Public attitudes, perceptions, and beliefs about bears and bear management

Technical report

Action A.2: Attitudes of humans toward bears and bear management

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In brief...

Opinions and beliefs of local general public are most likely the best indicator of society's mood about bears. We've documented high support for long-term bear conservation in all countries participating in the project LIFE DINALP BEAR. The effects of project dissemination activities during the first year of project implementation were clearly seen as many of our respondents, especially in Slovenia and Croatia have already heard about the project and also understand quite well project objectives.

Targeted informational and educational activities planned in the project should be adjusted in a way which will enable addressing directly specific segments of the society with carefully designed key messages. For example, it seems that older generations are much less likely to accept damage prevention measures as a human-bear conflict resolution approach, thus in order to maximize the project's effects, the focus should be on younger generations of farmers and other stakeholder groups that have problems with bears. Furthermore, understanding of bear biology and behaviour proved to be one of the most important predictors when exploring values that are generally also core values of our project (coexistence, long-term conservation, prevention of conflicts). While in general our respondents demonstrated good knowledge about bears, it seems important to prepare and communicate basic key messages with information on bear biology, especially those related to bear diet, where highest level of misconceptions was documented, also to the stakeholder groups that are likely not that interested in such knowledge (livestock farmers, bee keepers). Consequently, for those groups we traditionally focus on delivering information related to damage prevention and compensation approaches and processes.

Perceptions and beliefs about population size are probably one of the most important components shaping public expectations from the population management. If predominant belief among the constituency is that there are too few bears, they will oppose any interventions into the population which could reduce the population size and they would expect measures to better conserve the population. The same is for the opposite example – beliefs that there are too many bears will result with expectations of population size control. It is important that decision-makers have access to the information on public opinions and expectations, so that they can predict and manage public support for management decisions that need to be taken. Results of our study would suggest that social carrying capacity has been reached among the interested inhabitants of Slovenia, especially those in the Dinarics, while in other countries people would be willing to tolerate more bears. It is however important to note that many respondents in all countries but Austria did not have a concrete opinion about the bear population size in their country and choose "neither agree nor disagree".

Closely related to perceptions about bear population size is public support for lethal control of bears. Our data suggest that Italian and Austrian respondents do not support lethal control of bears. The Croatian respondents and those from the Alpine part of Slovenia were on average undecided, while the Slovenians from the Dinarics clearly recognized the need for lethal control of bear population size with their answers.

(Potential) benefits of having bears for local communities were recognized in responses in all participating countries although somewhat lower in the area with probably the highest densities of bears (Slovenian Dinarics).

On the other hand respondents in all participating countries do not like to tolerate conflict situations with bears. According to our data, Italians are willing to tolerate the most conflict situations as well as those that are younger, and more knowledgeable about bears. Respondents in all four countries acknowledged that damage prevention, correct organic waste management and public awareness are the most effective approaches in dealing with human-bear conflicts. Invasive measures such as culling and removal of problem bears were also recognized as efficient, however much more among the respondents from Croatia and Slovenia, than those from Italy and Austria. Supplemental feeding of bears as a conflict resolution measure was also recognized as effective, especially among Slovenian respondents and to some degree also Italian.

Introduction

Public awareness campaigns are often used as tools to improve human attitudes toward wildlife and wildlife management decisions. One of the main expected results of many large carnivore conservation projects, including LIFE DINALP BEAR, is improved public acceptance of the large carnivore(s) in question in their regions. Especially in areas that are being recolonized by large carnivores, there is often a debate how these large carnivores should be managed. This debate occurs because different stakeholder groups hold different values and subsequently have different or even opposing management goals. Because of that, it is important that decision-makers and all those involved in large carnivore conservation understand those values and how values influence attitudes and consequently also support or oppose the conservation goals. This study besides its capacity to increase understanding of how rural public in LIFE DINALP BEAR project area sees bears and bear management, also presents a baseline assessment which will allow for evaluation of the effectiveness of a public awareness campaign which is being implemented during the project. The data presented in this report were collected during 2015 (in Austria, Slovenia, and Croatia) and 2016 (in Italy).

Methods

Study area

Study area for the public attitude survey includes the entire LIFE DINALP BEAR project area (Figure 1). The sampling has been geographically stratified based on the hypotheses that political boundaries (national borders) and status of the bear population (Alpine vs. Dinaric region) will also define the results. Thus sampling was independently carried out in Croatia, Slovenia- Dinaric part, Slovenia – Alpine part, Italy and Austria. Furthermore, our goal was to target local rural public, thus only communities with fewer than 10 000 inhabitants were included in the sampling.

Figure 1: LIFE DINALP BEAR project area represents also the study area of the public attitude survey.

Questionnaires

In surveys, answers are of interest not intrinsically but because they are in relationship to something they are supposed to measure. In that sense designing a question for a questionnaire is designing a measure, not a conversational inquiry. For the purpose of this study, a questionnaire was designed by the project group based on the results of the focus group carried out earlier in the project area (Majić et al, 2015). The questionnaire was designed in English, translated to local languages – Croatian, Slovenian, Italian and German. Then it was tested locally and adjusted both locally (translations) and overall (additional questions designed) (see Annex 1 – Questionnaires).

Following topics were included in the questionnaire:

- Questions aiming to explore general attitudes toward bears and bear management.
- Questions aiming to explore tolerance limits, including acceptable perceived bear population size and support for bear conservation
- Beliefs about bears and a knowledge section made up of factual questions.
- Perceptions about human-bear conflicts and beliefs about potential solutions.
- Personal experience with bears.
- Familiarity with the LIFE DINALP BEAR project.

- Socio-demographic information about each respondent, including association with key stakeholder groups (hunter, farmer, and beekeeper).

The development of the questionnaires was partly based on the questionnaires previously used in Croatia and Slovenia. There are two main reasons for that:

- The questions used in the previous surveys were already tested and therefore we could largely omit additional pretesting of these questions.
- Similar questionnaires would allow direct comparisons of the results from before the start of the LIFE DINALPB BEAR project with our data, thus we have also directed our study towards more longitudinal monitoring of the attitudes and beliefs.

Sampling and data collection

The same approach to sampling was taken in all countries. The target group was local general public in (more) rural areas, thus only communities with fewer than 10 000 inhabitants were included in the sampling frame. Targeted sample sizes were 400 of adult (18 years of age or more) respondents per stratum, thus we planned to obtain sample of 2000 completed questionnaires in total.

The general public was randomly sampled proportional to the number of inhabitants in each community within the study area. In Croatia and Slovenia the questionnaires were implemented using postal services. In Slovenia the sample (name, surname and address of potential respondent) was obtained from the national register of inhabitants. In Croatia sample was obtained by randomly selecting potential respondents from an electronic telephone book. We've considered a minimal expected response rate using mail to be 20%, thus number of sent questionnaires was adjusted accordingly. The questionnaires were mailed together with additional envelope with prepaid postage for returning the filled questionnaire. Ten days after the mailing of the questionnaires, a reminder / thank you card (Figure 2) was sent in order to increase the response rate.
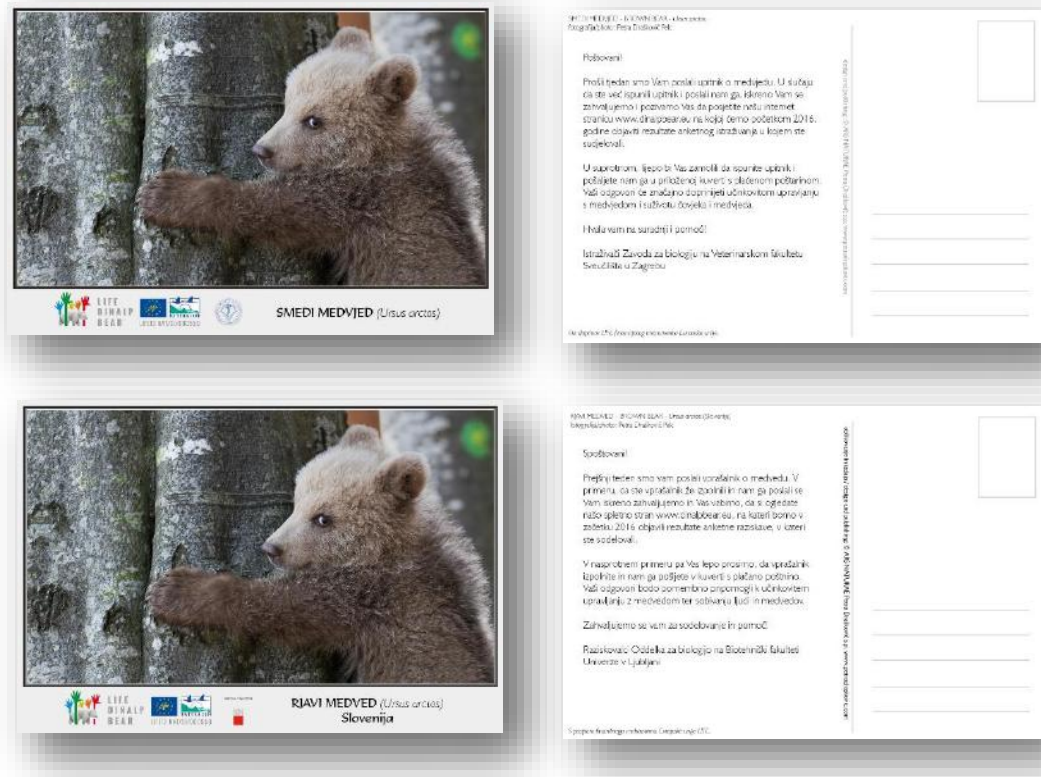
Figure 2: Reminder / Thank you! cards was sent to potential respondents in Croatia and Slovenia in order to increase the response rate.

In Austria and Italy, it was practically impossible to obtain data needed to create a representative sample of the targeted population, thus pre-existing panel samples owned by market research companies were used and questionnaire was implemented as on-line survey.

Data preparation

The questionnaire data was recorded in the pre-agreed table format in each country, and merged into a single database when the data collection was completed. We maintained the index key structure to preserve traceability of each physical questionnaire with its record in the database. We checked the data for consistency, data-entry errors and missing data. The records with unacceptable amount of missing data, missing data in key columns or inconsistencies we were not able to solve were removed and stored in a different database.

Some variables needed to be constructed by aggregation of data from several columns (has_livestock, big_livestock). We also calculated knowledge score as the number of correct answers to the four questions about bear biology included in the questionnaire. The question about bear number had too many missing data and was not asked in Italy at all, and was excluded from this score.

The questions for seeing bear in nature have been recoded to a new variable seennatureyesno - all people that reported seeing the bear in nature have been aggregated to "yes" since apart from Dinarics there has been only a small number of cases in the "yes, >10 times" category. This issue could be explored independently at a later stage.

Statistical analysis

All statistical analyses were done in R analytical environment within RStudio IDE. We followed the reproducible research paradigm by ensuring data consistency throughout analysis and documenting each analytical step (R code, comments, data and output) with RMarkdown.

Reduction of dimensionality using Principal Component Analysis (PCA)

There were three batches of questions that needed to have dimensionality reduced to enable interpretation. Since responses were collected using the Likert scale, we could assume ordinality and linearity of the responses and include them in Principal Component Analysis (PCA). We used R package psych to do this part of the analysis. We determined the number of meaningful components to extract using scree plot analysis, Kaiser-Guttman rule (eigenvalue > 1), Parallel Analysis, Optimal Coordinates, and Accelleration Factor. The components were rotated using the Varimax rotation to extract the interpretable components. Cases with unacceptable amount of missing data were excluded in the data preparation phase, and the remaining missing values were set to the mean of the variable to prevent unacceptable data loss. The extracted components were interpreted and included in the database table for downstream analysis.

Factors were normalized from -2 to 2, with 0 as neutral, direction has been checked to be logical with the interpretation of the variable. Original questions that were used for PCA were retained in the downstream dataset.

Attitudinal items (Q1-Q18)

There were 18 questions regarding the general attitudes towards bears and their conservation. Missing data was 1-3%, which is acceptable. We extracted three components:

bear_conservation - support for bear conservation. *bear_control* - support for bear control. *bear_value* - percieved value of bears.

Conflict items (Q19-Q27)

We extracted only one component: *conflict_tolerance* - how ready a person is to tolerate conflicts caused by bears.

Support of different solutions to bear problems (Q28-Q36)

There were three clear components:

sol_mitigation - preference for 'mitigation measures' solutions for bear problems *sol_culling* - preference for culling as a solution for bear problems *sol_feeding* - preference of a person for supplemental feeding as a solution for bear problems.

Q37 (other solutions), which is descriptive, is not usable in this type of analysis and was omitted.

Statistical modelling

We used Generalized Linear Models and information-theoretic approach to model selection and inference to model these highly complex data and enable interpretation of effects of otherwise confounded explanatory variables. We used the scores obtained by PCA variably as response or predictor variables, and explored their relation to other characteristics of the sample (Region, gender, education, etc.).

The general approach was as follows:

First, we checked the distribution of the response variables. Since they were PCA scores, we didn't expect a specific functional form, and we tried different probability distributions and transformations to select the correct distribution family and link function for GLM and ensure model fit.

We explored the missing data in the dataset. When meaningful (for some scalar variables) we replaced the missing values with the mean value of the variable, which shouldn't have much effect on fitting of models but prevented unacceptable data loss. At the model selection stage the remaining records with missing data were discarded to enable comparison of the fitted models, but the final (optimal) models were fitted with the entire dataset so that only the records that had missing data in the variables retained in the model were lost.

We constructed a global model with the selected distribution family and link function for each response variable where we fitted all variables we a-priori hypothesized (according to previous understanding of the problem) that they affect the response variable. We didn't fit any interactions between variables at this stage. We checked model fit by plotting standardised residuals against predicted values, checking for non-linearity, bias and heteroscedasticity. We checked for multicollinearity using Variance Inflation Factors (VIF).

We explored the model space of each global model by fitting all sub-models without interactions using R package MuMIn. We determined the importance of each variable as the proportion of models where it appears weighted by the Akaike's weight of each model. We constructed the optimal model without interactions by including all highly important variables (Importance > 0.9), and tested the effect of removal of each variable by comparing the second-order Akaike's information criterion (AICc) with the full model. We used dAICc > 3 as the threshold to retain a variable.

We fitted different two-way interactions between variables, selected a-priori using prior knowledge and hypotheses about the problem, and checked support of each model by the data using AICc. We also used dAICc > 3 as the criteria to retain a model. If the dAICc was between 0 and 3, we retained the model with lower number of parameters.

To fit the final optimal (most parsimonious) model with as much data as possible, we used the entire dataset and excluded the records that had missing data just in the variables retained in the model. We checked the data for high-leverage data points by calculating Cook's distances, and we excluded the records with Cook's distances larger than 4/N (model outliers), where N is

the number of records included in the model. We re-fitted the optimal model with this dataset without outliers, re-checked linearity and homoscedasticity, and used the fitted model for interpretation.

Data exploration and interpretation of modelling results

We plotted different aspects of the dataset to visually examine the raw data for the effects of different explanatory variables on the response variables. Since the explanatory variables are in many cases highly confounded and in practically all cases non-orthogonal, we used the most parsimonious models fitted in the statistical modelling exercise to directly explore the effect of single explanatory variables or their pre-determined interactions when the other parameters in the model are being controlled for. In other words, we examined the "pure" effect of a specific explanatory variable (e.g. age, education, etc.) on the response (e.g. support for bear conservation) controlling for the effect of other explanatory variables (e.g. Region, gender, etc.). In this manner we could provide an understanding of the actual effect of a certain explanatory variable even in the face of the high complexity and non-orthogonality of the data. The effects were explored using the R package *effects*.

For more information about the analysis please refer to the Annex 2 – Analysis Notes.

Results

Data set description

Following a data quality screening and exclusion of questionnaires with high ratio of missing data (n=24) and those filled out by persons younger than 18 years (n=12), 2306 questionnaires were included in the analysis. That is 306 more than we aimed for. Achieved sample sizes per study areas were Response rates for the mail questionnaire were 295 in Croatia, 671 in Slovenian Dinarics, 539 in Slovenian Alps, 401 in Italy and 400 in Austria. Response rates for questionnaires sent via post were 24.6% in Croatia, and 33.6% and 27% for the Dinaric and Alpine parts of Slovenia, respectively.

Overall, half of our respondents were females. Nevertheless, there were some variations at the country level. In Croatia, for example, over 60% of respondents were males, probably due to the sampling from the telephone book as traditionally males are considered heads of the households and their names are listed in the telephone books. In Italy, on the other hand, close to 56% of the respondents were females.

On average respondents to our questionnaire were close to 48 years old. The oldest respondents were from Croatia (median = 57) and Slovenia (median = 51). The sample in Italy and Austria (median = 37 and 44, respectively) was most likely somewhat biased towards younger generations, probably due to the online implementation of the questionnaire. Distribution by age is presented in Figure 3.

Majority of respondents had secondary (high school) education (52% overall). University degree or other form of higher education was reported by 22% (in Austria) to up to 37% (in the Slovenian Dinarics).
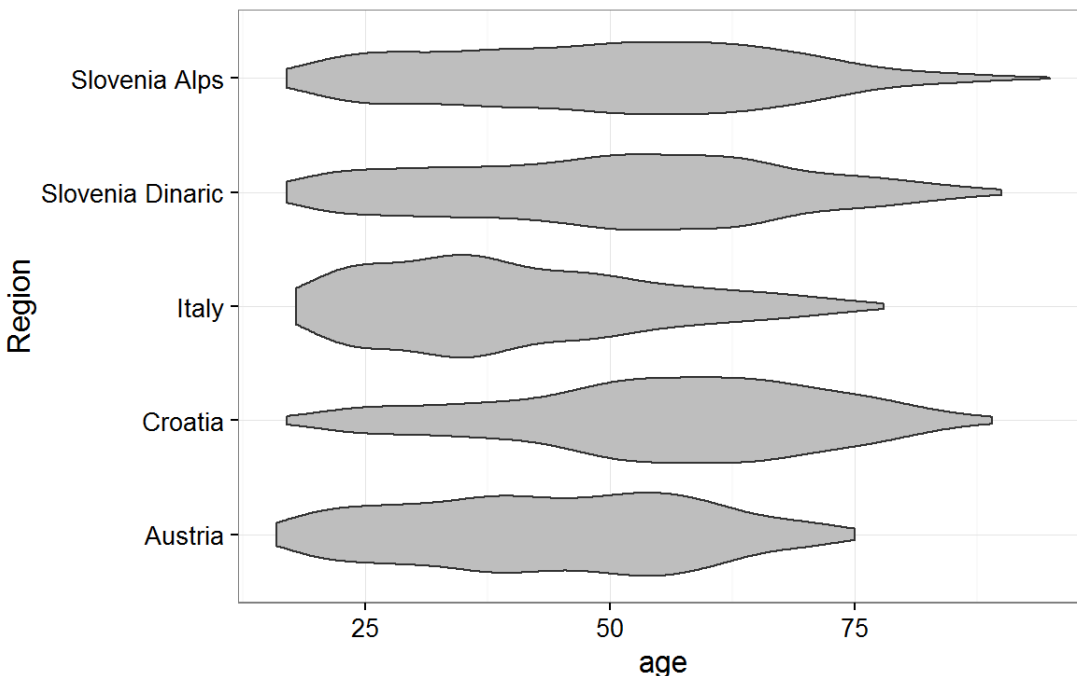
Figure 3: Distribution of respondents' age per study area.

Croatian respondents overall had the most direct experiences with bears. Close to 20% of them experienced damage caused by bears to their property. This percentage was much lower (just over 11%) in the Slovenian parts of the Dinaric. In the Alpine area only few respondents claimed experiencing damage by bears - 5% in Slovenia and around 2% in each Austria and Italy.

Majority (over 65%) of Croatian respondents reported seeing a bear in nature. This was followed by just over 46% of Slovenian respondents in the Dinaric region. Respondents from the Alpine regions mostly did not see a bear in nature (78%, 88% and 89% for Slovenia, Italy and Austria, respectively, Figure 4). Practically all of the respondents from Austria, Slovenia and Croatia reported seeing a captive bear (for example in a ZOO), while just over 20% of Italian respondents did not see a captive bear.
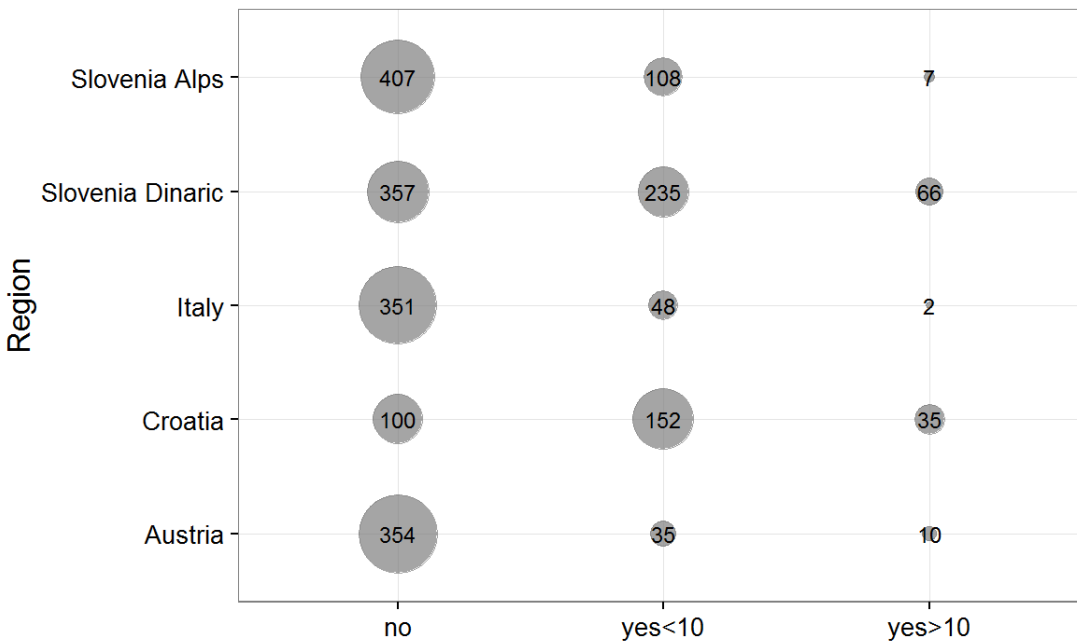
Figure 4: Number of respondents reporting either not seeing a bear in nature or seeing it fewer than or 10 or more times in their life.

Overall, there were 5.6% of hunters among our respondents, ranging from 2.8% in Slovenian Alps to up to 10.8% in Croatia. It seems that Slovenian Alps hunters and Austrian (4.3% in our sample) were the least motivated to respond to our questionnaire.

Beekeepers are another important stakeholder group in bear management. Just under 5% of our respondents reported having bees. Highest percentage was in Croatia (8.8%) and lowest in Slovenian Alps (3.2%).

Livestock farmers as one of the key stakeholder group in bear management were also specifically recognized within the survey (Figure 6). The highest share of livestock farmers was among Slovenian Alps respondents (21%), followed by Croatia (16%), and Slovenia Dinarics (15.6%). Among Austrian respondents there were close to 10% of livestock farmers, while the lowest share of farmers was recorded in the Italian sample (just under 8%).

Dog owners are an important target group for communicating ways of safe behavior in bear habitat. Share of dog owners in our sample is presented in Figure 5.
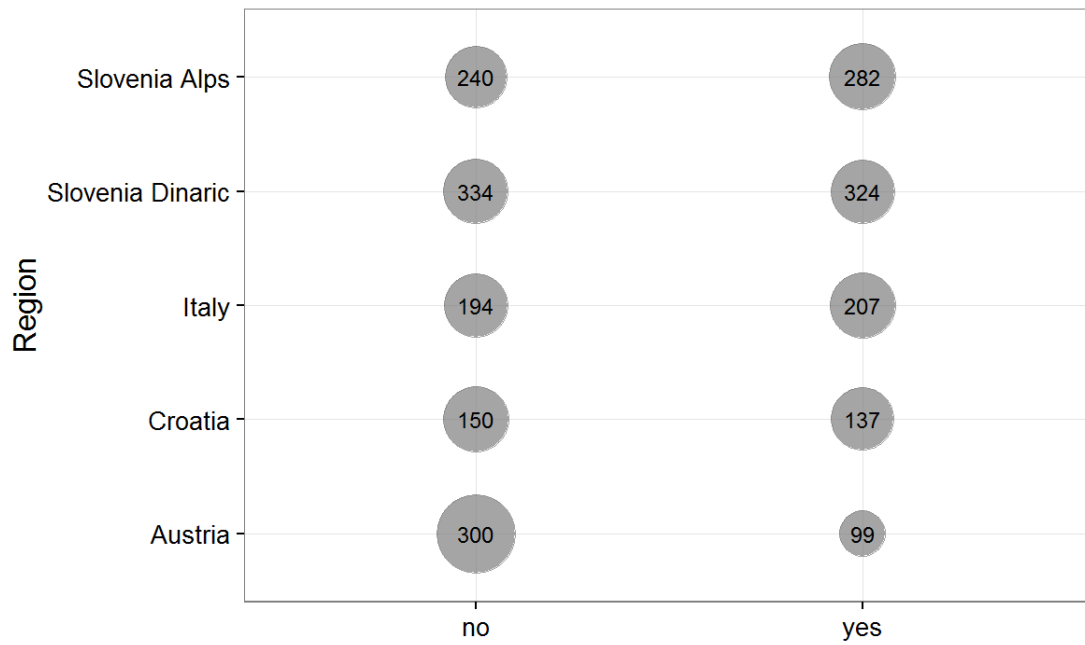
Figure 5: Respondents reported (not) owning a dog in their family.
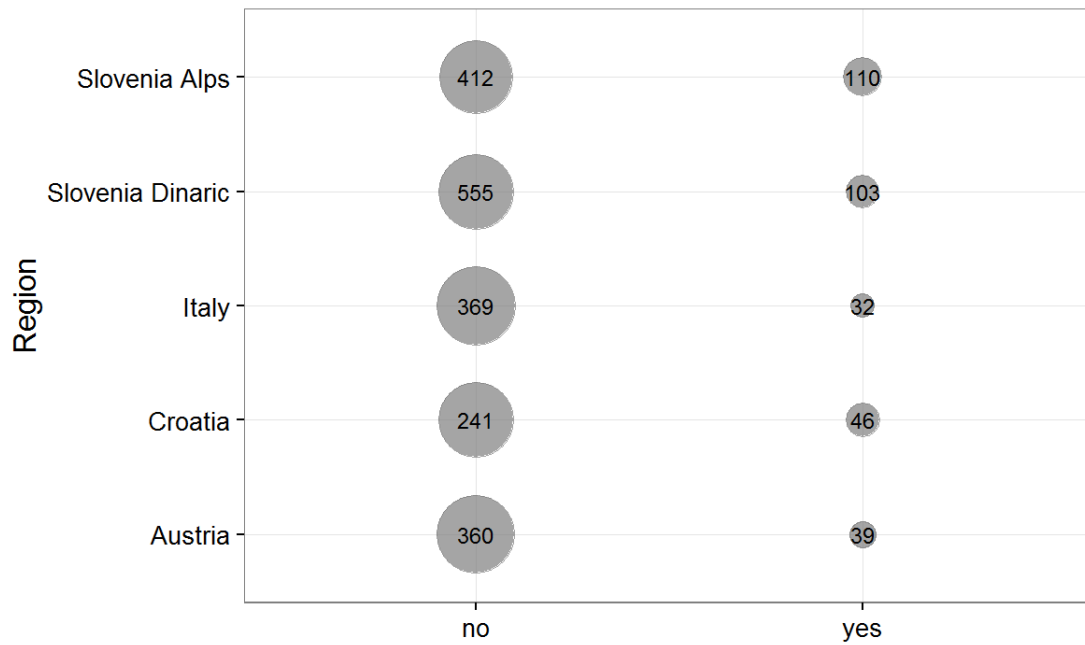
Figure 6: Respondents reported having livestock (sheep, goats, cattle and/or horses).

Project visibility

Overall 14.6% of our respondents have reported hearing about our project before (during the first year of project implementation). The highest share was recorded in Croatia, close to 22% and Slovenia (around 20%). In Italy and Austria 5.2% and 4% of respondents heard of the project, respectively (Figure 7).
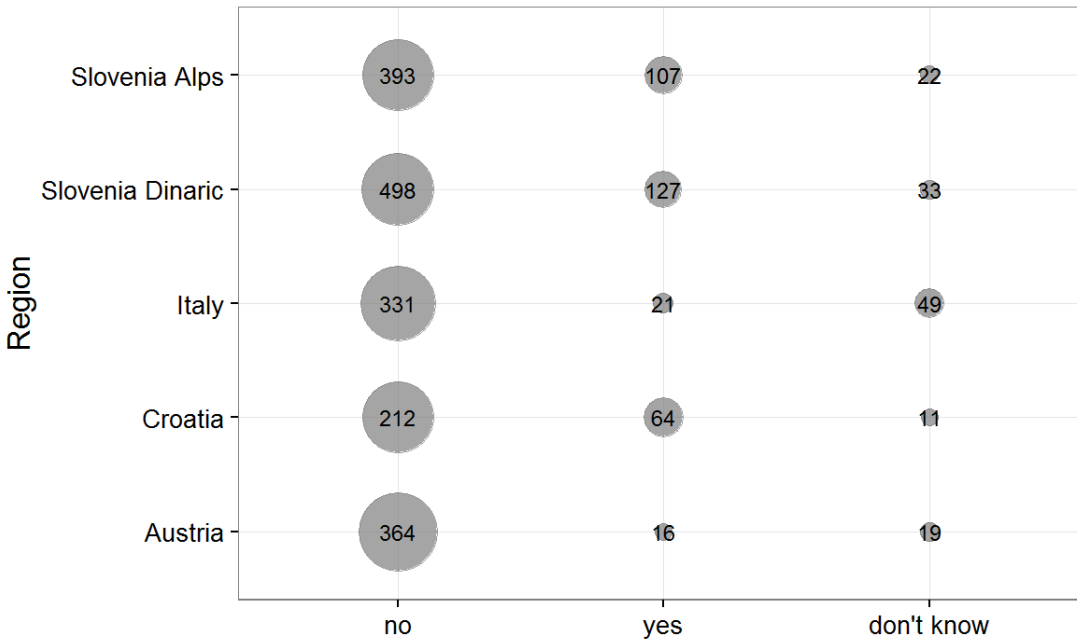
Figure 7: Number of respondents that did (not) hear about our project before receiving the questionnaire.

In order to assess the understanding of project objectives, we have further asked those that have heard about the project to choose what they think are the main objectives of the project (Figure 8). The respondents have primarily selected "to improve coexistence with bears" and "to study bears". There were regional differences, especially with regards to objectives "to prevent traffic accidents" and "to promote ecotourism", which is expected as project actions related to those two objectives are being carried out only in Slovenia and Croatia.
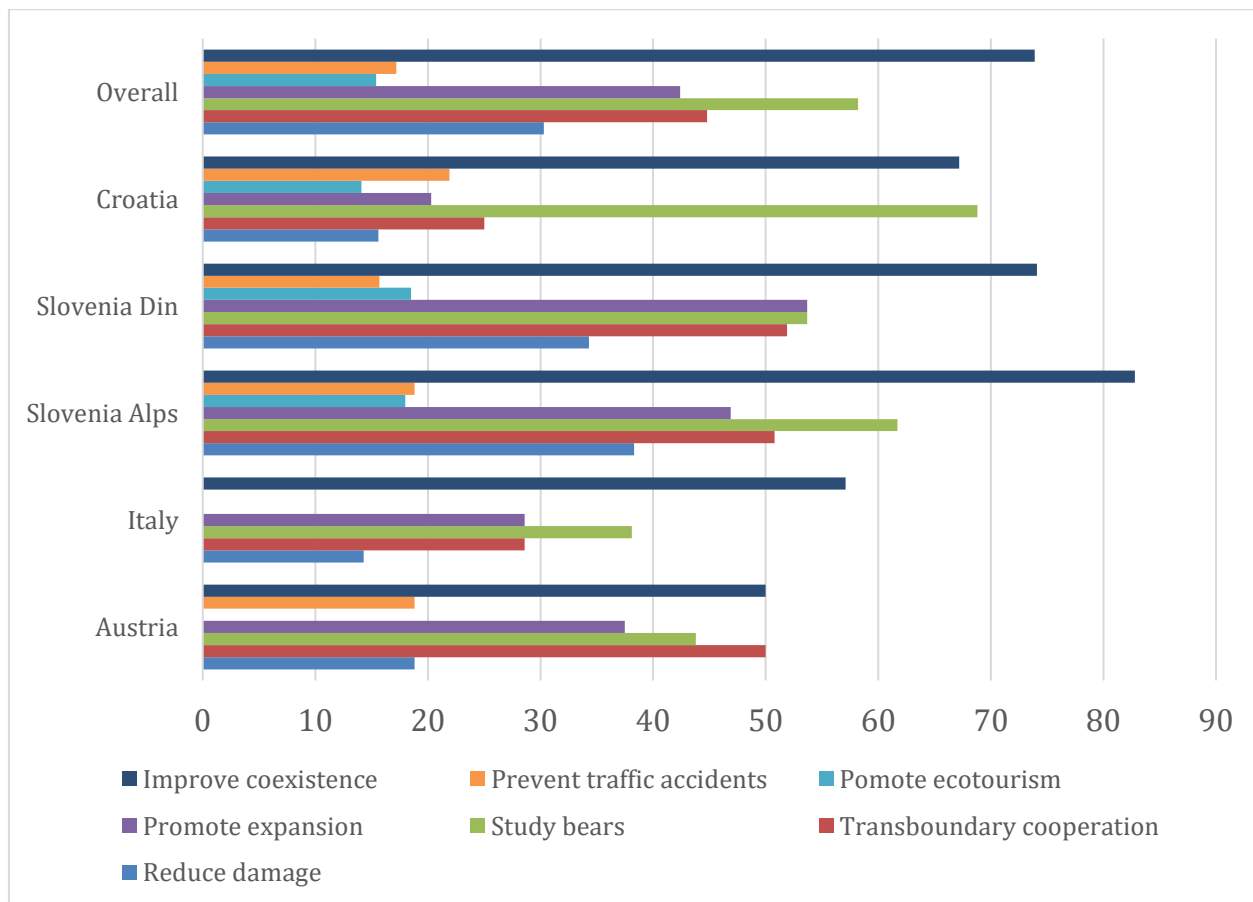
Figure 8: Main objectives of the LIFE DINALP BEAR as understood by the respondents.

Knowledge about bears

General bear biology and bear behaviour questions presented in Table 1 were used to assess respondents' general familiarity with bears as a species. Respondents in general demonstrated good knowledge about bears. The only question where we documented considerable misconceptions was the one related to the species diet as majority of respondents overestimated the share of animal food origin in bear's diet. Results for the knowledge items are presented in detail in Figure 9 to Figure 12.

These questions were also used to calculate "knowledge score" which ranged from 0 (none of the questions were correctly answered) to 4 (all of the questions were correctly answered). Overall, the highest level of knowledge was documented among Croatian respondents, followed by Slovenia Dinaric, Austria, and Slovenia Alps. Somewhat lower levels of knowledge were documented among Italian respondents (Figure 13).

Respondents in Slovenia, Croatia and Austria were also asked to write down the number of bears in their respective countries. In Italy this question was not asked. Median value for

Slovenia was 450 bears, for Croatia 775 bears and for Austria 15 bears. Due to a high number of missing data and many outliers, this questions was not used in calculating knowledge score.

Table 1: Knowledge questions used to calculate "knowledge score".

Question	Possible answers
Bears in SI/HR/IT/AT feed on:	a) Only food of animal origin. b) Mostly food of animal origin. c) Mostly food of plant origin. d) Food of animal and plant origin in approximately same ration. e) Don't know.
How many cubs are there in a litter most often?	a) One. b) Two. c) Three. d) Four. e) Don't know.
Bears in SI/HR/IT/AT are in general afraid of people.	a) No. b) Yes. c) Don't know.
Bear cubs in SI/HR/IT/AT usually leave their mothers:	a) As soon as they leave the den where they were born. b) During the first year of their life. c) During the second year of their life. d) During the third year of their life. e) During the fourth year of their life. f) Don't know.
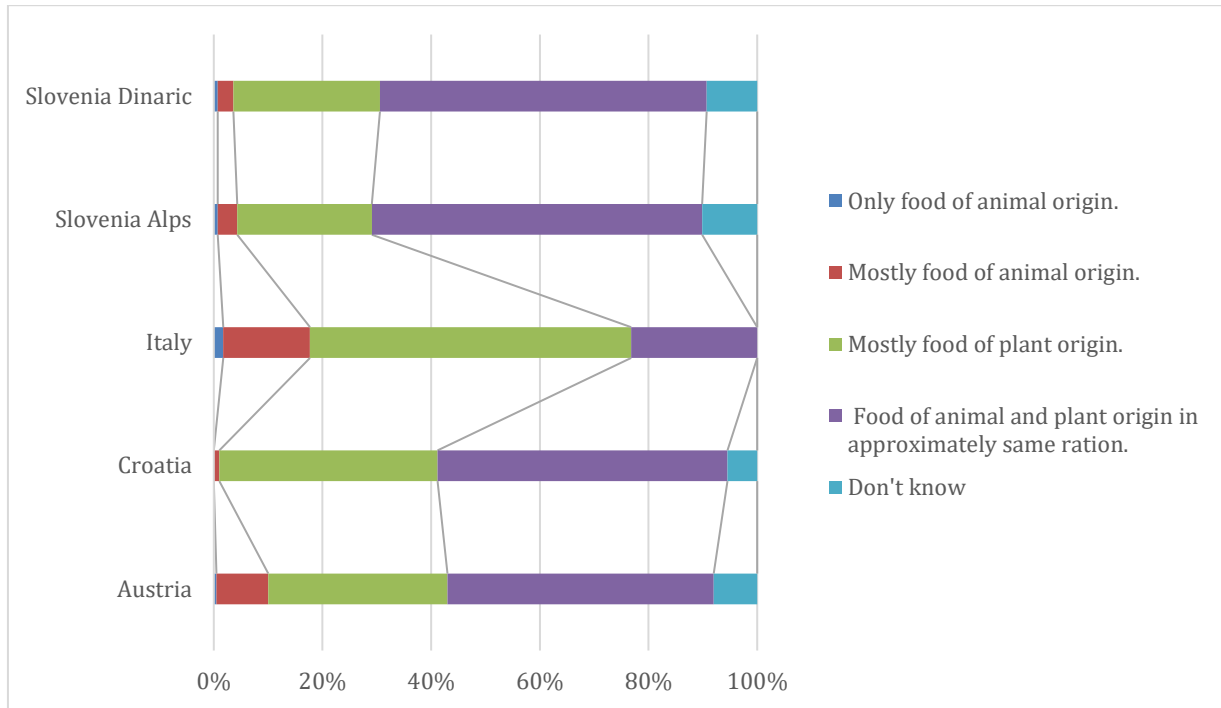
Figure 9: Answers to the question "Bears in SI/HR/IT/AT feed on:…". Correct answer is "Mostly food of plant origin", coloured green in the chart.
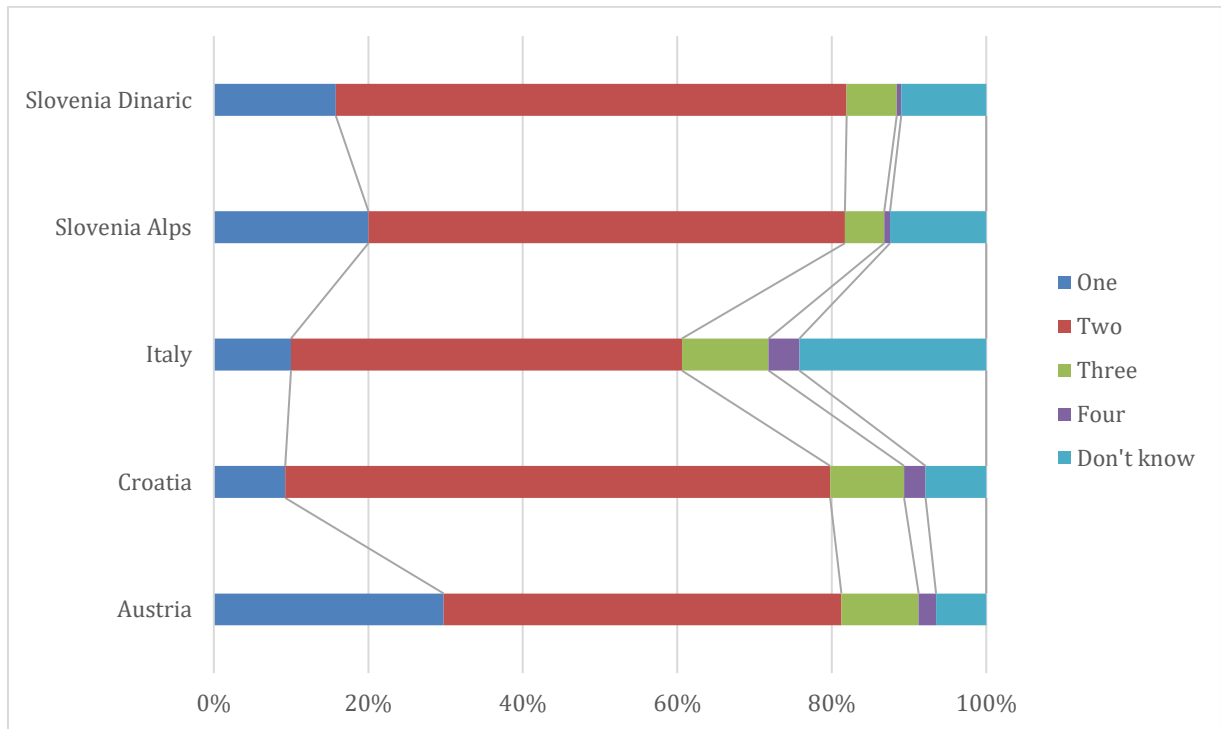
Figure 10: Answers to the question "How many cubs are there in a litter most often?". Two and three were considered as correct answers in further analysis (coloured red and green in the chart).
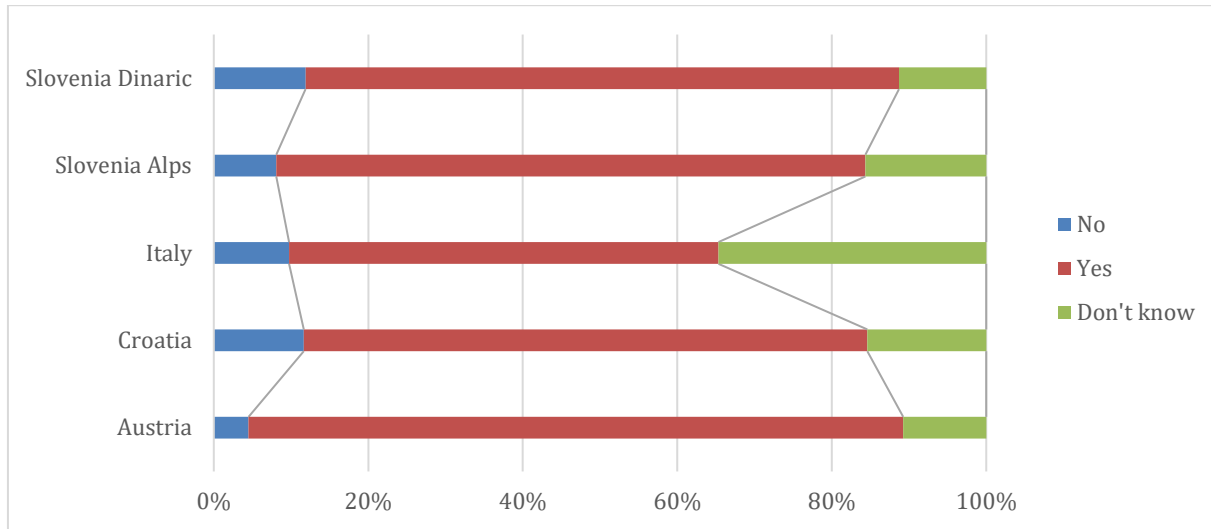
Figure 11: Answers to the question "Bears in SI/HR/IT/AT are in general afraid of people." Correct answer was "Yes" (coloured red in the chart).
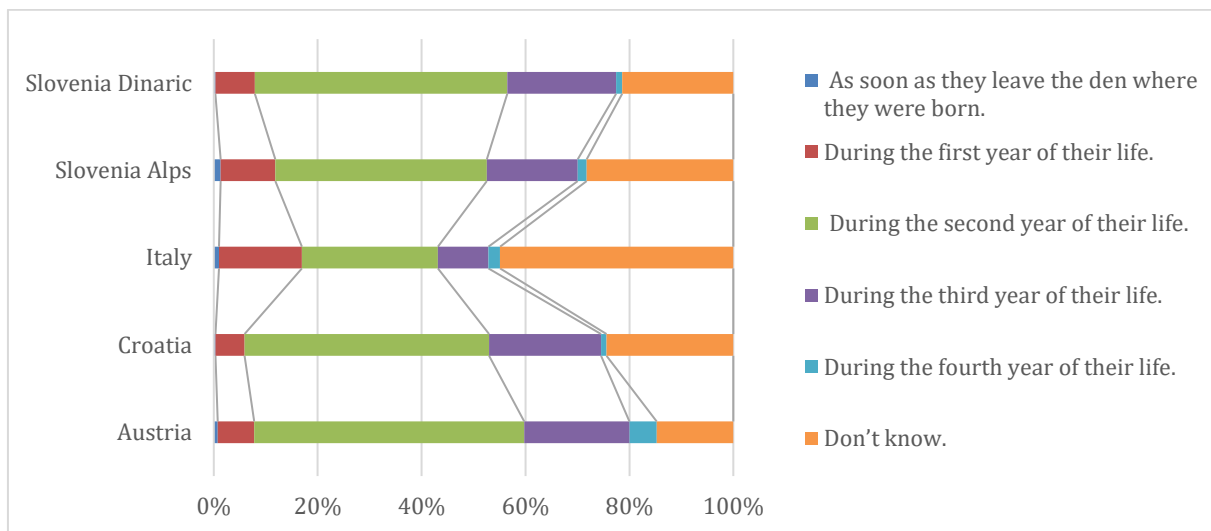
Figure 12: Answers to the question: "Bear cubs in SI/HR/IT/AT usually leave their mothers:…". Correct answer was "During the second year of their life" (coloured green in the chart).
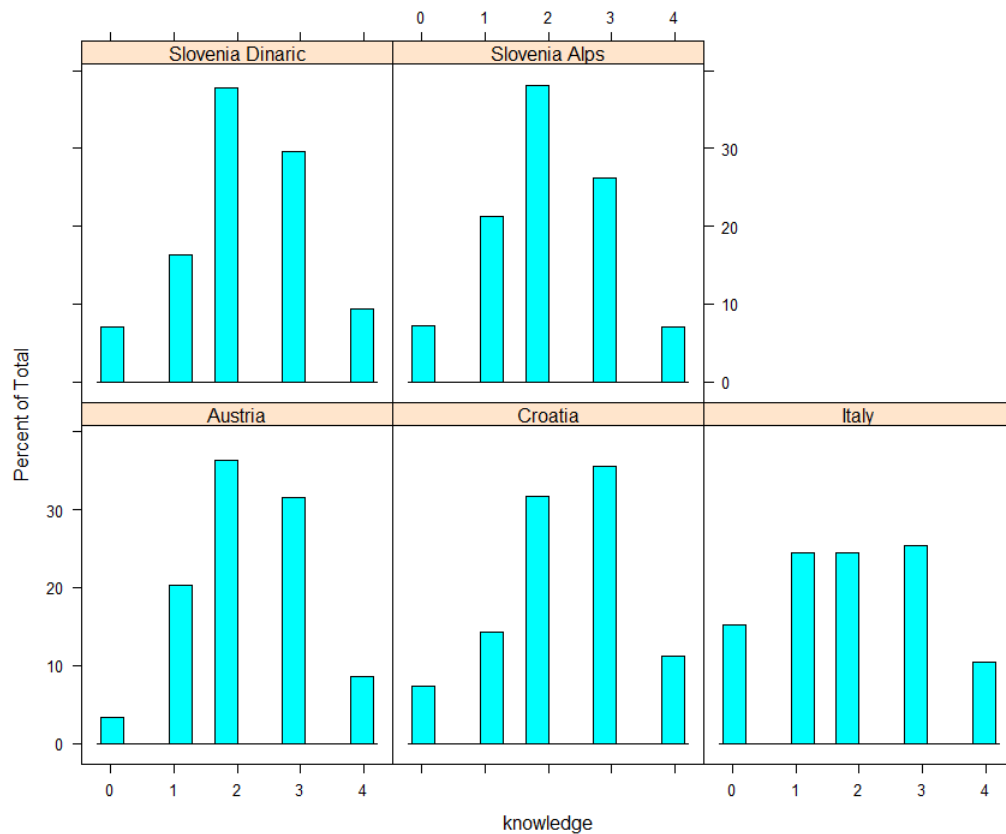
Figure 13: Distribution of knowledge score (0-4) across the study areas.

