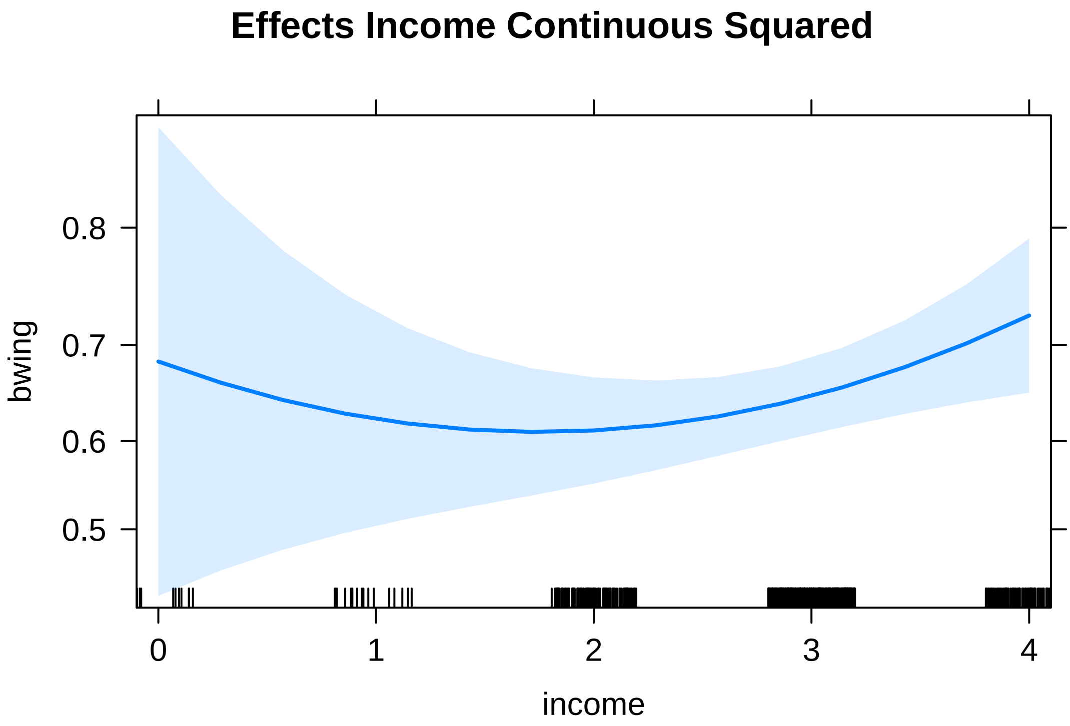
```r
Anova(bhm1_inc_cat_new, test="Wald")
```

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

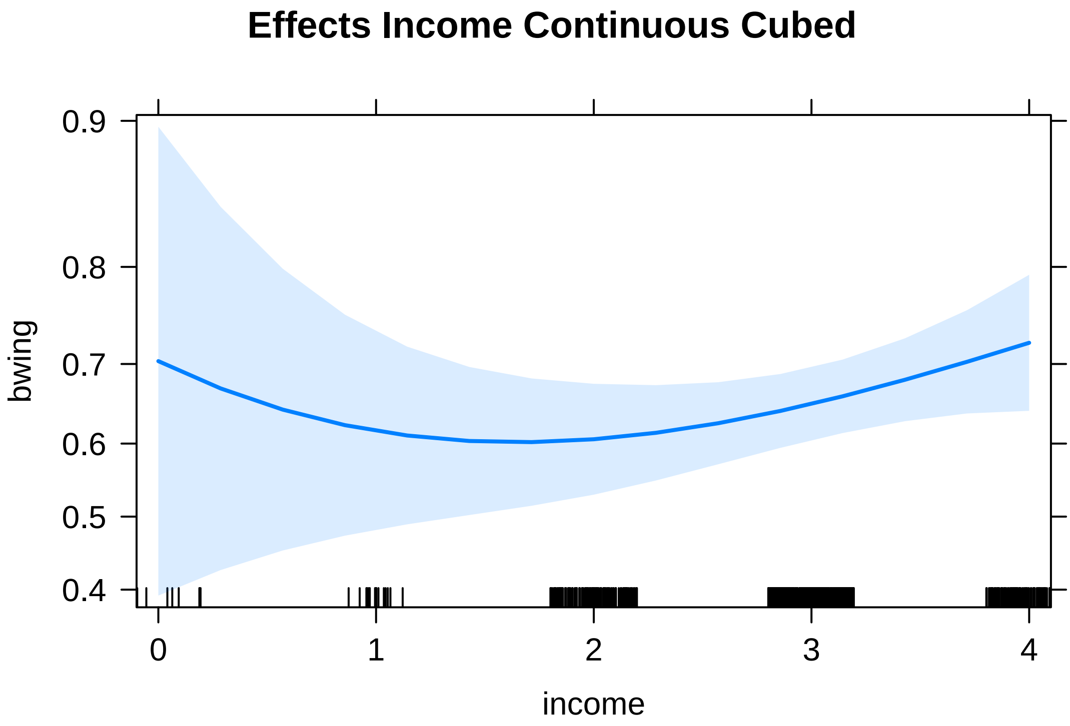
```r
plot(allEffects(bhm1_inc_con),ask=FALSE, main="Effects Income Continuous")
```



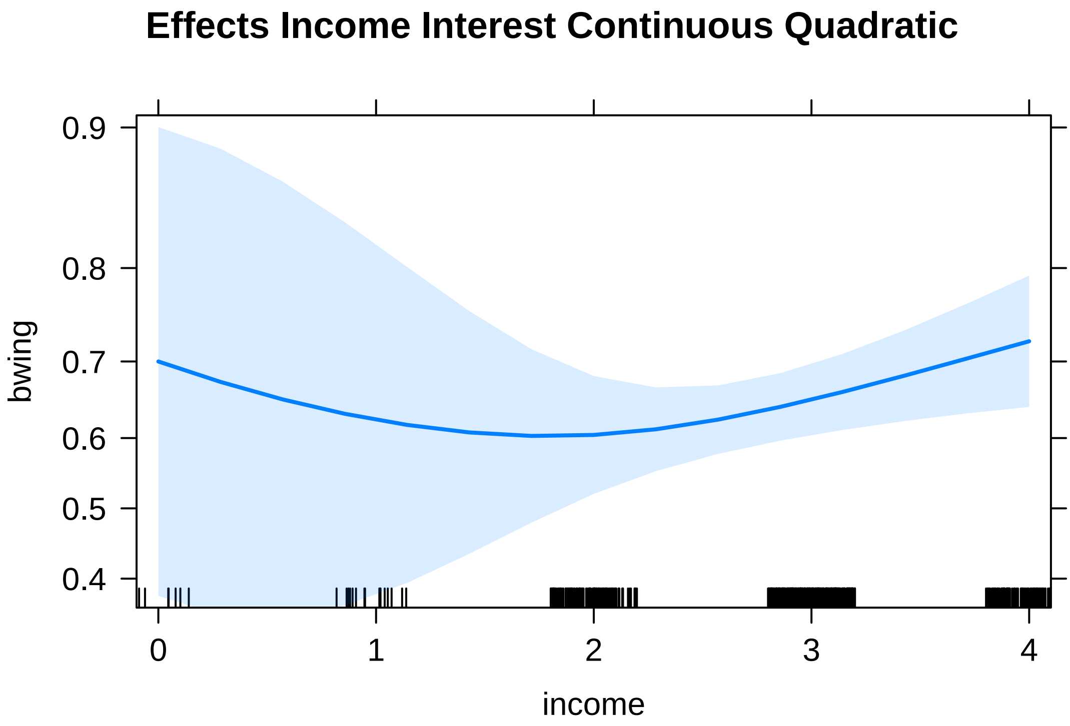

```r
plot(allEffects(bhm1_inc_con_sq),ask=FALSE,main="Effects Income Continuous Squared")
```



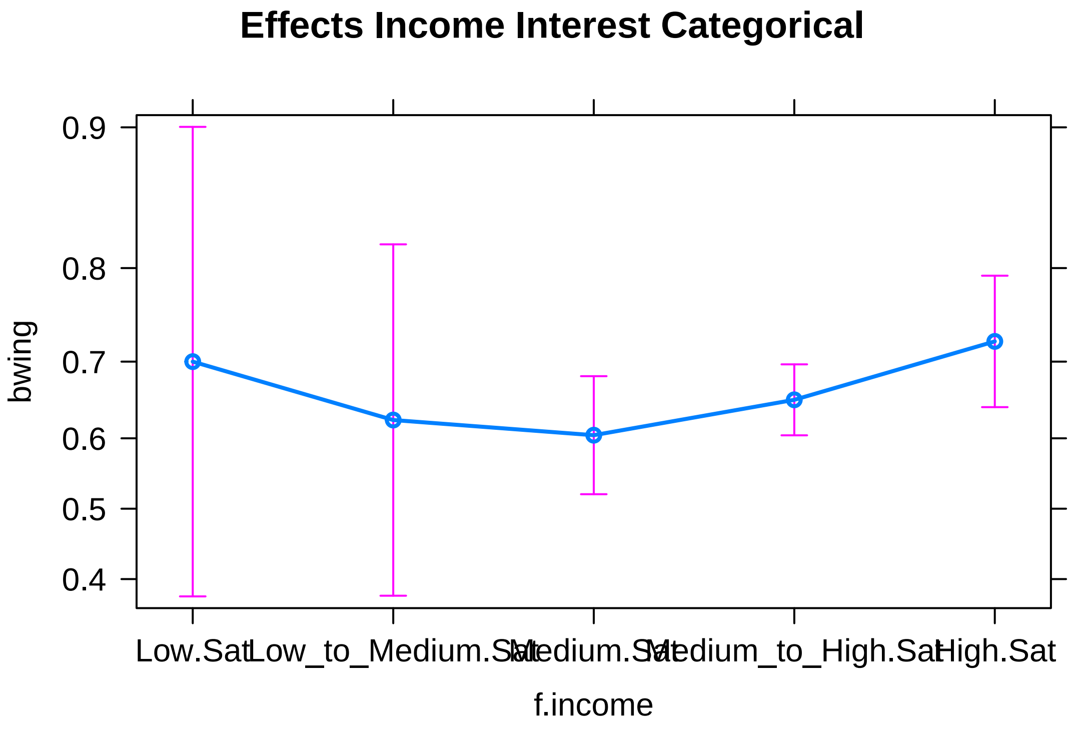

```
plot(allEffects(bhm1_inc_con_cb),ask=FALSE, main="Effects Income Continuous Cubed")
```



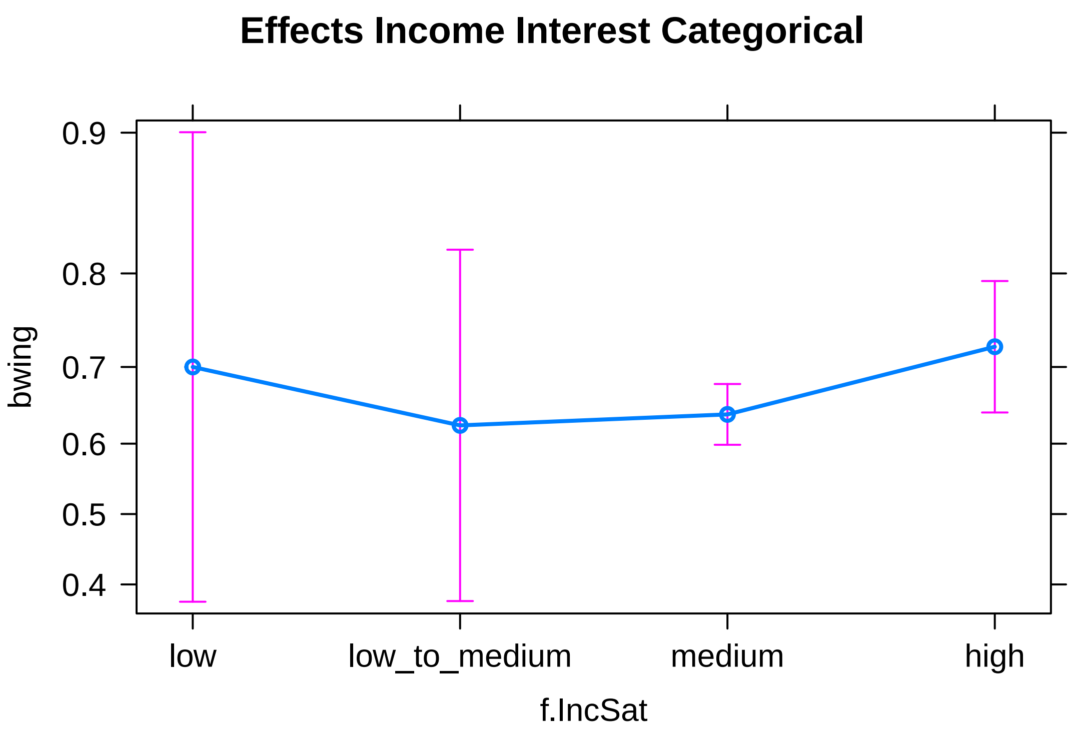

```
plot(allEffects(bhm1_inc_con_qd),ask=FALSE, main="Effects Income Interest Continuous Qua
```




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




```
plot(allEffects(bhm1_inc_cat_new),ask=FALSE, main="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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

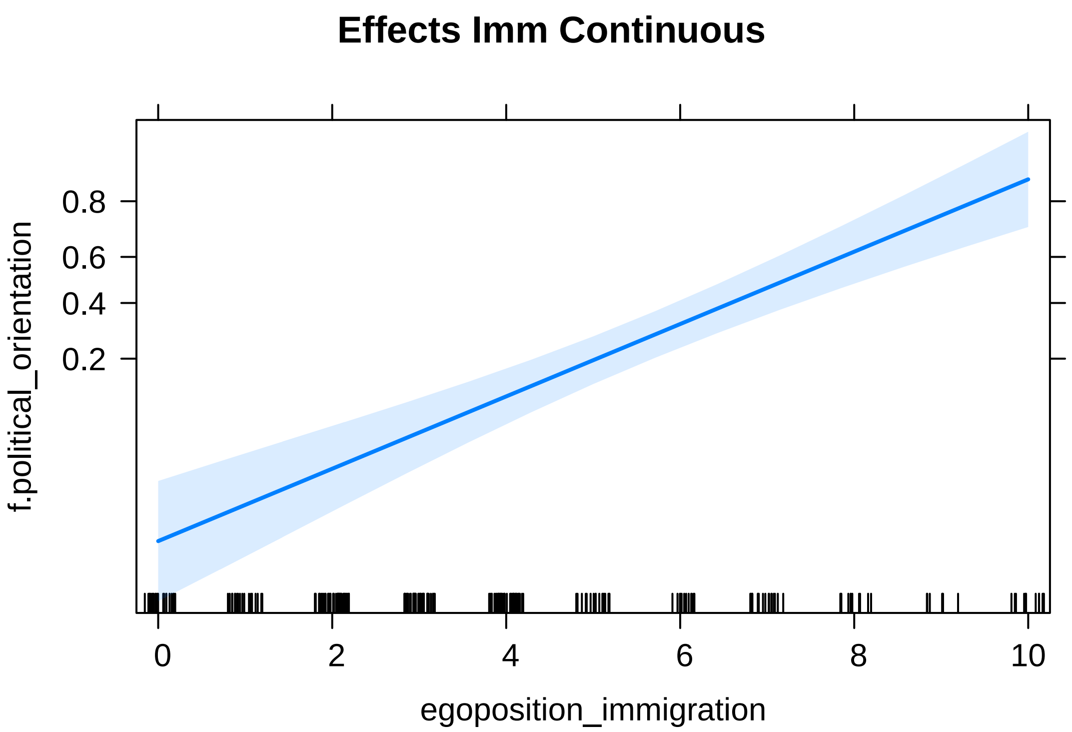
```r
Anova(bhm2_imm_cat, test="Wald")
```