Exploring human tolerance of bears

Perceptions about acceptable bear population size

Perceptions and beliefs about population size are probably one of the most important components shaping public expectations from the population management. If predominant belief among the constituency is that there are too few bears, they will oppose any interventions into the population which could reduce the population size and they would expect measures to better conserve the population. The same is for the opposite example – beliefs that there are too many bears will result with expectations of population size control. It is important that decision-makers have access to the information on public opinions and expectations, so that they can predict and manage public support for management decisions that need to be taken.

In the questionnaire we have asked two complementing questions regarding the respondents' opinion on local (national) bear population size: "In my opinion, there are too many bears in SI/HR/IT/AT" (Figure 14) and "I would agree with increasing bear numbers in SI/HR/IT/AT" (Figure 15). Italian, Austrian and Croatian respondents would agree with increasing number of bears in their respective countries, while Slovenian respondents mainly opposed this statement.

Many of the Slovenian respondents from the Dinaric region also agreed that there are too many bears in Slovenia. These results would suggest that social carrying capacity has been reached among the interested inhabitants of Slovenia, especially those in the Dinarics, while in other countries people would be willing to tolerate more bears. It is however important to note that many respondents in all countries but Austria did not have a concrete opinion about the bear population size in their country and choose "neither agree or disagree" (shown as "Neutral" in the graphs).
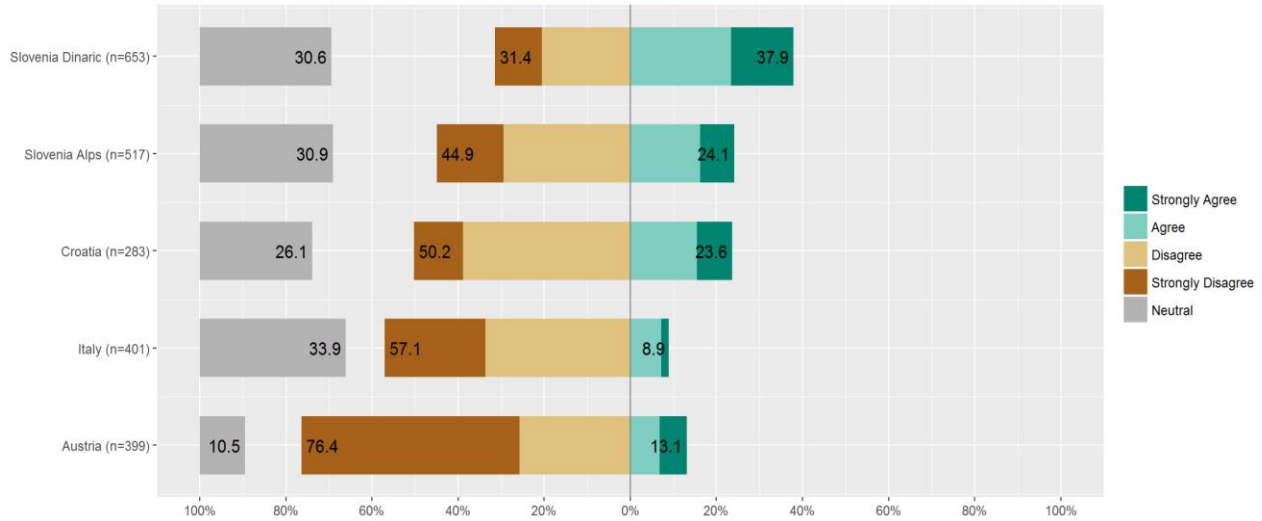
Figure 14: Results for the item "In my opinion, there are too many bears in SI/HR/IT/AT."
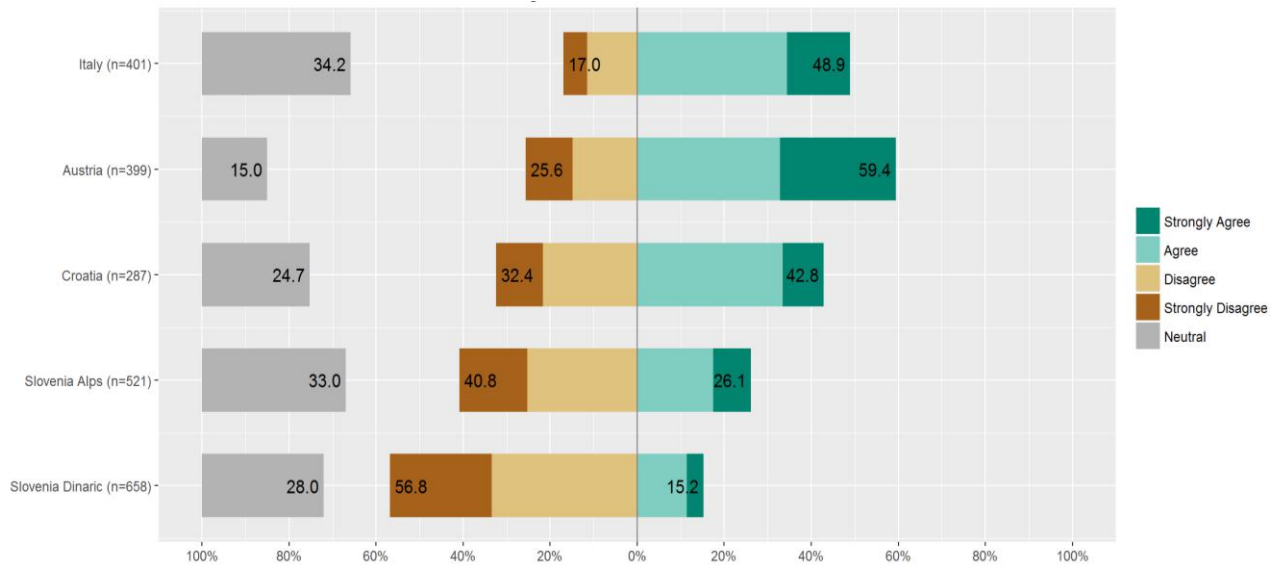
Figure 15: Results for the item "I would agree with increase in bear numbers in SI/HR/IT/AT."

Public support for bear conservation

Principal Components Analysis (PCA) presented in detail in Analysis Notes (Annex 2) allowed us to aggregate general attitudinal items into three interpretable scores. First one, explaining 51% of the variance was interpreted as "Support for bear conservation" (Figure 21). Raw results of the main items contributing to this component are presented in Figure 16 to Figure 20. The question presented in Figure 14 (In my opinion, there are too many bears in SI/HR/IT/AT" also contributed to this score with a standardized loading based upon a correlation matrix of -0.73.

By looking at the raw data, it is important to note a discrepancy in responses among the Austrian respondents. While less than 10% assessed their own attitudes toward bears as negative, over 20% disagreed that it is important to have bears in Austria for future generations and also agreed that it is not necessary to have bears in Austria since large populations already exist in other European countries.
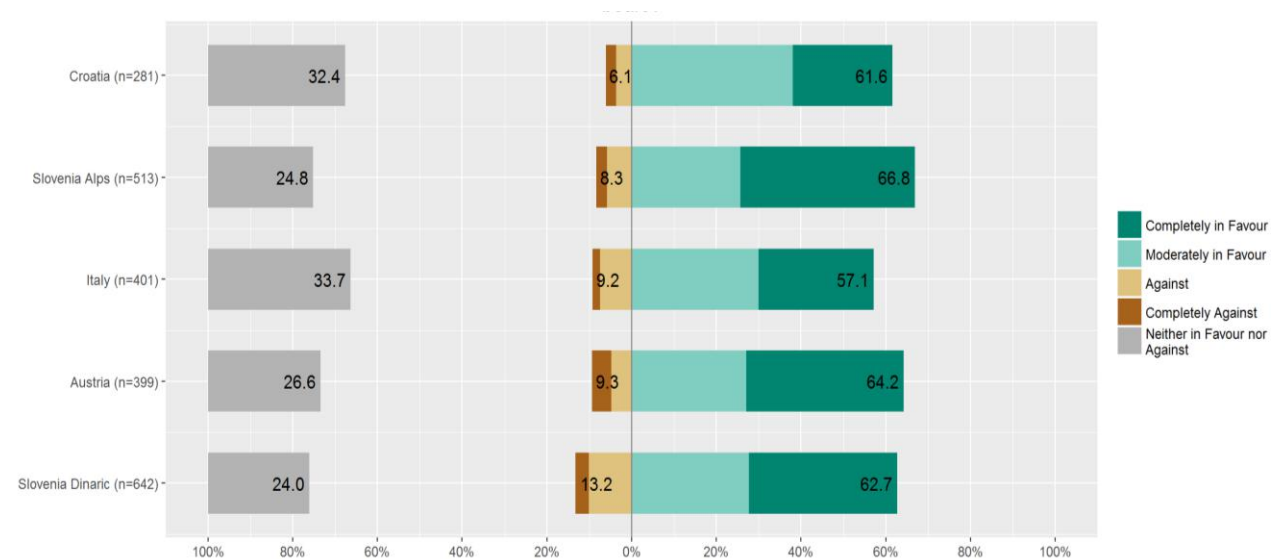
Figure 16: Results of the item: "Which answer best describes your feelings toward bears?". This item contributed to the PCA score "support for bear conservation" with a standardized loading of 0.81.
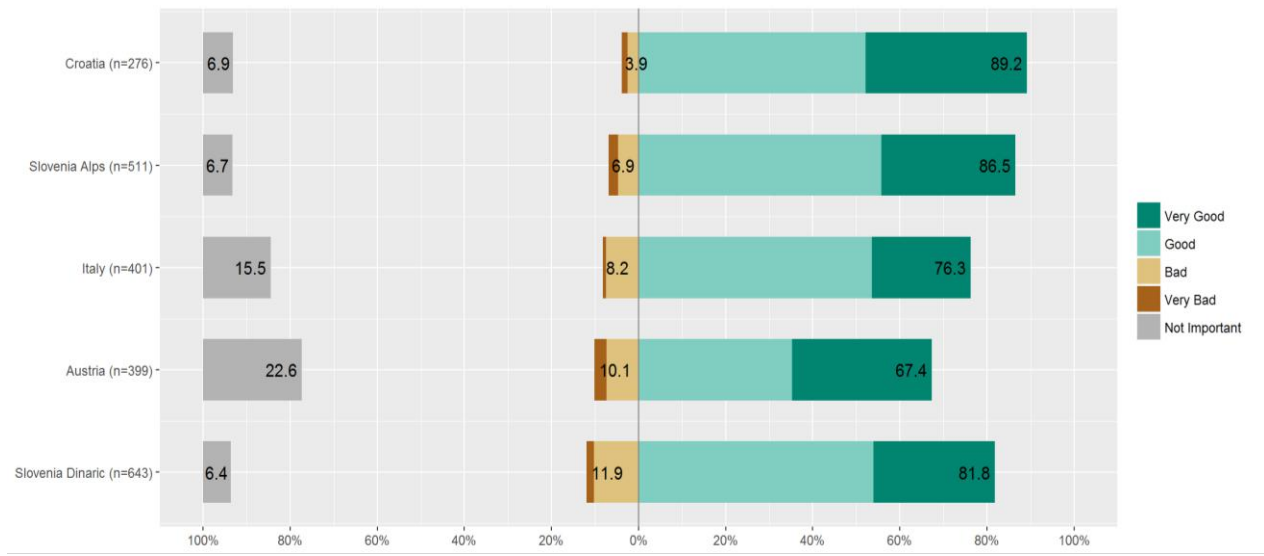
Figure 17: Results of the item: "Having bears in SI/HR/IT/AT is:…". This item contributed to the PCA score "support for bear conservation" with a standardized loading of 0.82.
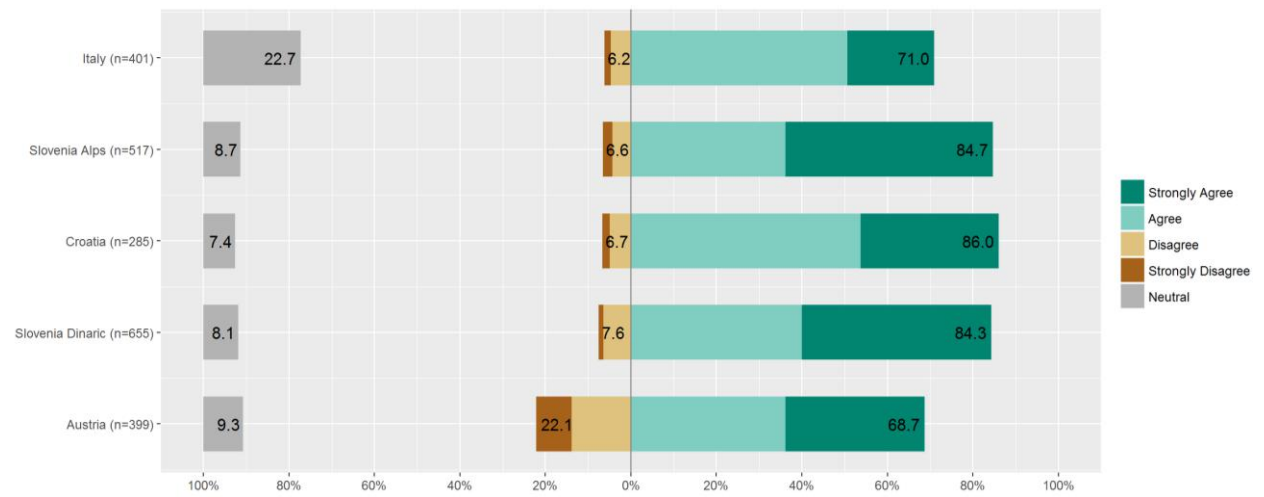
Figure 18: Results of the item "It is important to have bear population in SI/HR/IT/AT for the future generations.". This item contributed to the PCA score "support for bear conservation" with a standardized loading of 0.75.
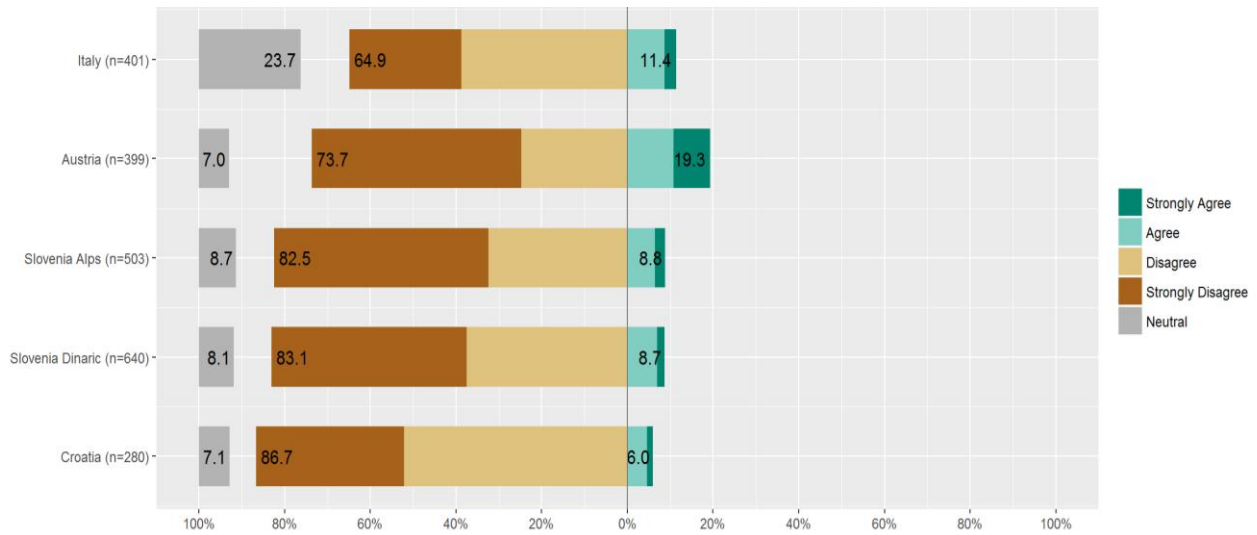
Figure 19: Results of the item "It is unnecessary to have bears in SI/HR/IT/AT because abundant populations of bears already exist in other European countries.". This item contributed to the PCA score "support for bear conservation" with a standardized loading of -0.73.
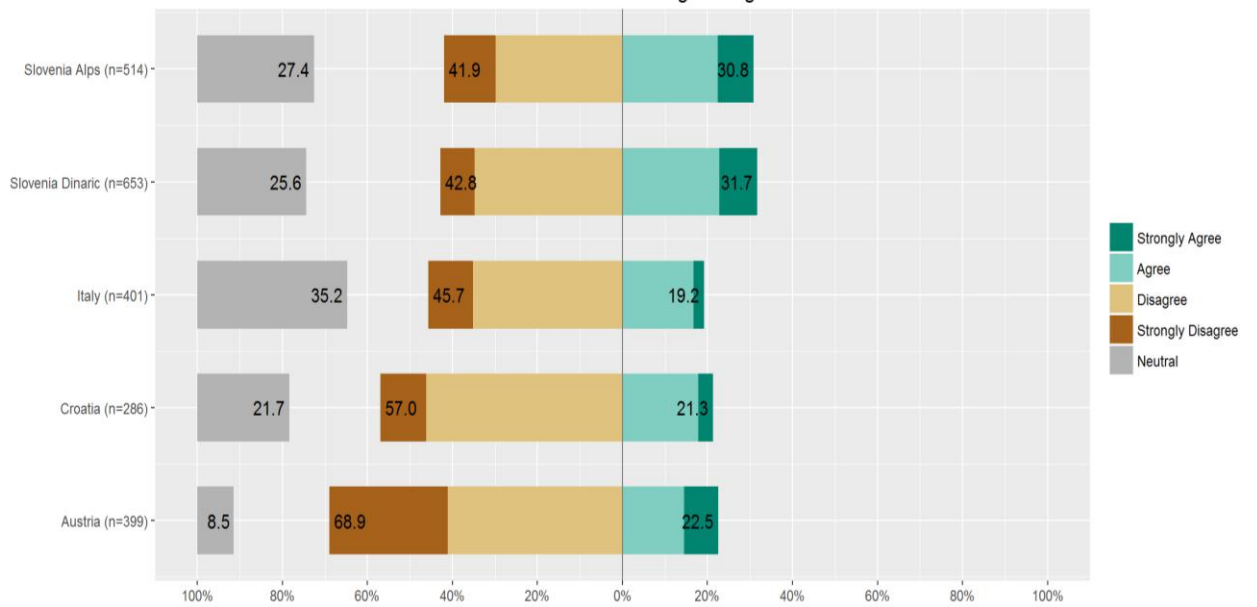
Figure 20: Results of the item "Bears cause unbearable damages in agriculture" This item contributed to the PCA score "support for bear conservation" with a standardized loading of -0.73.
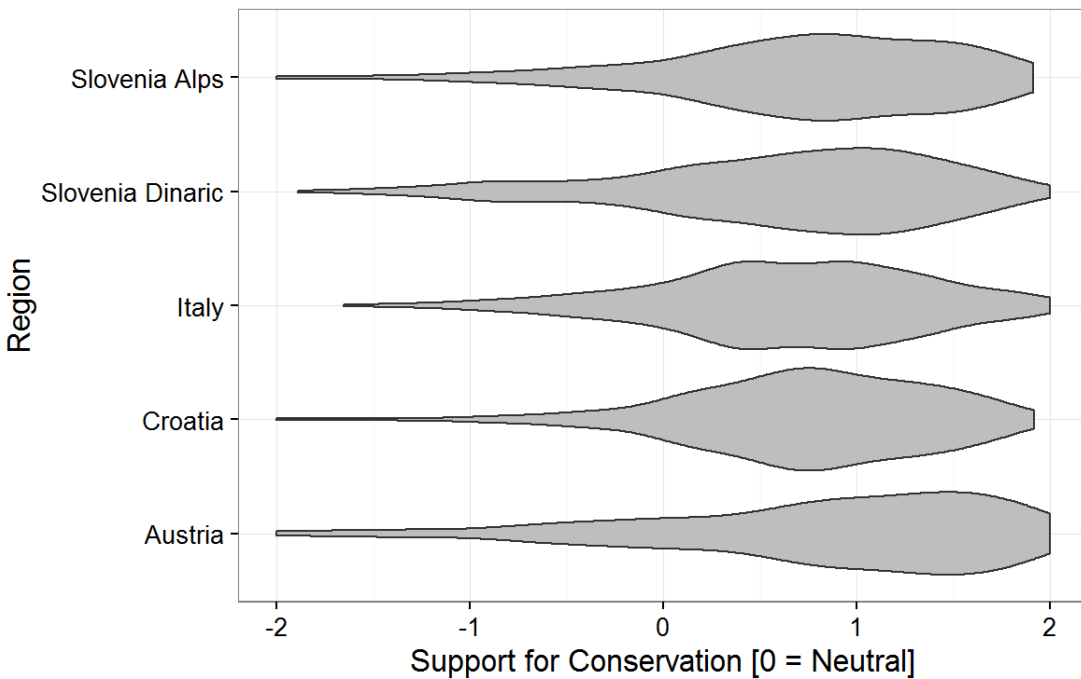
Figure 21: Distribution of the extracted PCA score "Support for bear conservation".

The final model for "Support for Conservation" had following structure: Support for conservation ~ Region + age + education + knowledge + has_livestock + knowledge:has_livestock + Region:age

Overall, all groups were supportive of bear conservation, but there were regional differences (Figure 22). The highest general support for bear conservation was documented in Austria, while in other countries it was somewhat lower. Younger generations support bear conservation more than the older ones (Figure 23). Respondents that have higher formal education (Figure 24) and especially those that have better knowledge of bear biology (Figure 25) also scored higher on the "Support for bear conservation". Effects of knowledge about bear biology were especially important among livestock owners (Figure 27), while owning livestock was a negative predictor for support for bear conservation (Figure 26).
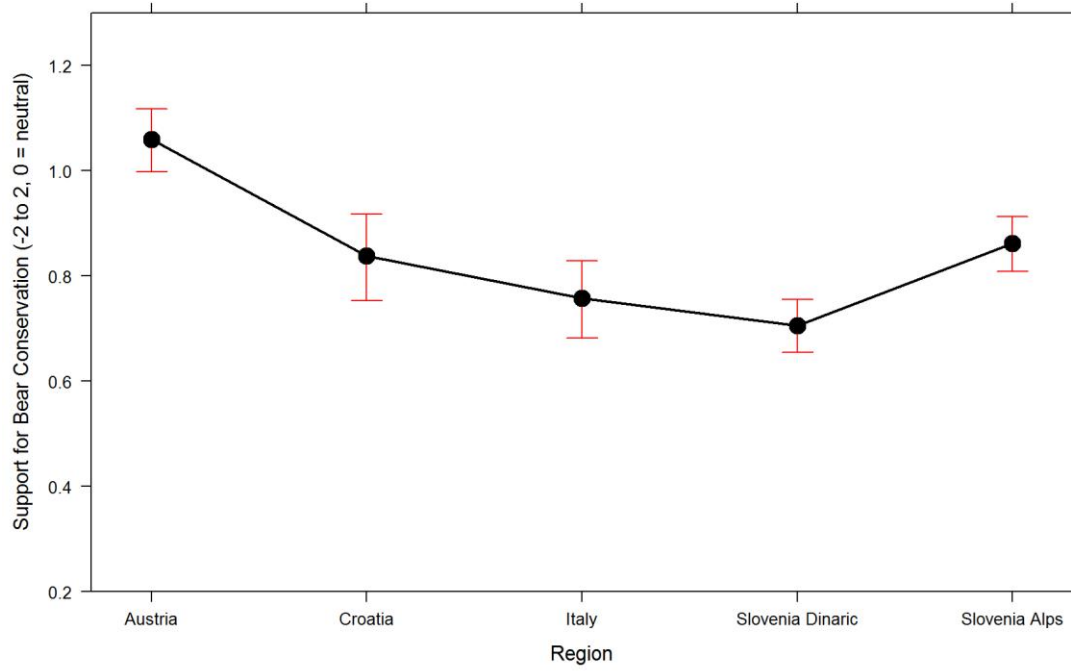
Figure 22: Effects of "region" to "Bear Conservation Support".
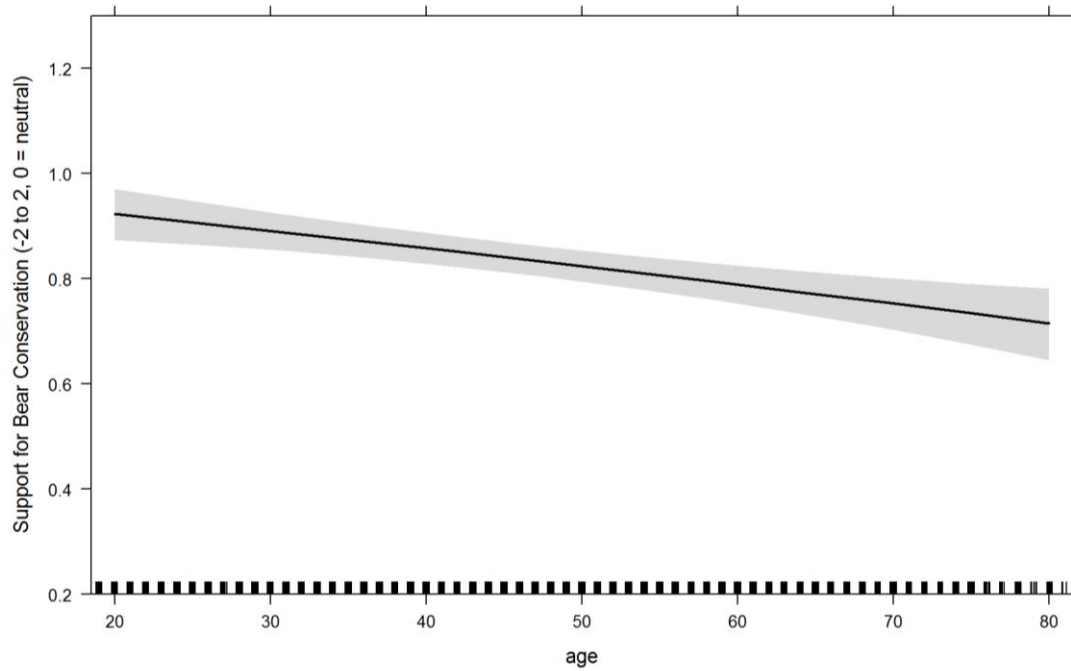
Figure 23: Effects of respondents' age on Support for conservation.
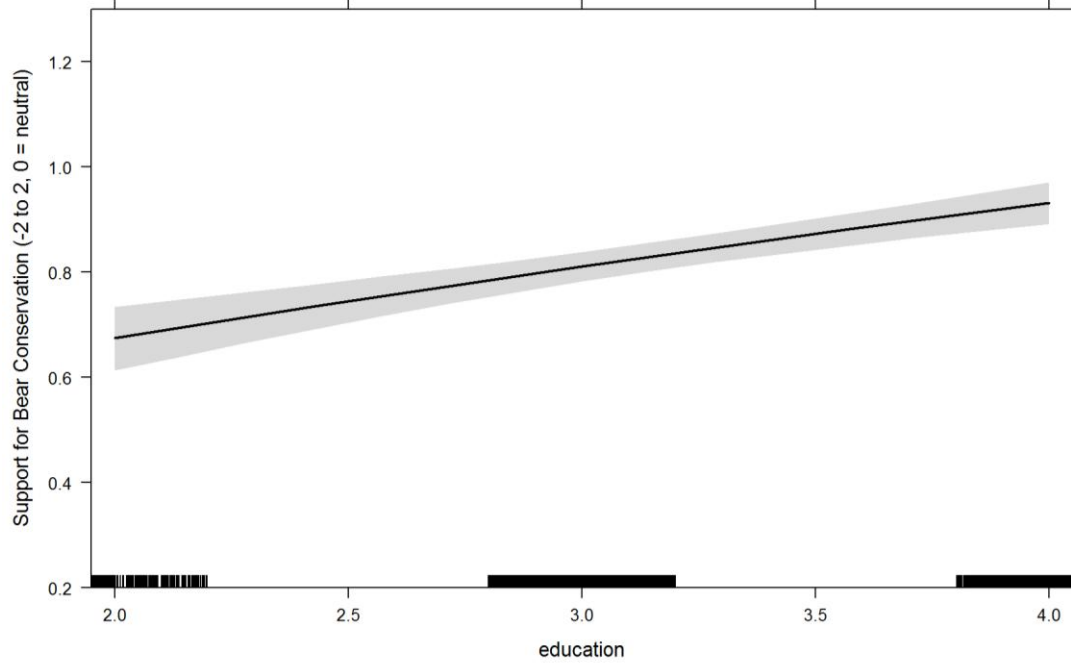
Figure 24: Effects of respondent's education on Support for Conservation.
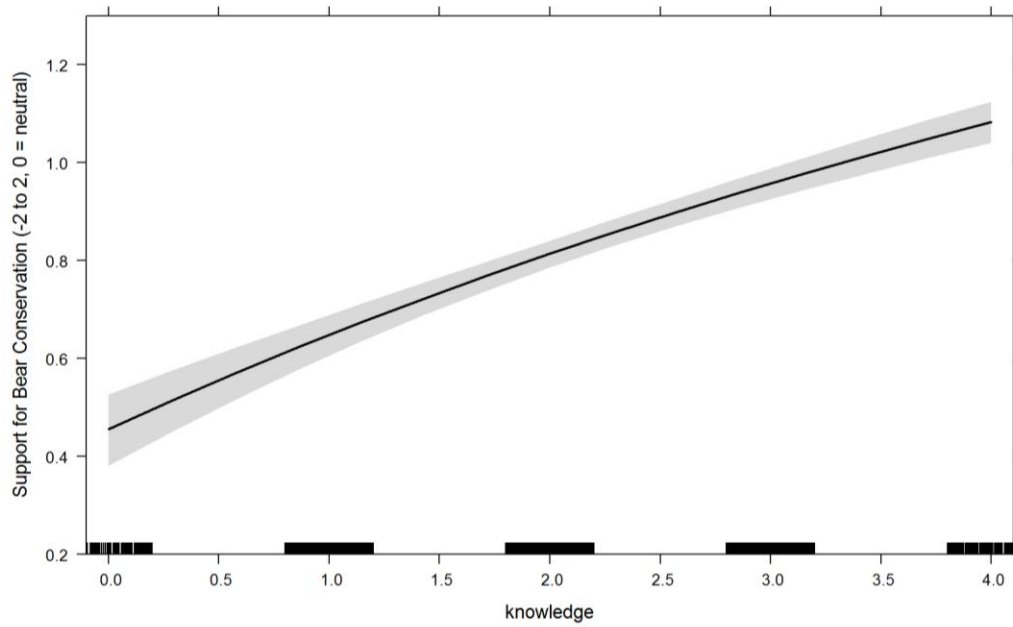
Figure 25: Effects of respondents' knowledge about bears on the Support for conservation.
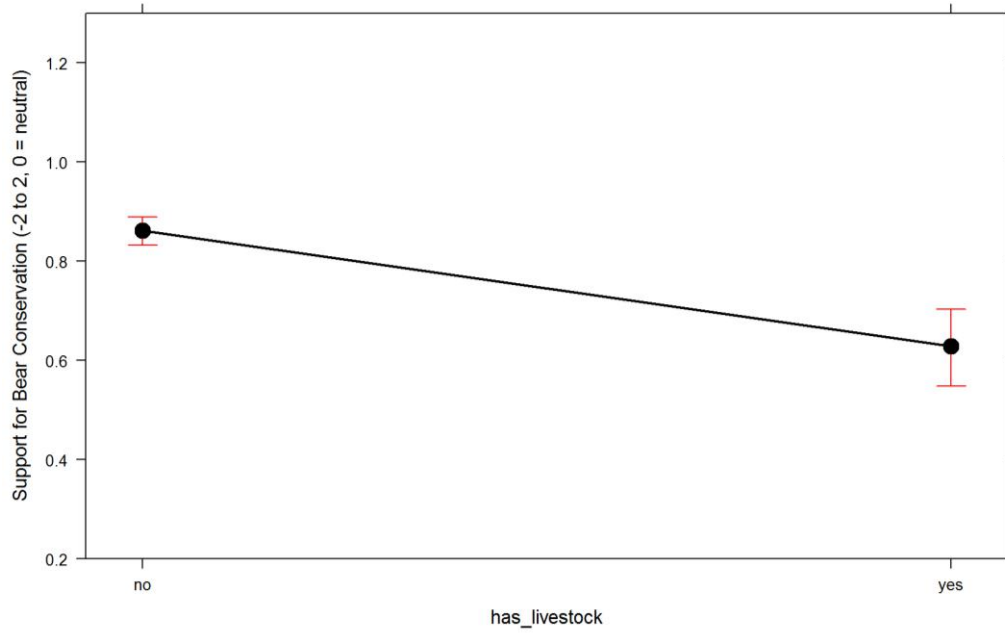
Figure 26: Effects of respondents' owning livestock on Support for conservation.
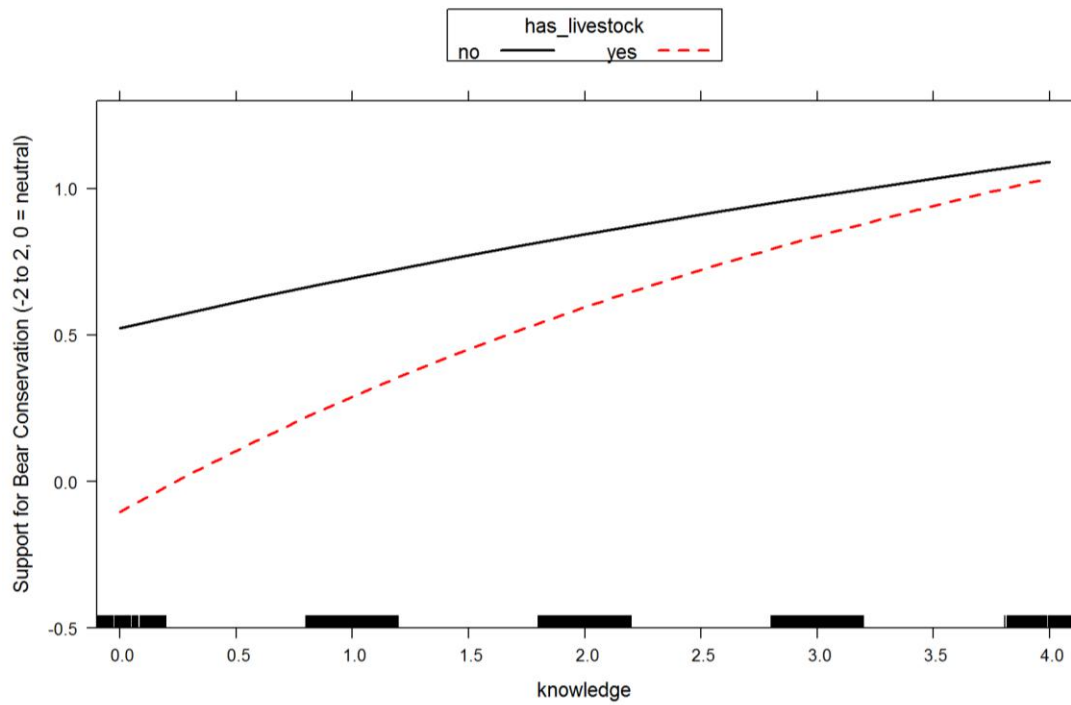
Figure 27: Combined effects of knowledge about bear biology and livestock ownership on Support for bear conservation (livestock ownership = dashed line).

Public support for lethal control of bear population

The second extracted PCA score was interpreted as "Support for lethal control of bears". It explained 59% of the variance. Raw results of the items contributing to this score are presented in: Figure 14 (with standardized loading of 0.86), Figure 15 (standardize loading of -0.80), Figure 28, Figure 29, and Figure 30. The results suggest that hunting of bears could be more or less acceptable to all studied groups except for Italian respondents which mainly disagreed with the statement. That it is necessary to shoot bears in order to control the population size was agreed to by Slovenian and Croatian respondents.
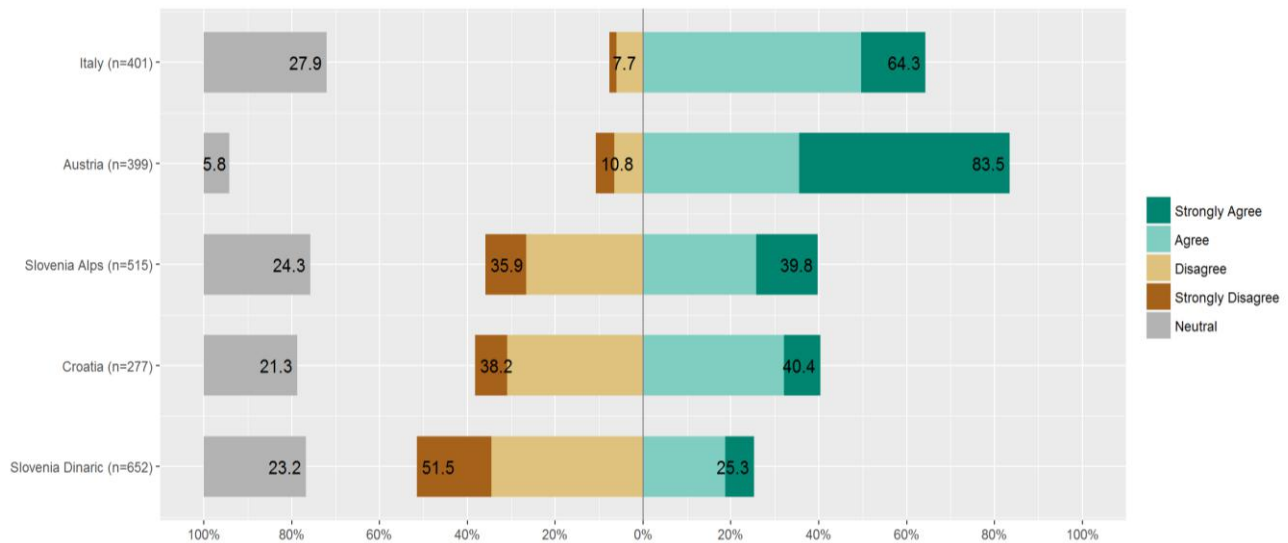
Figure 28: Results of the item "In my opinion, bear in SI/HR/IT/AT is an endangered species" This item contributed to the PCA score "support for lethal control" with a standardized loading of -0.73.
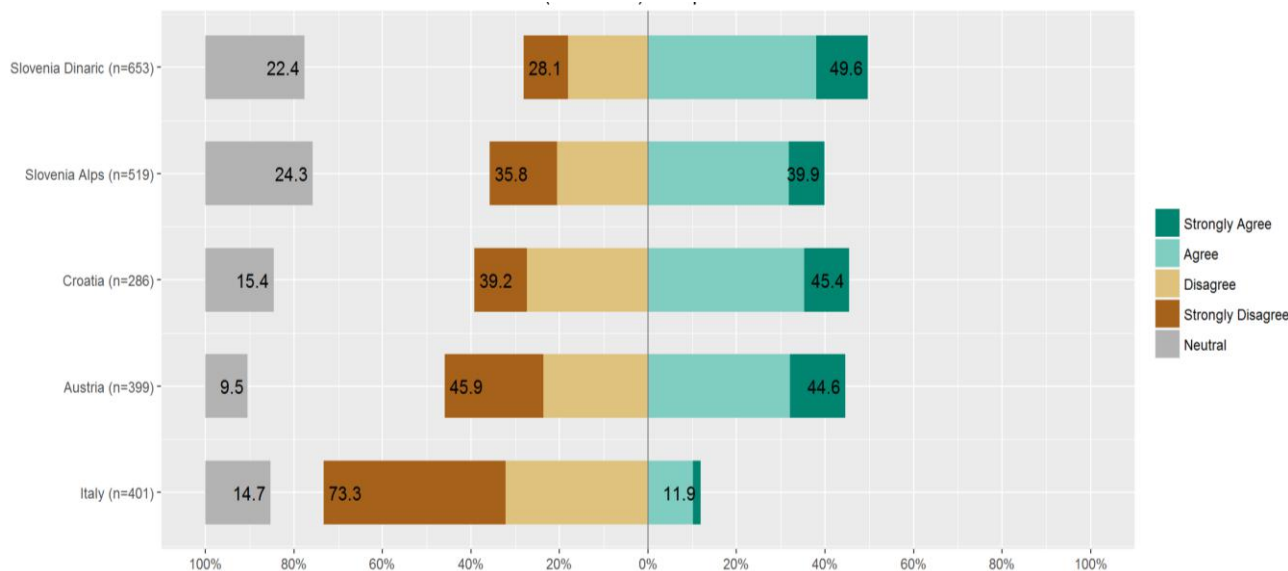
Figure 29: Results of the item "In my opinion, hunting of bears in SI/HR/IT/AT is (should be) acceptable" This item contributed to the PCA score "support for lethal control" with a standardized loading of 0.73.
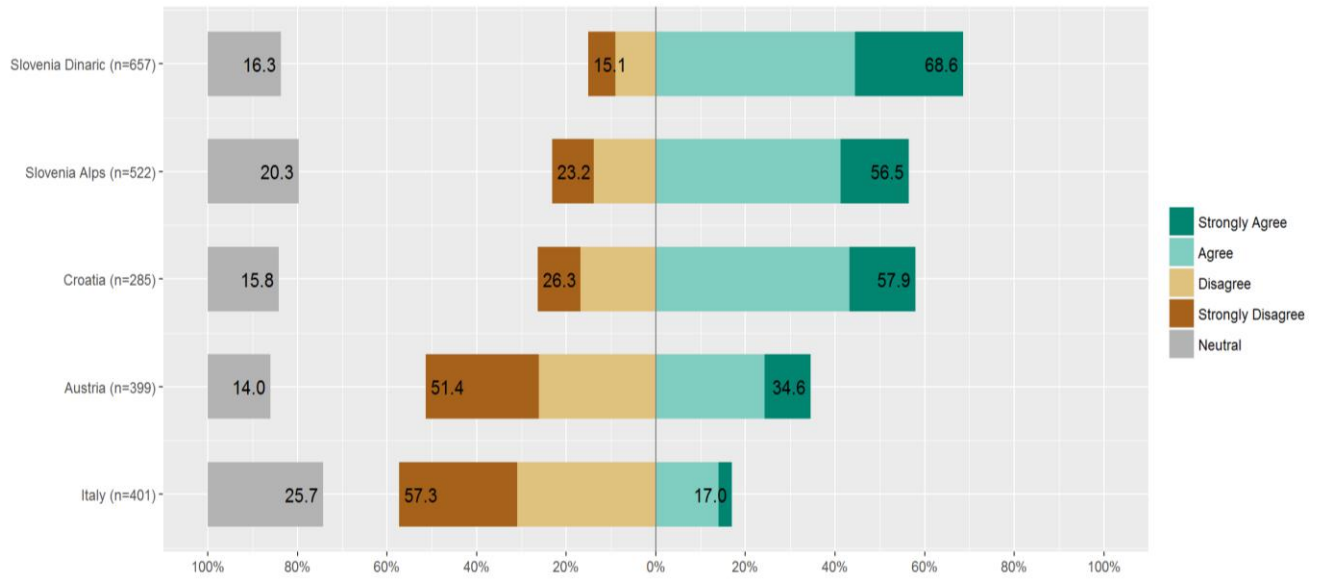
Figure 30: Results of the item "It is necessary to shoot bears in SI/HR/IT/AT in order to control the population size" This item contributed to the PCA score "support for lethal control" with a standardized loading of 0.80.
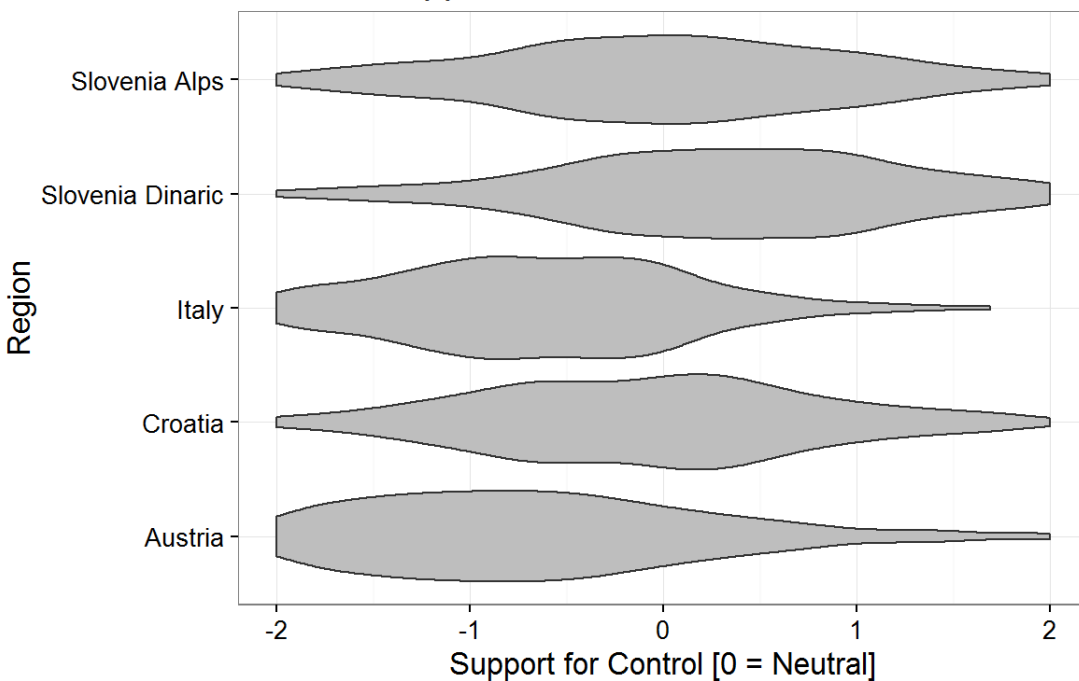
Figure 31: Distribution of the PCA score "Support for lethal control of bears".

Using the constructed model of population control support we can explore the effect of a single variable or a combination of variables while controlling for the effect of other variables. In this manner we can understand the effect of i.e. Region where the respondent lives (or any other parameter we wish to explore) without the confounding effects of other characteristics of the respondent (e.g. education, having livestock etc.)

The final model for "Support of lethal control" was structured as follows:

bear_control ~ Region + gender + age + education + knowledge + has_livestock + seennatureyesno + Region:age

According to our model, Italian and Austrian respondents do not support lethal control of bears. The Croatian respondents and those from the Alpine part of Slovenia were on average undecided, while the Slovenians from the Dinarics clearly recognized the need for lethal control of bear population size (Figure 32). The support for lethal control of bear population was shaped also by the age of the respondents, but only in Croatia and Slovenia, where older generations expressed considerably higher support for lethal control (Figure 33). Influence of gender was also documented and men were more likely to support lethal control than women (Figure 34). The same was for respondents with lower achieved formal education (Figure 35), less knowledge about bear biology (Figure 36), as well as those that own livestock (Figure 37).
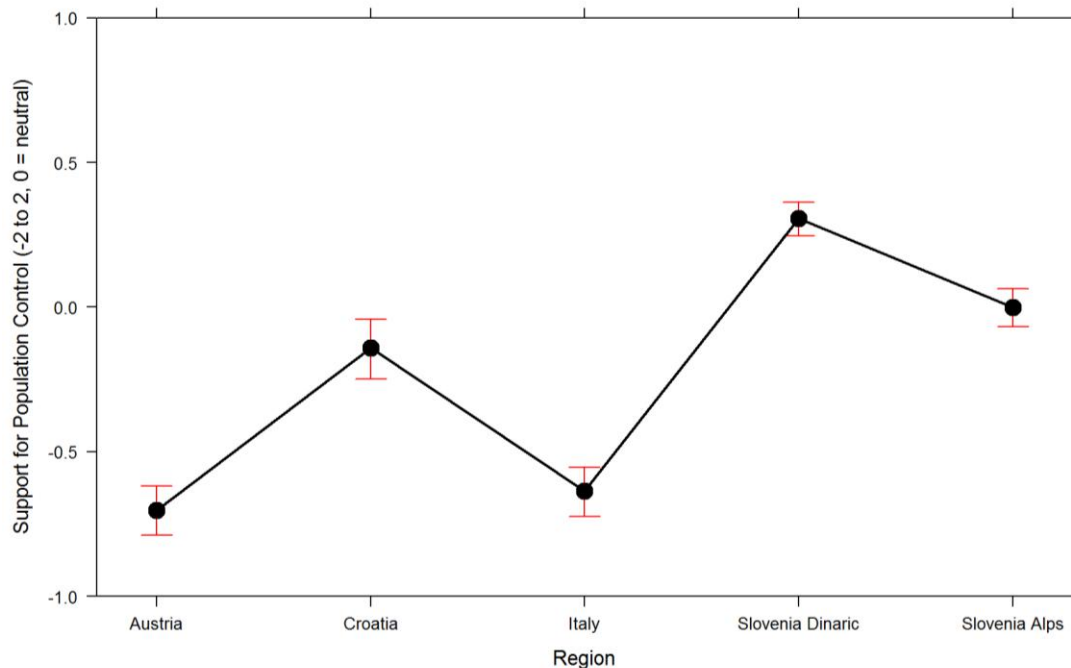
Figure 32: Effects of "region" on "Support for lethal control".
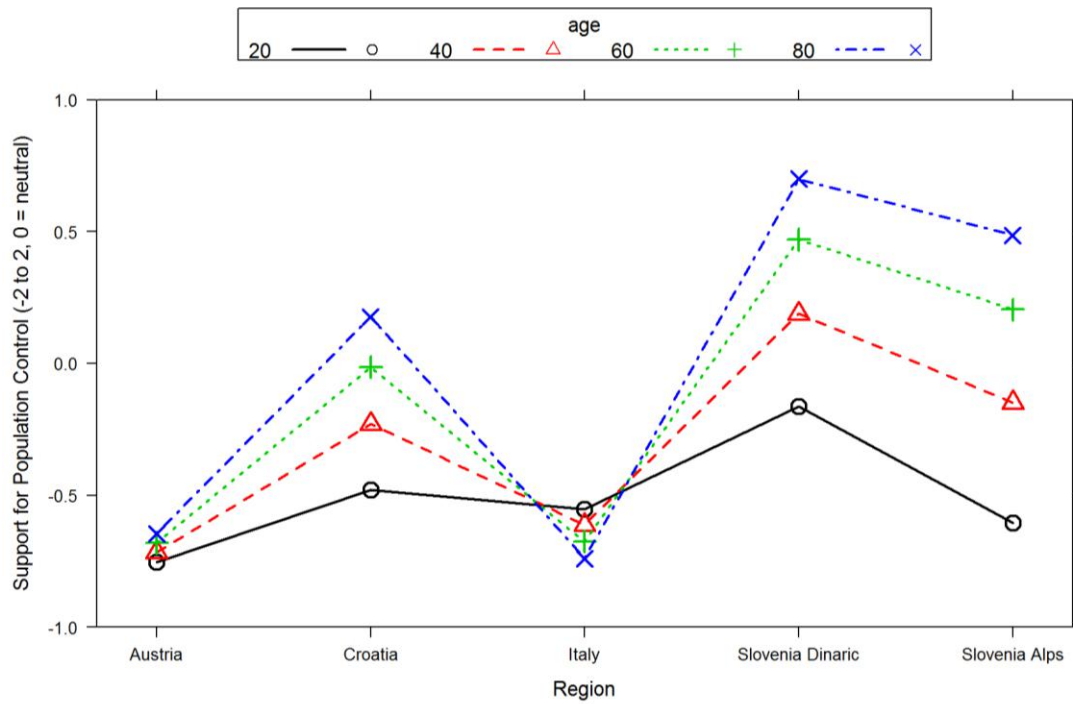
Figure 33: Combined effects of age and region on the Support for lethal population control.
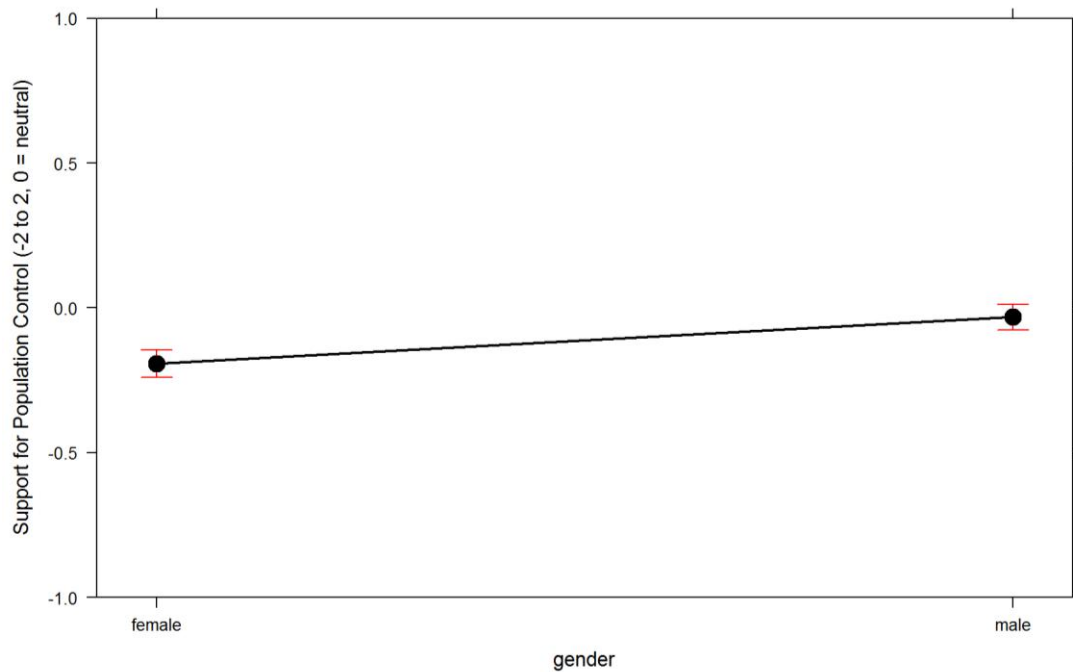
Figure 34: Effects of gender on the Support for lethal population control.
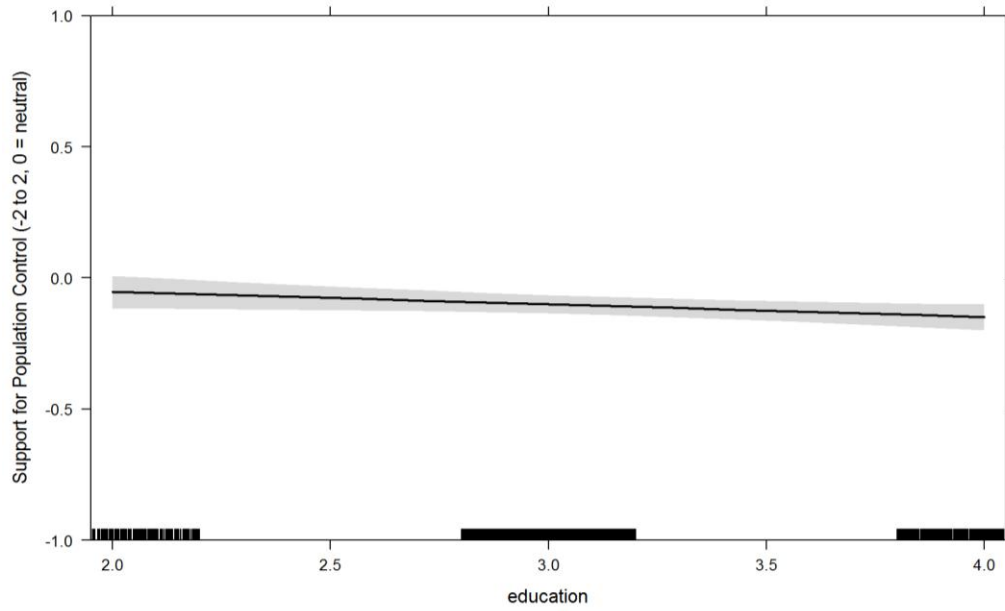
Figure 35: Effects of education on Support for lethal control.
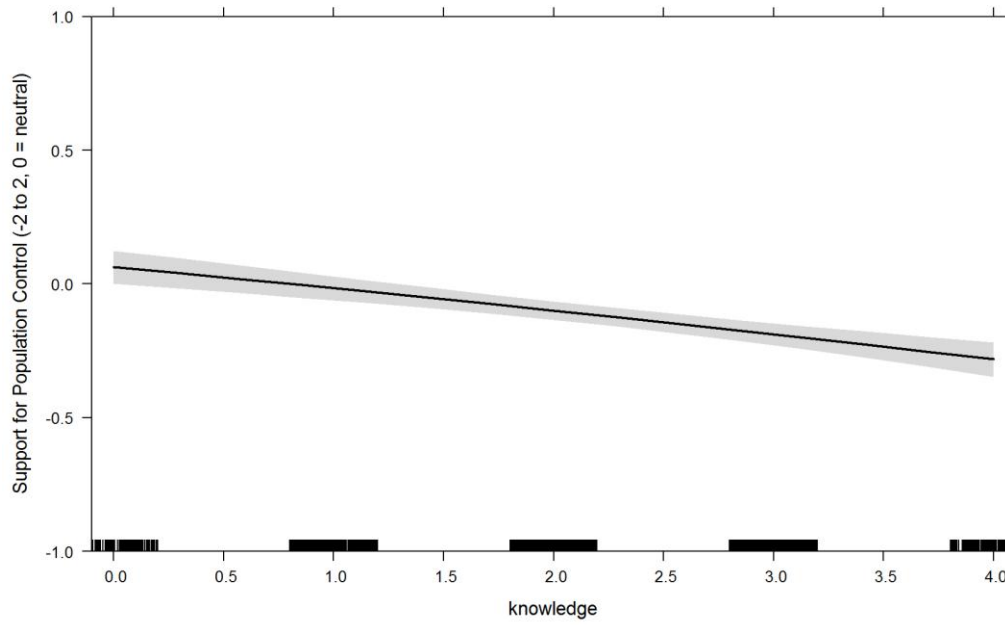
Figure 36: Effects of knowledge about bear biology on Support for lethal control.
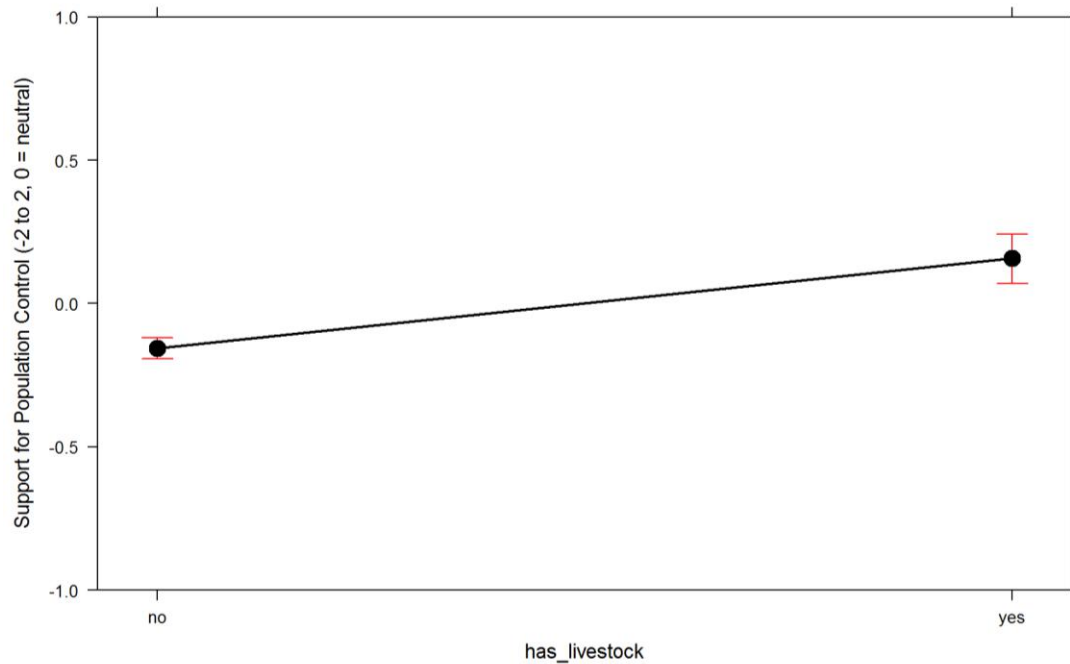
Figure 37: Effect of livestock ownership to Support for lethal control.

Value of bears

The third extracted PCA score was interpreted and labelled as "Value of bears" (Figure 40). Proportion of explained variance was 58%. This component describes the benefits of having bears, but it is important to note that question related to bears increasing value of a hunting ground and question related to consuming bear meat, did not load to this component, thus the score describes the benefits related to the non-consumptive use of bears.

Among the main items to contribute to this component were some that were already presented above:

- Figure 16: "Which answer best describes your feelings about bears?. This item contributed to the PCA score "value of bears" with a standardized loading of 0.82.
- Figure 17: "Having bears in SI/HR/IT/AT is…". This item contributed to the PCA score "value of bears" with a standardized loading of 0.85.
- Figure 18: "It is important to have bear population in SI/HR/IT/AT for the future generations". This item contributed to the PCA score "value of bears" with a standardized loading of 0.80.
- Figure 15: " I would agree with increasing bear numbers in SI/HR/IT/AT". This item contributed to the PCA score "value of bears" with a standardized loading of 0.70.

Other contributing items were related to assessing the potential of organized bear watching (Figure 38) and assessing the effects of bear presence to local economy (Figure 39).
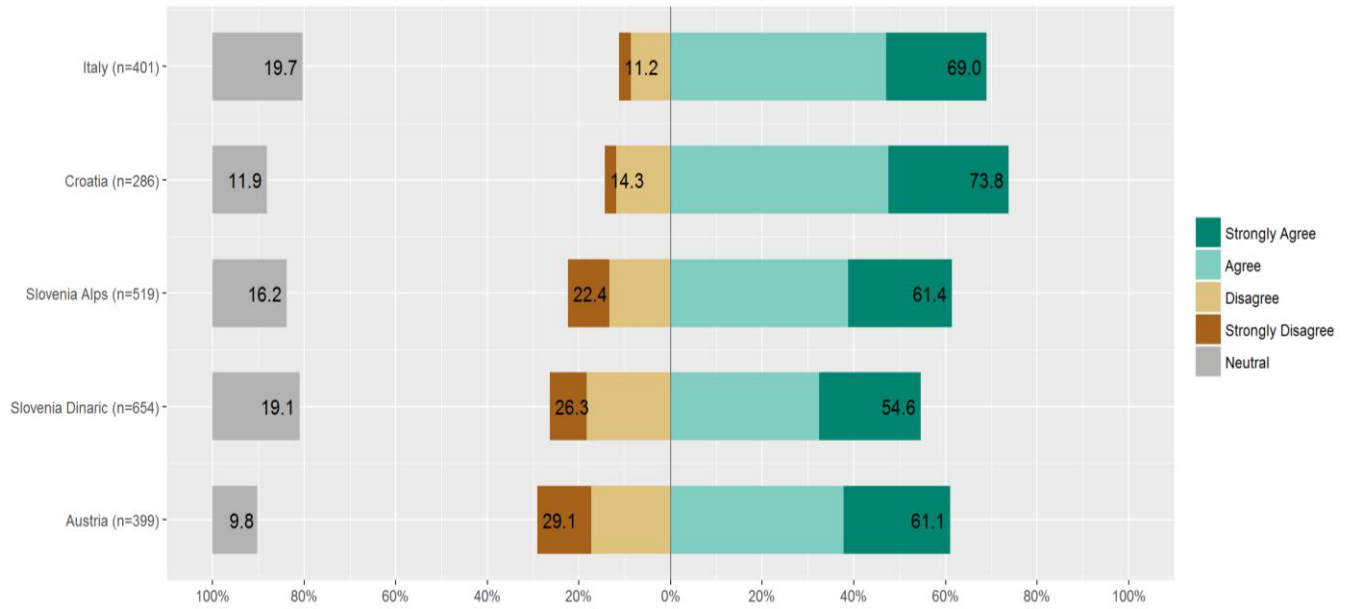
Figure 38: Results of the item "Bear watching could be an important part of touristic offer in my area" This item contributed to the PCA score "value of bears" with a standardized loading of 0.64.

Presence of bears can have an overall positive
impact on local economy.
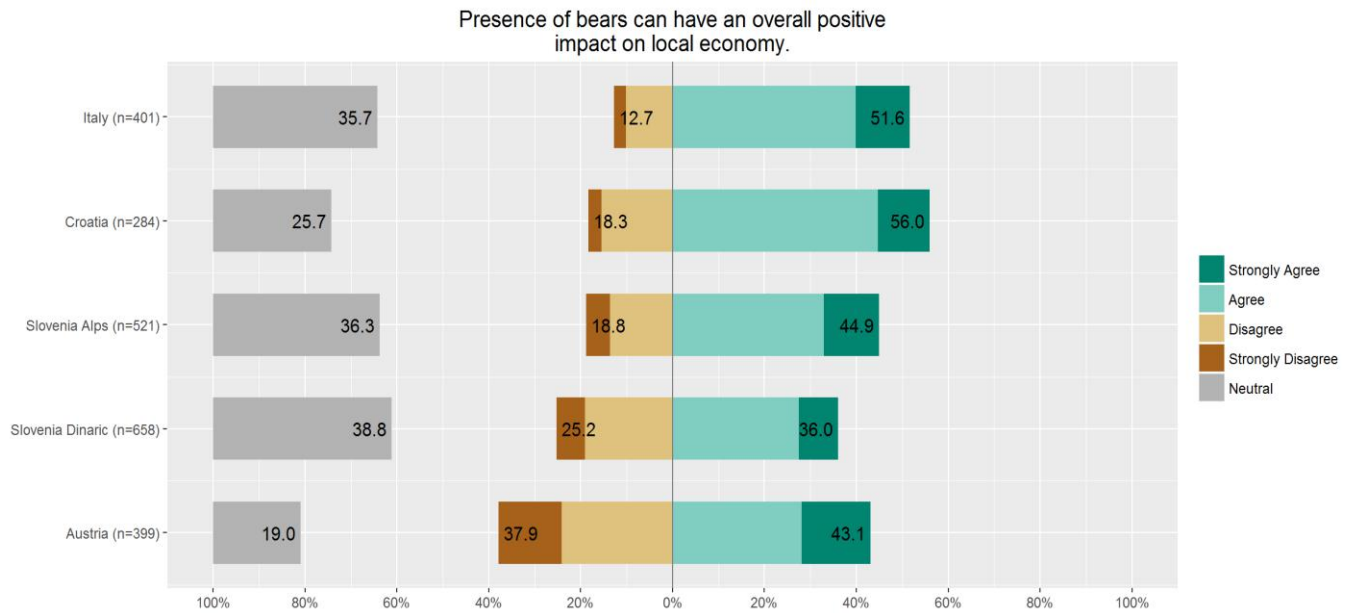
Figure 39: Results of the item "Presence of bears can have an overall positive impact on local economy" This item contributed to the PCA score "value of bears" with a standardized loading of 0.75.
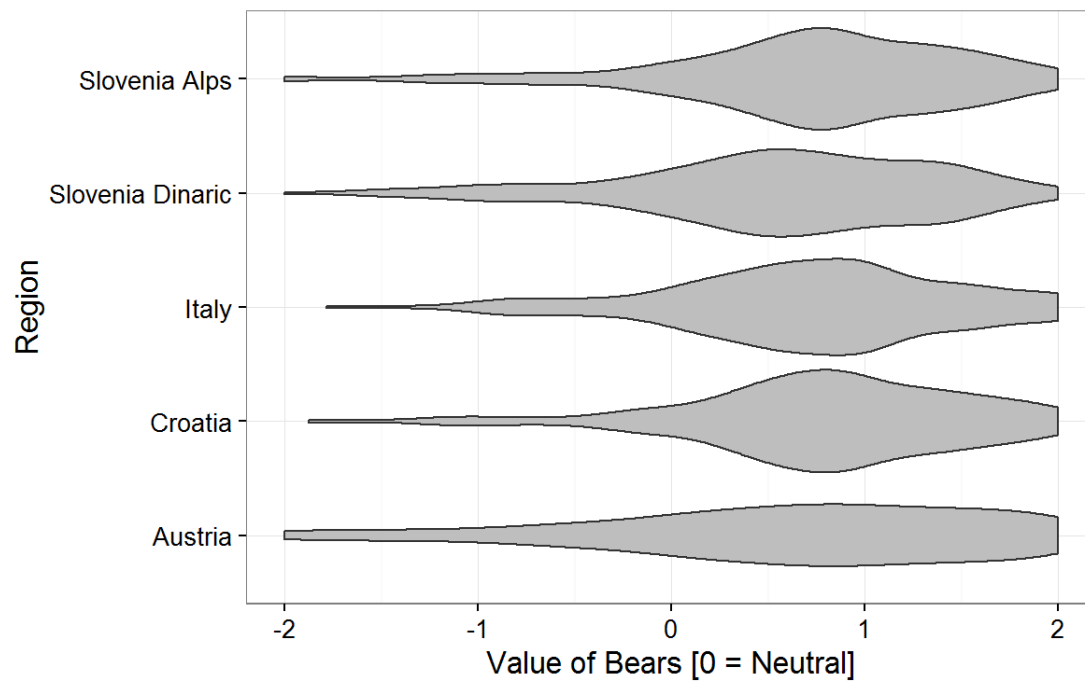
Figure 40: Distribution of the PCA score "Value of bears".

The final model for Value of bears had this structure: bear value ~ Region + age + education + knowledge +   has_livestock + knowledge:has_livestock

According to our model, in all regions respondent perceived bears as beneficial for the local communities (Figure 41). This was somewhat lower, but still positive, only among the respondents from the Dinaric part of Slovenia. Among other factors contributing to this component, knowledge of bear biology had the weightiest effect (Figure 44) also when combined with livestock ownership (Figure 46). Younger (Figure 42) and better educated (Figure 43) respondents tend to perceive bears as beneficial for local communities more than the older ones
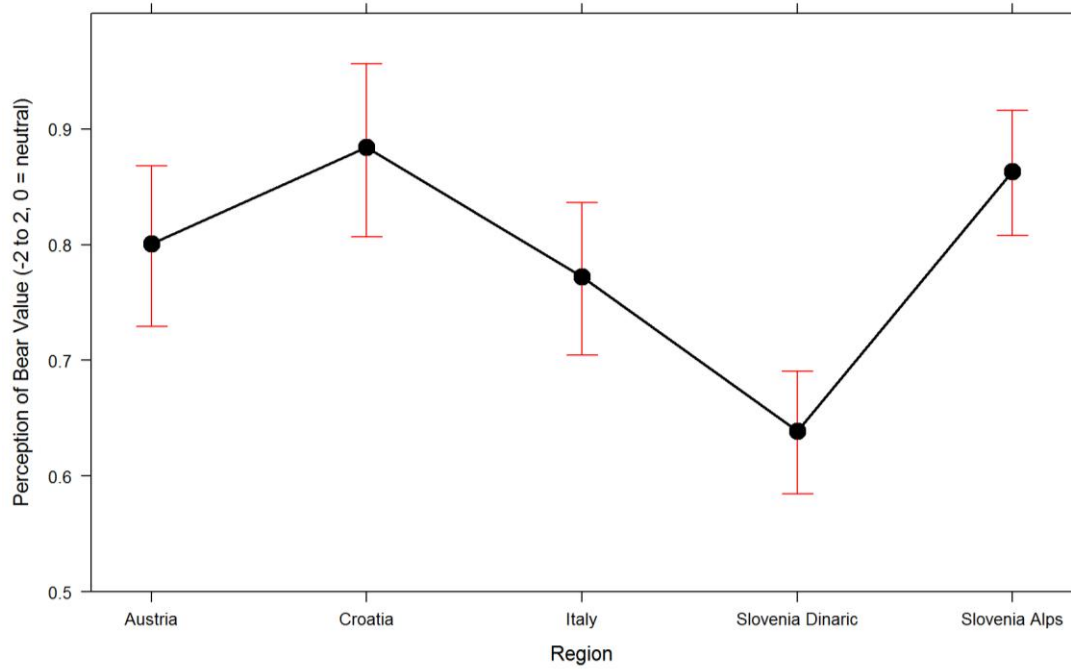
Figure 41: Effects of region on perception of bear value.
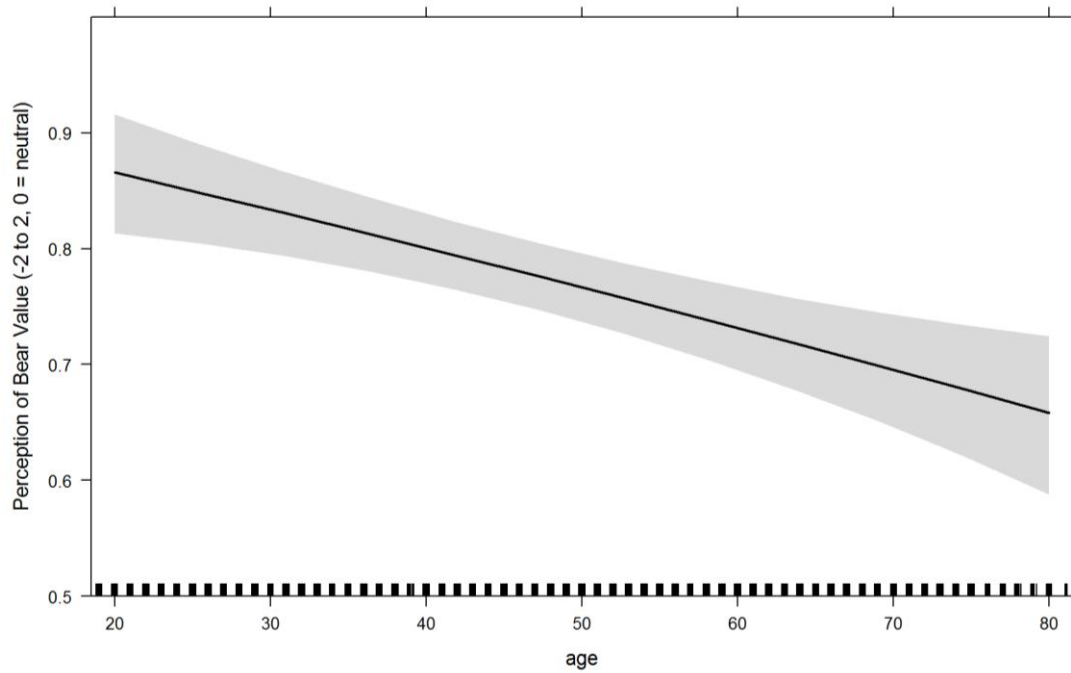
Figure 42: Effects of respondents' age on perception of bear value.
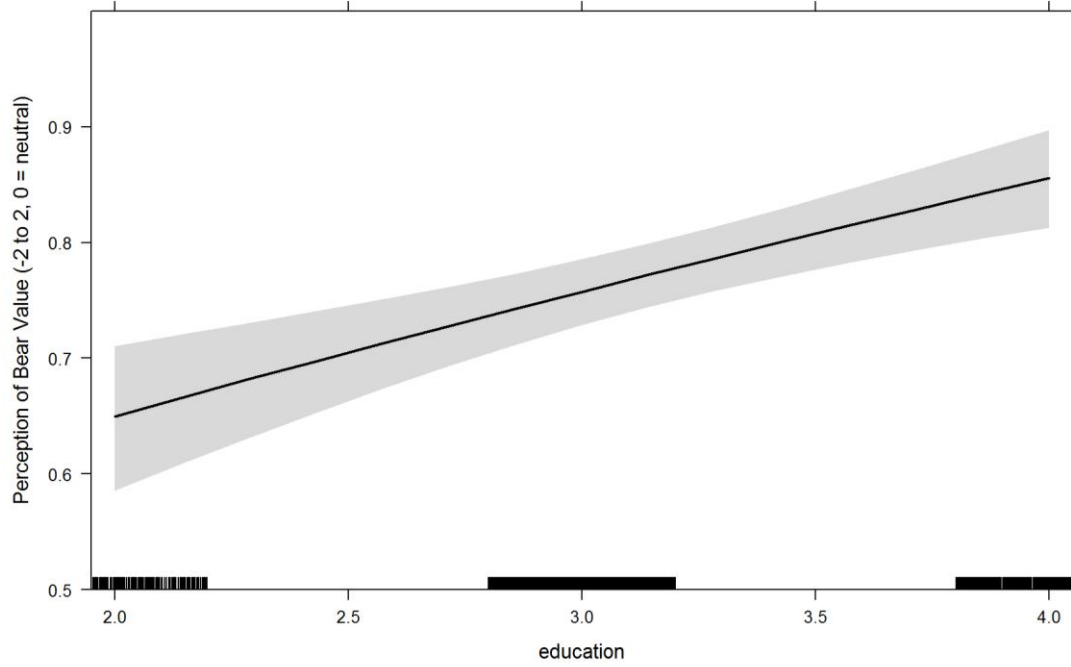
Figure 43: Effects of education on perception of bear value.
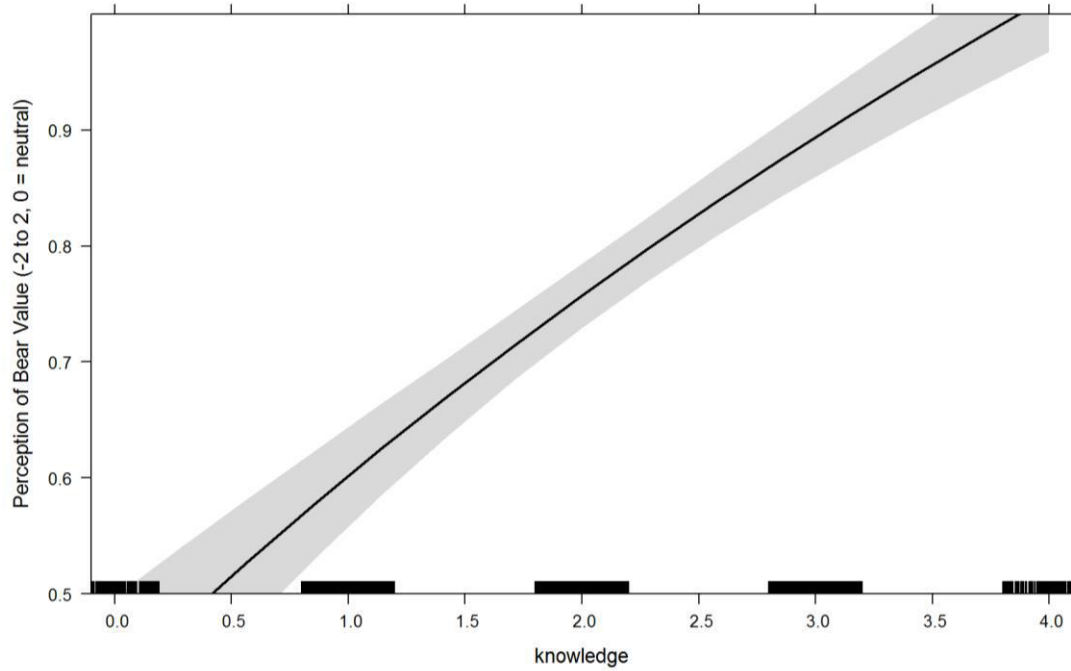
Figure 44: Effects of knowledge of bear biology on perception of value of bears.
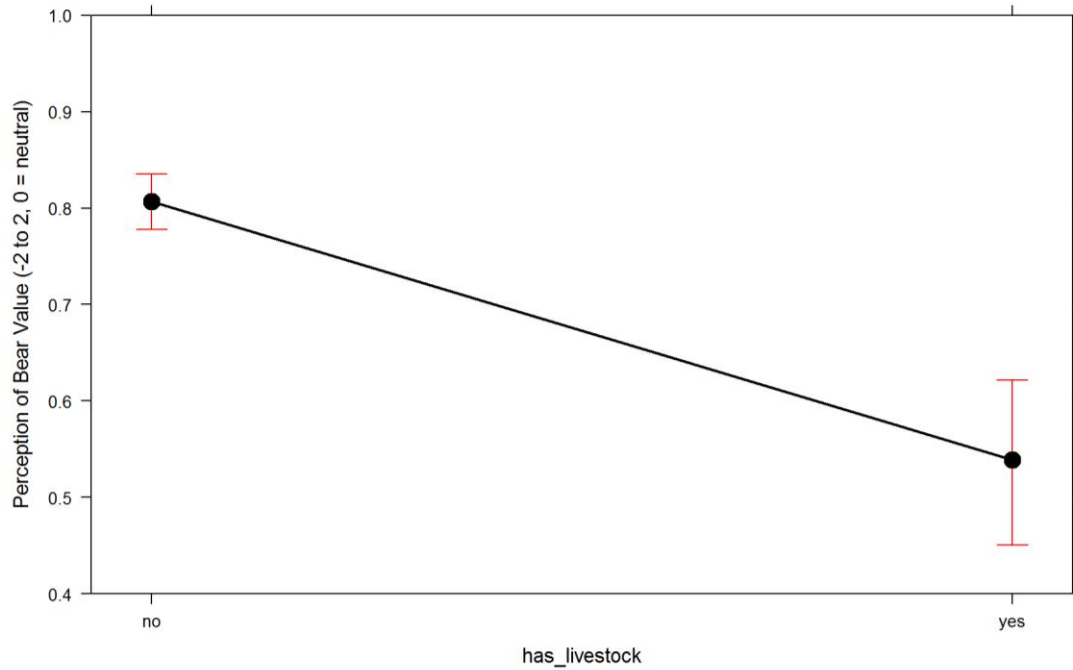
Figure 45: Effects of having livestock on perception of value of bears.
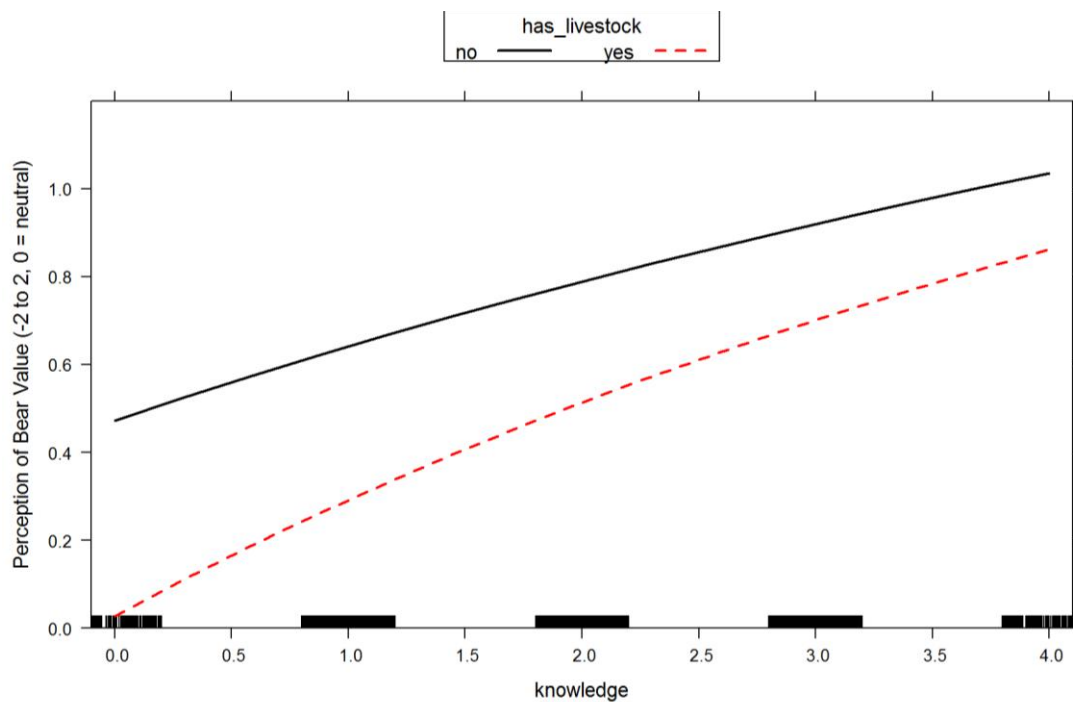
Figure 46: Combined effects of knowledge about bear biology and livestock ownership on perception of value of bears.