```
## 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
```

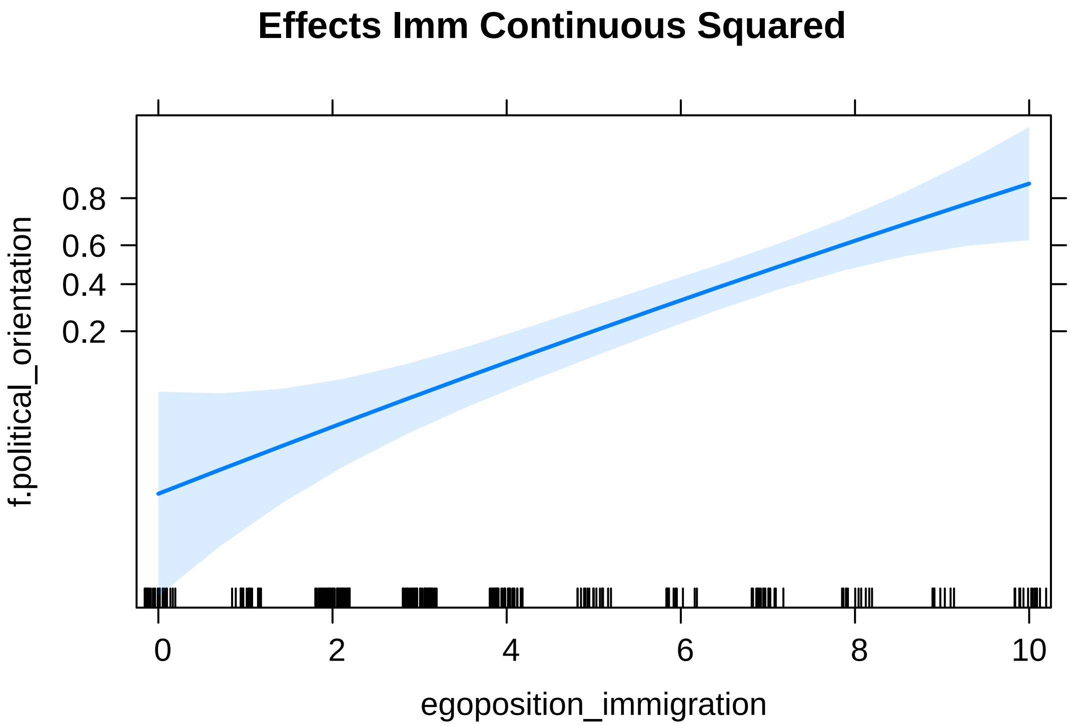
```r
Anova(bhm2_imm_cat_new, test="Wald")
```

```
## 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
```

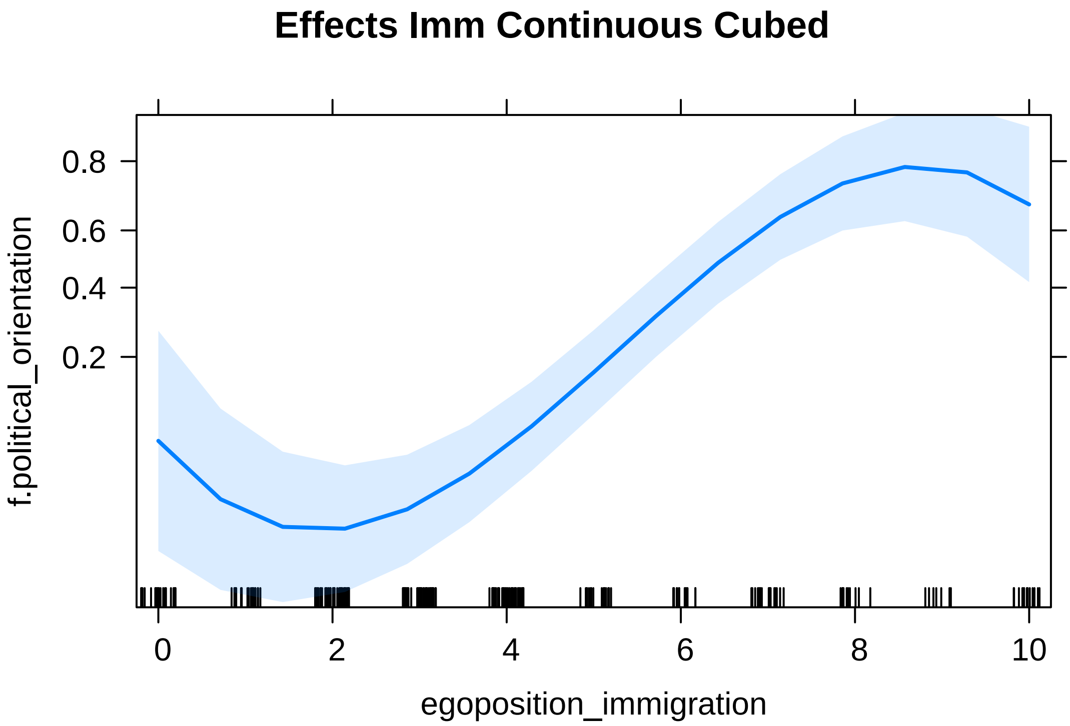
```r
plot(allEffects(bhm2_imm_con),ask=FALSE, main="Effects Imm Continuous")
```



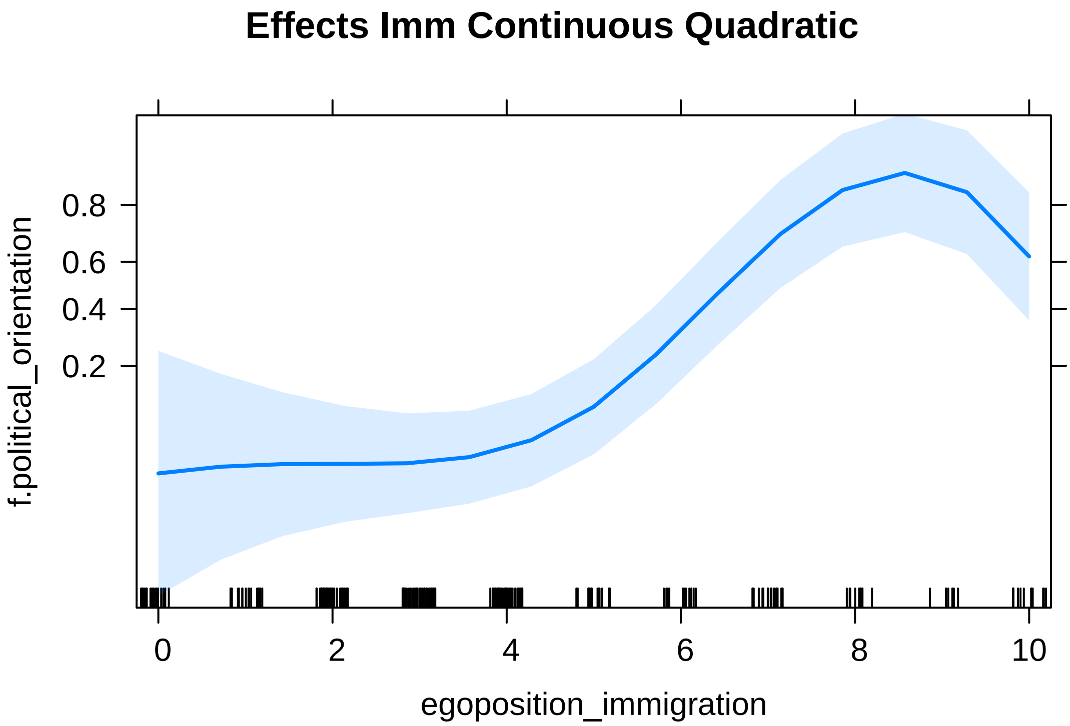