Perceptions about human-bear conflicts

Eight items were designed in the questionnaire with a purpose to explore respondents' perceptions about human bear conflict. The respondents were asked to assess how problematic (if at all) different situations with bears were for them personally. The scale ranges from "very problematic" to "I like the idea". The raw results for these items are presented in the Figure 47 to Figure 55. To varying degrees all of the presented situations were found problematic by our respondents. PCA analysis has not identified any significant structure, so one PCA score was extracted (Table 2) and interpreted as "tolerance of bear conflicts" (Figure 56).
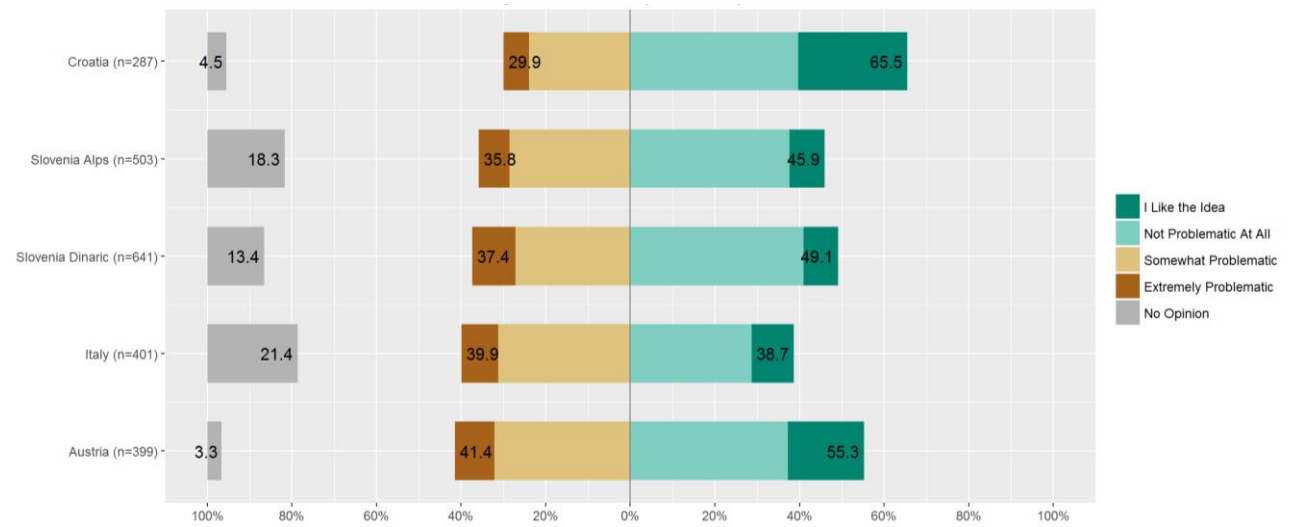
Figure 47: Results for the item "How problematic is for you knowing that bears are present in your area?".
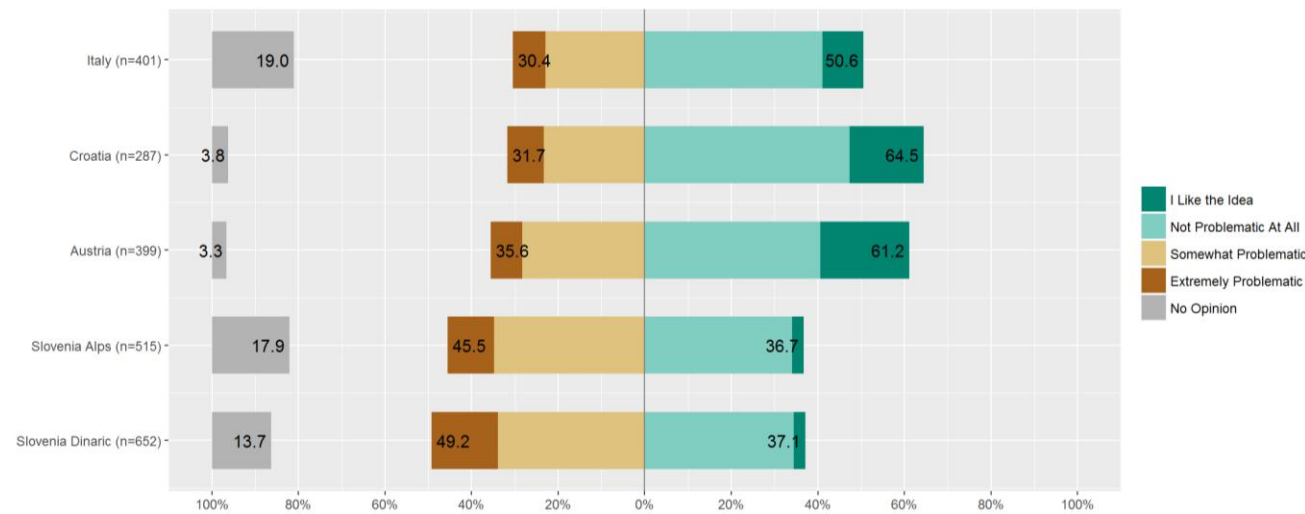
Figure 48: Results for the item "How problematic is for you seeing signs of bear presence (footprints, excrements…) in the nearby woods?".
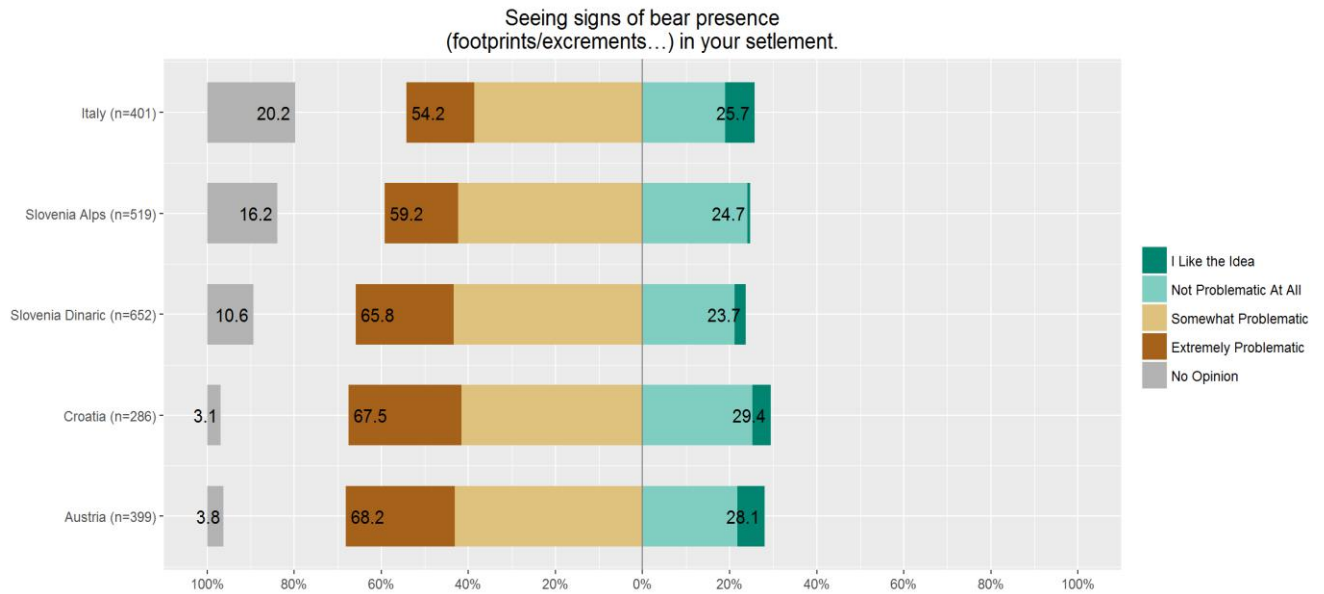
Figure 49: Results for the item "How problematic is for you seeing signs of bear presence (footprints, excrements…) in your settlement?".
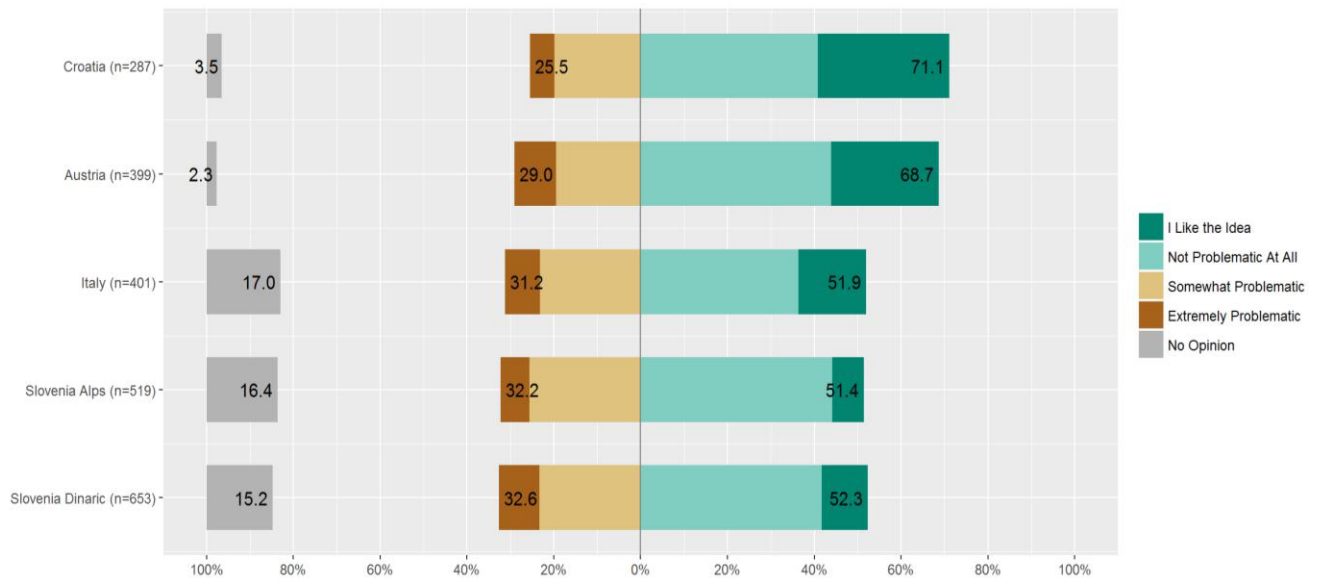
Figure 50: Results for the item "How problematic is for you seeing a bear from a car?".
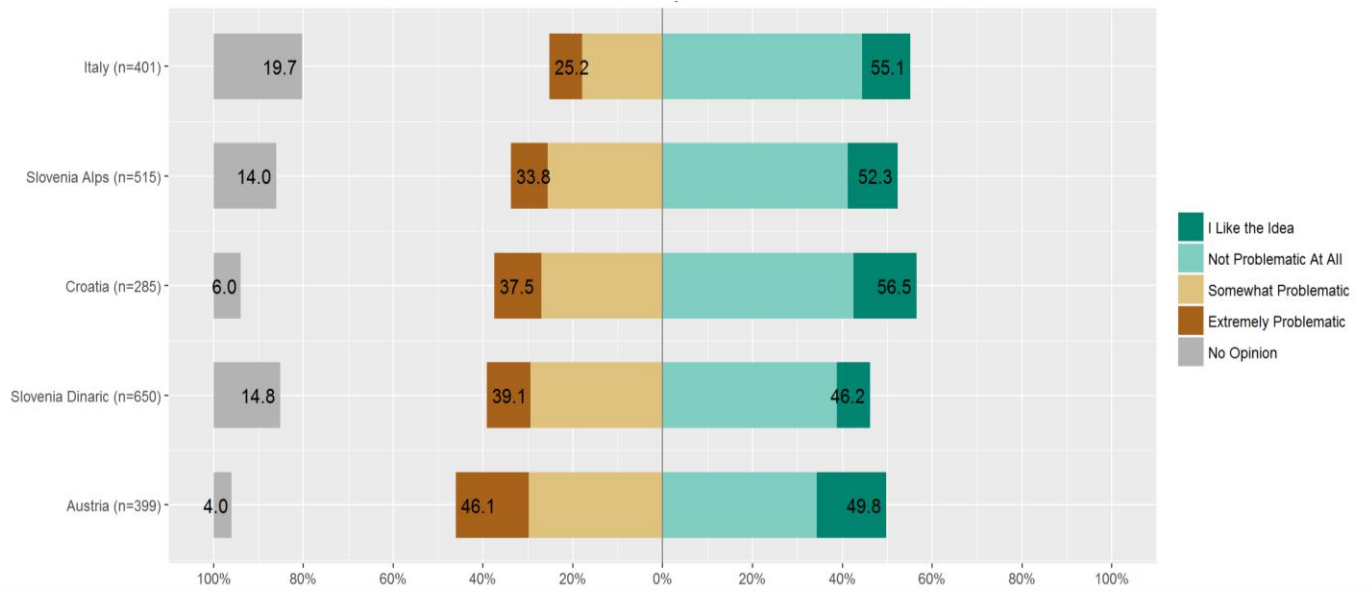
Figure 51: Results for the item "How problematic is for you encountering a bear in the woods when a bear runs away.
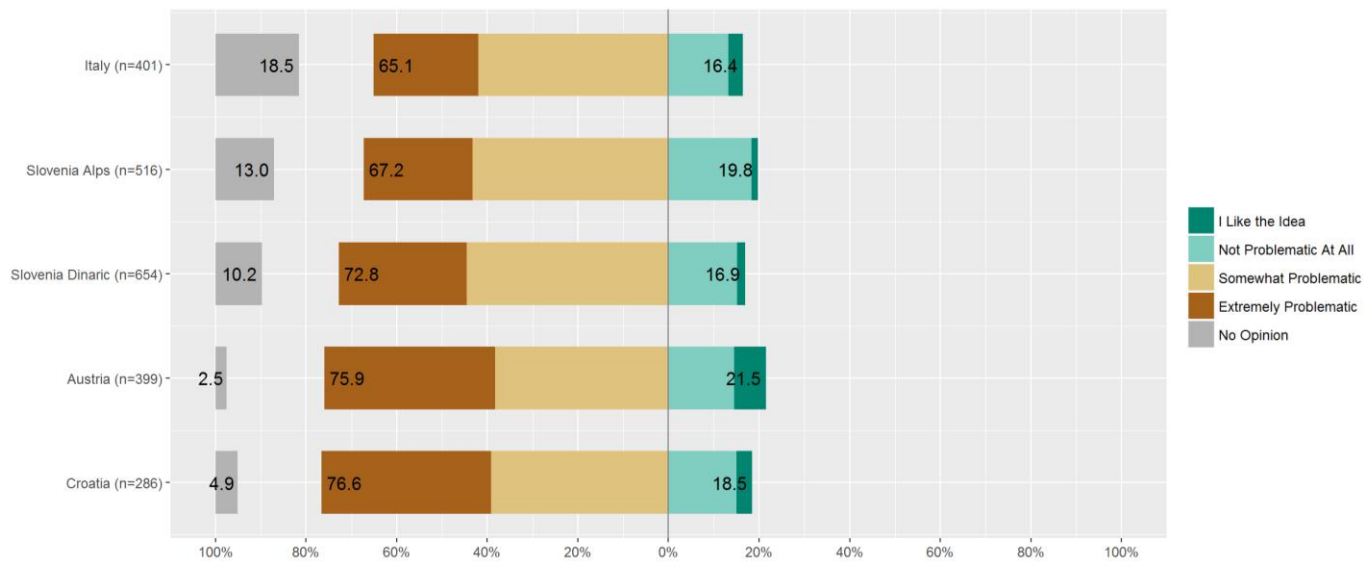
Figure 52: Results for the item "How problematic is for you encountering a bear near your house.
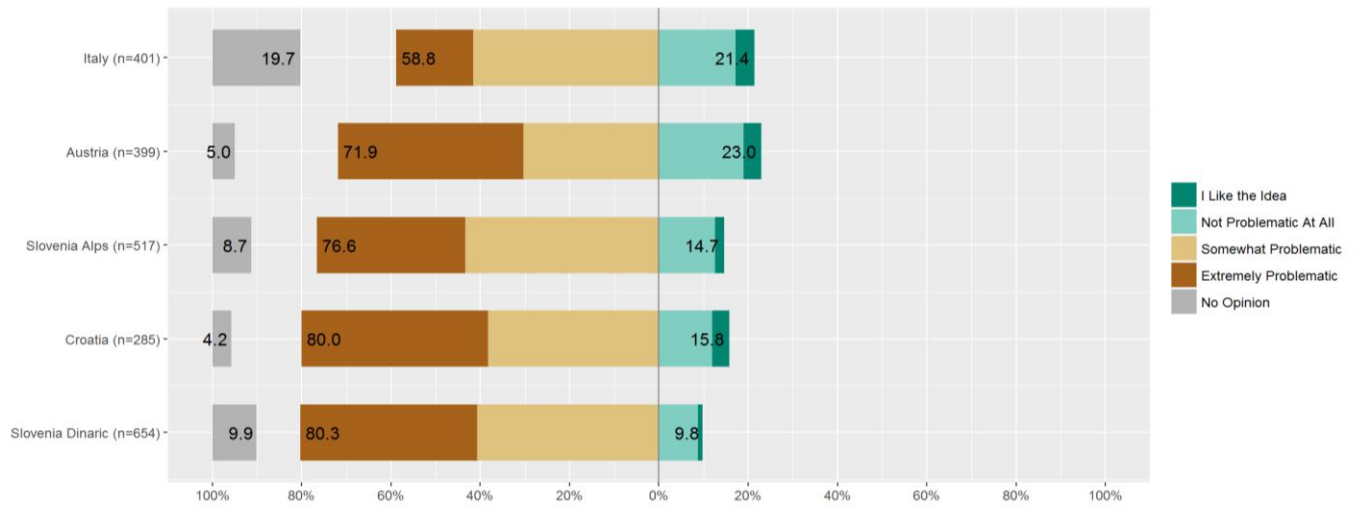
Figure 53: Results for the item "How problematic is for you experiencing a bear feeding in your garden or orchard.
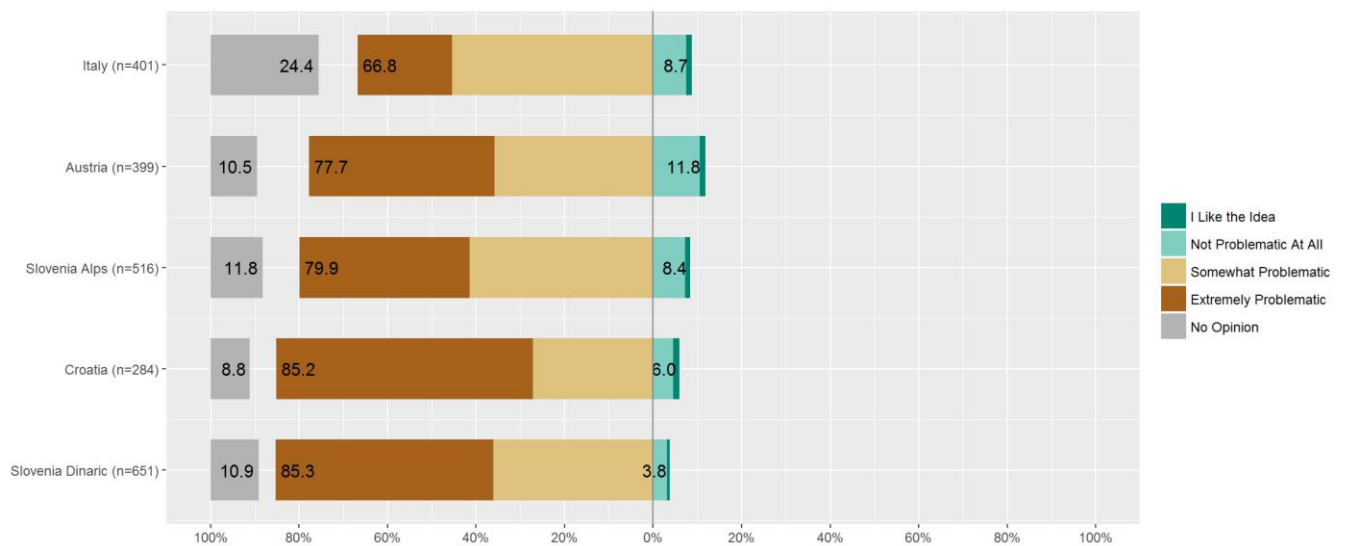
Figure 54: Results for the item "How problematic is for you experiencing a bear feeding on your beehives.
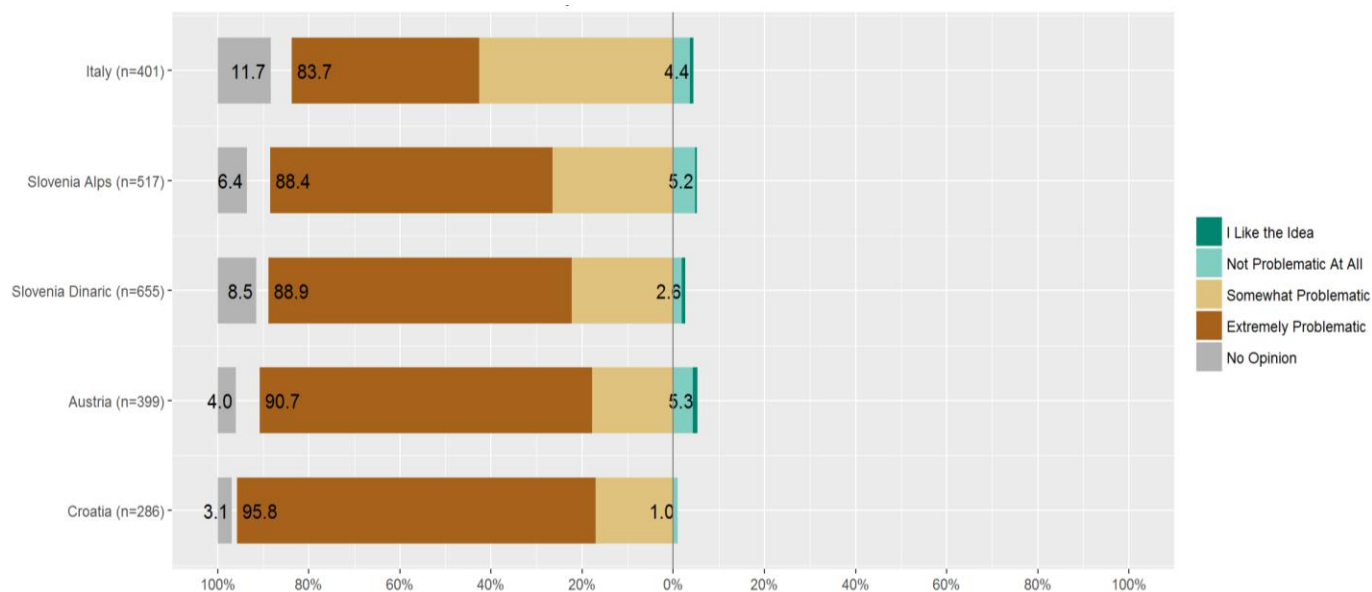
Figure 55: Results for the item "How problematic is for you experiencing a bear attacking and feeding on your domestic animals."

Table 2: Standardized PCA loadings of the items for the PCA score "Tolerance of bear conflicts".

How problematic is for you…	Standardized PCA loading
… knowing that bears are present in your area	0.73
…seeing signs of bear presence (footprints, excrements…) in the nearby woods	0.77
… seeing signs of bear presence (footprints, excrements…) in your settlement	0.82
… seeing a bear from a car	0.68
… encountering a bear in the woods when a bear runs away.	0.70
… encountering a bear near your house.	0.84
… experiencing a bear feeding in your garden or orchard.	0.81
… experiencing a bear feeding on your beehives.	0.67
…experiencing a bear attacking and feeding on your domestic animals	0.58
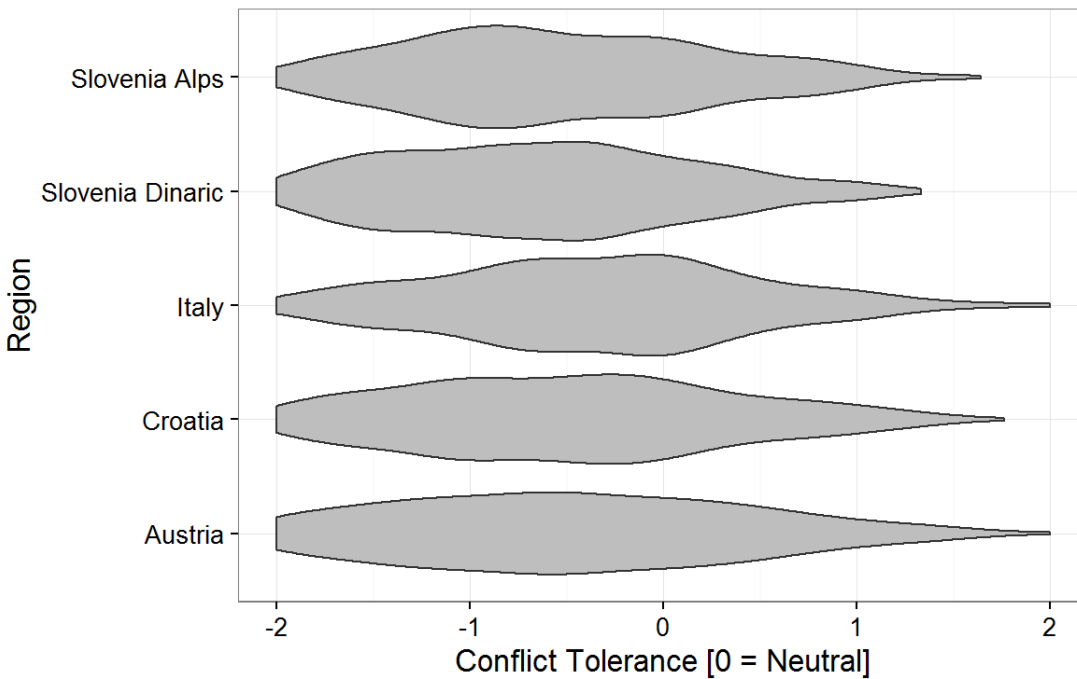
Figure 56: Distribution of "tolerance of conflicts" score.

The final model for "conflict tolerance" was structured as follows: ~georegion + gender + age + knowledge + dogowner + georegion:gender

According to our model, Italians can tolerate the most conflict situations although all groups loaded negative on the "conflict tolerance" score (Figure 57). Younger generations, males, dog owners and knowledgeable about bear biology were more tolerant of conflicts with bears (Figure 58, Figure 59, Figure 60, Figure 61).
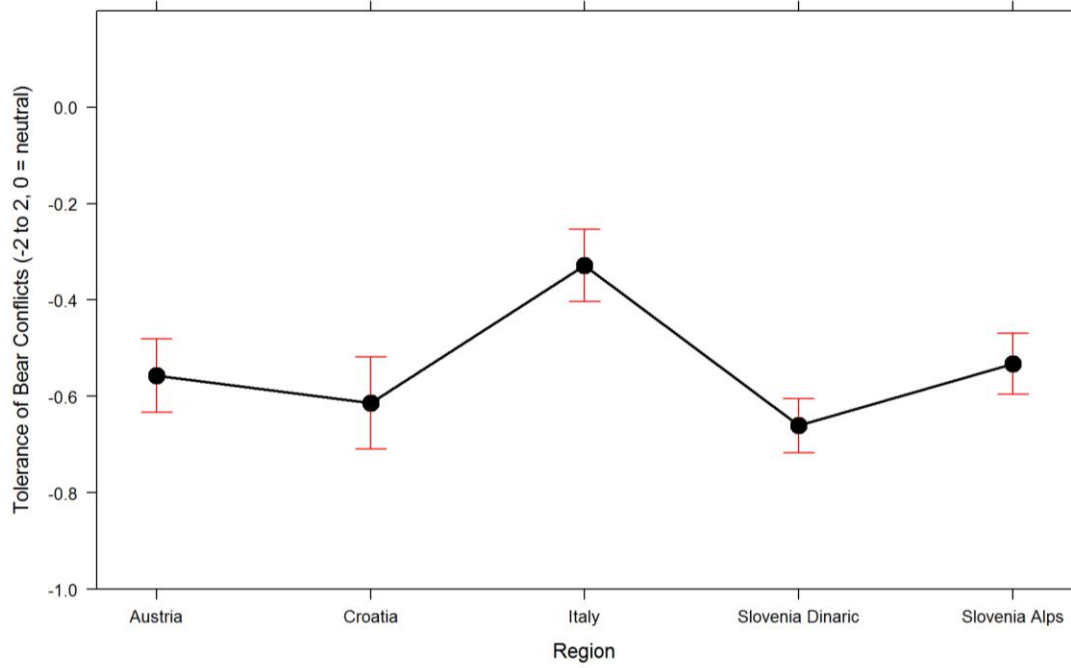
Figure 57: Effects of region on "bear conflict tolerance".
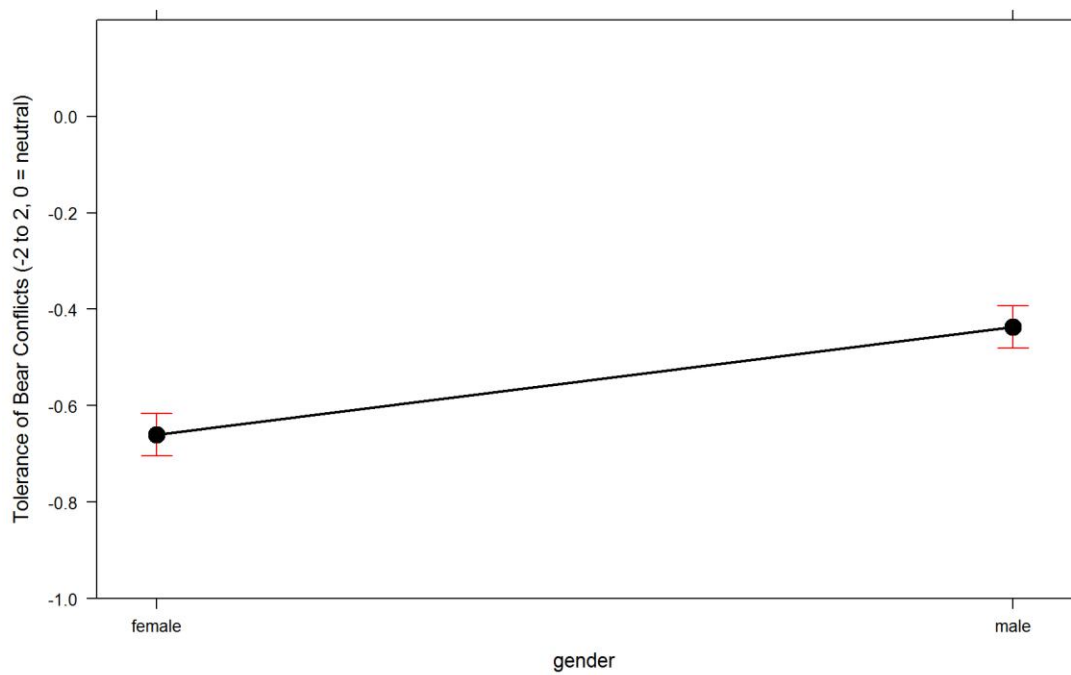
Figure 58: Effects of gender on "bear conflict tolerance".
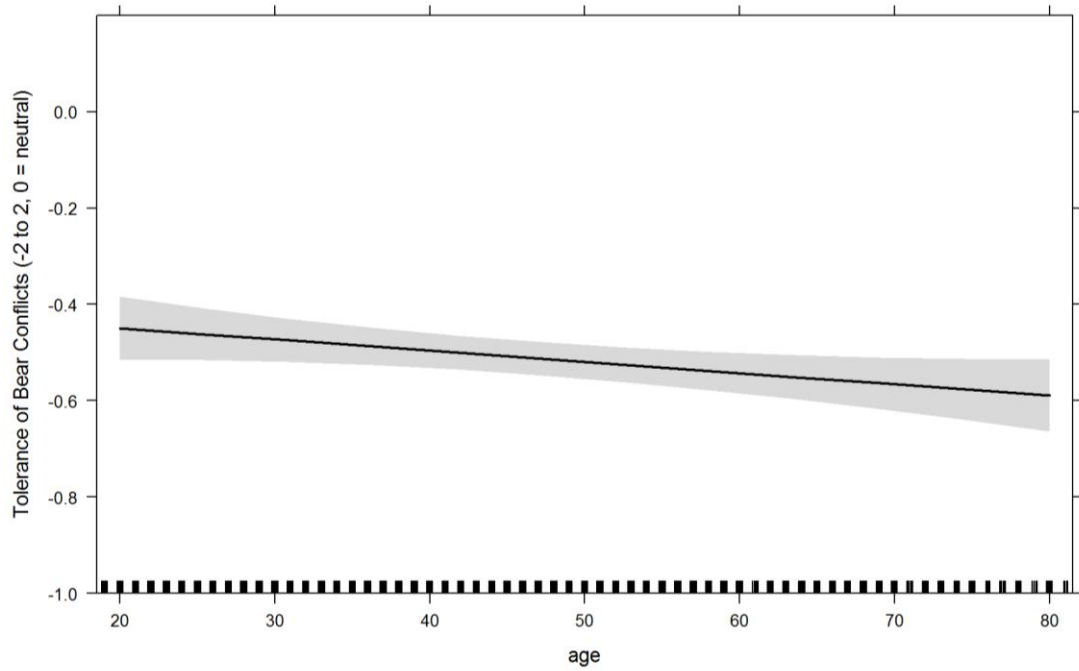
Figure 59: Effects of age of the respondents on "bear conflict tolerance".
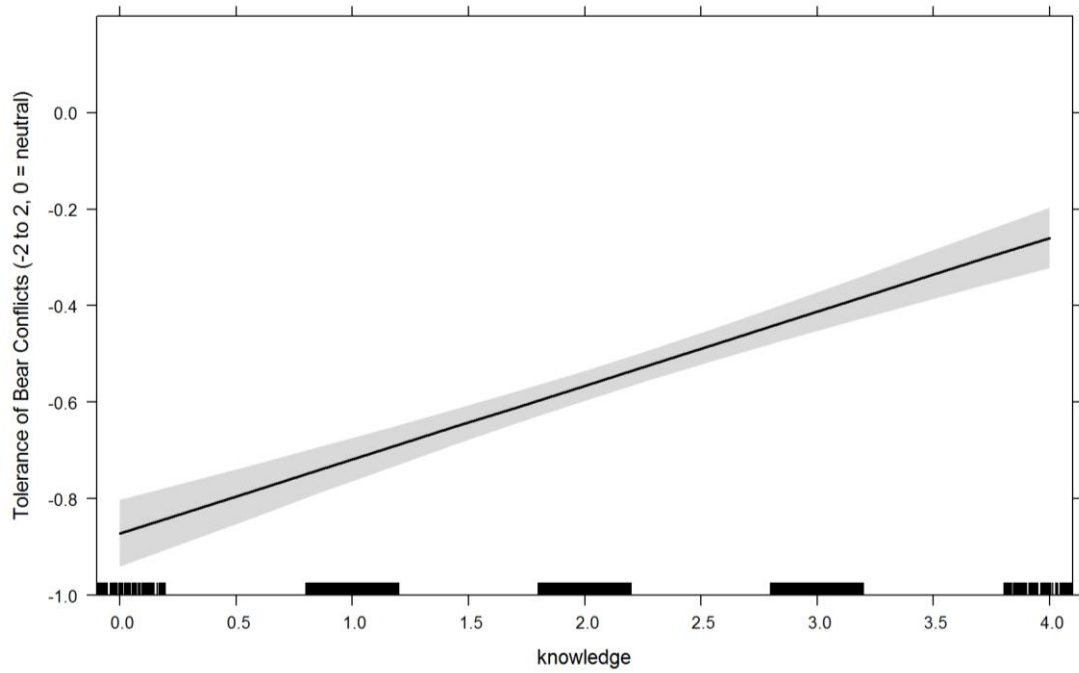
Figure 60: Effects of knowledge of bear biology on "bear conflict tolerance".
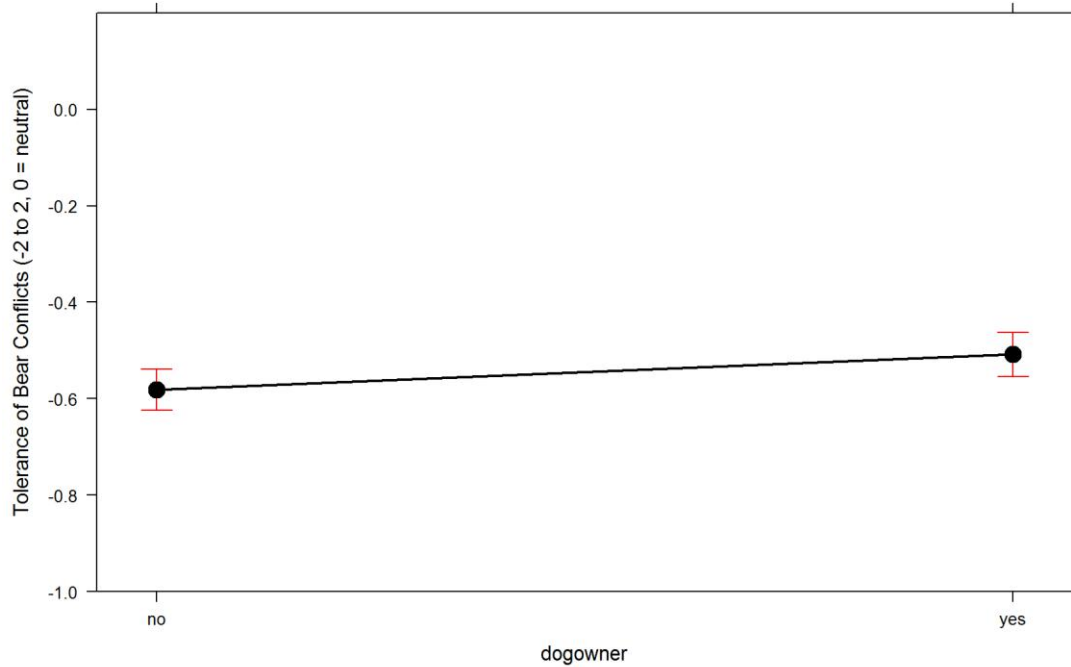
Figure 61: Effects of owning a dog on "bear conflict tolerance".