```r
plot(allEffects(bhm2_imm_con_sq),ask=FALSE,main="Effects Imm Continuous Squared")
```



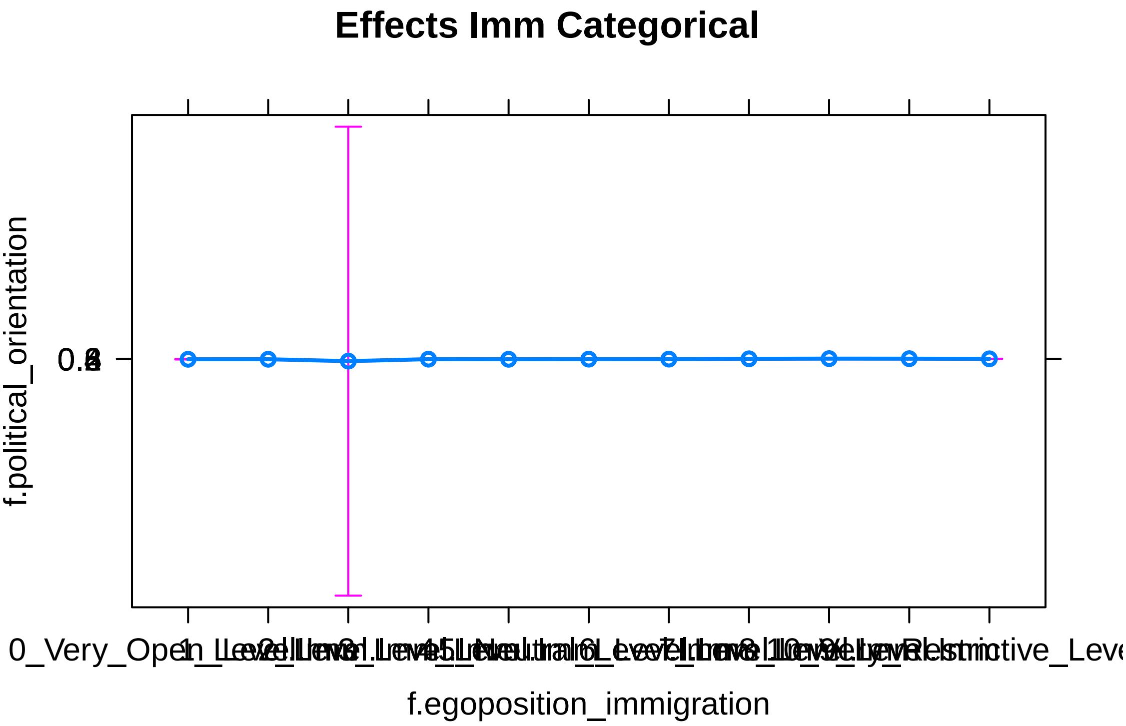

```
plot(allEffects(bhm2_imm_con_cb),ask=FALSE, main="Effects Imm Continuous Cubed")
```



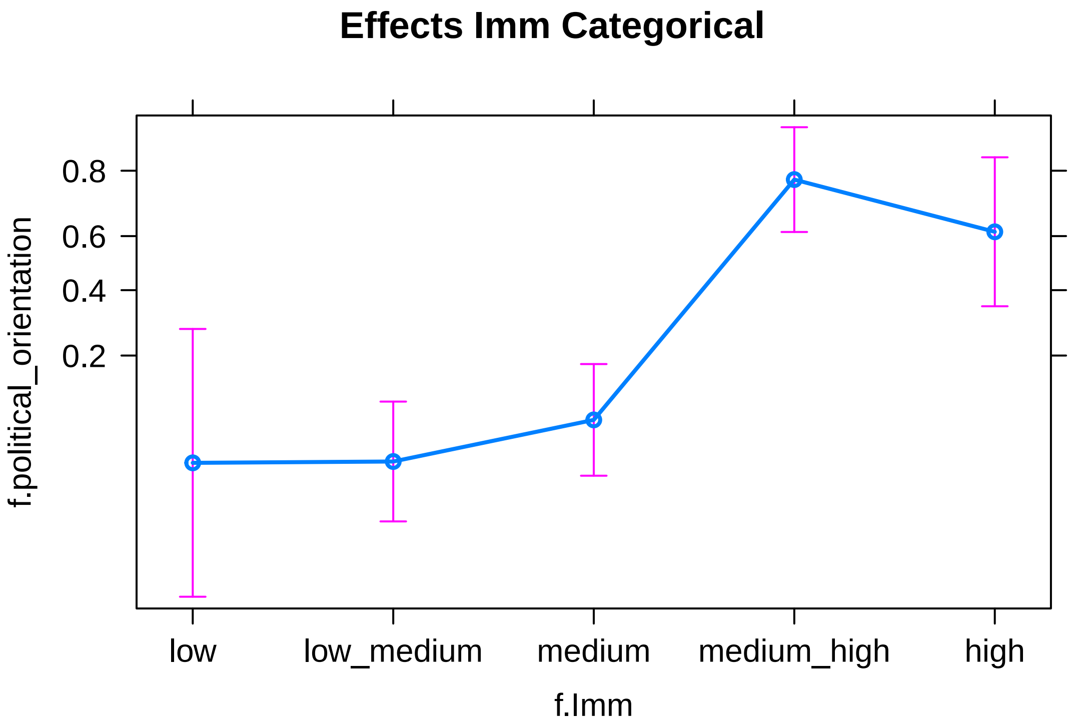

```
plot(allEffects(bhm2_imm_con_qd),ask=FALSE, main="Effects Imm Continuous Quadratic")
```




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




```r
plot(allEffects(bhm2_imm_cat_new),ask=FALSE, main="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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

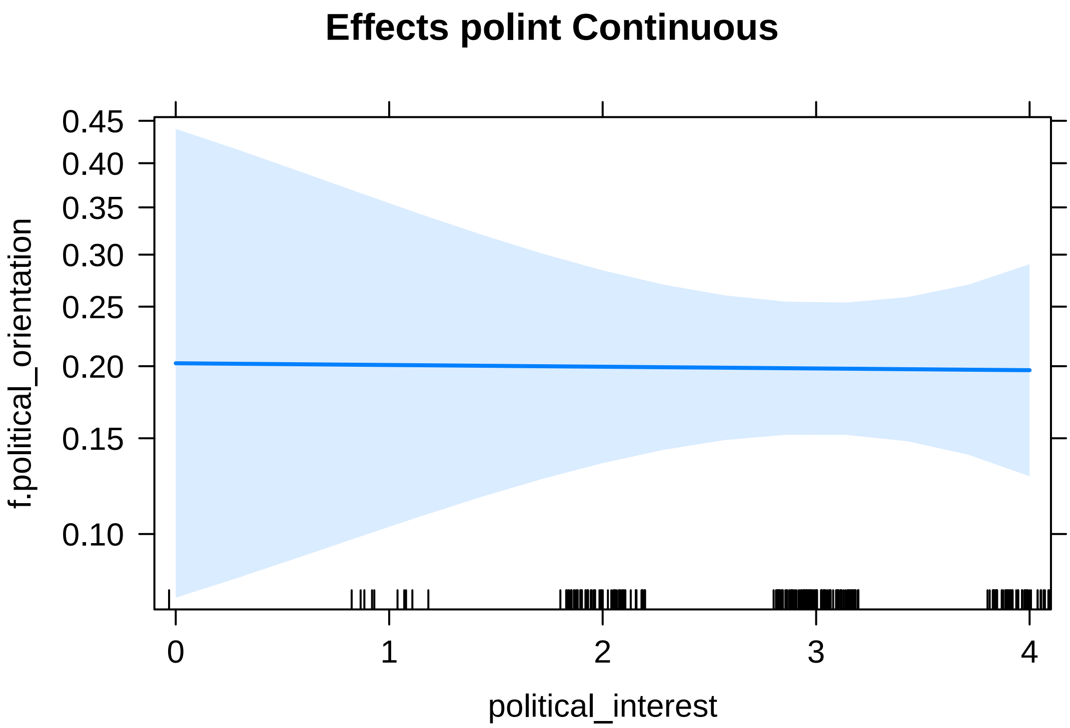
```r
Anova(bhm2_polint_cat, test="Wald")
```

```
## 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")
```

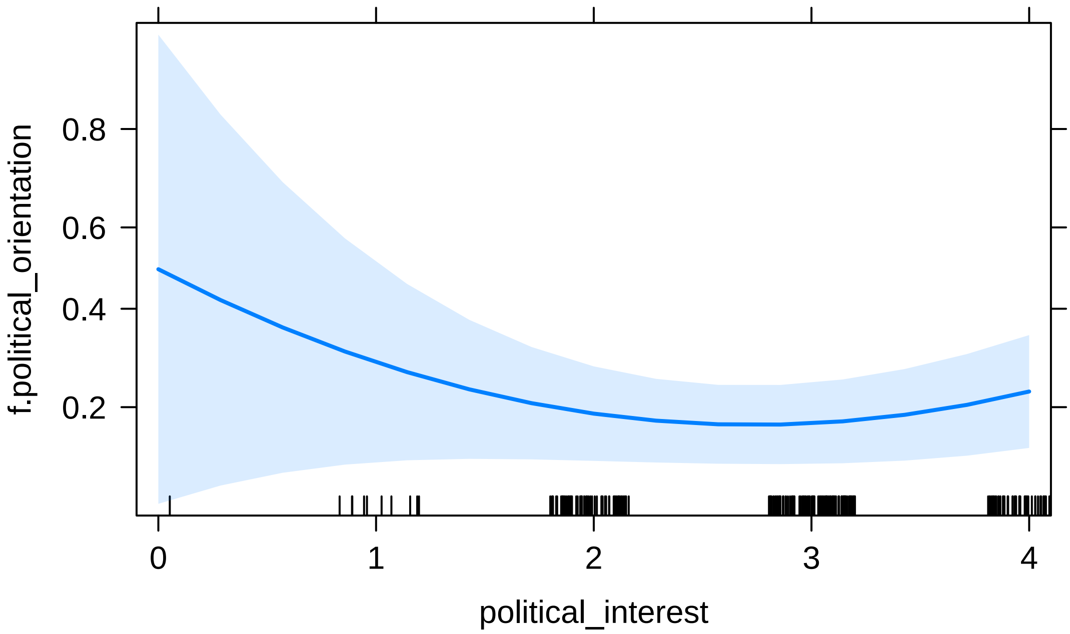
```
## Analysis of Deviance Table (Type II tests)
##
## Response: f.political_orientation
##          Df  Chisq Pr(>Chisq)
## f.PolInt  2 0.2351     0.8891
```

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



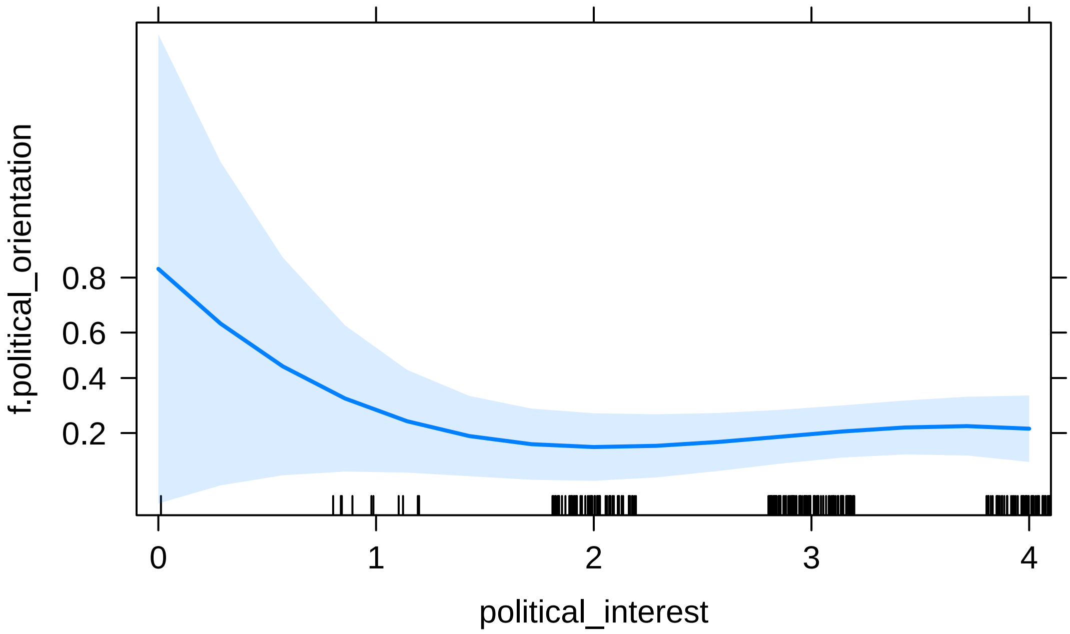

```
plot(allEffects(bhm2_polint_con_sq),ask=FALSE,main="Effects polint Continuous Squared")
```