Beliefs about solutions to human-bear conflicts

Nine items were designed in the questionnaire with a purpose to investigate respondents' perceptions about the effectiveness of possible solutions to human-bear conflicts. The respondents were asked to assess how (if) effective different solutions to bear conflict were according to their personal opinion. The scale ranged from "measure is actually increasing the problem" to "very effective". Raw data for the nine items are presented in Figure 62 to Figure 70.
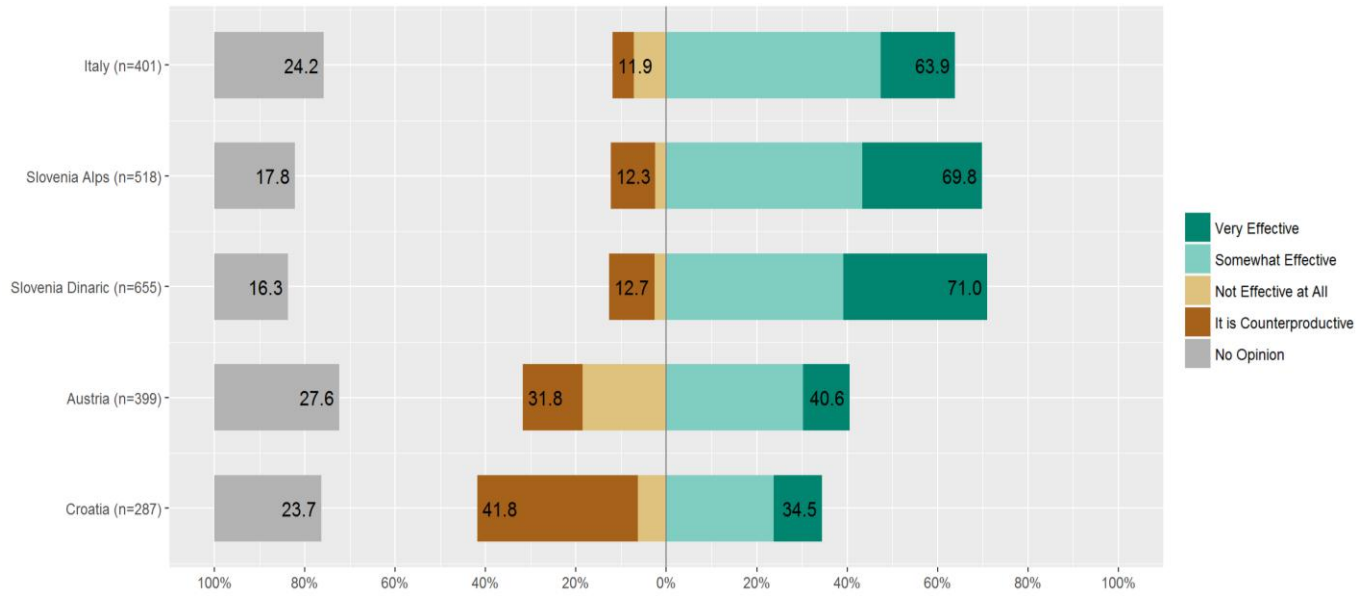
Figure 62: Results for the item "How effective in mitigating human-bear conflicts is providing protein food sources (carcasses) for bears in the forest".
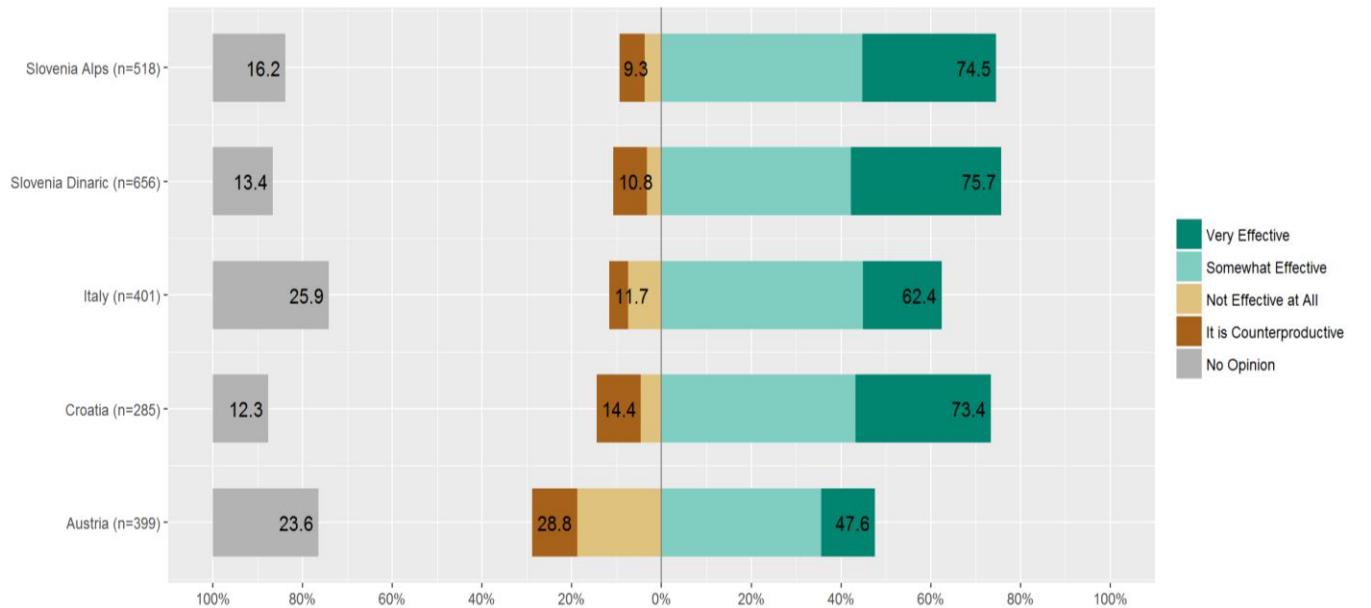
Figure 63: Results for the item "How effective in mitigating human-bear conflicts is providing corn and other food of plant origin for bears in the forest".
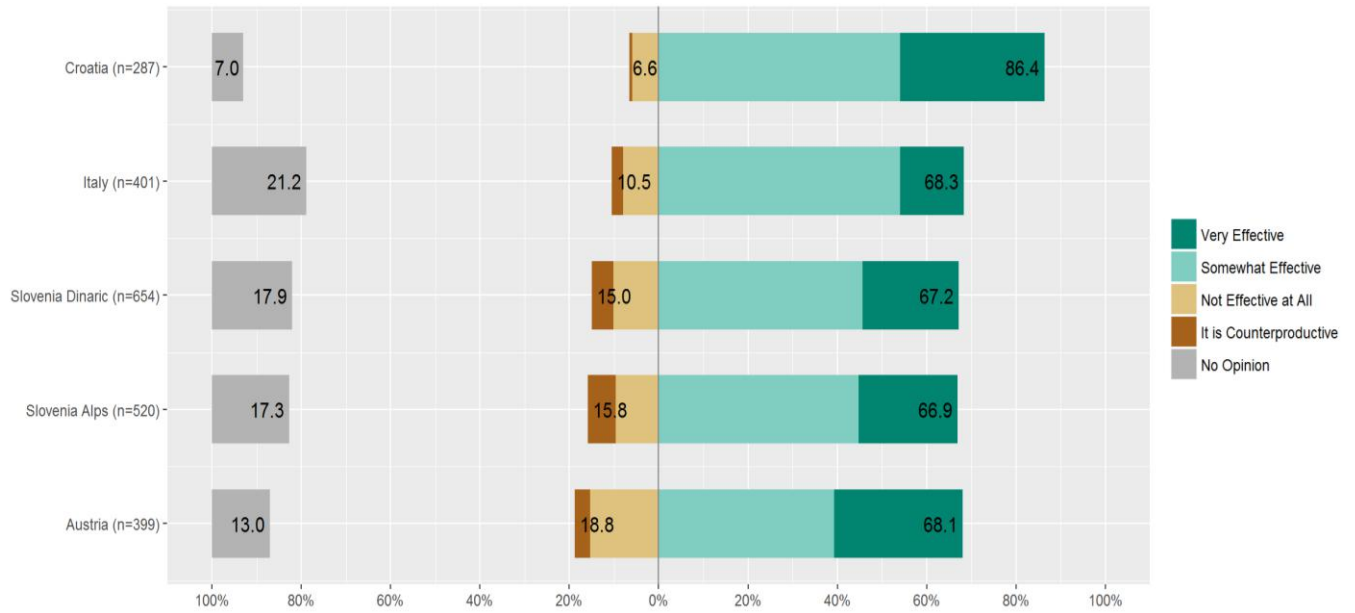
Figure 64: Results for the item "How effective in mitigating human-bear conflicts is introducing livestock guarding dogs to the flocks of grazing livestock."
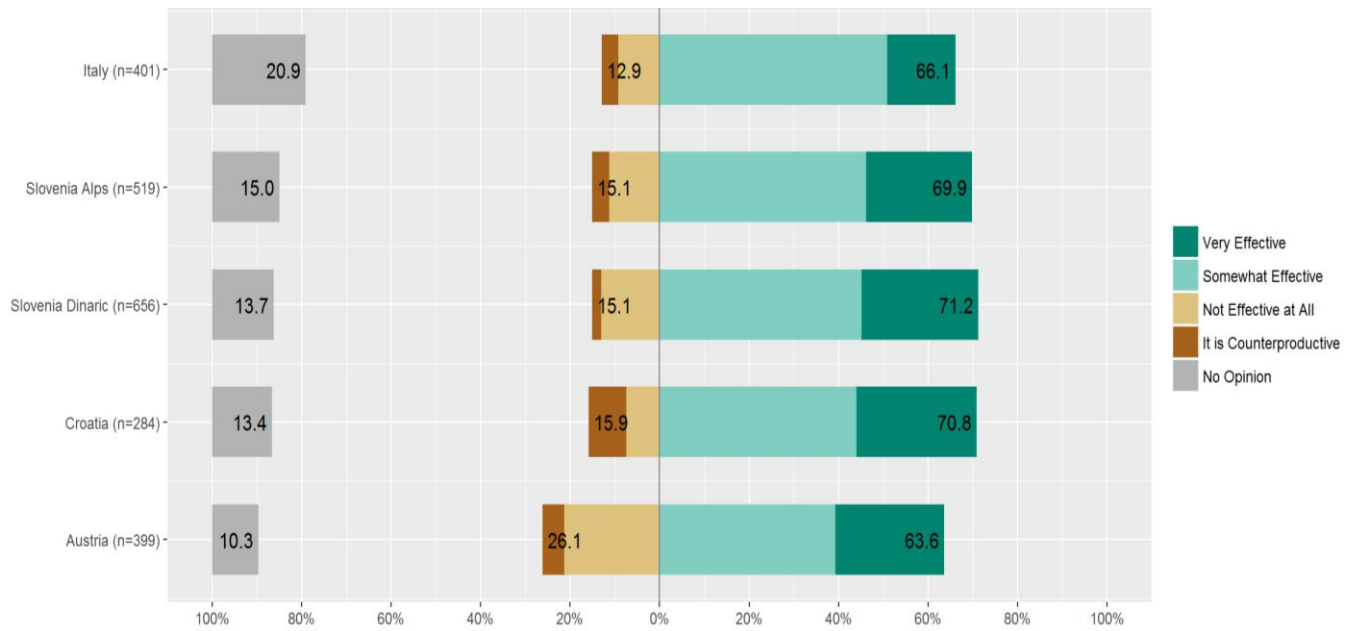
Figure 65: Results for the item "How effective in mitigating human-bear conflicts is use of electric fences or nets to prevent damages in agriculture."
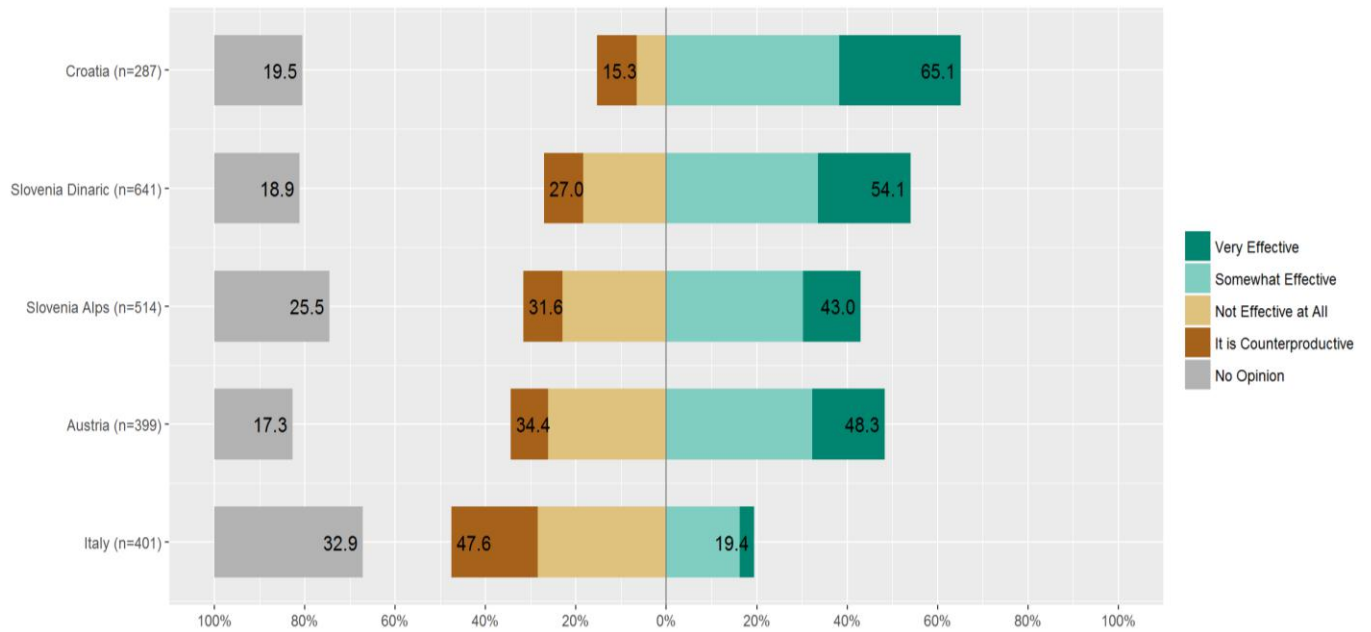
Figure 66: Results for the item "How effective in mitigating human-bear conflicts is a regular quota for hunting of bears."
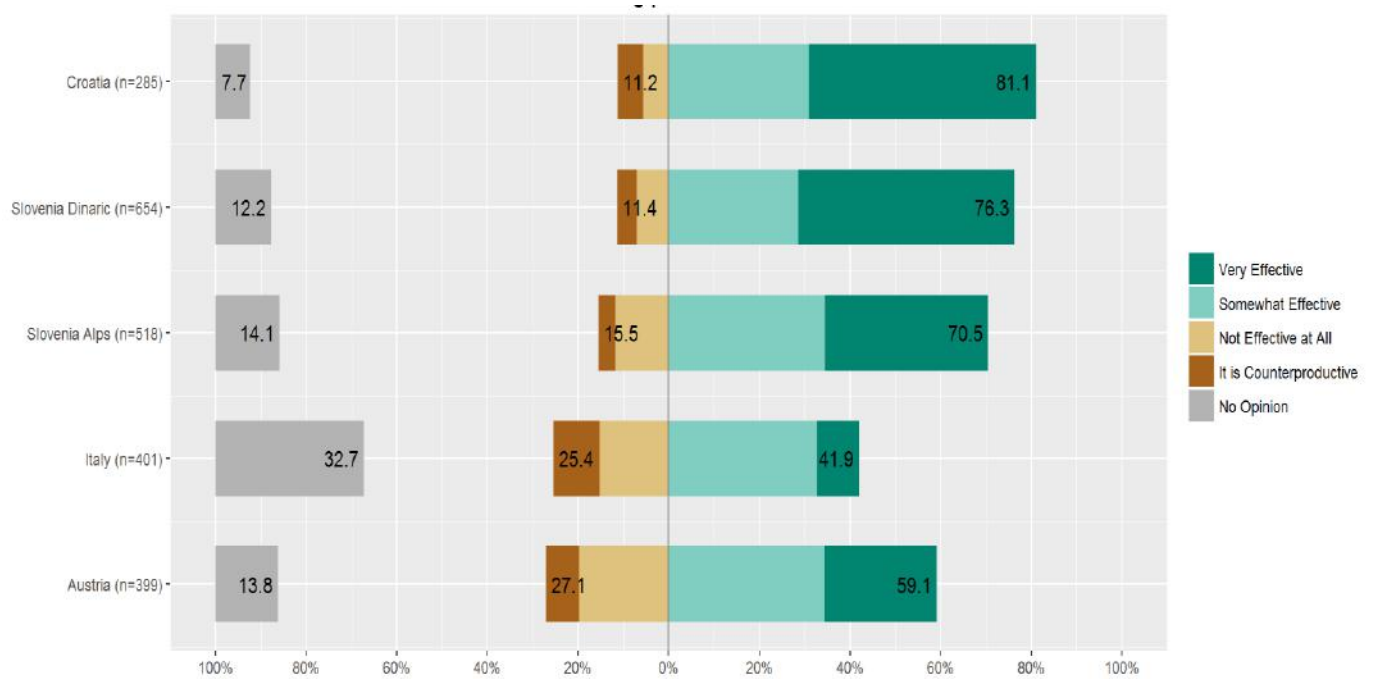
Figure 67: Results for the item "How effective in mitigating human-bear conflicts is removal of problem bears".
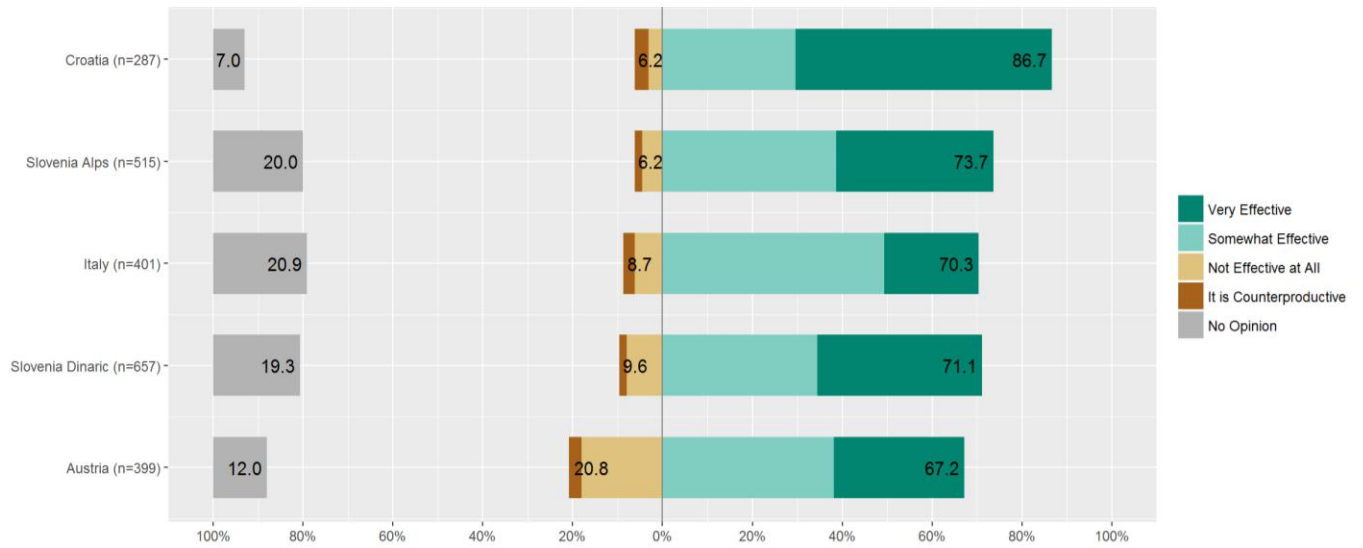
Figure 68: Results for the item "How effective in mitigating human-bear conflicts is use of bear proof garbage bins and bear proof garbage management in general".
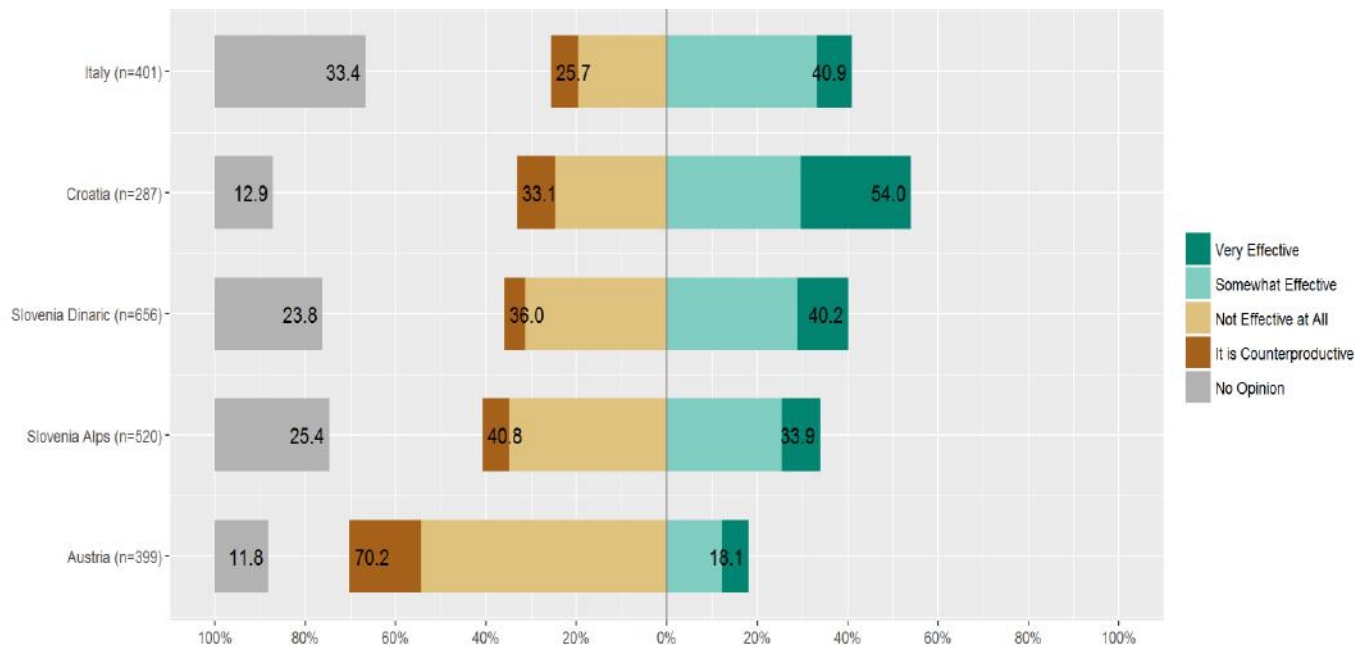
Figure 69: Results for the item "How effective in mitigating human-bear conflicts is clearing out bushes and trees in near vicinity of the villages".
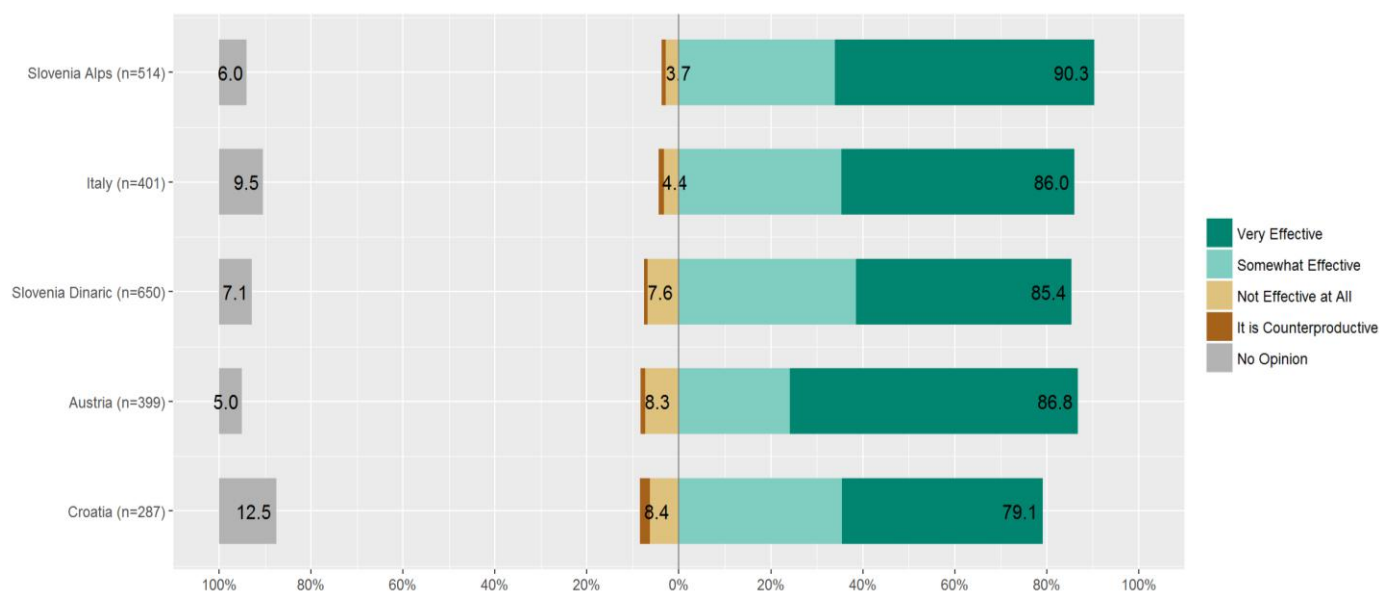
Figure 70: Results for the item "How effective in mitigating human-bear conflicts is educating people about safe behaviour in bear areas."

PCA analysis of the nine solutions items has clearly structured the data into three logical and interpretable components. Structure of the three components is presented in Table 3. First one was interpreted as "conflict mitigation and education" as the main items contributing to this component included use prevention measures in agriculture (guarding dogs, electric fences, responsible waste management and educating people). The second component was defined by solutions that are invasive towards bears: regular culling of bears and removal of problem bears. The third component was defined by the two questions related to supplemental feeding of bears. Distributions of the three factors are shown in Figure 71 (conflict mitigation), Figure 72 (culling), and Figure 73 (supplemental feeding). Already by looking at the distributions it is possible to conclude that there are considerable differences among the regions in the latter two factors.

Table 3: Standardized PCA loadings for the three components within the conflict resolution cluster.

How effective in mitigating human-bear conflicts is	Conflict mitigation score – PCA loadings	Culling score – PCA loadings	Supplemental feeding score – PCA loadings
… providing protein food sources (carcasses) for bears in the forest	-	-	0.90
… providing corn and other food of plant origin for bears in the forest	-	-	0.90
…introducing livestock guarding dogs to the flocks of grazing livestock.	0.72	-	-
… use of electric fences or nets to prevent damages in	0.69	-	-

agriculture			
…a regular quota for hunting of bears	-	0.90	-
… removal of problem bears	-	0.90	-
… use of "bear proof" garbage bins and responsible organic waste management	0.69	-	-
…cutting bushes and trees in near vicinity of villages	-	-	-
…educating people about the proper ways of behavior in the bear area	0.64	-	-
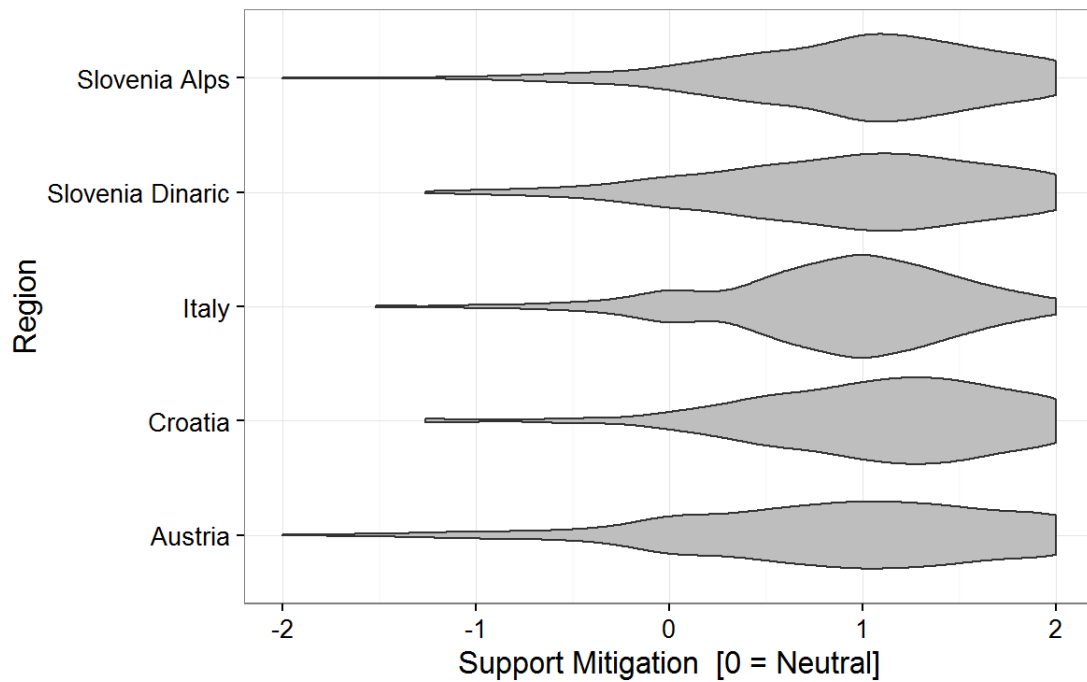
Figure 71: Distribution of "mitigation measures" PCA score.
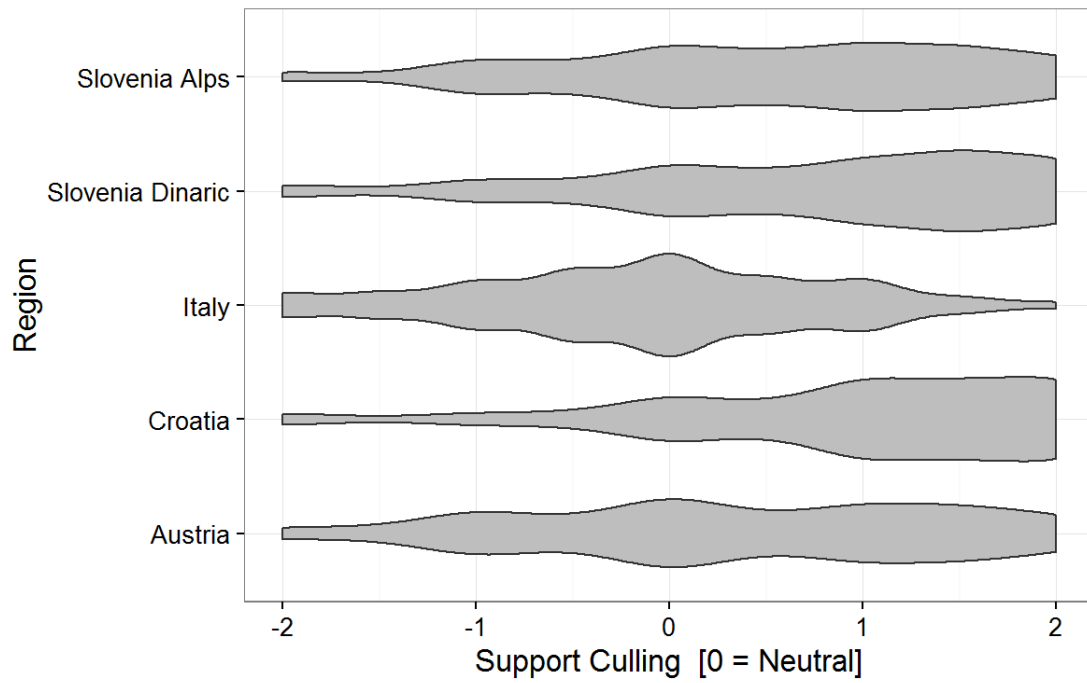
Figure 72: Distribution of "culling of bears" PCA score.
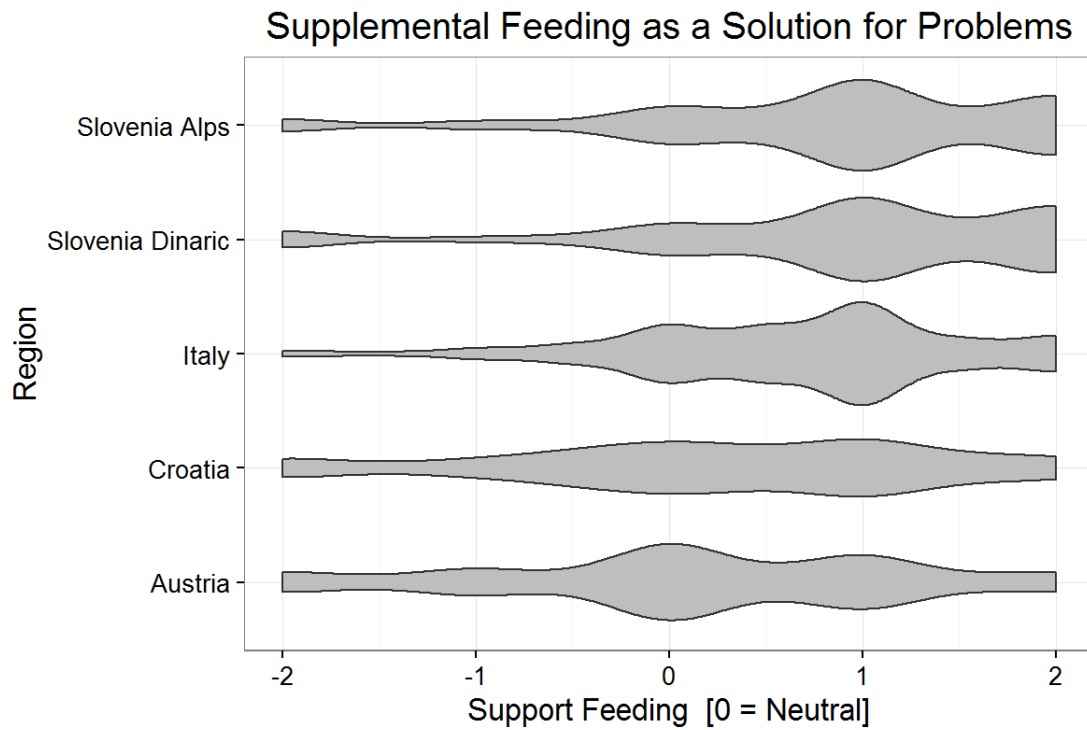
Figure 73: Distribution of "supplemental feeding" PCA score.

When modelling "mitigation measures" we can see that respondents in all regions acknowledged the effectiveness of mitigation measures. In Croatia this was a bit more pronounced and in Italy a bit less than in other regions (Figure 74). Owners of livestock were less inclined to supporting mitigation measures as the effective solution, however they were still overall supportive (Figure 75). Knowledge of bear biology proved to be important in predicting support for mitigation measures, especially among the livestock owners (Figure 76). Besides that also dog owners and better educated respondents seemed to acknowledge the effectiveness of mitigation measures for resolving human-bear conflicts.
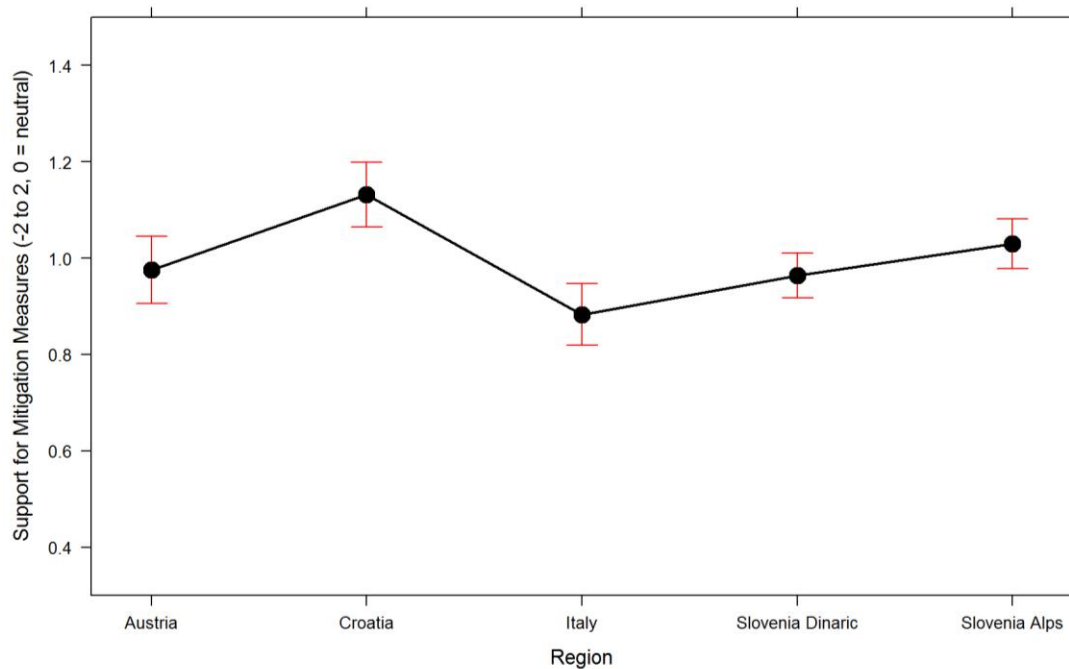
Figure 74: Effects of region on public support of mitigation measures for resolving human-bear conflicts.
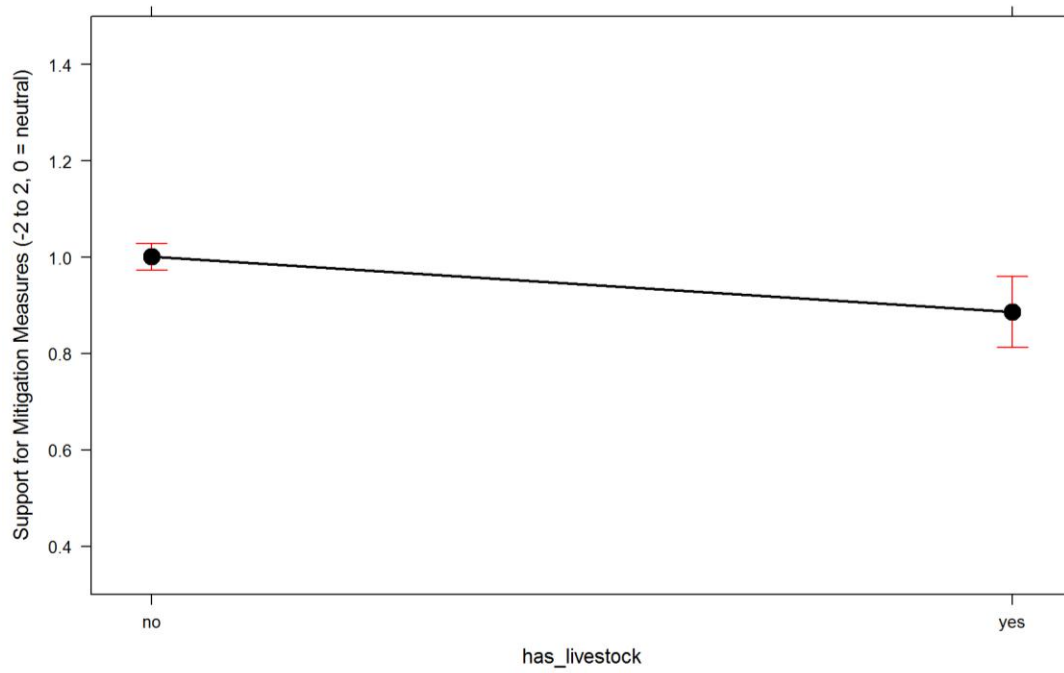
Figure 75: Effects of livestock ownership on support of mitigation measures for resolving human-bear conflicts.
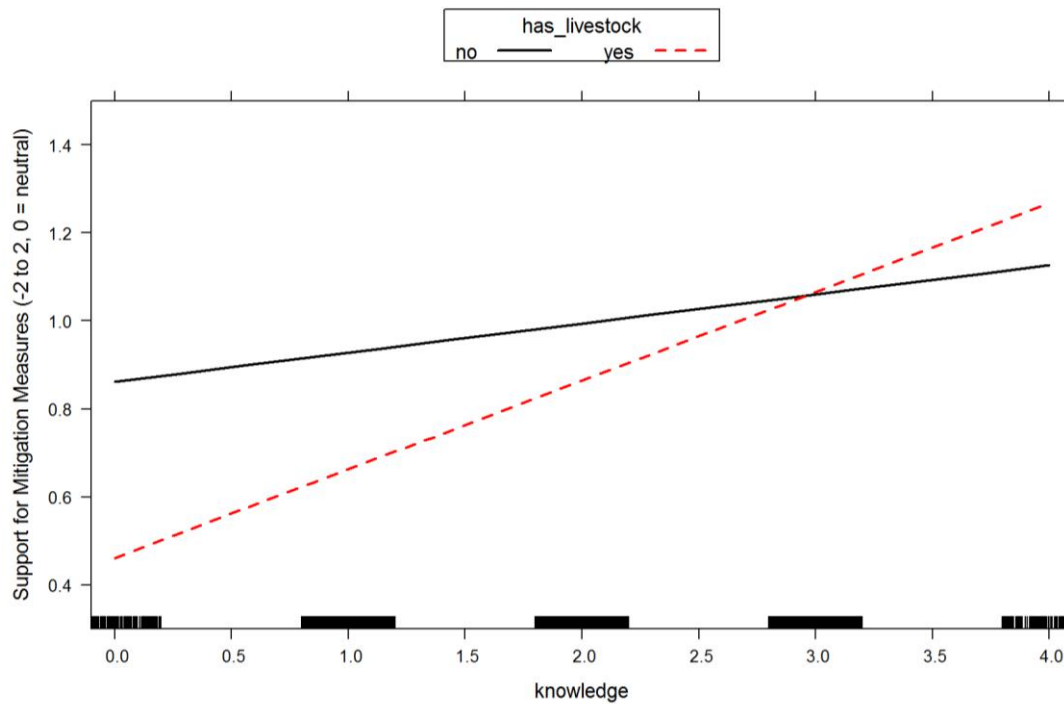
Figure 76: Combined effects on livestock ownership and knowledge of bear biology on support of mitigation measures for resolving human-bear conflicts.

Model for "culling" revealed considerable differences in respondents' perceptions among the regions. While all groups scored positive on this factor, meaning that all groups acknowledge effectiveness of culling in resolving human problems with bears, respondents from Croatia and Slovenia scored much higher than those from Austria and Italy (Figure 77). Also livestock owners (Figure 78) and males (Figure 79) were more likely to support culling as a conflict resolution tool.

Supplemental feeding of bears as a conflict resolution measure was also recognized as effective, especially among Slovenian respondents and to some degree also Italian (Figure 80. Respondents that were more knowledgeable about bears and have seen a bear in nature tend to support more supplemental feeding as management tool.
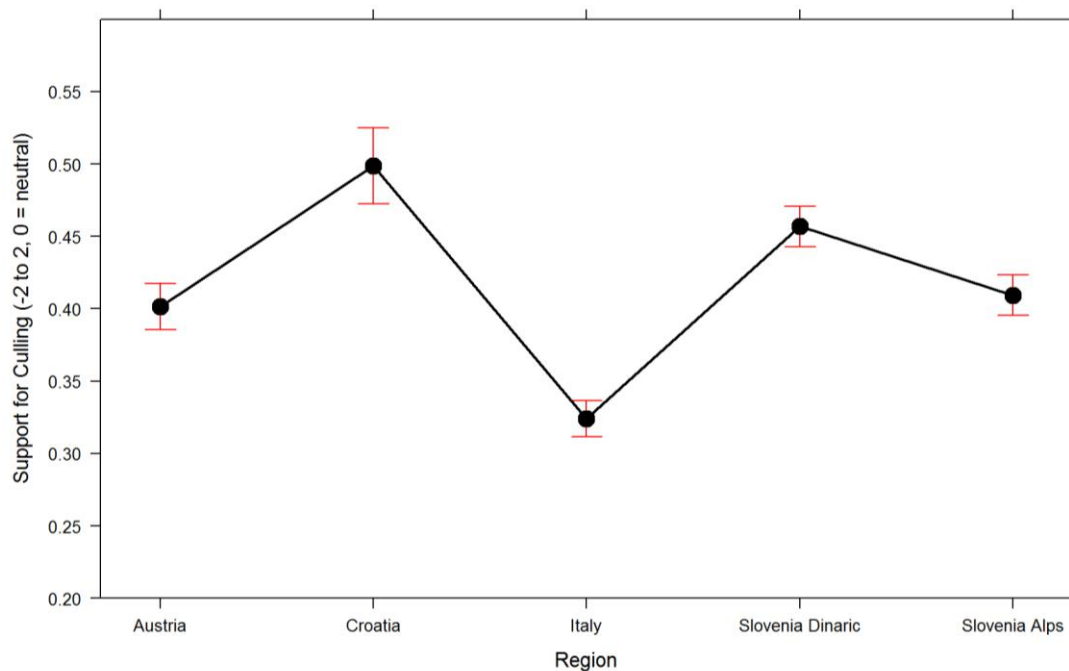
Figure 77: Effects of region on predicting support for culling as a conflict resolution measure.
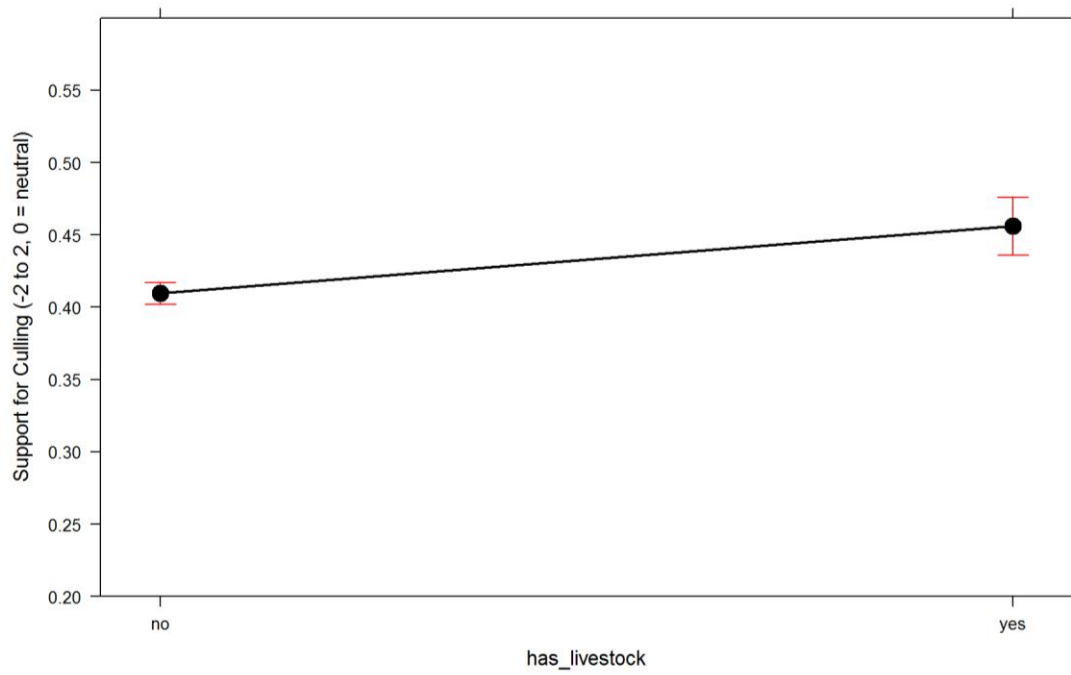
Figure 78: Effects of livestock ownership on "support for culling" in conflict resolution.
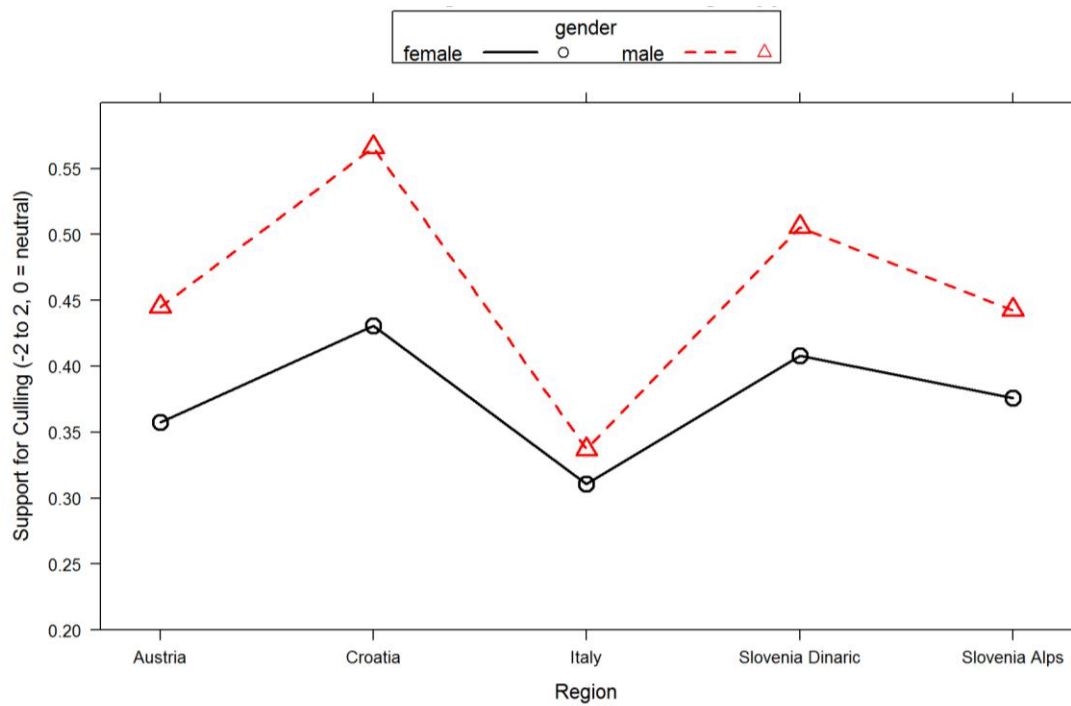
Figure 79: Combined effects of region and gender on "support for culling" in conflict resolution.
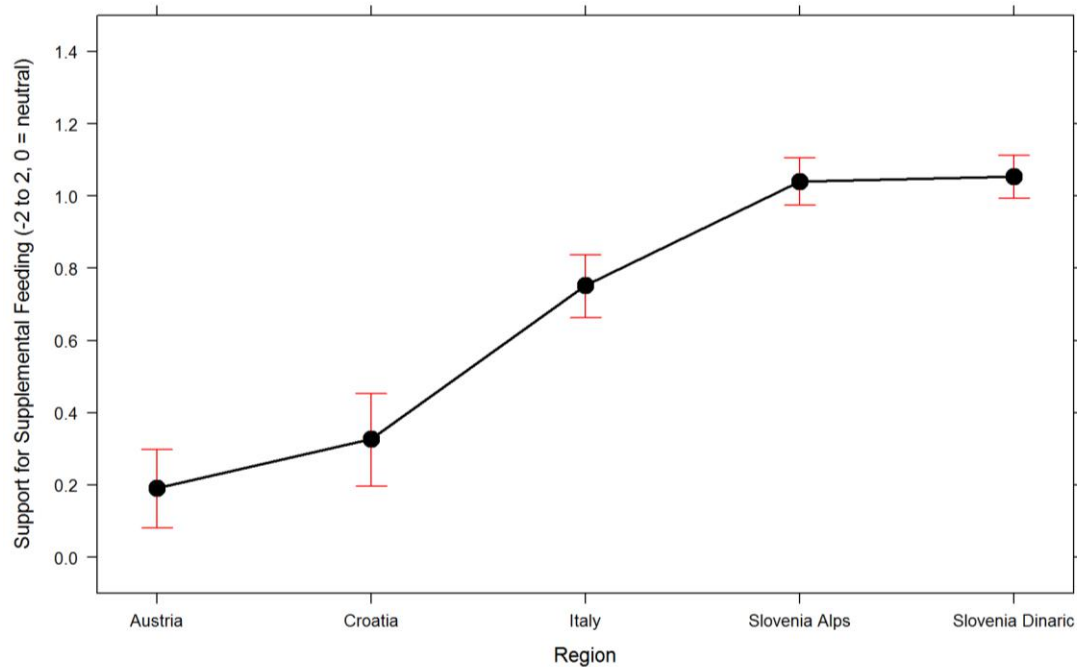
Figure 80: Effects of region on support of "supplemental feeding" as a human-bear conflict resolution tool.

Conclusions

Opinions and beliefs of local general public are most likely the best indicator of society's mood about bears. We've documented high support for long-term bear conservation in all countries participating in the project LIFE DINALP BEAR. The effects of project dissemination activities during the first year of project implementation were clearly seen as many of our respondents, especially in Slovenia and Croatia have already heard about the project and also understand quite well project objectives.

Targeted informational and educational activities planned in the project should be adjusted in a way which will enable addressing directly specific segments of the society with carefully designed key messages. For example, it seems that older generations are much less likely to accept damage prevention measures as a human-bear conflict resolution approach, thus in order to maximize the project's effects, the focus should be on younger generations of farmers and other stakeholder groups that have problems with bears. Furthermore, understanding of bear biology and behaviour proved to be one of the most important predictors when exploring values that are generally also core values of our project (coexistence, long-term conservation, prevention of conflicts). While in general our respondents demonstrated good knowledge about bears, it seems important to prepare and communicate basic key messages with information on bear biology, especially those related to bear diet, where highest level of misconceptions was

documented, also to the stakeholder groups that usually are not that interested in such knowledge (livestock farmers, bee keepers). To those groups we traditionally focus on delivering information related to damage prevention and compensation approaches and processes, nevertheless it seems that carefully delivered information about bear biology has the potential to create cognitive dissonance resulting in improved coexistence.

Perceptions and beliefs about population size are probably one of the most important components shaping public expectations from the population management. If predominant belief among the constituency is that there are too few bears, they will oppose any interventions into the population which could reduce the population size and they would expect measures to better conserve the population. The same is for the opposite example – beliefs that there are too many bears will result with expectations of population size control. It is important that decision-makers have access to the information on public opinions and expectations, so that they can predict and manage public support for management decisions that need to be taken. Results of our study would suggest that social carrying capacity has been reached among the interested inhabitants of Slovenia, especially those in the Dinarics, while in other countries people would be willing to tolerate more bears. It is however important to note that many respondents in all countries but Austria did not have a concrete opinion about the bear population size in their country and choose "neither agree nor disagree".

Closely related to perceptions about bear population size is public support for lethal control of bears. Our data suggest that Italian and Austrian respondents do not support lethal control of bears. The Croatian respondents and those from the Alpine part of Slovenia were on average undecided, while the Slovenians from the Dinarics clearly recognized the need for lethal control of bear population size with their answers.

(Potential) benefits of having bears for local communities were recognized in responses in all participating countries although somewhat lower in the area often believed to have one of the highest densities of bears (Slovenian Dinarics).

On the other hand respondents in all participating countries do not like to tolerate conflict situations with bears. According to our data, Italians are willing to tolerate the most conflict situations as well as those that are younger, and more knowledgeable about bears. Respondents in all four countries acknowledged that damage prevention, correct organic waste management and public awareness are the most effective approaches in dealing with human-bear conflicts. Invasive measures such as culling and removal of problems bears were also recognized as efficient, however much more among the respondents from Croatia and Slovenia, than those from Italy and Austria. Supplemental feeding of bears as a conflict resolution measure was also recognized as effective, especially among Slovenian respondents and to some degree also Italian.

Annex 1: Questionnaires

Stavovi javnosti o medvjedima i gospodarenju populacijom medvjeda

Anketa (Akcija A.2)

Poštovani!

Zajedno sa partnerima iz Slovenije, Italije i Austrije provodimo projekt „Upravljanje i zaštita populacije smeđih medvjeda u sjevernim Dinaridima i Alpama" (LIFE DINALP BEAR). Jedan od ciljeva projekta je poboljšati suživot medvjeda s ljudima te obogatiti naše znanje o činiteljima i mehanizmima koji utječu na populaciju medvjeda. Jedan od posebnih ciljeva projekta je procjena javnog prihvaćanja medvjeda, kako u području stalne, tako i u području njegove povremene rasprostranjenosti u Hrvatskoj.

Vaše ime i adresu pribavili smo isključivo za potrebe ove studije. Nasumično ste odabrani da sudjelujete u studiji ispitivanja javnog mišljenja o medvjedima i o gospodarenju medvjedima u Hrvatskoj. Molimo Vas da odgovorite na sva pitanja i što prije vratite upitnik u priloženoj kuverti s upisanom adresom i plaćenom poštarinom. Ohrabrujemo Vas da izrazite svoje stavove bez obzira da li ste za, protiv ili neutralni prema očuvanju medvjeda. Vaše mišljenje je važna pomoć u donošenju budućih odluka o gospodarenju populacijom medvjeda. Vaše sudjelovanje je potpuno anonimno, pojedinačni odgovori su tajni i za potrebe studije bit će analizirani zajedno sa ostalima.

Ako imate pitanja o ovom istraživanju ili želite saznati više o cijelom projektu slobodno nas nazovite na 01/ 2390 141 ili kontaktirajte na e-mail adrese: almajic@gmail.com ili lidijus@gmail.com. Rezultati studije bit će objavljeni na web stranici projekta www.dinalpbear.eu.

Hvala Vam! Jako cijenimo Vaše sudjelovanje u ovom istraživanju!

Sa štovanjem,

Aleksandra Majić Skrbinšek, koordinator studije

Lidija Bernardić, voditelj za Hrvatsku

1. Koji odgovor najbolje opisuje Vaš stav prema medvjedima?

a) Potpuno sam protiv.

d) Naklonjen sam.

b) Protiv.

e) Potpuno sam naklonjen.

c) Nisam niti protiv niti naklonjen.

2. Koji je vaš stav o činjenici da u Hrvatskoj obitavaju medvjedi?

a) To je vrlo loše.

d) To je dobro.

b) To je loše.

e) To je vrlo dobro.

c) To je nevažno.

Broj pitanja	Pitanje	Jako se ne slažem	Ne slažem se	Neutralan sam/ Ne znam	Slažem se	Jako se slažem
3.	Važno je očuvati populaciju medvjeda u Hrvatskoj za užitak budućih naraštaja.	1	2	3	4	5
4.	Nepotrebno je imati medvjede u Hrvatskoj, jer puno medvjeda živi u drugim zemljama Europe.	1	2	3	4	5
5.	Po mom mišljenju, medvjed u Hrvatskoj je ugrožena vrsta.	1	2	3	4	5
6.	Bojim se hodati šumom u kojoj ima medvjeda.	1	2	3	4	5

Broj pitanja	Pitanje	Jako se ne slažem	Ne slažem se	Neutralan sam/ Ne znam	Slažem se	Jako se slažem
7.	Po mom mišljenju u Hrvatskoj ima previše medvjeda.	1	2	3	4	5
8.	Medvjedi izazivaju nepodnošljive štete u poljoprivredi.	1	2	3	4	5
9.	Po mom mišljenju lov na medvjede u Hrvatskoj je prihvatljiv.	1	2	3	4	5
10.	Nužno je odstrjeljivati medvjede u Hrvatskoj radi kontrole veličine populacije.	1	2	3	4	5
11.	Prisutnost medvjeda znatno povećava vrijednost lovišta.	1	2	3	4	5
12.	Promatranje medvjeda bi trebalo biti važan dio turističke ponude u mom kraju.	1	2	3	4	5
13.	Prisutnost medvjeda može imati opći pozitivni učinak na lokalnu ekonomiju.	1	2	3	4	5
14.	Jeo/jela bih meso medvjeda bez etičkih problema.	1	2	3	4	5
15.	Prihvatio / prihvatila bih da u Hrvatskoj bude više medvjeda.	1	2	3	4	5
16.	Nezakonito ubijanje medvjeda je opravdano ako gospodarenje ne rješava probleme.	1	2	3	4	5
17.	Prihvatljivo je da lovac nezakonito ubije medvjeda za trofej.	1	2	3	4	5

18. Koliko je vjerojatno da medvjed napadne čovjeka?

a) Vrlo vjerojatno.

d) Samo kad je izazvan.

b) Povremeno.

e) Nije uopće vjerojatno

c) Nemam mišljenje.

Poznato je da medvjedi povremeno dolaze u konflikt s ljudima.
Koliko bi za Vas bile problematične sljedeće situacije?
Molimo da u svakom pitanju odaberete jedan odgovor koji najbolje opisuje Vaše osjećaje i mišljenje.

Broj pitanja	Pitanje	Jako problematično	Donekle problematično	Nemam mišljenje	Nije problematično	Sviđa mi se
19.	Znati da ima medvjeda u mom kraju.	1	2	3	4	5
20.	Vidjeti znakove prisutnosti medvjeda (otiske šapa, izmet...) u obližnjoj šumi.	1	2	3	4	5
21.	Vidjeti znakove prisutnosti medvjeda (otiske šapa, izmet...) u Vašem naselju.	1	2	3	4	5

Broj pitanja	Pitanje	Jako problematično	Donekle problematično	Nemam mišljenje	Nije problematično	Sviđa mi se
22.	Vidjeti medvjeda iz auta.	1	2	3	4	5
23.	Susresti medvjeda u šumi dok bježi od Vas.	1	2	3	4	5
24.	Susresti medvjeda blizu Vaše kuće.	1	2	3	4	5
25.	Iskusiti da se medvjed hrani u Vašem vrtu ili voćnjaku.	1	2	3	4	5
26.	Iskusiti da se medvjed hrani na Vašim košnicama.	1	2	3	4	5
27.	Iskusiti da medvjed napada i jede Vaše domaće životinje.	1	2	3	4	5

Broj pitanja	Pitanje	To je kontraproduktivno	Nema nikakvog učinka	Nemam mišljenje	Donekle učinkovito	Vrlo učinkovito
	Koliko su sljedeće mjere učinkovite u sprječavanju naših sukoba s medvjedima? Molimo da u svakom pitanju odaberete jedan odgovor koji najbolje opisuje Vaše osjećaje i mišljenje.					
28.	**Davanje hrane bogate bjelančevinama (lešine životinja) medvjedima u šumi.**	1	2	3	4	5
29.	**Davanje kukuruza i druge biljne hrane medvjedima u šumi.**	1	2	3	4	5
30.	**Korištenje pasa čuvara za zaštitu stada na pašnjacima.**	1	2	3	4	5
31.	**Korištenje električne ograde za zaštitu.**	1	2	3	4	5
32.	**Redovni odstrel medvjeda (kvota).**	1	2	3	4	5

Broj pitanja	Pitanje	To je kontraproduktivno	Nema nikakvog učinka	Nemam mišljenje	Donekle učinkovito	Vrlo učinkovito
33.	Uklanjanje problematičnih medvjeda.	1	2	3	4	5
34.	Korištenje kanti za smeće i gospodarenje otpadom na način da bude nedostupan medvjedu.	1	2	3	4	5
35.	Uklanjanje grmlja i drveća oko naselja.	1	2	3	4	5
36.	Širenjem svijesti o sigurnom ponašanju u području medvjeda.	1	2	3	4	5

37. Koje druge mjere smatrate da bi bile učinkovite u rješavanju problema s medvjedima?

_____
_____
_____
_____
_____

38. **Koliko medvjeda mislite da živi u Hrvatskoj?**   _____

39. **Medvjedi u Hrvatskoj jedu:**

a) Isključivo hranu životinjskog porijekla.

b) Uglavnom hranu životinjskog porijekla.

c) Uglavnom hranu biljnog porijekla.

d) Podjednako hranu životinjskog i biljnog porijekla.

e) Ne znam.

40. **Koliko je najčešće medvjedića u leglu?**

a) Jedan

b) Dva.

c) Tri.

d) Četiri

e) Ne znam.

41. **Medvjedi u Hrvatskoj se općenito boje ljudi.**

a) Ne.   b) Da.   c) Ne znam.

42. **U Hrvatskoj medvjedići se obično odvajaju od majke:**

a) Nakon izlaska iz brloga u kojem su okoćeni.

b) Tijekom prve godine njihova života.

c) Tijekom druge godine njihova života.

d) Tijekom treće godine njihova života.

e) Tijekom četvrte godine njihova života.

f) Ne znam.

43. Jeste li ikada vidjeli medvjeda u zatočeništvu (npr. u ZOO-u)?

a) Ne.   b) Da.

44. Jeste li ikada vidjeli medvjeda u prirodi?

a) Ne, nikada.   c) Da, mnogo puta (više od 10 puta).

b) Da, samo nekoliko puta (manje od 10 puta).

45. Je li vam medvjed ikad nanio neku vrstu štete?

a) Ne.   b) Da.

46. Ako ste zaokružili „da", jeste li tražili odštetu?

a) Ne.   b) Da.

47. Ako ste zaokružili „da", jeste li dobili odštetu?

a) Ne.   b) Da.

48. Ako niste dobili odštetu, zašto?

_____
_____
_____

49. Spol: _____

50. Dob: _____ godine.

51. Obrazovanje:

    a) Nepotpuna osnovna škola.   c) Završena srednja škola.

    b) Završena osnovna škola.   d) Sveučilišno obrazovanje.

52. Jeste li lovac?

    a) Ne.   b) Da.

53. Jeste li pčelar?

    a) Ne.   b) Da.

54. Imate li psa?

    a) Ne.   b) Da.

55. Ako posjedujete stoku, koje vrste imate? Moguće je zaokružiti više odgovora:

    a) Ovce i/ili koze.   c) Konje.

    b) Goveda.   d) Drugo: _____.

56. **Da li ste ikada čuli o LIFE DINALP BEAR projektu?**

   a) Ne.   b) Da.   c) Ne znam.

57. **Ako jeste, znate li o čemu se radi u projektu LIFE DINALP BEAR? Moguće je zaokružiti više odgovora:**

   a) Kontroliranju veličine populacije medvjeda.

   b) Smanjivanju šteta nastalih od medvjeda.

   c) Prekograničnoj suradnji.

   d) Istraživanju populacije medvjeda.

   e) Poticanju širenja medvjeda u Alpama.

   f) Poticanju turističkog iskorištavanja medvjeda.

   g) Sprečavanju sudara medvjeda sa vozilima.

   h) Poboljšavanju suživota ljudi s medvjedima.

   Zahvaljujemo Vam na suradnji i sudjelovanju!

   Ako imate bilo kakvih dodatnih komentara o temi ili o samom upitniku, molimo Vas da ih ovdje upišete:

   _____
   _____
   _____
   _____
   _____
   _____
   _____
   _____
   _____

LIFE
DINALP
BEAR

Celovito upravljanje in varstvo rjavega medveda v severnih Dinaridih in Alpah

Spoštovani!

Skupaj s partnerji iz Hrvaške, Italije in Avstrije izvajamo projekt imenovan ''Celovito upravljanje in varstvo rjavega medveda v severnih Dinaridih in Alpah'' (LIFE DINALP BEAR). Namen projekta je izboljšanje sobivanja rjavega medveda in ljudi ter razumevanje dejavnikov in mehanizmov, ki vplivajo na širjenje populacije rjavega medveda. En izmed pomembnih ciljev projekta je ocena tolerance javnosti do medveda v različnih delih projektnega območja (območja, kjer so medvedi prisotni in območja, kjer se medvedi le redko pojavljajo ali jih ni). Sledeči vprašalnik je pomembno orodje za izvedbo raziskave mnenj.

Vi in mnogi drugi odrasli prebivalci Slovenije ste vabljeni k sodelovanju v raziskavi o odnosu javnosti do rjavega medveda in do upravljanja z medvedjo populacijo v Sloveniji. Prosimo, da čim bolj v celoti odgovorite na vsa vprašanja in nam izpolnjen vprašalnik v priloženi kuverti s plačano poštnino čim prej vrnete.

Vljudno vas prosimo, da podate svoje mnenje o ohranitvi rjavega medveda (za, proti ali nevtralno). Vaše mnenje je pomembno in bo pomagalo pri prihodnjih odločitvah glede upravljanja z rjavim medvedom. Vaše sodelovanje pri izpolnjevanju vprašalnika je popolnoma anonimno, vaši odgovori bodo za namene analize združeni z odgovori drugih.

Če imate kakršnakoli vprašanja o raziskavi ali bi radi izvedeli kaj več o projektu, me lahko kontaktirate na: 01/ 320 3336 (med delavniki, 10.00–14.00) ali na almajic@gmail.com. Rezultati raziskave bodo objavljeni na spletni strani projekta: www.dinalpbear.eu.

Za vaše sodelovanje se vam že vnaprej najlepše zahvaljujemo!

S spoštovanjem,

Aleksandra Majić Skrbinšek, koordinatorka raziskave

Biotehniška fakulteta, Univerza v Ljubljani

2

Prvih nekaj vprašanj se nanaša na vaš odnos do medvedov in prisotnosti medvedov na splošno. Prosimo, da pri vsakem vprašanju obkrožite tisti odgovor, ki najbolje opiše vaše občutke in mnenja.

1. **Kater izmed naštetih odgovorov najbolje opiše vaš odnos do medvedov?**

   a) Povsem negativen.   d) Delno pozitiven.

   b) Negativen.   e) Povsem pozitiven.

   c) Nevtralen.

2. **Dejstvo, da so medvedi prisotni v Sloveniji, ocenjujem kot:**

   a) Zelo slabo.   d) Dobro.

   b) Slabo.   e) Zelo dobro.

   c) Ni pomembno.

	Vprašanje	Se nikakor ne strinjam	Se ne strinjam	Nimam mnenja / ne vem	Se strinjam	Se popolnoma strinjam
3.	Menim, da je medvedjo populacijo v Sloveniji potrebno ohraniti za prihodnje generacije.	1	2	3	4	5
4.	Menim, da prisotnost medvedov v Sloveniji ni potrebna, saj so medvedi pogosti v ostalih evropskih državah.	1	2	3	4	5
5.	Menim, da je medved v Sloveniji ogrožena vrsta.	1	2	3	4	5

3

	Vprašanje	Se nikakor ne strinjam	Se ne strinjam	Nimam mnenja / ne vem	Se strinjam	Se popolnoma strinjam
6.	Strah me je iti v gozd na območju medveda.	1	2	3	4	5
7.	Menim, da je v Sloveniji preveč medvedov.	1	2	3	4	5
8.	Medvedi povzročajo nesprejemljivo škodo v kmetijstvu	1	2	3	4	5
9.	Menim, da je lov na medvede v Sloveniji sprejemljiv.	1	2	3	4	5
10.	Odstrel medvedov je v Sloveniji potreben za uravnavanje velikosti populacije.	1	2	3	4	5
11.	Prisotnost medvedov pomembno poveča vrednost lovišč.	1	2	3	4	5
12.	Organizirano opazovanje medvedov bi lahko predstavljalo pomemben del turistične ponudbe na mojem območju.	1	2	3	4	5
13.	Prisotnost medvedov ima lahko na splošno pozitiven učinek na lokalno ekonomijo.	1	2	3	4	5
14.	Brez etičnih zadržkov bi jedel/la medvedje meso.	1	2	3	4	5
15.	Strinjam se s povečanjem števila medvedov v Sloveniji.	1	2	3	4	5

	Vprašanje	Se nikakor ne strinjam	Se ne strinjam	Nimam mnenja / ne vem	Se strinjam	Se popolnoma strinjam
16.	Nezakonito ubijanje (krivolov) medvedov je upravičen, če upravljanje z medvedom ne rešuje problemov.	1	2	3	4	5

18. Kako verjetno je, da medved napade človeka?

a) Zelo verjetno.

d) Samo, če je izzvan.

b) Manj verjetno.

e) Nikoli.

c) Nimam mnenja/ne vem.

Medvedi včasih ljudem povzročajo težave. Ocenite, kako problematične se vam zdijo naslednje situacije. Prosimo, da za vsako vprašanje izberete tisti odgovor, ki najbolje opiše vaše občutke in mnenja.

		Zelo problematično	Problematično	Nimam mnenja	Sploh ni problematično	Ta ideja mi je všeč
19.	Zavedanje, da so medvedi prisotni v vašem območju.	1	2	3	4	5
20.	Medved se nahaja **v gozdovih** blizu vašega bivališča (opazite stopinje, iztrebke …).	1	2	3	4	5

		Zelo problematično	Problematično	Nimam mnenja	Sploh ni problematično	Ta ideja mi je všeč
21.	Opazite sledi medveda (stopinje, iztrebke …) **v vašem naselju.**	1	2	3	4	5
22.	Srečanje z medvedom iz avtomobila.	1	2	3	4	5
23.	Srečanje z medvedom v gozdu in medved zbeži.	1	2	3	4	5
24.	Srečanje z medvedom v bližini vašega doma.	1	2	3	4	5
25.	Medved se hrani na vašem vrtu ali v sadovnjaku.	1	2	3	4	5
26.	Medved se hrani na vašem čebelnjaku.	1	2	3	4	5
27.	Medved napade in se hrani z vašo živino.	1	2	3	4	5

Kaj menite, kako uspešni bi bili naslednji ukrepi pri reševanju konfliktov med medvedi in ljudmi? Prosimo, da za vsako vprašanje izberete tisti odgovor, ki najbolje opiše vaše občutke in mnenja.

	Vprašanje	Ukrep celo poveča konflikt	Povsem brez učinka	Nimam mnenja	Delno učinkovito	Zelo učinkovito
28.	Namestitev beljakovinskih virov hrane (mrhovine) za medvede v gozdu.	1	2	3	4	5
29.	Namestitev koruze in ostale hrane rastlinskega izvora za medvede v gozdu.	1	2	3	4	5
30.	Uporaba pastirskih psov za zaščito pašnih živalih.	1	2	3	4	5
31.	Uporaba električnih ograj ali mrež za preprečitev škod v kmetijstvu.	1	2	3	4	5
32.	Odstrel medvedov.	1	2	3	4	5
33.	Odstrel problematičnih medvedov.	1	2	3	4	5
34.	Uporaba t.i. medovarnih smetnjakov in odgovorno upravljanje z odpadki.	1	2	3	4	5
35.	Sečnja grmovja in dreves v bližini vasi.	1	2	3	4	5

Vprašanje	Ukrep celo poveča konflikt	Povsem brez učinka	Nimam mnenja	Delno učinkovito	Zelo učinkovito
36. Izobraževanje ljudi o pravilnem obnašanju na območju medveda.	1	2	3	4	5

37. Kaj menite, kateri drugi ukrepi bi še lahko bili učinkoviti pri reševanju konfliktov med ljudmi in medvedi?

_____

_____

_____

_____

_____

Naslednja vprašanja so namenjena vašemu vedenju o medvedih. Prosimo, da pri vsakem vprašanju napišete ali obkrožite odgovor, za katerega menite, da je pravilen.

38. Koliko medvedov živi v Sloveniji?   _____

39. Medvedi v Sloveniji jedo:

a) Samo hrano živalskega izvora.

b) Predvsem hrano živalskega izvora.

c) Predvsem hrano rastlinskega izvora.

d) Hrano živalskega in rastlinskega izvora jedo v približno enakem razmerju.

e) Ne vem.

8

40. Koliko mladičev je najpogosteje v enem leglu?

a) En mladič.

d) Štirje mladiči.

b) Dva mladiča.

e) Ne vem.

c) Trije mladiči.

41. Medvedi v Sloveniji se na splošno bojijo ljudi.

a) Ne.

b) Da.

c) Ne vem.

42. Medvedji mladiči v Sloveniji ponavadi zapustijo mamo:

a) Takoj, ko zapustijo brlog v katerem so rojeni.

d) V tretjem letu svoje starosti.

e) V četrtem letu svoje starosti.

b) V prvem letu svoje starosti.

f) Ne vem.

c) V drugem letu svoje starosti.

Naslednja vprašanja so namenjena vašim osebnim izkušnjam z medvedi. Prosimo, da pri vsakem vprašanju obkrožite en odgovor.

43. Ali ste kdaj videli medveda v ujetništvu (npr. v živalskem vrtu)?

a) Ne.

b) Da.

44. Ali ste kdaj videli medveda v naravi?

a) Nikoli.

c) Da, več kot 10-krat.

b) Da, manj kot 10-krat.

9

45. Ali je medved kdaj že oškodoval vašo lastnino?

   a) Ne.   b) Da.

   Če ste na vprašanje 45. odgovorili z »Ne«, nadaljujte pri vprašanju št. 50.

46. Če je medved že kdaj oškodoval vašo lastnino, ali ste zahtevali odškodnino?

   a) Ne.   b) Da.

47. Če ste zahtevali odškodnino, ali ste jo prejeli?

   a) Ne.   b) Da.

49.   Če odškodnine niste prejeli, morda veste zakaj? Prosimo, če na kratko obrazložite situacijo.

_____

_____

_____

Zadnja vprašanja se nanašajo na vas. Pomagala nam bodo analizirati rezultate in preveriti, kako reprezentativen je izbran vzorec. Prosimo, da odgovorite na vsa vprašanja.

50. Spol: a) Ženska.   b) Moški.

51. Starost: _____ let.

52. Izobrazba:

a) Nedokončana osnovna šola.   c) Dokončana srednja šola.

b) Dokončana osnovna šola.   d) Univerzitetna izobrazba ali višja.

53. Ali ste lovec?

    a) Ne.   b) Da.

54. Ali ste čebelar?

    a) Ne.   b) Da.

55. Ali ste vi oz. vaši družinski člani lastniki psa?

    a) Ne.   b) Da.

56. Če imate v lasti domače živali, katere vrste imate (možnih je več odgovorov)?

a) Ovce in/ali koze.   c) Konje.

b) Govedo.   d) Drugo: _____.

57. Ali ste kdaj slišali za projekt LIFE DINALP BEAR?

    a) Ne.   b) Da.   c) Ne vem.

58. Če ste na vprašanje 57. odgovorili da, kateri menite, da so cilji projekta LIFE DINALP BEAR (možnih je več odgovorov)?

a) Upravljanje z rjavim medvedom na nivoju populacije.

b) Zmanjševanje škod, ki jih povzroči rjavi medved.

c) Čezmejno sodelovanje.

d) Preučevanje medvedje populacije.

e) Promocija naravnega širjenja rjavega medveda iz Dinaridov v Alpe.

f) Promocija uporabe medvedov kot eko-turistične zanimivosti.

g) Preprečevanje prometnih nesreč z medvedom.

h) Izboljšanje sobivanja med ljudmi in medvedi.

Najlepša hvala za vaše sodelovanje!

Če imate še kakšne dodatne komentarje v zvezi s temo vprašalnika, jih prosimo napišite tu:

_____

_____

_____

_____

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_____
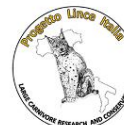
LIFE
DINALP
BEAR

Gestione e conservazione dell'orso
bruno a livello di popolazione sui monti
Dinarici del nord e sulle Alpi

Caro residente!

In collaborazione con partner provenienti da Croazia, Slovenia e Austria stiamo attuando un progetto denominato "*Gestione e conservazione dell'orso bruno a livello di popolazione e conservazione sui monti Dinarici del nord e sulle Alpi*" (LIFE DINALP BEAR). Il progetto mira a migliorare la coesistenza degli orsi con l'uomo aumentando la nostra comprensione per quei fattori e meccanismi che influenzano l'espansione della popolazione di orso. Uno degli obiettivi specifici è la valutazione della tolleranza nei confronti dell'orso in diverse parti dell'area di progetto (in cui sono presenti gli orsi e nelle zone in cui gli orsi sono assenti o solo occasionalmente presenti) e il presente questionario è il principale strumento per l'attuazione di questo studio di atteggiamenti.

Lei e molte altre persone residenti scelte a caso nell'Italia Alpina centro-orientale sono invitate a partecipare allo studio dell'attitudine del pubblico verso gli orsi e la loro gestione nel nostro paese. Si prega di rispondere a tutte le domande nel modo più completo possibile. La compilazione del questionario vi porterà via 10 minuti.

Vi incoraggio a esprimere la vostra opinione sia nel caso che sia favorevole, contraria o neutra nei confronti della conservazione dell'orso. La sua opinione è importante e aiuterà a operare le giuste scelte gestionali in futuro. La vostra partecipazione è completamente anonima, le singole risposte sono strettamente confidenziali e ai fini dell'analisi saranno raggruppate con quelli degli altre persone.

Se avete domande circa lo studio o se volete saperne di più sul progetto non esitate a contattarmi allo 01/320 3336 (in un giorno lavorativo, 10:00-14:00) o presso l'indirizzo di posta elettronica sonia.calderola@regione.veneto.it . I risultati dello studio saranno pubblicati sulla pagina web del progetto www.dinalpbear.eu .

Grazie! Il vostro supporto a questa ricerca è molto apprezzata!

Cordiali saluti,

Sonia Calderola, coordinatore dello studio in Italia

Le prime domande riguardano I vostri atteggiamenti verso l'orso e la presenza di orsi nel vsotro territorio in generale. Si prega di scegliere una sola risposta per ogni domanda, quella che meglio descrive i suoi sentimenti e opinioni.

1. **Quale risposta descrive al meglio la sua percezione nei confronti degli orsi?**

    a) Completamente contrario.

    b) Contrario.

    c) Né a favore né contro.

    d) Moderatamente favorevole.

    e) Completamente favorevole.

2. **La presenza dell'orso nelle Alpi italiane è:**

    a) Molto negativa.

    b) Negativa.

    c) Non importante/Indifferente.

    d) Positiva.

    e) Molto positiva.

	Questione	Per niente d'accordo	In disaccordo	Indifferente /non so	D'accordo	Pienamente d'accordo)
3.	È importante avere una popolazione di orso nelle Alpi italiane in maniera tale che le future generazioni ne possano godere	1	2	3	4	5
4.	Non è necessario avere orsi nelle Alpi italiane perché comunque esistono popolazioni abbondanti in altri paesi europei.	1	2	3	4	5
5.	Secondo me l'orso nelle Alpi italiane é una specie a rischio.	1	2	3	4	5

	Questione	Per niente d'accordo	In disaccordo	Indifferente /non so	D'accordo	Pienamente d'accordo)
6.	Ho paura ad andare a camminare nel bosco in aree di presenza dell'orso.	1	2	3	4	5
7.	Secondo me, ci sono troppi orsi nelle Alpi italiane.	1	2	3	4	5
8.	L'orso provoca danni insostenibili all'agricoltura.	1	2	3	4	5
9.	Secondo me, la caccia all'orso nelle Alpi italiane sarebbe accettabile.	1	2	3	4	5
10.	È necessario abbattere orsi nelle Alpi italiane per tenerne sotto controllo il numero.	1	2	3	4	5
11.	L'osservazione degli orsi (bear watching) potrebbe essere un aspetto importante dell'offerta turistica nella mia area.	1	2	3	4	5
12.	La presenza dell'orso può avere un impatto generalmente positivo per l'economia locale.	1	2	3	4	5
13.	Mangerei carne di orso senza alcun problema di carattere etico.	1	2	3	4	5

	Questione	Per niente d'accordo	In disaccordo	Indifferente /non so	D'accordo	Pienamente d'accordo)
14.	Sarei favorevole di avere più orsi nelle Alpi italiane.	1	2	3	4	5
15.	L'abbattimento illegale degli orsi è giustificabile se la gestione non è in grado di risolvere i problemi.	1	2	3	4	5
16.	È accettabile che i cacciatori uccidano gli orsi illegalmente per il trofeo.	1	2	3	4	5

18. Quanto é probabile che un orso attacchi un uomo?

a) Molto probabile.

b) Probabile.

c) Non ho idea.

d) Solo se provocato.

e) Mai.

È noto che saltuariamente gli orsi creino dei problemi all'uomo. Quanto sarebbero problematiche per lei personalmente le seguenti situazioni? Per favore scelga una risposta ad ogni domanda, quella che descrive meglio il suo pensiero.

	Questione	Estremamente problematico	Abbastanza problematico	Non lo so	Per niente problematico	Mi piace l'idea
19.	Sapere che l'orso è presente nella sua area.	1	2	3	4	5

5

	Questione	Estremamente problematico	Abbastanza problematico	Non lo so	Per niente problematico	Mi piace l'idea
20.	Trovare segni di presenza dell'orso (impronte/escrementi…) nei boschi dei dintorni.	1	2	3	4	5
21.	Trovare segni di presenza dell'orso (impronte/escrementi…) nel suo abitato.	1	2	3	4	5
22.	Vedere un orso dalla macchina.	1	2	3	4	5
23.	Incontrare un orso nel bosco, se l'orso scappa via.	1	2	3	4	5
24.	Incontrare un orso nelle vicinanze della sua casa.	1	2	3	4	5
25.	Scoprire che un orso ha mangiato nel suo giardino o frutteto.	1	2	3	4	5
26.	Scoprire che un orso ha distrutto le sue arnie.	1	2	3	4	5
27.	Scoprire che un orso ha attaccato e mangiato i suoi animali domestici.	1	2	3	4	5

In che misura le seguenti misure sono efficaci per la soluzione dei conflitti uomo-orso? Per favore scelga una risposta ad ogni domanda, quella che descrive meglio il suo pensiero.

	Questione	È controproduttivo	Per niente efficace	Non lo so	In qualche modo efficace	Molto efficace
28.	Assicurare la disponibilità di fonti alimentari proteiche (carcasse) per gli orsi nel bosco.	1	2	3	4	5
29.	Assicurare la disponibilità di grano e di altri alimenti di origine vegetale per gli orsi nel bosco.	1	2	3	4	5
30.	Introdurre cani da guardiania a protezione delle greggi al pascolo.	1	2	3	4	5
31.	Utilizzare reti elettrificate per prevenire i danni all'agricoltura.	1	2	3	4	5
32.	Piano di abbattimento venatorio dell'orso.	1	2	3	4	5
33.	Rimuovere gli orsi problematici.	1	2	3	4	5
34.	Utilizzare cassonetti per i rifiuti anti-orso e gestire in generale il problema dell'accessibilità ai rifiuti da parte dell'orso.	1	2	3	4	5
35.	Tagliare i cespugli e gli alberi nelle vicinanze dei villaggi.	1	2	3	4	5

	Questione	È controproduttivo	Per niente efficace	Non lo so	In qualche modo efficace	Molto efficace
36.	Avviare una campagna di sensibilizzazione e informazione sui comportamenti più sicuri da adottare nelle aree di presenza dell'orso.	1	2	3	4	5

37. Quali altre misure pensa possono essere efficaci? (Risposta libera)

_____

_____

_____

_____

_____

Le seguenti domande vi chiederanno qual'é la vostra opinione sugli orsi. Scegliete o scrivete la risposta che credete sia giusta.

38. **Quanti orsi pensa che vivano nelle Alpi italiane?** _____

39. **Gli orsi nelle Alpi italiane mangiano:**

    a) Solo cibo di origine animale.

    b) Soprattutto cibo di origine animale.

    c) Soprattutto cibo di origine vegetale.

    d) In egual misura cibo di origine animale e vegetale.

    e) Non lo so.

40. **Quanti orsi ci sono più comunemente in una cucciolata?**

    a) Un cucciolo.

    b) Due cuccioli.

    c) Tre cuccioli.

    d) Quattro cuccioli.

    e) Non lo so.

41. **In generale, gli orsi nelle Alpi italiane hanno paura dell'uomo.**

    a) No.   b) Si.   c) Non lo so.

42. **Nelle Alpi italiane, i cuccioli si separano dalla propria madre::**

    a) Subito dopo l'uscita della tana di nascita.

    b) Durante il primo anno di vita.

    c) Durante il secondo anno di vita.

    d) Durante il terzo anno di vita.

    e) Durante il quarto anno di vita.

    f) Non lo so

le seguenti domande vi chiedono qual'é la vostra esperienza personale con gli orsi.

43. **Ha mai visto un orso in cattività (p.es. in uno zoo)?**

   a) No.   b) Si.

44. **Ha mai visto un orso in natura?**

   a) No, mai.   c) Si, spesso (più di 10 volte).

   b) Si, raramente (meno di 10 volte).

45. **Ha mai subito danni causati dall'orso?**

   a) No.   b) Si.

46. **Se si, ha fatto richiesta di risarcimento danni?**

   a) No.   b) Si.

47. **Se si, ha ricevuto il risarcimento dei danni?**

   a) No.   b) Si.

48. **Se invece no, perché?**

_____

_____

_____

Le ultime domande sono su di lei e ci aiuteranno ad analizzare i risultati e a verificare quanto sia rappresentativo il nostro campione su tutta la popolazione. Si prega di rispondere a tutte le deomande.

49. Sesso:

_____

50. Età: _____

51. Titolo di studio:

a) Nessun titolo di studio.

b) Scuola elementare.

c) Scuola superiore.

d) Università o superiore.

52. È un cacciatore?

a) No.

b) Si.

53. È un apicoltore?

a) No.

b) Si.

54. Possiede un cane?

a) No.

b) Si.

55. Se possiede bestiame domestico, di che specie si tratta?

a) pecore/capre.

b) vacche.

c) cavalli.

d) Altri: _____.

56. Ha mai sentito parlare del progetto LIFE DINALP BEAR?

a) No.   b) Si.   c) Non sono sicuro.

57. Se sì, il progetto LIFE DINALP BEAR riguarda (è possibile una risposta multipla):

a)   controllo numerico della popolazione dell'orso,

b) riduzione dei danni causati dagli orsi,

c) collaborazione transfrontaliera,

d) studio della popolazione di orso,

e) promozione dell'espansione degli orsi nelle Alpi,

f) promozione degli orsi come attrazione turistica,

g) prevenzione di collisioni tra orsi e autovetture,

h) Miglioramento della coesistenza tra uomo e orso.

Molte grazie per la sua collaborazione!

Se ha ulteriori commenti in merito all'argomento di questa inchiesta, é pregato di scrivere nello spazio sottostante:

_____

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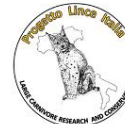
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EINLEITUNG:

Liebe Teilnehmerinnen und Teilnehmer,

zusammen mit Partnern aus Slowenien, Kroatien und Italien führt das Forschungsinstitut für Wildtierkunde und Ökologie (FIWI) der Veterinärmedizinischen Universität Wien das Projekt „Management und Schutz des Braunbären auf Populationsniveau im dinarischen Gebirge und in den Alpen" (LIFE DINALP BEAR) durch.

Dieses Projekt hat zum Ziel, das Zusammenleben von Mensch und Bär zu verbessern und ein tieferes Verständnis von den Faktoren und Mechanismen zu erreichen, die die natürliche Ausbreitung beeinflussen. Eine der spezifischen Fragestellungen ist das Erheben der öffentlichen Einstellung zum Bären und Bärenmanagement in den verschiedenen Teilen des Projektgebiets, was mittels dieses Fragebogens erfolgt.

Mehr Informationen über das Projekt finden Sie auf: www.dinalpbear.eu

Zunächst ein paar Fragen zu Ihrer Meinung und Einstellung zu Bären im Allgemeinen. Bitte wählen Sie die Antwort aus, die Ihre Meinung am besten beschreibt.

1. Was ist Ihre **grundsätzliche Einstellung** gegenüber Bären?

   Bin absolut dafür, dass es bei uns Bären gibt 5
   Bin dafür 4
   Bin weder dafür noch dagegen 3
   Bin dagegen 2
   Bin völlig dagegen, dass es bei uns Bären gibt 1

   Weiß nicht, kann ich nicht sagen 6

2. Wenn **Bären in Österreich** leben, ist das aus Ihrer Sicht –

   sehr gut 5
   gut 4
   mir nicht wichtig 3
   schlecht 2
   sehr schlecht 1

   Weiß nicht, kann ich nicht sagen 6

3. Nachfolgend finden Sie einige **Aussagen zum Thema Bären in Österreich**. Geben Sie bitte jeweils an, wie sehr Sie persönlich diesen Aussagen zustimmen. Gehen Sie dabei nach folgender Skala:

   5 = stimme voll und ganz zu
   4 = stimme eher zu
   2 = stimme eher nicht zu
   1 = stimme überhaupt nicht zu
   3 = neutral, weiß nicht

   Es ist wichtig, Bären in Österreich zu haben, damit zukünftige Generationen sich daran erfreuen können .... 5 / 4 / 2 / 1 / 3
   Es ist unnötig Bären in Österreich zu haben, da es ja in anderen Ländern genug gibt .... 5 / 4 / 2 / 1 / 3
   Meiner Meinung nach sind Bären in Österreich eine gefährdete Art .... 5 / 4 / 2 / 1 / 3
   Ich habe Angst, wenn ich in einem Gebiet mit Bären wandern gehe .... 5 / 4 / 2 / 1 / 3
   Meiner Meinung nach gibt es bereits zu viele Bären in Österreich .... 5 / 4 / 2 / 1 / 3
   Bären verursachen untragbare Schäden in der Landwirtschaft .... 5 / 4 / 2 / 1 / 3
   Falls es irgendwann in Österreich wieder einen großen Bärenbestand gibt, könnten die Bären von mir aus auch bejagt werden ... 5 / 4 / 2 / 1 / 3
   Es ist notwendig, Bären in Österreich zur Bestandskontrolle zu bejagen .... 5 / 4 / 2 / 1 / 3
   Die Anwesenheit von Bären erhöht den Wert einer Landschaft .... 5 / 4 / 2 / 1 / 3
   Orte, an denen man Bären beobachten kann, könnten eine touristische Attraktion in meinem Gebiet sein .... 5 / 4 / 2 / 1 / 3
   Bären können insgesamt einen positiven Einfluss auf die wirtschaftliche Entwicklung der Region haben .... 5 / 4 / 2 / 1 / 3
   Ich würde Bärenfleisch ohne ethische Probleme essen .... 5 / 4 / 2 / 1 / 3
   Es sollte mehr Bären in Österreich geben .... 5 / 4 / 2 / 1 / 3
   Illegale Abschüsse von Bären sind gerechtfertigt, wenn die Behörden vorhandene Probleme nicht lösen können .... 5 / 4 / 2 / 1 / 3
   Es ist akzeptabel, wenn Jäger Bären wegen der Trophäe illegal schießen .... 5 / 4 / 2 / 1 / 3

4. Was glauben Sie: wie wahrscheinlich **greift ein Bär** in freier Wildbahn von sich aus einen **Menschen an**?

Sehr wahrscheinlich 1
Wahrscheinlich.. 2
Nur wenn er provoziert wurde.. 4
Niemals 5

Weiß nicht, keine Meinung 3

5. Bären verursachen bekannter Maßen manchmal **Probleme** für Menschen. Wie problematisch wären für Sie die folgenden Situationen? Bitte wählen Sie die Antwort aus, die Ihre Meinung am besten beschreibt, gehen Sie dabei nach folgender Skala:

1 = extrem problematisch
2 = etwas problematisch
4 = nicht problematisch
5 = mir gefällt der Gedanke
3 = neutral, keine Meinung

Zu wissen, dass es Bären in meiner Nähe gibt .... 1 / 2 / 4 / 5 / 3
Das Finden von Anzeichen für Bären (Abdrücke, Exkremente) in nahen Wäldern .... 1 / 2 / 4 / 5 / 3
Das Finden von Anzeichen für Bären (Abdrücke, Exkremente) in meiner Siedlung...................... 1 / 2 / 4 / 5 / 3
Einen Bären vom Auto aus sehen .... 1 / 2 / 4 / 5 / 3
Einen Bären im Wald treffen, wenn ein Bär davon rennt .... 1 / 2 / 4 / 5 / 3
Einen Bären nahe meinem Haus zu treffen .... 1 / 2 / 4 / 5 / 3
Ein Bär frisst in meinem (Obst-) Garten .... 1 / 2 / 4 / 5 / 3
Ein Bär plündert meine Bienenstöcke .... 1 / 2 / 4 / 5 / 3
Ein Bär greift meine Haustiere an und frisst sie.. 1 / 2 / 4 / 5 / 3

6. Was glauben Sie: wie effektiv sind die folgenden Maßnahmen, um Probleme mit Bären zu verhindern? Bitte wählen Sie die Antwort aus, die Ihre Meinung am besten beschreibt, gehen Sie dabei nach folgender Skala:

5 = sehr effektiv
4 = etwas effektiv, hilft etwas
2 = nicht effektiv
1 = kontraproduktiv, bewirkt eher das Gegenteil
3 = neutral, weiß nicht

Ausbringen von Kadavern als Proteinquellen im Wald.. 5 / 4 / 2 / 1 / 3
Ausbringen von Getreide und anderer pflanzlicher Nahrung für Bären im Wald......................... 5 / 4 / 2 / 1 / 3
Einsatz von Schutzhunden, um Herden von grasendem Vieh zu beschützen .... 5 / 4 / 2 / 1 / 3
Einsatz von Elektrozäunen oder -netzen zum Schutz landwirtschaftlicher Kulturen .... 5 / 4 / 2 / 1 / 3
Geregelte Jagd auf Bären (anhand von Abschussquoten) .... 5 / 4 / 2 / 1 / 3
Entfernen von Problembären .... 5 / 4 / 2 / 1 / 3
Verwendung von bärensicheren Müllcontainern und -tonnen .... 5 / 4 / 2 / 1 / 3
Entfernen von Büschen, Bäumen und anderen Deckungsmöglichkeiten in der Nähe von Städten und Dörfern............................. 5 / 4 / 2 / 1 / 3
Information der Bevölkerung zum richtigen und sicheren Verhalten in Bärengebieten .... 5 / 4 / 2 / 1 / 3

7. Welche anderen Maßnahmen könnten bei Problemen mit Bären helfen?

....