Effects polint Continuous Squared

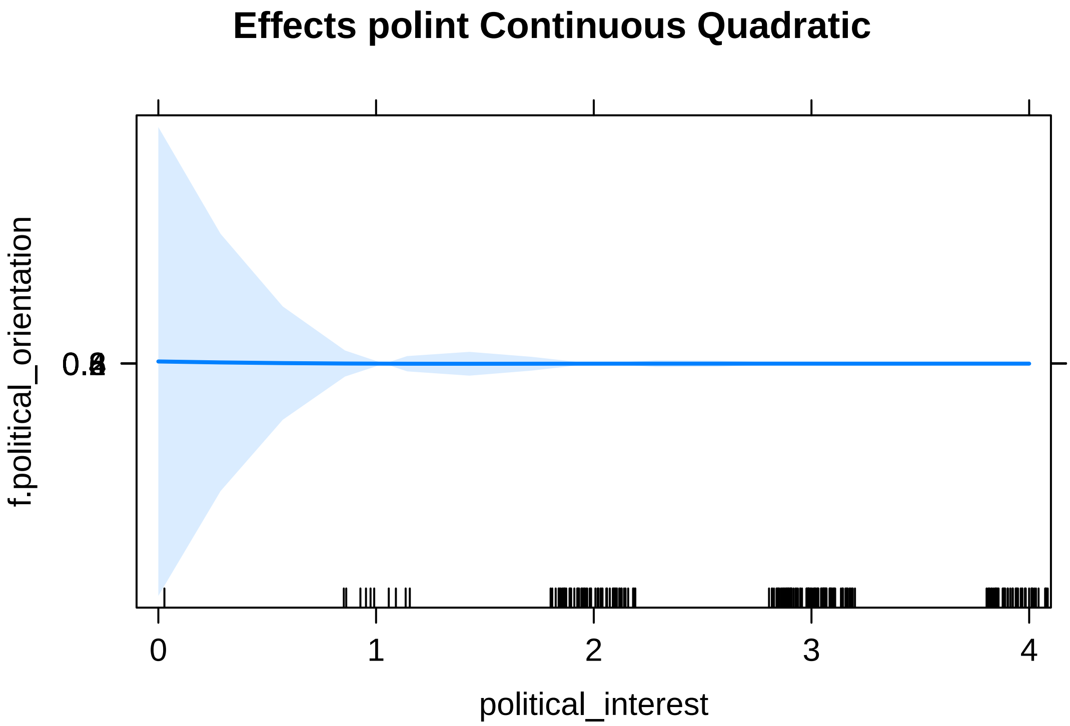



```
plot(allEffects(bhm2_polint_con_cb),ask=FALSE, main="Effects polint Continuous Cubed")
```

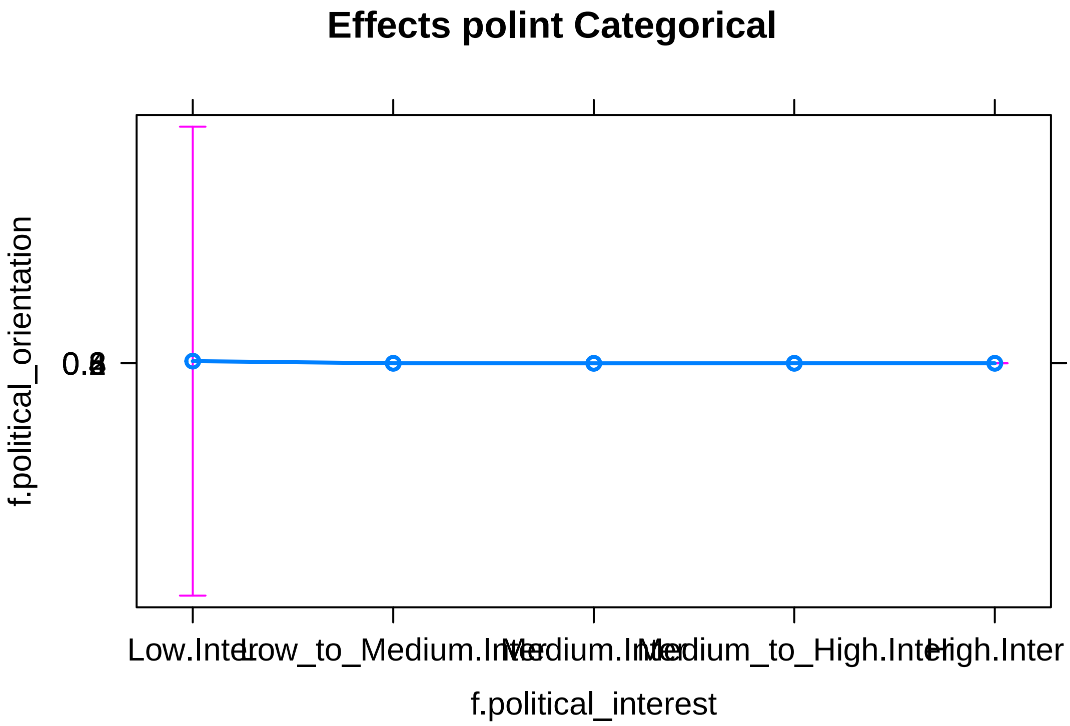
Effects polint Continuous Cubed



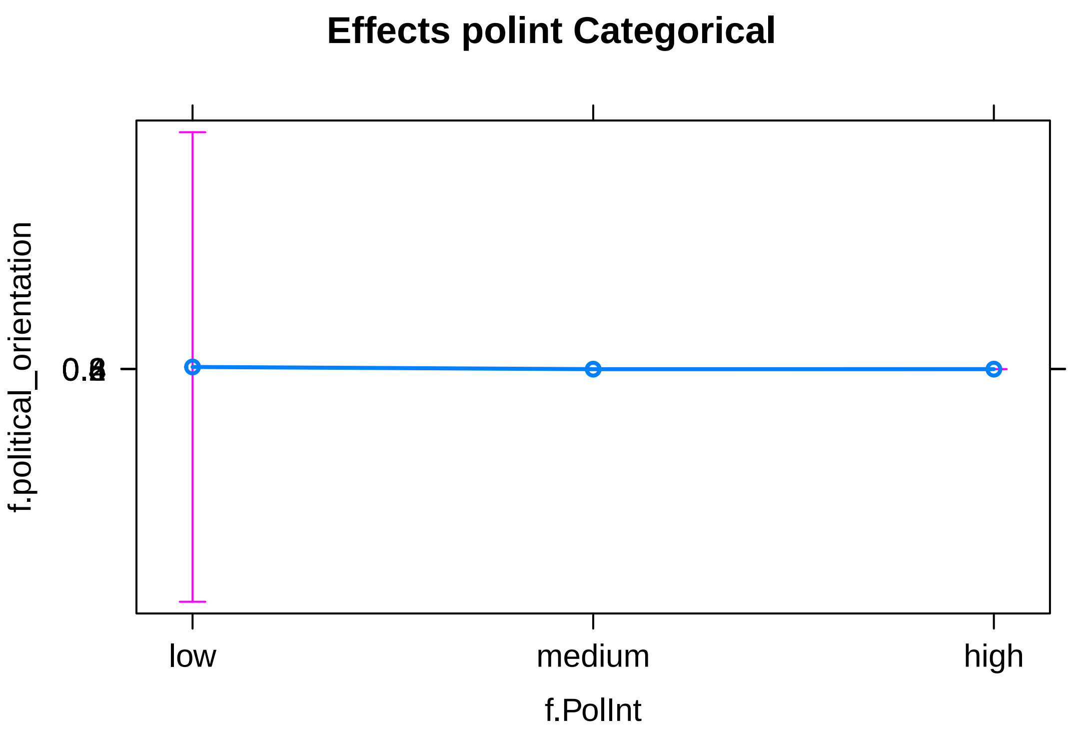

```
plot(allEffects(bhm2_polint_con_qd),ask=FALSE, main="Effects polint Continuous Quadrati
```




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




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

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

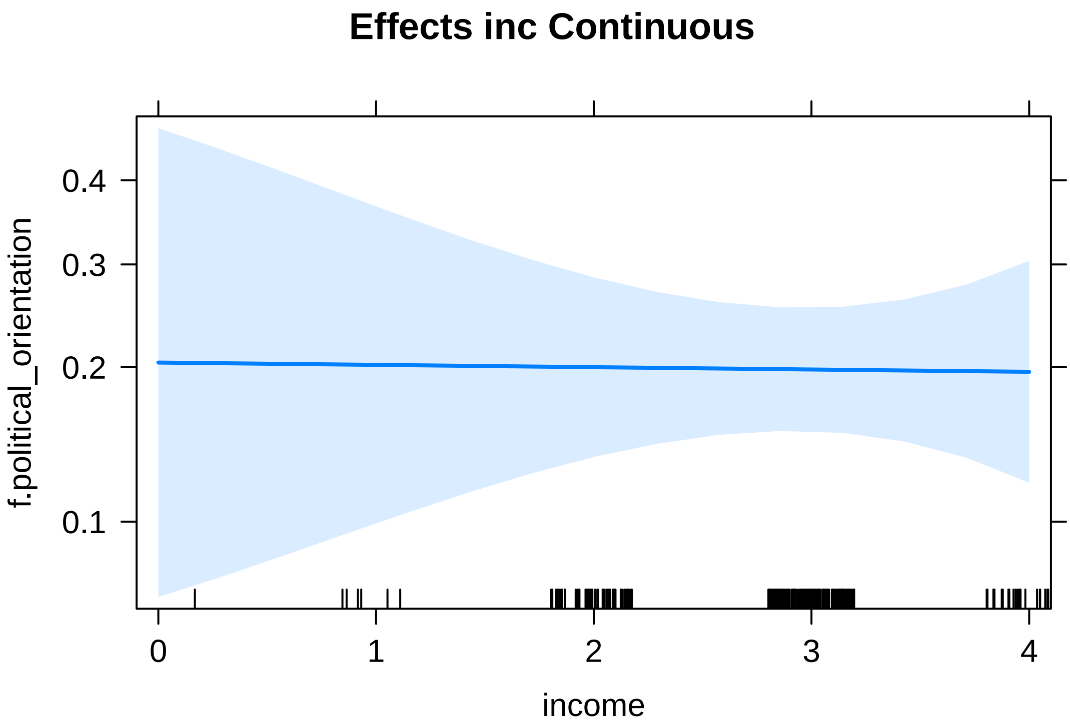
```r
Anova(bhm2_inc_cat, test="Wald")
```

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

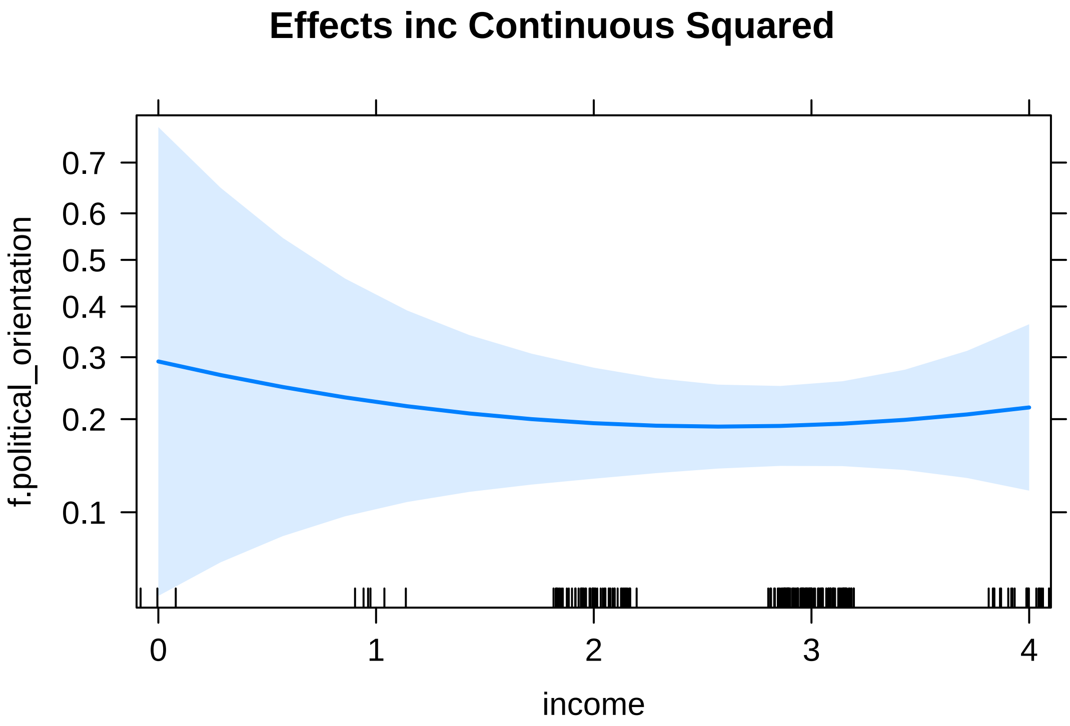
```r
Anova(bhm2_inc_cat_new, test="Wald")
```

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

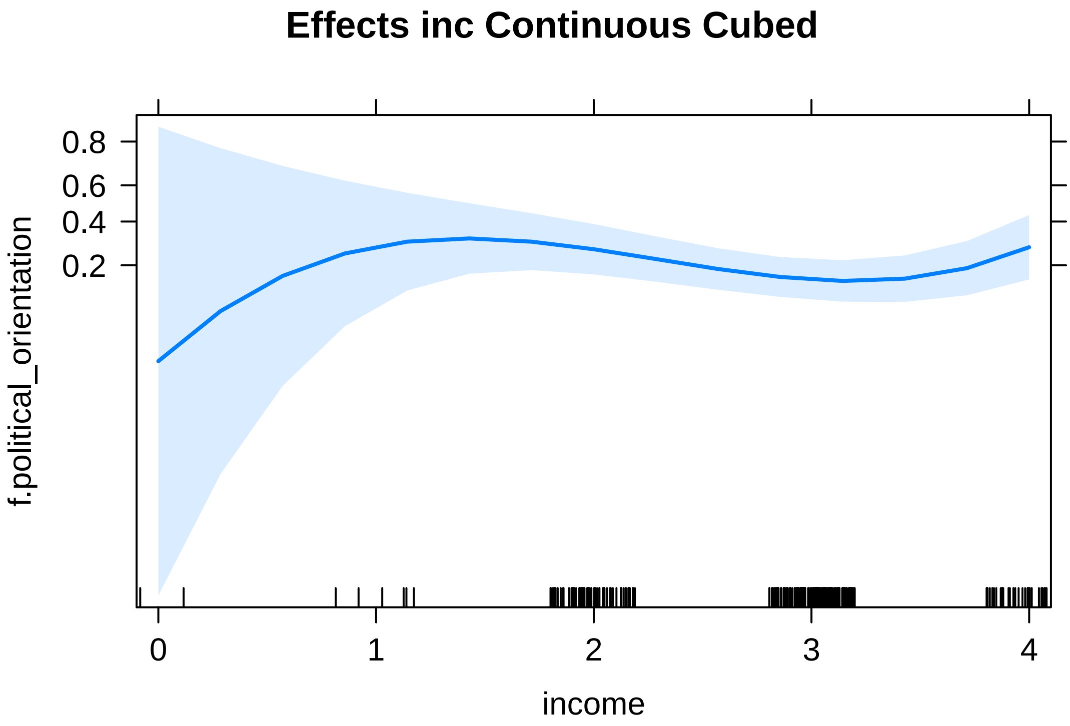
```r
plot(allEffects(bhm2_inc_con),ask=FALSE, main="Effects inc Continuous")
```