....

Die folgenden Fragen betreffen wiederum die Bärensituation in Österreich und Ihr dazu vorhandenes bzw. vermutetes Wissen.

8. Was glauben Sie: wie viele Bären leben derzeit in etwa in Österreich?

_____ Bären
Weiß nicht, kann ich nicht sagen... 999

9. Wie würden Sie das Fressverhalten der Bären am ehesten einschätzen? Bären in Österreich fressen – (*nur eine Angabe*)

nur tierische Nahrung 1
hauptsächlich tierische Nahrung.. 2
etwa gleich viel tierische wie pflanzliche Nahrung...................................... 4
hauptsächlich pflanzliche Nahrung 3
nur pflanzliche Nahrung 6

Weiß nicht, kann ich nicht sagen.. 5

10. Was glauben Sie: Was ist die häufigste Wurfgröße bei Bären?

Ein Junges... 1
Zwei Junge.. 2
Drei Junge... 3
Vier Junge 4

Weiß nicht, kann ich nicht sagen... 5

11. Würden Sie sagen, dass Bären im Allgemeinen scheu gegenüber Menschen sind?

Ja 2
Nein 1
Nicht sicher, kann ich nicht sagen 3

12. Wann, glauben Sie, verlassen Bärenjunge in der Regel ihre Mutter?

Gleich nach der Geburt 1
Während des ersten Lebensjahres... 2
Während des zweiten Lebensjahres 3
Während des dritten Lebensjahres 4
Während des vierten Lebensjahres.. 5
Nicht sicher, kann ich nicht sagen 6

Nun noch ein paar Fragen zu Ihrer persönlichen Erfahrungen mit Bären.

13. Haben Sie schon einmal einen Bären im Zoo oder Wildpark gesehen?

Ja 2
Nein 1
Nicht sicher, kann ich nicht sagen 3

14. Haben Sie jemals einen Bären in der freien Natur gesehen?

Ja, aber weniger als 10 Mal 2
Ja, schon 10 Mal und mehr 3
Nein, niemals... 1
Nicht sicher, kann ich nicht sagen 4

15. Hat ein Bär bei Ihnen (z.B. bei Haus, Garten, Auto usw.) einen Schaden verursacht?

Ja 2
Nein 1
Nicht sicher, kann ich nicht sagen 3

Nur falls Frage 15 = 2, sonst gleich zur Statistik!
16. Und haben Sie in diesem Fall um Schadensersatz angesucht?

Ja 2
Nein 1
Nicht sicher, kann ich nicht sagen 3

Nur falls Frage 16 = 2, sonst gleich zur Statistik!
17. Und haben Sie einen Schadensersatz zugesprochen bekommen?

Ja 2
Nein 1
Nicht sicher, kann ich nicht sagen 3

Nur falls Frage 17 = 1, sonst gleich zur Statistik!
18. Warum wurde nicht gezahlt?

....

....

STATISTIK

S1. Geschlecht

    Männlich................................ 2
    Weiblich................................ 1

S2. Alter in Jahren: _____ Jahre

S10. Bezirk

Klagenfurt Stadt.................... 1	Sankt Veit / Glan 6
Villach Stadt 2	Spittal an der Drau 7
Feldkirchen 3	Villach Land 8
Hermagor.............................. 4	Völkermarkt 9
Klagenfurt Land.................... 5	Wolfsberg...................................10

S11. Postleitzahl:_____

S3. Bildung

    Ohne Schulabschluss 1
    Hauptschulabschluss, Lehre.. 2
    Matura.................................... 3
    Universität 4

S4. Sind Sie Jäger?

    Ja... 2
    Nein 1

S5. Sind Sie Imker?

    Ja... 2
    Nein 1

S6. Haben Sie einen Hund?

    Ja...2
    Nein 1

S7. Haben Sie Nutztiere? Wenn JA, welche? (*mehrere Antworten möglich*)

    Schafe und/oder Ziegen........1
    Rinder 2
    Pferde 3
    Andere, und zwar:_____.4

    NEIN, habe keine Nutztiere...5

S8. Haben Sie vor dieser Befragung jemals vom LIFE DINALP BEAR Projekt gehört?

    Ja...2
    Nein 1
    Weiß nicht, nicht sicher 3

Nur falls Frage S8 = 2!

S9. Womit beschäftigt sich aus Ihrer Sicht das LIFE DINALP BEAR Projekt? (*mehrere Antworten möglich*)

    Bestandskontrolle bei Bären 1
    Reduzierung der Bärenschäden 2
    Grenzübergreifende Zusammenarbeit... 3
    Forschung 4
    Werben für die Ausbreitung der Bären in den Alpen 5
    Werben für Bären als Touristenattraktion 6
    Vermeiden von Verkehrsunfällen mit Bären 7
    Verbessern des Zusammenlebens von Mensch und Bär 8

    Weiß nicht, kann ich nicht sagen 9

Vielen Dank für Ihre Teilnahme!

Wenn Sie Anmerkungen zu dieser Umfrage oder noch weitere Anmerkungen zum Thema Bären haben, können Sie sie hier niederschreiben:

....

....

....

....

Annex 2: Analysis notes

DinAlp Bear Questionnaire 2016 - Anaylsis Notes

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September 2016

General Description of the Dataset and the Analytical Approach

Data Preparation

The questionnaire data was recorded in the pre-agreed table format in each area, and merged into a single database when the field-surveys were completed. We maintained the index key structure to preserve trackability of each physical questionnaire with its record in the database. Since the questionnaires had some core-area or respondent-group specific questions, we made the "union" of the tables to preserve all data. We checked the data for consistency, data-entry errors and missing data. The records with unacceptable amount of missing data, missing data in key columns or inconsistencies we were not able to solve were removed and stored in a different database.

Some variables needed to be constructed by aggregation of data from several columns (*has_livestock, big_livestock*). We also calculated *knowledge score* as the number of correct answers to the four questions about wolf biology included in the questionnaire. The question about bear number had too many missing data and was not asked in Italy at all, and was excluded from this score.

The questions for seeing bear in nature have been recoded to a new variable *seennatureyesno* - all people that reported seeing the bear in nature have been aggregated to "yes" since apart from Dinarics there has been only a small number of cases in the "yes, >10 times" category. This issue could be explored independently at a later stage.

Statistical analysis

All statistical analyses were done in R analytical environment within RStudio IDE. We followed the reproducible research paradigm by ensuring data consistency throughout analysis and documenting each analytical step (R code, comments, data and output) with RMarkdown.

Reduction of dimensionality using Principal Component Analysis (PCA)

There were three batches of questions that needed to have dimensionality reduced to enable interpretation. Since responses were collected using the Likert scale, we could assume ordinality and linearity of the responses and include them in Principal Component Analysis (PCA). We used R package *psych* to do this part of the analysis. We determined the

number of meaningful components to extract using screeplot analysis, Kaiser-Guttman rule (eigenvalue > 1), Parallel Analysis, Optimal Coordinates, and Accelleration Factor. The components were rotated using the Varimax rotation to exstract the interpretable components. Cases with unnacceptable amount of missing data were excluded in the data preparation phase, and the remaining missing values were set to the mean of the variable to prevent unacceptable data loss. The extracted components were interpreted and included in the database table for downstream analysis.

Factors were normalized from -2 to 2, with 0 as neutral, direction has been checked to be logical with the interpretation of the variable. Original questions that were used for PCA were retained in the downstream dataset.

Atitudinal questions (Q1-Q18)

There were 18 questions regarding the attitudes towards bears and their conservation. Missing data was 1-3%, which is acceptable. We extracted three components:

bear_conservation - support for bear conservation. *bear_control* - support for bear control. *bear_value* - percieved value of bears.

Conflict questions (Q19-Q27)

We extracted only one component: *conflict_tolerance* - how ready a person is to tolerate conflicts caused by bears.

Support of different solutions to bear problems (Q28-Q36)

There were three clear components:

sol_mitigation - preference for 'mitigation measures' solutions for bear problems *sol_culling* - preference for culling as a solution for bear problems *sol_feeding* - preference of a person for supplemental feeding as a solution for bear problems.

Q37 (other solutions), which is descriptive, is not usable in this type of analysis and was omitted.

Statistical modelling

We used Generalized Linear Models and information-theoretic approach to model selection and inference to model these highly complex data and enable interpretation of effects of otherwise confounded explanatory variables. We used the scores obtained by PCA variably as response or predictor variables, and explored their relation to other characteristics of the sample (Region, gender, education, etc.).

The general approach was as follows:

First, we checked the distribution of the response variables. Since they were PCA scores, we didn't expect a specific functional form, and we tried different probability distributions and

transformations to select the correct distribution family and link function for GLM and ensure model fit.

We explored the missing data in the dataset. When meaningful (for some scalar variables) we replaced the missing values with the mean value of the variable, which shouldn't have much effect on fitting of models but prevented unacceptable data loss. At the model selection stage the remaining records with missing data were discarded to enable comparison of the fitted models, but the final (optimal) models were fitted with the entire dataset so that only the records that had missing data in the variables retained in the model were lost.

We constructed a global model with the selected distribution family and link function for each response variable where we fitted all variables we a-priori hypothesized (according to previous understanding of the problem) that they affect the response variable. We didn't fit any interactions between variables at this stage. We checked model fit by plotting standardised residuals against predicted values, checking for non-linearity, bias and heteroscedascity. We checked for multicollinearity using Variance Inflation Factors (VIF).

We explored the model space of each global model by fitting all sub-models without interactions using R package MuMIn. We determined the importance of each variable as the proportion of models where it appears weighted by the Akaike's weight of each model. We constructed the optimal model without interactions by including all highly important variables (Importance > 0.9), and tested the effect of removal of each variable by comparing the second-order Akaike's information criterion (AICc) with the full model. We used dAICc > 3 as the threshold to retain a variable.

We fitted different two-way interactions between variables, selected a-priori using prior knowledge and hypotheses about the problem, and checked support of each model by the data using AICc. We also used dAICc > 3 as the criteria to retain a model. If the dAICc was between 0 and 3, we retained the model with lower number of parameters.

To fit the final optimal (most parsimonious) model with as much data as possible, we used the entire dataset and exluded the records that had missing data just in the variables retained in the model. We checked the data for high-leverage data points by calculating Cook's distances, and we excluded the records with Cook's distances larger than 4/N (model outliers), where N is the number of records included in the model. We re-fitted the optimal model with this dataset without outliers, re-checked linearity and homoscedascity, and used the fitted model for interpretation.

Data exploration and interpretation of modelling results

We plotted different aspects of the dataset to visually examine the raw data for the effects of different explanatory variables on the response variables. Since the explanatory variables are in many cases higly confounded and in practically all cases non-orthogonal, we used the most parsiomonious models fitted in the statistical modelling exercise to directly explore the effect of single explanatory variables or their pre-determined interactions when the other parameters in the model are being controlled for. In other words, we examined the "pure" effect of a specific explanatory variable (e.g. age, education,

etc.) on the response (e.g. support for bear conservation) controlling for the effect of other explanatory varaiables (e.g. Region, gender, etc.). In this manner we could provide an understanding of the actual effect of a certain explanatory variable even in the face of the high complexity and non-orthogonallity of the data. The effects were explored using the R package *effects*.

Analysis Notes

Getting the data ready for analysis, reduction of dimensionality through PCA

Data loading & preparation

Load data. For most questions the question number was kept. In most cases I didn't recode factors - will be done in R.

Data cleanup

How many bears - we made an average when a range was given, a logical number when a number with some text was given (e.g. more than 1000 -> 1001 etc.). Anything unclear was missing data. The entire vector was turned into a numeric. Also, in excel Slovenia Dinaric and Alps are mixed up - fixed here

```
# levels(qdata$Region) = c('Austria','Croatia','Italy','Slovenia
# Dinaric','Slovenia Alps')
qdata$X43seencaptive = as.factor(qdata$X43seencaptive)
levels(qdata$X43seencaptive) = c("no", "yes")
qdata$X45hadbeardamage = as.factor(qdata$X45hadbeardamage)
levels(qdata$X45hadbeardamage) = c("no", "yes")
qdata$X46requiredcompensations = as.factor(qdata$X46requiredcompensations)
levels(qdata$X46requiredcompensations) = c("no", "yes")
qdata$X47gotcompensations = as.factor(qdata$X47gotcompensations)
levels(qdata$X47gotcompensations) = c("no", "yes")
qdata$hunter = as.factor(qdata$hunter)
levels(qdata$hunter) = c("no", "yes")
qdata$beekeeper = as.factor(qdata$beekeeper)
levels(qdata$beekeeper) = c("no", "yes")
qdata$dogowner = as.factor(qdata$dogowner)
levels(qdata$dogowner) = c("no", "yes")
qdata$gender = as.factor(qdata$gender)
levels(qdata$gender) = c("female", "male")
qdata$heardproject = as.factor(qdata$heardproject)
levels(qdata$heardproject) = c("no", "yes", "don't know")
```

```
qdata$X44seennature = as.factor(qdata$X44seennature)
levels(qdata$X44seennature) = c("no", "yes<10", "yes>10")
```

Recoding factors. For yes/no, no=0, yes=1 Otherwise a,b,c -> 1,2,3..

Some variables need to be constructed (has livestock, has large livestock, knowledge score). For knowledge score we had to solve differently for each country the "number of beaers living in XXX". We also recoded seeing bear in nature to a yes-no varaible, and regions in Dinaric/Alpine.

Also, the livestock/pets variables the "no" seems to be coded in some cases (e.g. Austria) as "NA". Will fix.

```
# #corectness of answers to pop size ##OBSOLETE, THIS HAD TOO MUCH MISSING
DATA
# qdata = rbind( qdata %>% filter((Region == 'Slovenia Alps')|(Region ==
# 'Slovenia Dinaric')) %>% mutate(knowspopsize = as.numeric((X38howmanybears
>=
# 400)&(X38howmanybears <= 600))), qdata %>% filter(Region == 'Croatia') %>%
# mutate(knowspopsize = as.numeric((X38howmanybears >= 800)&(X38howmanybears
<=
# 1200))), qdata %>% filter(Region == 'Austria') %>% mutate(knowspopsize =
# as.numeric((X38howmanybears >= 0)&(X38howmanybears <= 5))), qdata %>%
# filter(Region == 'Italy') %>% mutate(knowspopsize =
as.numeric((X38howmanybears
# >= 40)&(X38howmanybears <= 70))) ) #NA in knowspopsize is considered a 0
# (doesn't know) for knowledge score #OBSOLETE - ITALY DIDN'T CODE THIS AT
ALL,
# ONLY NA'S qdata$knowspopsize[is.na(qdata$knowspopsize)]=0
#'No' has been coded as NA
qdata$hassheep[is.na(qdata$hassheep)] = 0
qdata$hascattle[is.na(qdata$hascattle)] = 0
qdata$hashorses[is.na(qdata$hashorses)] = 0
# recode factors
qdata$hassheep = as.factor(qdata$hassheep)
levels(qdata$hassheep) = c("no", "yes")
qdata$hascattle = as.factor(qdata$hascattle)
levels(qdata$hascattle) = c("no", "yes")
qdata$hashorses = as.factor(qdata$hashorses)
levels(qdata$hashorses) = c("no", "yes")
qdata = mutate(qdata, big_livestock = as.factor((hascattle == "yes") |
(hashorses ==
    "yes")), has_livestock = as.factor((hascattle == "yes") | (hashorses ==
"yes") |
    (hassheep == "yes")), knowledge = (X39bearseat == 3) + (X40howmanycubs ==
2) +
    (X41bearsfearpeople == 2) + (X42cubsleavemom == 3))  #knowspopsize+
# remove knowledge variables
qdata = subset(qdata, select = -c(X39bearseat, X40howmanycubs,
X41bearsfearpeople,
```

```
    X42cubsleavemom))
levels(qdata$big_livestock) = c("no", "yes")
levels(qdata$has_livestock) = c("no", "yes")
# define geographic regions
qdata$georegion = qdata$Region
levels(qdata$georegion) = c("Alps", "Dinarics", "Alps", "Dinarics", "Alps")
# seen bear in nature >10 times has very low number of cases. Also
aggregated.
qdata$seennatureyesno = qdata$X44seennature
levels(qdata$seennatureyesno) = c("no", "yes", "yes")
```

Let's check how complete the dataset is.

```
missingdata = apply(qdata, 2, FUN = function(x) sum(is.na(x)))
missingdata
```

```
##                     ID                    IdOld                    PostNum
##                      0                        0                       1006
##                 Region                X1attitude              X2bearspresent
##                      0                       36                         41
##       X3futuregenerations        X4bearsnotneeded           X5bearsthreatened
##                     17                       52                         32
##             X6fearforest           X7toomanybears         X8unacceptabledamage
##                     17                       27                         26
##       X9huntingacceptable           X10cullneeded    X11increasehuntingvalue
##                     21                       14                        425
##           X12bearwatching       X13economybenefit             X14eatbearmeat
##                     20                       16                         18
##       X15bearnumberincrease         X16poachingok               X18bearattack
##                     11                       18                         21
##           X19bearsinarea        X20bearsinforest             X21bearintown
##                     48                       30                         23
##       X22meetbearfromcar    X23meetbearinforest         X24meetbearnearhome
##                     22                       30                         24
##       X25bearfeedsgarden        X26bearfeedsbees      X27bearkillslivestock
##                     26                       31                         24
##           X28feedcarrion           X29feedcorn          X30useguardingdogs
##                     18                       19                         17
##       X31useelectricfence           X32killbears          X33killproblematic
##                     19                       40                         21
##       X34responsiblegarbage       X35removebushes            X36educatepeople
##                     19                       15                         22
##           X37otheractivities        X38howmanybears            X43seencaptive
##                   1001                     1138                         20
##           X44seennature    X45hadbeardamage X46requiredcompensations
##                     24                       29                       2072
##       X47gotcompensations    X49whynotcompensation                     gender
##                   2161                     2238                         26
##                    age                education                     hunter
##                     31                       43                         24
```

```
##              beekeeper                    dogowner                  hassheep
##                     33                          28                         0
##               hascattle                    hashorses              heardproject
##                      0                           0                        55
##           pr_lessdamage            pr_transboundary             pr_studybears
##                   1522                        1517                      1518
##          pr_bearexpansion              pr_ecotourism         pr_trafficaccidents
##                   1519                        1525                      1522
##           pr_coexistence                    comments             big_livestock
##                   1516                        1448                         0
##            has_livestock                   knowledge                 georegion
##                      0                          44                         0
##          seennatureyesno
##                     24
```

Ok, some of these seem quite useless. Let's check which have more than 3% missing data cases (>69), and kick them out.

```
missingdata[missingdata > 69]
```

```
##                 PostNum  X11increasehuntingvalue      X37otheractivities
##                    1006                      425                    1001
##         X38howmanybears  X46requiredcompensations    X47gotcompensations
##                    1138                     2072                    2161
##     X49whynotcompensation           pr_lessdamage       pr_transboundary
##                    2238                     1522                    1517
##           pr_studybears          pr_bearexpansion          pr_ecotourism
##                    1518                     1519                    1525
##      pr_trafficaccidents          pr_coexistence                comments
##                    1522                     1516                    1448
```

```
uselessVars = names(missingdata[missingdata > 69])
qdata = qdata[, names(qdata)[!names(qdata) %in% uselessVars]]
```

An interesting one is "how many bears" (Q38). This has not been recorded in Italy at all, and has a lot of missing data elsewhere. Kicked out.

Let's check by cases, remove all cases where there are more than 7 missing data. The rest will be handled in case-by-case manner downstream.

```
table(apply(qdata, 1, FUN = function(x) sum(is.na(x))))
```

```
                                1   1   1   1   1   1   1   2   3   3   3   4
    0   1   2   3   4   5 6 7   8 9 0   1   2   3   4   6   7   0   0   1   5   2
  186  26   7   2   1   1 9 7   1 7 4   2   3   2   2   3   1   1   1   1   1   1
    6   1   2   9   2   1         0
```

```
# View(qdata[apply(qdata, 1, FUN=function(x) sum(is.na(x)))>4,])
okcases = apply(qdata, 1, FUN = function(x) sum(is.na(x))) < 8
qdata = qdata[okcases, ]
```

Need to check age... below 18 years should not be included in this. The cases with missing age will be put on median - not to loose data but to introduce as little noise into the dataset as possible.

```
qdata$age[is.na(qdata$age)] = median(qdata$age, na.rm = T)
sum(qdata$age < 18, na.rm = T)

## [1] 8

# Ok, 8 people < 18 years. Remove.
qdata1 = qdata[qdata$age >= 18, ]
```

8 respondents younger than 18 years were removed from the dataset.

We'll put some other on median - education, knowledge. We'll also recode NA's in dogowner, beekeeper, hunter, heardproject, seennatureyesno, X44seennature to "no" since this is probably why they didn't circle that. X43seencaptive will be set to yes since this is the most probable answer.

There are very few cases of unfinished primary school - I'll recode these as 2 (finished primary school) since otherwise they're basically outliers.

There are also not many people (except for Austria where this may be an error) that have not finished high school. I'll recode these into another variable as "finished university yes/no"

```
qdata$education[qdata$education == 1] = 2  #unfinished primary as finished
primary school
qdata$ed_university = as.factor(ifelse(qdata$education == 4, "yes", "no"))
qdata$education[is.na(qdata$education)] = median(qdata$education, na.rm = T)
qdata$knowledge[is.na(qdata$knowledge)] = median(qdata$knowledge, na.rm = T)
qdata$dogowner[is.na(qdata$dogowner)] = "no"
qdata$beekeeper[is.na(qdata$beekeeper)] = "no"
qdata$hunter[is.na(qdata$hunter)] = "no"
qdata$heardproject[is.na(qdata$heardproject)] = "no"
qdata$seennatureyesno[is.na(qdata$seennatureyesno)] = "no"
qdata$X44seennature[is.na(qdata$X44seennature)] = "no"
qdata$X43seencaptive[is.na(qdata$X43seencaptive)] = "yes"

qdata %>% group_by(Region, heardproject) %>% summarize(hear =
length(heardproject))
```

Region	heardproject	hear
Austria	no	364
Austria	yes	16
Austria	don't know	19
Croatia	no	212
Croatia	yes	64
Croatia	don't know	11

Italy	no	331
Italy	yes	21
Italy	don't know	49
Slovenia Alps	no	393
Slovenia Alps	yes	107
Slovenia Alps	don't know	22
Slovenia Dinaric	no	498
Slovenia Dinaric	yes	127
Slovenia Dinaric	don't know	33

```
qdata %>% group_by(Region, X43seencaptive) %>% summarize(hear =
length(X43seencaptive))
```

Region	X43seencaptive	hear
Austria	no	31
Austria	yes	368
Croatia	no	18
Croatia	yes	269
Italy	no	82
Italy	yes	319
Slovenia Alps	no	11
Slovenia Alps	yes	511
Slovenia Dinaric	no	7
Slovenia Dinaric	yes	651

```
qdata %>% group_by(Region, gender) %>% summarize(hear = length(gender))
```

Region	gender	hear
Austria	female	204
Austria	male	195
Croatia	female	97
Croatia	male	184
Croatia	NA	6
Italy	female	224
Italy	male	177
Slovenia Alps	female	267
Slovenia Alps	male	253
Slovenia Alps	NA	2
Slovenia Dinaric	female	333
Slovenia Dinaric	male	322

Slovenia Dinaric   NA   3

```
qdata %>% group_by(Region, X44seennature) %>% summarize(seenNature =
length(X44seennature))
```

Region	X44seennature	seenNature
Austria	no	354
Austria	yes<10	35
Austria	yes>10	10
Croatia	no	100
Croatia	yes<10	152
Croatia	yes>10	35
Italy	no	351
Italy	yes<10	48
Italy	yes>10	2
Slovenia Alps	no	407
Slovenia Alps	yes<10	108
Slovenia Alps	yes>10	7
Slovenia Dinaric	no	357
Slovenia Dinaric	yes<10	235
Slovenia Dinaric	yes>10	66

```
qdata %>% group_by(Region, hascattle) %>% summarize(hascattle1 =
length(hascattle))
```

Region	hascattle	hascattle1
Austria	no	388
Austria	yes	11
Croatia	no	266
Croatia	yes	21
Italy	no	393
Italy	yes	8
Slovenia Alps	no	452
Slovenia Alps	yes	70
Slovenia Dinaric	no	596
Slovenia Dinaric	yes	62

PCA Exploration - Attitudinal Components

This concerns questions Q1-Q18

First we try to reduce dimensionality with PCA. We're using R package 'psych' for analysis. We include all variables measuring attitude and support for conservation (the first batch of questions).

First, we need to solve missing values.

```r
PCAVariables_Attitudes = c("X1attitude", "X2bearspresent",
"X3futuregenerations",
    "X4bearsnotneeded", "X5bearsthreatened", "X6fearforest",
"X7toomanybears", "X8unacceptabledamage",
    "X9huntingacceptable", "X10cullneeded", "X12bearwatching",
"X13economybenefit",
    "X14eatbearmeat", "X15bearnumberincrease", "X16poachingok",
"X18bearattack")
pcadata_att = qdata[, PCAVariables_Attitudes]
summary(pcadata_att)
```

	X1attitude	X2bearspresent	X3futuregenerations	X4bearsnotneeded	X5bearsthreatened	X6fearforest	X7toomanybears	X8unacceptabledamage	X9huntingacceptable	X10cullneeded	X12bearwatching	X13economybenefit	X14eatbearmeat	X15bearnumberincrease	X16poachingok	X18bearattack
Min.	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00	Min. :1.00
1st Qu.	1st Qu.:3.00	1st Qu.:4.00	1st Qu.:4.00	1st Qu.:1.00	1st Qu.:2.00	1st Qu.:2.00	1st Qu.:2.00	1st Qu.:2.00	1st Qu.:2.00	1st Qu.:2.00	1st Qu.:3.00	1st Qu.:3.00	1st Qu.:1.00	1st Qu.:2.00	1st Qu.:1.00	1st Qu.:2.00
Median	Median :4.00	Median :4.00	Median :4.00	Median :2.00	Median :3.00	Median :3.00	Median :3.00	Median :3.00	Median :3.00	Median :3.00	Median :4.00	Median :3.00	Median :2.00	Median :3.00	Median :2.00	Median :4.00

Mean :3.84	Mean :3.992	Mean :4.045	Mean :1.933	Mean :3.248	Mean :3.008	Mean :2.613	Mean :2.704	Mean :2.868	Mean :3.176	Mean :3.564	Mean :3.269	Mean :2.437	Mean :2.944	Mean :1.977	Mean :3.252
3rd Qu.:5.00	3rd Qu.:5.00	3rd Qu.:5.000	3rd Qu.:2.000	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:3.000	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:2.000	3rd Qu.:4.000
Max. :5.00	Max. :5.00	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000
NA's :31	NA's :37	NA's :10	NA's :44	NA's :23	NA's :7	NA's :14	NA's :14	NA's :9	NA's :3	NA's :8	NA's :4	NA's :6	NA's :1	NA's :9	NA's :15

Not too bad - just a 1-3% missing data. To avoid loosing data, these missing values will be replaced by average for the column, which shouldn't bias the PCA.

```r
for (i in 1:ncol(pcadata_att)) pcadata_att[is.na(pcadata_att[, i]), i] =
mean(pcadata_att[,
    i], na.rm = T)
```

Do the first PCA, see if things start making sense.

```r
ev <- eigen(cor(pcadata_att))  # get eigenvalues
ap <- parallel(subject = nrow(pcadata_att), var = ncol(pcadata_att), rep =
100, cent = 0.05)
nS <- nScree(x = ev$values, aparallel = ap$eigen$qevpea)
plotnScree(nS)
```

Non Graphical Solutions to Scree Test
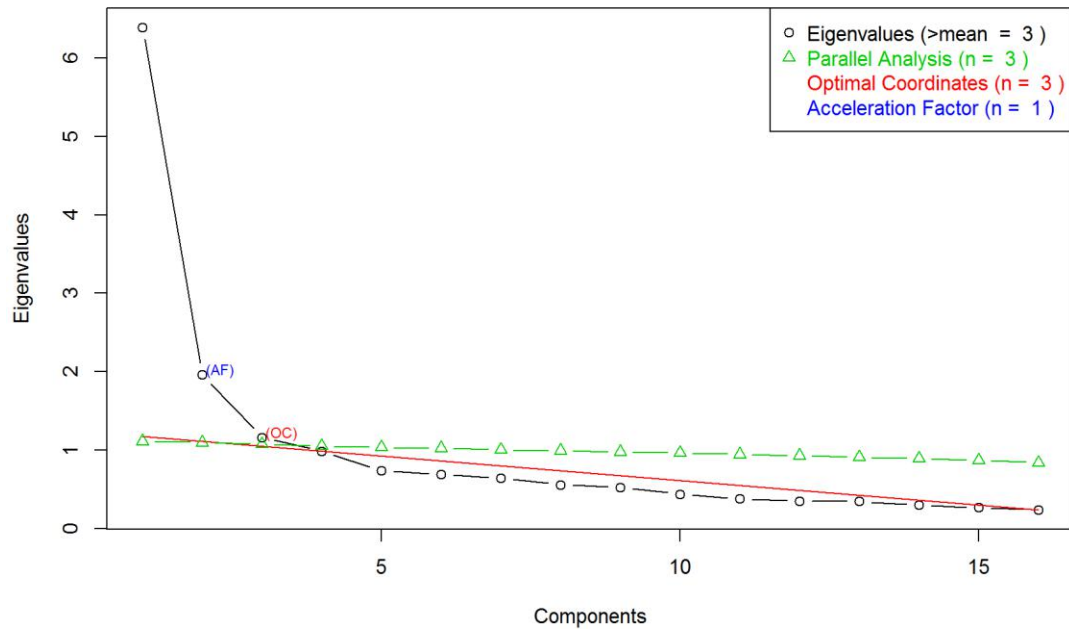
It seems to make sense to retain three components according to Kaiser-Guttman rule (eigenvalue > 1), Parallel Analysis and Optimal Coordinates. Accelleration Factor does max-out at 2 (supporting 1 component). Eigenvalue of PC2 is considerably smaller than that of PC1 and PC3 has low eigenvalue, so some caution is warranted.

Let's check interpretability of *three components*.

```
pca_all = principal(pcadata_att, rotate = "varimax", nfactors = 3, scores =
T, missing = F)
plot(pca_all, cex = 0.9, labels = names(pcadata_att), choose = c(1, 2), xlim
= c(-0.8,
    0.8), ylim = c(-0.8, 0.8), title = "PCA - all variables")
```

PCA - all variables
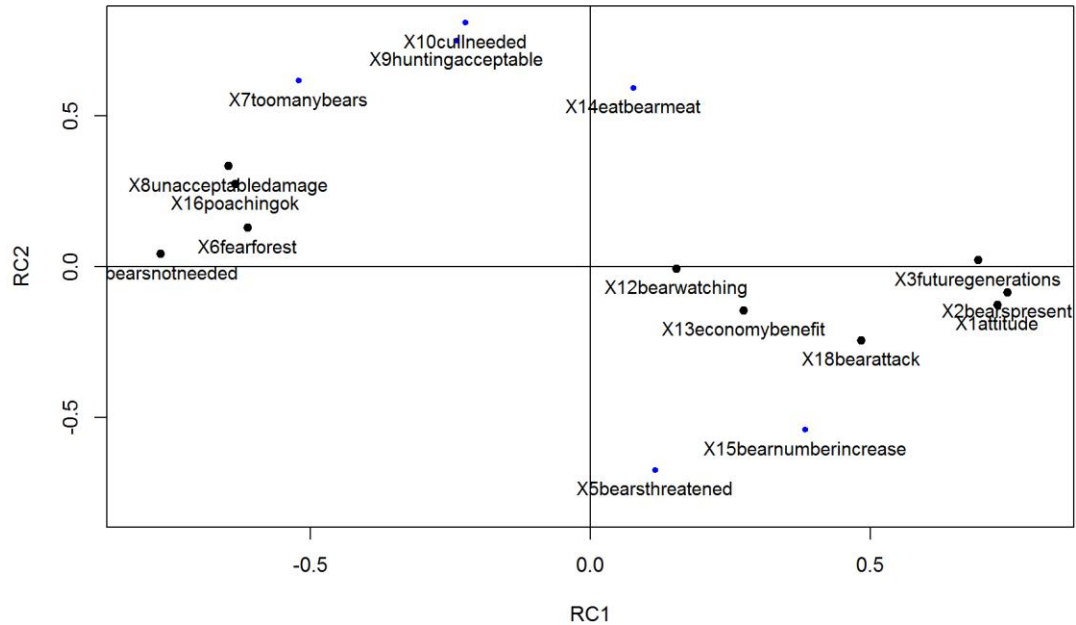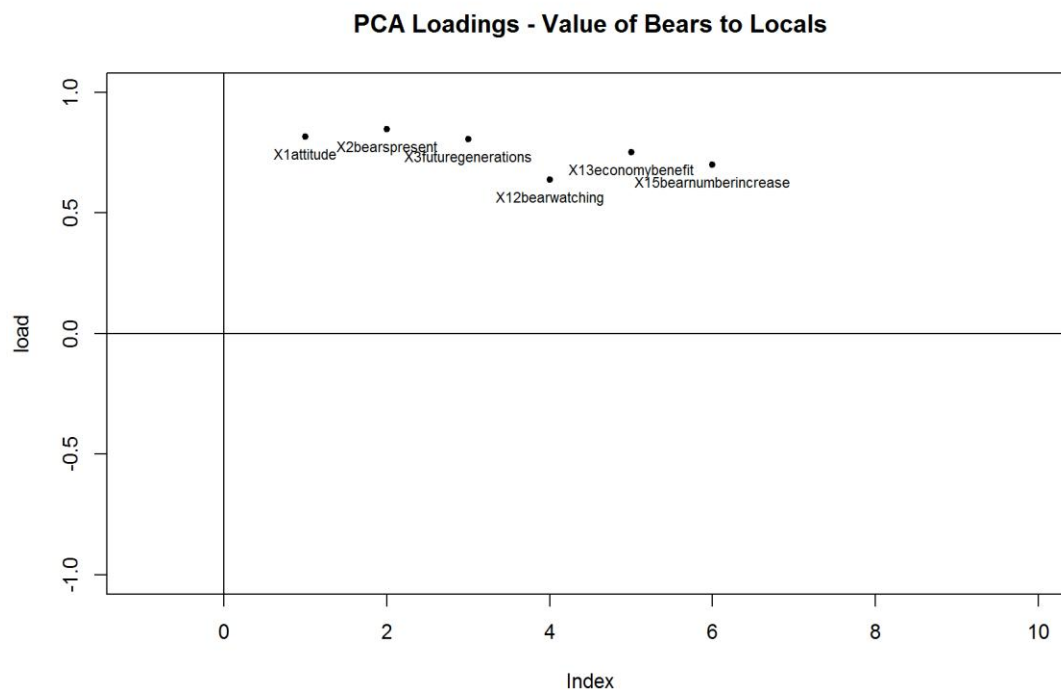


```
pca_all

## Principal Components Analysis
## Call: principal(r = pcadata_att, nfactors = 3, rotate = "varimax",
##      scores = T, missing = F)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                          RC1    RC2    RC3   h2   u2  com
## X1attitude              0.73  -0.13   0.35 0.67 0.33 1.5
## X2bearspresent          0.74  -0.09   0.40 0.72 0.28 1.6
## X3futuregenerations     0.69   0.02   0.41 0.65 0.35 1.6
## X4bearsnotneeded       -0.77   0.04  -0.12 0.61 0.39 1.1
## X5bearsthreatened       0.12  -0.67   0.35 0.59 0.41 1.6
## X6fearforest           -0.61   0.13  -0.11 0.41 0.59 1.2
## X7toomanybears         -0.52   0.62  -0.24 0.71 0.29 2.3
## X8unacceptabledamage   -0.65   0.33  -0.12 0.55 0.45 1.6
## X9huntingacceptable    -0.24   0.75  -0.05 0.62 0.38 1.2
## X10cullneeded          -0.22   0.81  -0.08 0.71 0.29 1.2
## X12bearwatching         0.15  -0.01   0.81 0.68 0.32 1.1
## X13economybenefit       0.27  -0.15   0.78 0.71 0.29 1.3
## X14eatbearmeat          0.08   0.59   0.27 0.43 0.57 1.4
## X15bearnumberincrease   0.38  -0.54   0.47 0.66 0.34 2.8
## X16poachingok          -0.63   0.27   0.10 0.49 0.51 1.4
## X18bearattack           0.48  -0.24   0.14 0.31 0.69 1.7
##
##                          RC1   RC2   RC3
## SS loadings             4.23  3.01  2.28
## Proportion Var          0.26  0.19  0.14
## Cumulative Var          0.26  0.45  0.59
```

```
## Proportion Explained  0.44 0.32 0.24
## Cumulative Proportion 0.44 0.76 1.00
##
## Mean item complexity =  1.5
## Test of the hypothesis that 3 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.06
##  with the empirical chi square  2164.69  with prob <  0
##
## Fit based upon off diagonal values = 0.97
```

The "eatbearmeat" variable clusters on its own and doesn't seem to be connected to the attitude components extracted. Remove, run without it.

```r
pcadata_ng = pcadata_att[, -13]
pca_ng = principal(pcadata_ng, rotate = "varimax", nfactors = 3, scores = T,
missing = F)
par(mfrow = c(2, 2))
plot(pca_ng, cex = 0.9, labels = names(pcadata_ng), choose = c(1, 2), xlim =
c(-1,
    1), ylim = c(-1, 1), title = "PCA - no gastronomy, PC1:PC2")
plot(pca_ng, cex = 0.9, labels = names(pcadata_ng), choose = c(1, 3), xlim =
c(-1,
    1), ylim = c(-1, 1), title = "PCA - no gastronomy, PC1:PC3")
plot(pca_ng, cex = 0.9, labels = names(pcadata_ng), choose = c(2, 3), xlim =
c(-1,
    1), ylim = c(-1, 1), title = "PCA - no gastronomy, PC2:PC3")
par(mfrow = c(1, 1))
```


PCA - no gastronomy, PC1:PC2

PCA - no gastronomy, PC1:PC3

PCA - no gastronomy, PC2:PC3
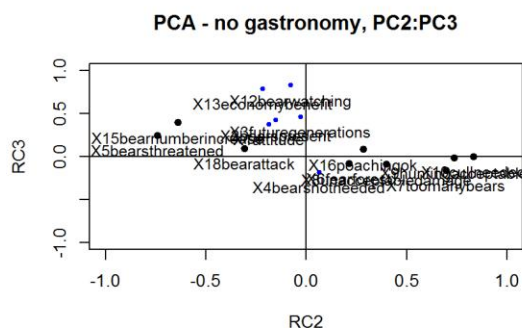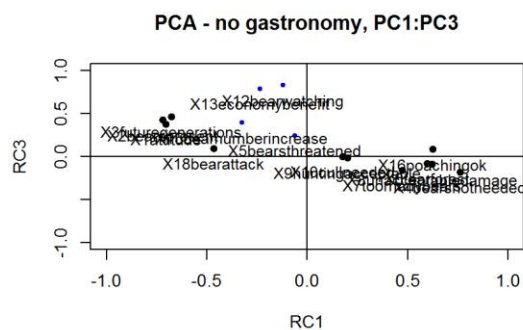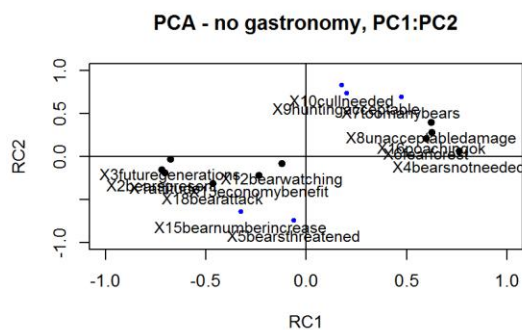
```
pca_ng

## Principal Components Analysis
## Call: principal(r = pcadata_ng, nfactors = 3, rotate = "varimax", scores =
T,
##      missing = F)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                          RC1   RC2   RC3   h2   u2 com
## X1attitude             -0.71 -0.19  0.38 0.68 0.32 1.7
## X2bearspresent         -0.72 -0.15  0.43 0.73 0.27 1.7
## X3futuregenerations    -0.68 -0.03  0.47 0.68 0.32 1.8
## X4bearsnotneeded        0.76  0.07 -0.18 0.62 0.38 1.1
## X5bearsthreatened      -0.06 -0.74  0.25 0.62 0.38 1.2
## X6fearforest            0.60  0.21 -0.08 0.41 0.59 1.3
## X7toomanybears          0.47  0.70 -0.16 0.73 0.27 1.9
## X8unacceptabledamage    0.62  0.40 -0.09 0.55 0.45 1.8
## X9huntingacceptable     0.20  0.74 -0.01 0.59 0.41 1.1
## X10cullneeded           0.18  0.83  0.00 0.72 0.28 1.1
## X12bearwatching        -0.12 -0.08  0.83 0.72 0.28 1.1
## X13economybenefit      -0.24 -0.22  0.79 0.73 0.27 1.3
## X15bearnumberincrease  -0.33 -0.64  0.40 0.67 0.33 2.2
## X16poachingok           0.62  0.28  0.09 0.48 0.52 1.4
## X18bearattack          -0.47 -0.31  0.10 0.32 0.68 1.8
##
##                          RC1  RC2  RC3
## SS loadings             3.89 3.18 2.18
## Proportion Var          0.26 0.21 0.15
## Cumulative Var          0.26 0.47 0.62
## Proportion Explained    0.42 0.34 0.24
## Cumulative Proportion   0.42 0.76 1.00
##
## Mean item complexity =  1.5
## Test of the hypothesis that 3 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.06
##   with the empirical chi square  1768.05  with prob <  0
##
## Fit based upon off diagonal values = 0.98
```

A bit tricky to interpret. First component seems support for conservation [conservation]. The second is support for bear control[control], third seems to be about value for locals [value].