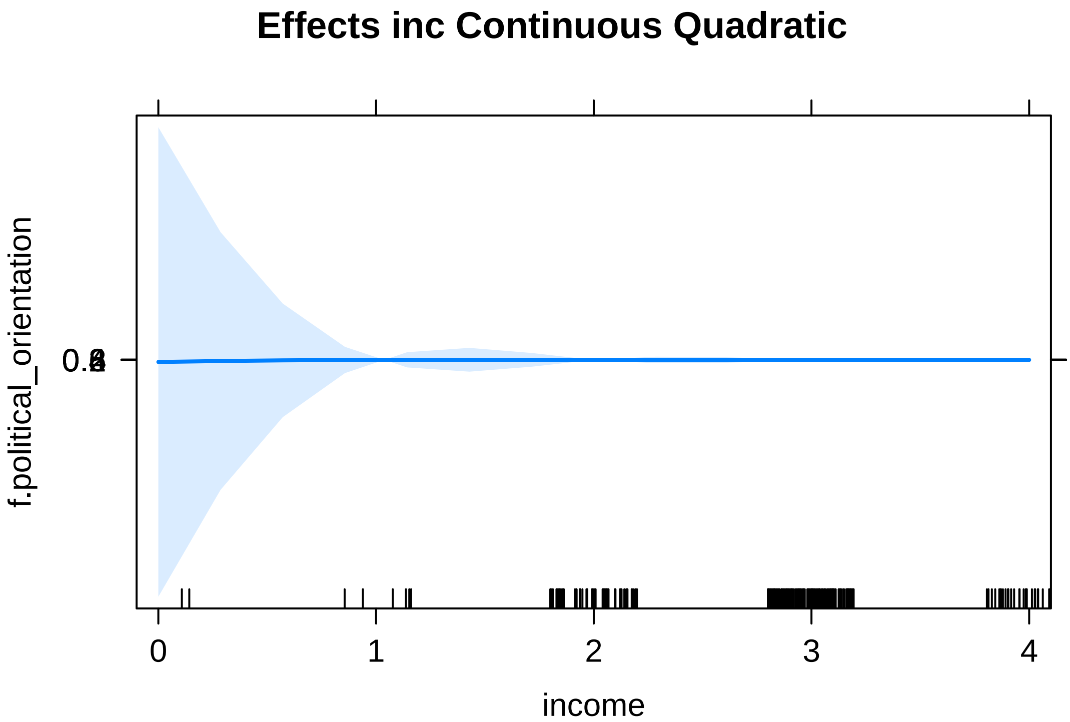

```r
plot(allEffects(bhm2_inc_con_sq),ask=FALSE,main="Effects inc Continuous Squared")
```



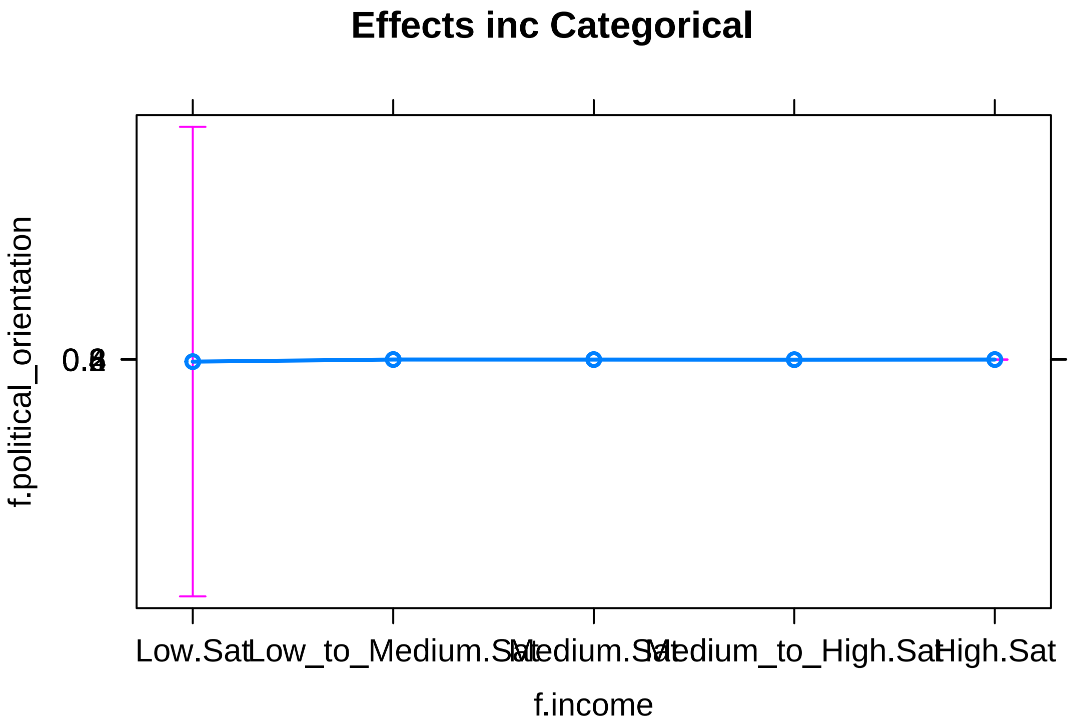

```
plot(allEffects(bhm2_inc_con_cb),ask=FALSE, main="Effects inc Continuous Cubed")
```



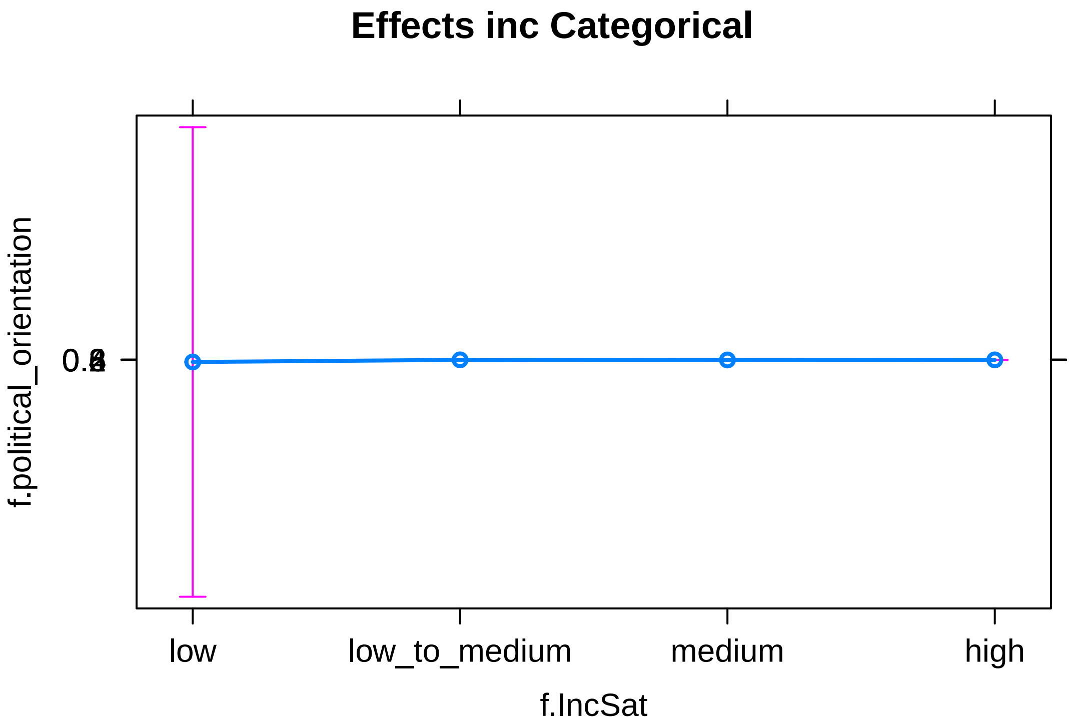

```
plot(allEffects(bhm2_inc_con_qd),ask=FALSE, main="Effects inc Continuous Quadratic")
```




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




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


Effects inc Categorical
f.political_orientation
0.4
low
low_to_medium
medium
high
f.IncSat