First, let's extract the [conservation] component. All variables with loadings >0.4.

```
pcadata_conservation = pcadata_ng[, -c(5, 9:13)]
pca_conservation = principal(pcadata_conservation, rotate = "varimax",
nfactors = 1,
    scores = T, missing = F)
plot(pca_conservation, labels = names(pcadata_conservation), xlim = c(-1,
```

```
13), ylim = c(-1,
    1), title = "PCA Loadings - Support for Bear Conservation", cex = 0.7)
```

PCA Loadings - Support for Bear Conservation
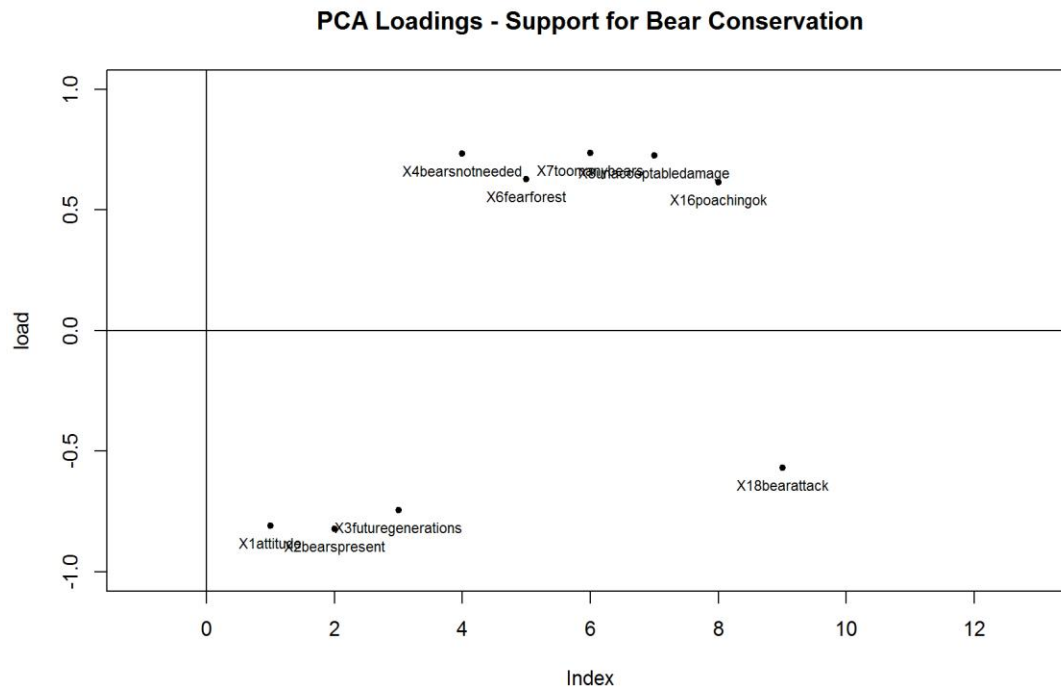

```
pca_conservation

## Principal Components Analysis
## Call: principal(r = pcadata_conservation, nfactors = 1, rotate =
"varimax",
##      scores = T, missing = F)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                         PC1   h2   u2 com
## X1attitude             -0.81 0.66 0.34   1
## X2bearspresent         -0.82 0.68 0.32   1
## X3futuregenerations    -0.75 0.56 0.44   1
## X4bearsnotneeded        0.73 0.54 0.46   1
## X6fearforest            0.63 0.39 0.61   1
## X7toomanybears          0.73 0.54 0.46   1
## X8unacceptabledamage    0.73 0.53 0.47   1
## X16poachingok           0.61 0.38 0.62   1
## X18bearattack          -0.57 0.32 0.68   1
##
##                   PC1
## SS loadings      4.59
## Proportion Var   0.51
##
## Mean item complexity =  1
## Test of the hypothesis that 1 component is sufficient.
##
```

```
## The root mean square of the residuals (RMSR) is  0.09
##  with the empirical chi square  1268.13  with prob <  2.7e-250
##
## Fit based upon off diagonal values = 0.96
```

Second, the [control] component. All variables with loadings >0.4.

```
pcadata_control = pcadata_ng[, -c(1:4, 6, 11, 12, 14, 15)]
pca_control = principal(pcadata_control, rotate = "varimax", nfactors = 1,
scores = T,
    missing = F)
plot(pca_control, labels = names(pcadata_control), ylim = c(-1, 1), xlim =
c(0, 10),
    title = "PCA Loadings - Support for Bear Control", cex = 0.7)
```

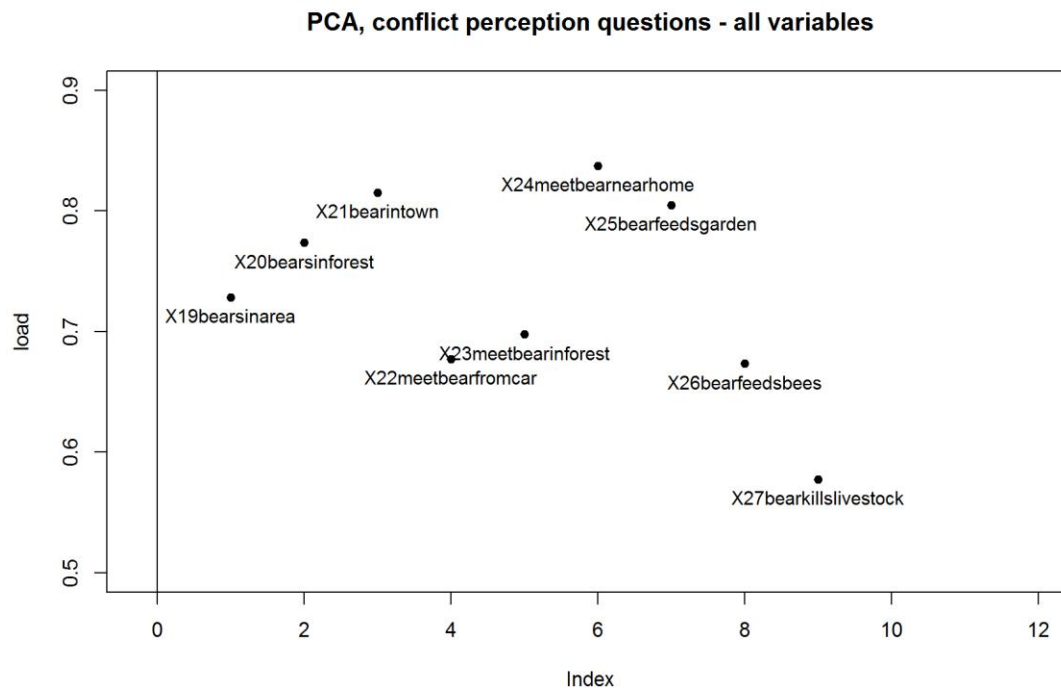**PCA Loadings - Support for Bear Control**
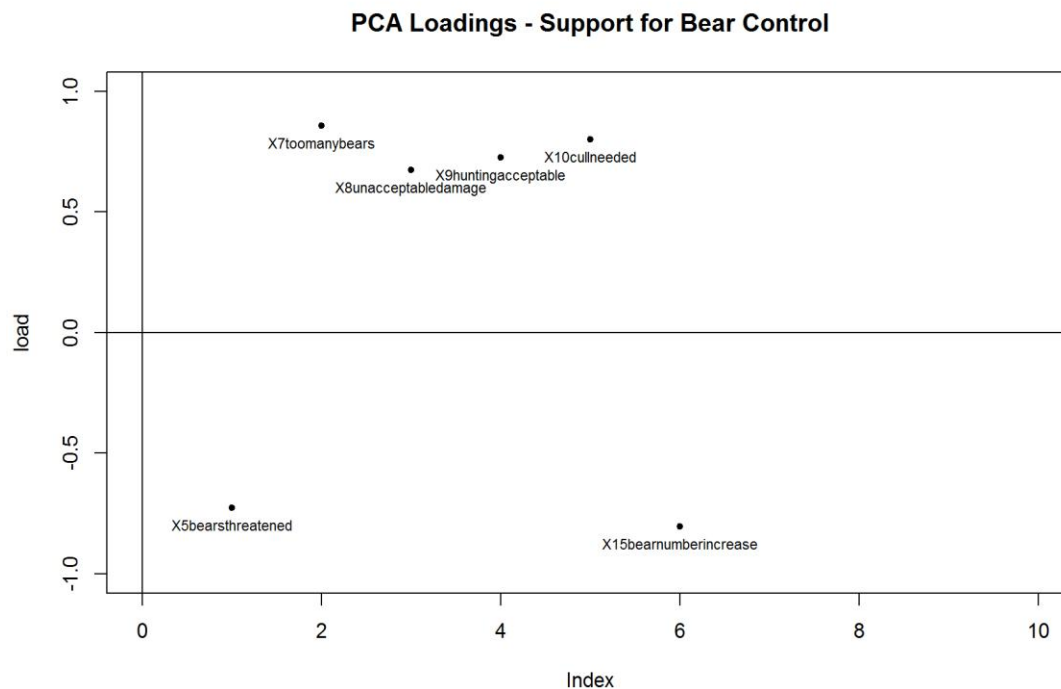

```
pca_control

## Principal Components Analysis
## Call: principal(r = pcadata_control, nfactors = 1, rotate = "varimax",
##     scores = T, missing = F)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                       PC1   h2    u2 com
## X5bearsthreatened     -0.73 0.53 0.47   1
## X7toomanybears         0.86 0.74 0.26   1
## X8unacceptabledamage   0.67 0.45 0.55   1
## X9huntingacceptable    0.73 0.53 0.47   1
## X10cullneeded          0.80 0.64 0.36   1
## X15bearnumberincrease -0.80 0.65 0.35   1
```

```
##
##                  PC1
## SS loadings     3.53
## Proportion Var 0.59
##
## Mean item complexity =  1
## Test of the hypothesis that 1 component is sufficient.
##
## The root mean square of the residuals (RMSR) is  0.11
##  with the empirical chi square  787.33  with prob <  1.1e-163
##
## Fit based upon off diagonal values = 0.96
```

Third, the [value] component. All variables with loadings >0.4.

```
pcadata_value = pcadata_ng[, -c(4:10, 14, 15)]
pca_value = principal(pcadata_value, rotate = "varimax", nfactors = 1, scores
= T,
    missing = F)
plot(pca_value, labels = names(pcadata_value), xlim = c(-1, 10), ylim = c(-1,
1),
    title = "PCA Loadings - Value of Bears to Locals", cex = 0.7)
```


PCA Loadings - Value of Bears to Locals

```
pca_value
```

```
## Principal Components Analysis
## Call: principal(r = pcadata_value, nfactors = 1, rotate = "varimax",
##      scores = T, missing = F)
```

```
## Standardized loadings (pattern matrix) based upon correlation matrix
##                           PC1    h2    u2 com
## X1attitude               0.82 0.67 0.33    1
## X2bearspresent           0.85 0.72 0.28    1
## X3futuregenerations      0.80 0.65 0.35    1
## X12bearwatching          0.64 0.41 0.59    1
## X13economybenefit        0.75 0.57 0.43    1
## X15bearnumberincrease    0.70 0.49 0.51    1
##
##                    PC1
## SS loadings       3.50
## Proportion Var    0.58
##
## Mean item complexity =  1
## Test of the hypothesis that 1 component is sufficient.
##
## The root mean square of the residuals (RMSR) is  0.12
##  with the empirical chi square  908.36  with prob <  9.8e-190
##
## Fit based upon off diagonal values = 0.95
```

To facilitate interpretation of PCA scores we need to find the "neutral" PCA score (all answers are 3).

```
JoeNeutral = pcadata_ng[1, ]
JoeNeutral[, 1:15] = rep(3, 15)
JoeConservation = predict(object = pca_conservation, data = JoeNeutral[, -
c(5, 9:13)],
    old.data = pcadata_ng[, -c(5, 9:13)])[1, 1]
JoeControl = predict(object = pca_control, data = JoeNeutral[, -c(1:4, 6, 11,
12,
    14, 15)], old.data = pcadata_ng[, -c(1:4, 6, 11, 12, 14, 15)])[1, 1]
JoeValue = predict(object = pca_value, data = JoeNeutral[, -c(4:10, 14, 15)],
old.data = pcadata_ng[,
    -c(4:10, 14, 15)])[1, 1]
```

Now all PCA scores are going to be centered on "JoeNeutral" and re-scaled to -2 to +2, where 0 is neutral. This can be easily converted to Likert scale if need be just by adding 3. A new data frame with variables interesting for interpretation and PCA scores will be produced

```
nonPCAvariables = names(qdata)[!names(qdata) %in% PCAVariables_Attitudes]
#the variables not included in PCA scores are preserved
# conservation centering/rescaling
conservation = scale(pca_conservation$scores[, 1], center = JoeConservation,
scale = F)
conservation = (conservation/max(abs(conservation), na.rm = T)) * 2
conservation = -1 * conservation  #needs to be inverted to correctly depict
positive/negative
hist(conservation, xlab = "Support for Bear Conservation", main = "Histogram
```

```
of Support for Conservation",
    nclass = 50, xlim = c(-2, 2))
```

Histogram of Support for Conservation

Support for Bear Conservation
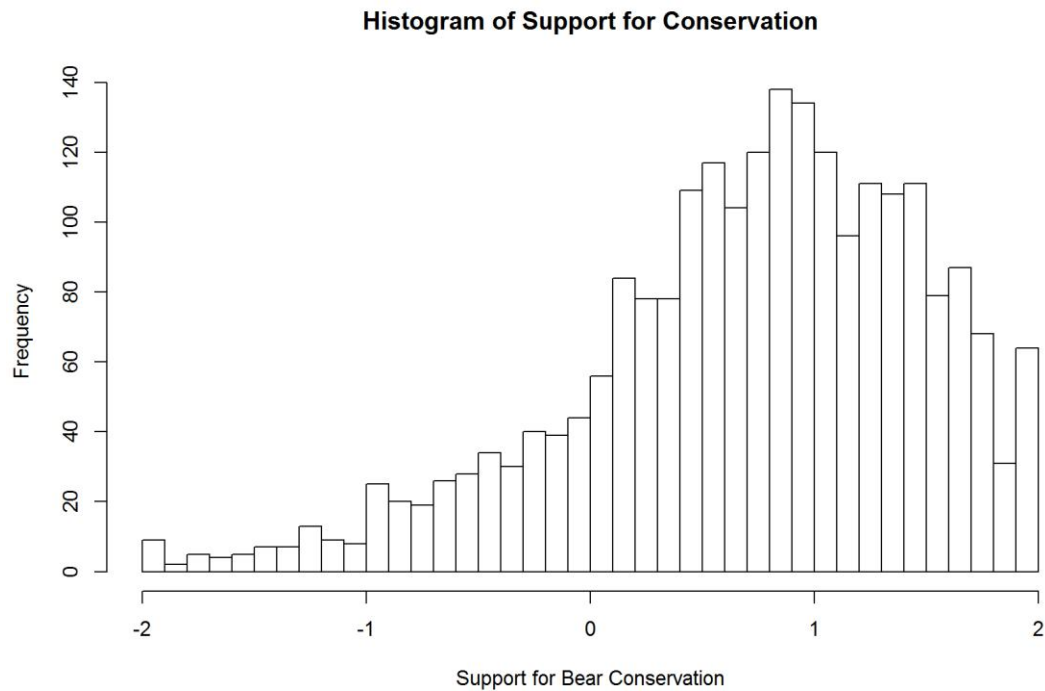
```
# control centering/rescaling
control = scale(pca_control$scores[, 1], center = JoeControl, scale = F)
control = (control/max(abs(control), na.rm = T)) * 2
hist(control, xlab = "Support for Bear Population Control", main = "Histogram
of Support for Bear Populatoin Control",
    nclass = 50, xlim = c(-2, 2))
```

Histogram of Support for Bear Populatoin Control
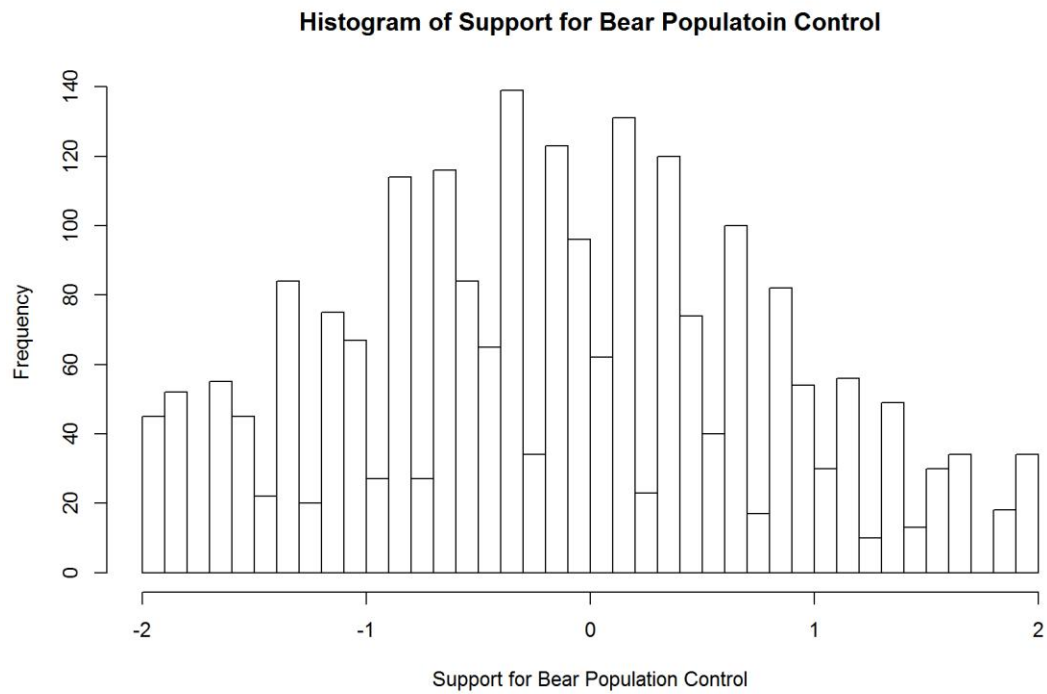

```r
# value centering/rescaling
value = scale(pca_value$scores[, 1], center = JoeValue, scale = F)
value = (value/max(abs(value), na.rm = T)) * 2
hist(value, xlab = "Perceived Value of Bears", main = "Histogram of Percieved
Value of Bears",
    nclass = 50, xlim = c(-2, 2))
```

Histogram of Percieved Value of Bears


```
modeldata = data.frame(qdata[, nonPCAvariables], bear_conservation =
conservation,
    bear_control = control, bear_value = value)
```

PCA Exploration - Conflict perception

This looks at the conflict perception questions (Q19 - Q27). We'll also reduce dimensionality through PCA. Downstream these can be used either as response or predictor variables.

First, we need subset data and solve missing values.

```
PCAVariables_Conflict = c("X19bearsinarea", "X20bearsinforest",
"X21bearintown",
    "X22meetbearfromcar", "X23meetbearinforest", "X24meetbearnearhome",
"X25bearfeedsgarden",
    "X26bearfeedsbees", "X27bearkillslivestock")
pcadata_conf = qdata[, PCAVariables_Conflict]
summary(pcadata_conf)
```

X19be arsina rea	X20be arsinfo rest	X21be arinto wn	X22mee tbearfro mcar	X23mee tbearinf orest	X24meet bearnear home	X25bear feedsga rden	X26bea rfeeds bees	X27bear killslives tock
Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000
1st	1st	1st	1st	1st	1st	1st	1st	1st

Qu.:2.000	Qu.:2.000	Qu.:2.000	Qu.:2.000	Qu.:2.000	Qu.:1.000	Qu.:1.000	Qu.:1.000	Qu.:1.000
Median :3.000	Median :3.000	Median :2.000	Median :4.000	Median :4.000	Median :2.000	Median :2.000	Median :2.000	Median :1.000
Mean :3.165	Mean :3.051	Mean :2.458	Mean :3.343	Mean :3.156	Mean :2.212	Mean :2.099	Mean :1.875	Mean :1.517
3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:3.000	3rd Qu.:3.000	3rd Qu.:2.000	3rd Qu.:2.000
Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000
NA's :36	NA's :13	NA's :10	NA's :8	NA's :17	NA's :11	NA's :11	NA's :16	NA's :9

Not too bad - just a 1-2% missing data. To avoid loosing data, these missing values will be replaced by average for the column, which shouldn't bias the PCA.

```
for (i in 1:ncol(pcadata_conf)) pcadata_conf[is.na(pcadata_conf[, i]), i] =
mean(pcadata_conf[,
    i], na.rm = T)
```

Do the first PCA, see if things start making sense.

```
ev <- eigen(cor(pcadata_conf))  # get eigenvalues
ap <- parallel(subject = nrow(pcadata_conf), var = ncol(pcadata_conf), rep =
100,
    cent = 0.05)
nS <- nScree(x = ev$values, aparallel = ap$eigen$qevpea)
plotnScree(nS)
```

Non Graphical Solutions to Scree Test
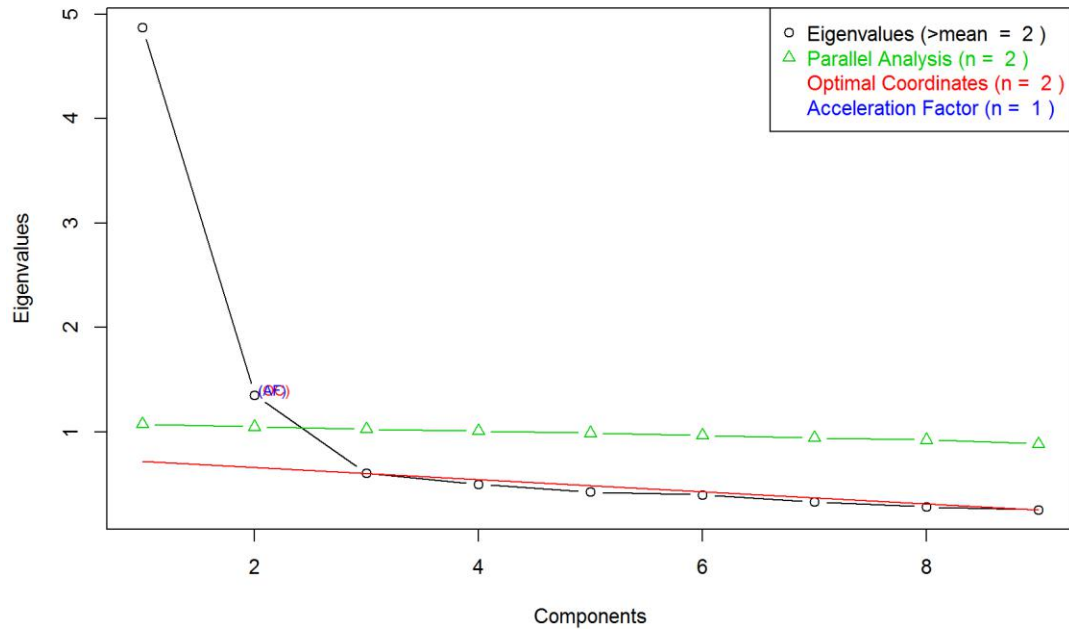
It seems to make sense to retain two components according to Kaiser-Guttman rule (eigenvalue > 1), Parallel Analysis and Optimal Coordinates. Accelleration Factor does max-out at 2 (supporting 1 component). Eigenvalue of PC2 is considerably smaller than that of PC1. Need to check interpretability.

Let's check interpretability of *two components*.

```
pca_conf = principal(pcadata_conf, rotate = "varimax", nfactors = 2, scores =
T,
    missing = F)
plot(pca_conf, cex = 0.9, labels = names(pcadata_conf), title = "PCA,
conflict perception questions - all variables",
    xlim = c(-0.2, 1), ylim = c(-0.2, 1))
```

**PCA, conflict perception questions - all variables**
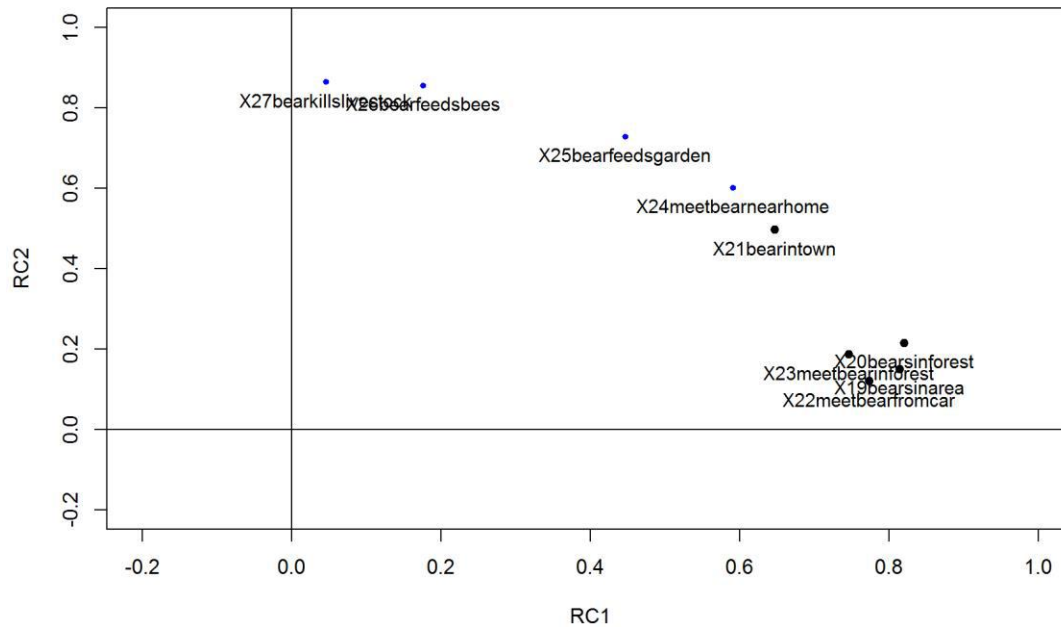

```
pca_conf

## Principal Components Analysis
## Call: principal(r = pcadata_conf, nfactors = 2, rotate = "varimax",
##      scores = T, missing = F)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                          RC1   RC2   h2    u2   com
## X19bearsinarea          0.81  0.15  0.69  0.31  1.1
## X20bearsinforest        0.82  0.22  0.72  0.28  1.1
## X21bearintown           0.65  0.50  0.66  0.34  1.9
## X22meetbearfromcar      0.77  0.12  0.61  0.39  1.0
## X23meetbearinforest     0.75  0.19  0.59  0.41  1.1
## X24meetbearnearhome     0.59  0.60  0.71  0.29  2.0
## X25bearfeedsgarden      0.45  0.73  0.73  0.27  1.7
## X26bearfeedsbees        0.18  0.86  0.76  0.24  1.1
## X27bearkillslivestock   0.05  0.86  0.75  0.25  1.0
##
##                          RC1   RC2
## SS loadings             3.49  2.74
## Proportion Var          0.39  0.30
## Cumulative Var          0.39  0.69
## Proportion Explained    0.56  0.44
## Cumulative Proportion   0.56  1.00
##
## Mean item complexity =  1.3
## Test of the hypothesis that 2 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.07
```

```
##   with the empirical chi square  698.49  with prob <  7.5e-136
##
## Fit based upon off diagonal values = 0.98
```

One component makes sense.

```
pca_conf = principal(pcadata_conf, rotate = "varimax", nfactors = 1, scores =
T,
    missing = F)
plot(pca_conf, cex = 0.9, labels = names(pcadata_conf), title = "PCA,
conflict perception questions - all variables",
    xlim = c(-0.2, 12), ylim = c(0.5, 0.9))
```


PCA, conflict perception questions - all variables

```
pca_conf
```

```
## Principal Components Analysis
## Call: principal(r = pcadata_conf, nfactors = 1, rotate = "varimax",
##      scores = T, missing = F)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                     PC1   h2   u2 com
## X19bearsinarea      0.73 0.53 0.47   1
## X20bearsinforest    0.77 0.60 0.40   1
## X21bearintown       0.82 0.66 0.34   1
## X22meetbearfromcar  0.68 0.46 0.54   1
## X23meetbearinforest 0.70 0.49 0.51   1
## X24meetbearnearhome 0.84 0.70 0.30   1
## X25bearfeedsgarden  0.81 0.65 0.35   1
## X26bearfeedsbees    0.67 0.45 0.55   1
```

```
## X27bearkillslivestock 0.58 0.33 0.67    1
##
##                    PC1
## SS loadings      4.87
## Proportion Var 0.54
##
## Mean item complexity =  1
## Test of the hypothesis that 1 component is sufficient.
##
## The root mean square of the residuals (RMSR) is  0.12
##  with the empirical chi square  2287.96  with prob <  0
##
## Fit based upon off diagonal values = 0.94
```

To facilitate interpretation of PCA scores we need to find the "neutral" PCA score (all answers are 3).

```
JoeNeutral = pcadata_conf[1, ]
JoeNeutral[, 1:9] = rep(3, 9)
JoeConflict = predict(object = pca_conf, data = JoeNeutral, old.data =
pcadata_conf)[1,
    1]
```

Now all PCA scores are going to be centered on "JoeNeutral" and re-scaled to -2 to +2, where 0 is neutral. This can be easily converted to Likert scale if need be just by adding 3. A new data frame with variables interesting for interpretation and PCA scores will be produced

```
nonPCAvariables2 = names(modeldata)[!names(modeldata) %in%
PCAVariables_Conflict]  #the variables not included in PCA scores are
preserved
# will code this as tolerance of bears
conflict_tolerance = scale(pca_conf$scores[, 1], center = JoeConflict, scale
= F)
conflict_tolerance = (conflict_tolerance/max(abs(conflict_tolerance), na.rm =
T)) *
    2
hist(conflict_tolerance, xlab = "Tolerance of Bear Conflicts", main =
"Histogram of Tolerance of Bear Conflicts",
    nclass = 50, xlim = c(-2, 2))
```

Histogram of Tolerance of Bear Conflicts
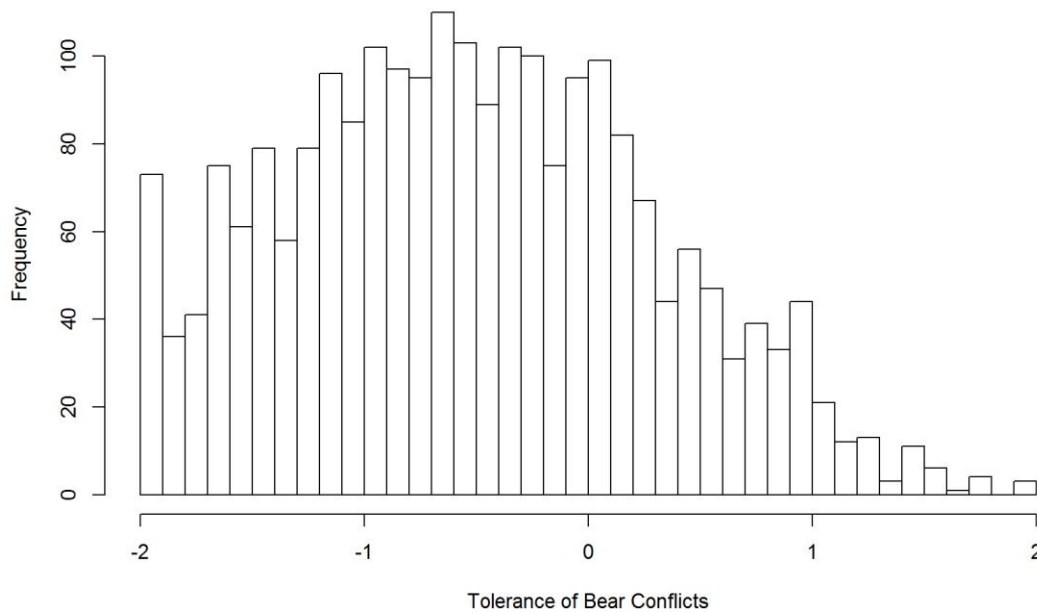

```
modeldata2 = data.frame(modeldata[, nonPCAvariables2], conflict_tolerance)
```

End product - tolerance of conflicts caused by bears. +2 = bears can do whatever, -2 = bears should behave completely, 0 = I don't care.

PCA Exploration - conflict resolution activities

This looks at the questions about solutions to conflicts with bears (Q28 - Q36). We'll also reduce dimensionality through PCA. Downstream these can be used either as response or predictor variables.

First, we need subset data and solve missing values.

```
PCAVariables_Solutions = c("X28feedcarrion", "X29feedcorn",
"X30useguardingdogs",
    "X31useelectricfence", "X32killbears", "X33killproblematic",
"X34responsiblegarbage",
    "X35removebushes", "X36educatepeople")
pcadata_sol = qdata[, PCAVariables_Solutions]
summary(pcadata_sol)
```

X28fee dcarri on	X29f eedc orn	X30useg uardingd ogs	X31usee lectricfe nce	X32k illbea rs	X33killp roblema tic	X34respo nsiblegar bage	X35rem ovebus hes	X36edu catepeo ple
Min. :1.000	Min. :1.00 0	Min. :1.00	Min. :1.000	Min. :1.00 0	Min. :1.000	Min. :1.000	Min. :1.00	Min. :1.000

1st Qu.:3.000	1st Qu.:3.000	1st Qu.:3.00	1st Qu.:3.000	1st Qu.:2.000	1st Qu.:3.00	1st Qu.:3.000	1st Qu.:2.00	1st Qu.:4.000
Median :4.000	Median :4.000	Median :4.00	Median :4.000	Median :3.000	Median :4.000	Median :4.000	Median :3.00	Median :5.000
Mean :3.485	Mean :3.719	Mean :3.75	Mean :3.712	Mean :3.195	Mean :3.774	Mean :3.952	Mean :2.99	Mean :4.307
3rd Qu.:4.000	3rd Qu.:5.000	3rd Qu.:4.00	3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:5.00	3rd Qu.:5.000	3rd Qu.:4.00	3rd Qu.:5.000
Max. :5.000	Max. :5.000	Max. :5.00	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.00	Max. :5.000
NA's :7	NA's :8	NA's :6	NA's :8	NA's :25	NA's :10	NA's :8	NA's :4	NA's :16

Not too bad - just a 1-2% missing data. To avoid loosing data, these missing values will be replaced by average for the column, which shouldn't bias the PCA.

```r
for (i in 1:ncol(pcadata_sol)) pcadata_sol[is.na(pcadata_sol[, i]), i] =
mean(pcadata_sol[,
    i], na.rm = T)
```

Do the first PCA, see if things start making sense.

```r
ev <- eigen(cor(pcadata_sol))  # get eigenvalues
ap <- parallel(subject = nrow(pcadata_sol), var = ncol(pcadata_sol), rep =
100, cent = 0.05)
nS <- nScree(x = ev$values, aparallel = ap$eigen$qevpea)
plotnScree(nS)
```

Non Graphical Solutions to Scree Test
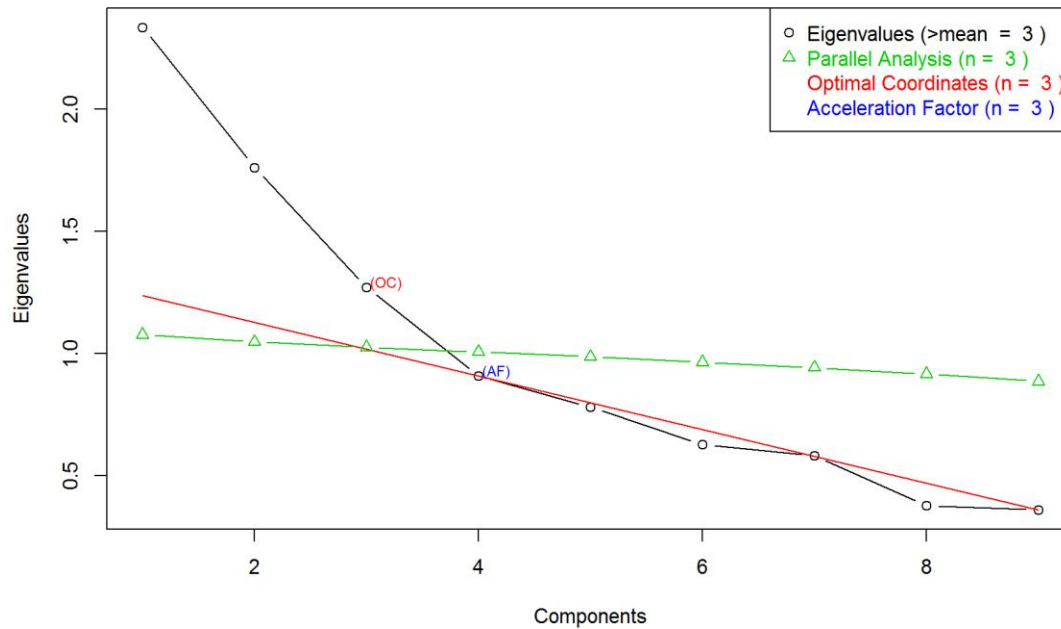
It seems to make sense to retain three components according to all criteria. Let's check interpretability of *three components*.

```
pca_sol = principal(pcadata_sol, rotate = "varimax", nfactors = 3, scores =
T, missing = F)
par(mfrow = c(2, 2))
plot(pca_sol, cex = 0.9, labels = names(pcadata_sol), choose = c(1, 2), xlim
= c(-1,
    1), ylim = c(-1, 1), title = "PCA - conflict solutions, PC1:PC2")
plot(pca_sol, cex = 0.9, labels = names(pcadata_sol), choose = c(1, 3), xlim
= c(-1,
    1), ylim = c(-1, 1), title = "PCA - conflict solutions, PC1:PC3")
plot(pca_sol, cex = 0.9, labels = names(pcadata_sol), choose = c(2, 3), xlim
= c(-1,
    1), ylim = c(-1, 1), title = "PCA - conflict solutions, PC2:PC3")
par(mfrow = c(1, 1))
```

PCA - conflict solutions, PC1:PC2

PCA - conflict solutions, PC1:PC3

PCA - conflict solutions, PC2:PC3
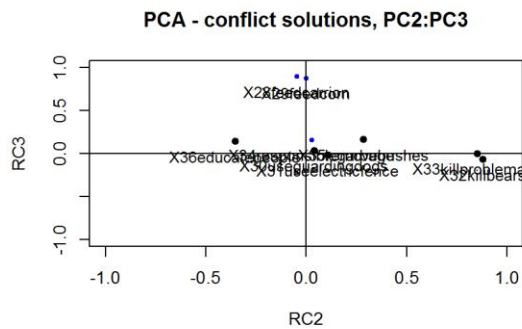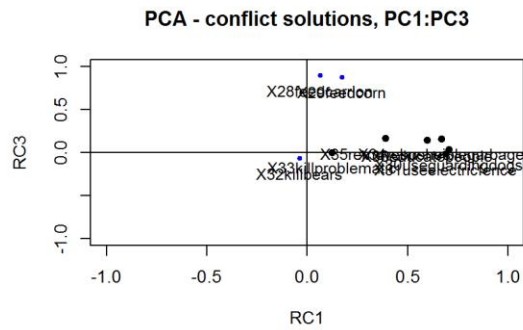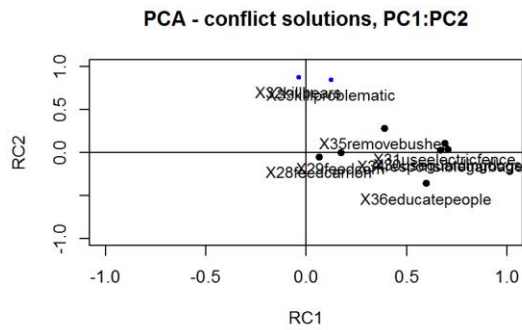
```
pca_sol

## Principal Components Analysis
## Call: principal(r = pcadata_sol, nfactors = 3, rotate = "varimax",
##     scores = T, missing = F)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                         RC1   RC2   RC3   h2   u2 com
## X28feedcarrion         0.06 -0.05  0.90 0.81 0.19 1.0
## X29feedcorn            0.17  0.00  0.88 0.80 0.20 1.1
## X30useguardingdogs     0.70  0.04  0.04 0.50 0.50 1.0
## X31useelectricfence    0.69  0.11 -0.02 0.49 0.51 1.0
## X32killbears          -0.04  0.88 -0.07 0.78 0.22 1.0
## X33killproblematic     0.12  0.85  0.00 0.74 0.26 1.0
## X34responsiblegarbage  0.67  0.03  0.16 0.47 0.53 1.1
## X35removebushes        0.39  0.28  0.17 0.26 0.74 2.2
## X36educatepeople       0.60 -0.35  0.14 0.51 0.49 1.8
##
##                         RC1  RC2  RC3
## SS loadings            1.98 1.72 1.66
## Proportion Var         0.22 0.19 0.18
## Cumulative Var         0.22 0.41 0.60
## Proportion Explained   0.37 0.32 0.31
## Cumulative Proportion  0.37 0.69 1.00
##
## Mean item complexity =  1.3
## Test of the hypothesis that 3 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.1
```

```
##  with the empirical chi square  1511.16  with prob <  1.5e-316
##
## Fit based upon off diagonal values = 0.82
```

All three components are interpretable. PC1 = conflict mitigation & education, PC2 = bear culling, PC3 = supplemental feeding.

```
pca_mit = principal(pcadata_sol[, c(3, 4, 7, 9)], rotate = "varimax",
nfactors = 1,
    scores = T, missing = F)
plot(pca_mit, cex = 0.9, labels = names(pcadata_sol[, c(3, 4, 7, 9)]), title
= "PCA, solutions PC1 - conflict mitigation",
    xlim = c(-0.2, 6), ylim = c(0.4, 0.8))
```

PCA, solutions PC1 - conflict mitigation
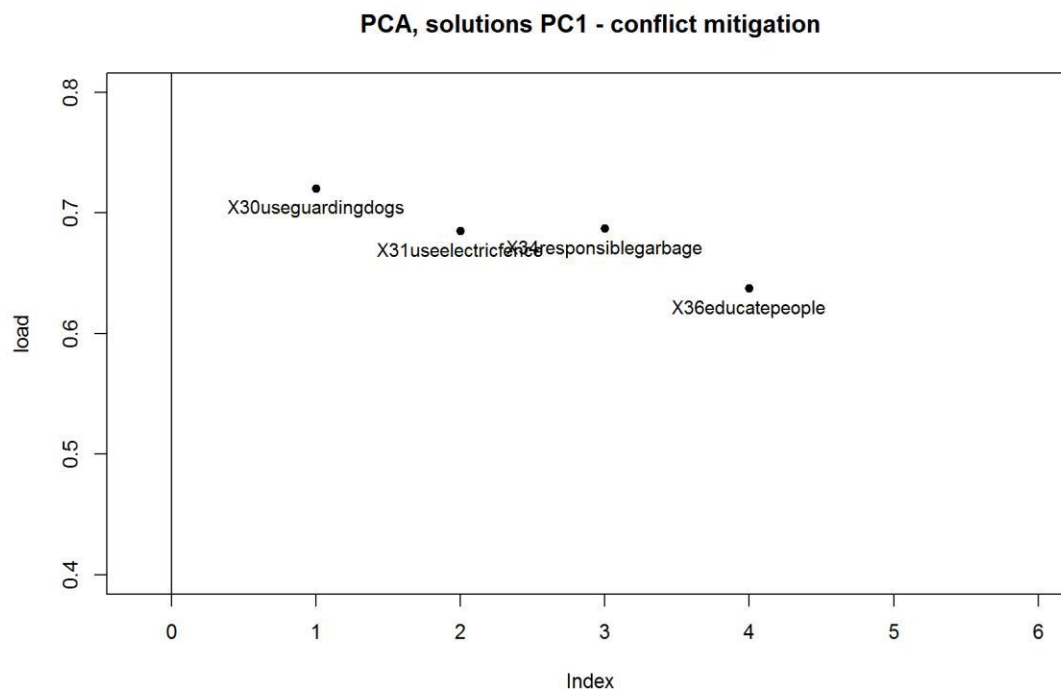

```
pca_mit
```

```
## Principal Components Analysis
## Call: principal(r = pcadata_sol[, c(3, 4, 7, 9)], nfactors = 1, rotate =
"varimax",
##      scores = T, missing = F)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                        PC1   h2   u2 com
## X30useguardingdogs    0.72 0.52 0.48   1
## X31useelectricfence   0.69 0.47 0.53   1
## X34responsiblegarbage 0.69 0.47 0.53   1
## X36educatepeople      0.64 0.41 0.59   1
##
##                  PC1
```

```
## SS loadings     1.87
## Proportion Var 0.47
##
## Mean item complexity =  1
## Test of the hypothesis that 1 component is sufficient.
##
## The root mean square of the residuals (RMSR) is  0.19
##  with the empirical chi square  941.77  with prob <  3.1e-205
##
## Fit based upon off diagonal values = 0.6
```

To facilitate interpretation of PCA scores we need to find the "neutral" PCA score (all answers are 3).

```
JoeNeutral = pcadata_sol[1, c(3, 4, 7, 9)]
JoeNeutral[, 1:4] = rep(3, 4)
JoeMitigation = predict(object = pca_mit, data = JoeNeutral, old.data =
pcadata_sol[,
    c(3, 4, 7, 9)])[1, 1]
```

Now for the "culling" component.

```
pca_cull = principal(pcadata_sol[, c(5, 6)], rotate = "varimax", nfactors =
1, scores = T,
    missing = F)
plot(pca_cull, cex = 0.9, labels = names(pcadata_sol[, c(5, 6)]), title =
"PCA, solutions PC2 - culling",
    xlim = c(-0.2, 2.5), ylim = c(-0.2, 2))
```


PCA, solutions PC2 - culling
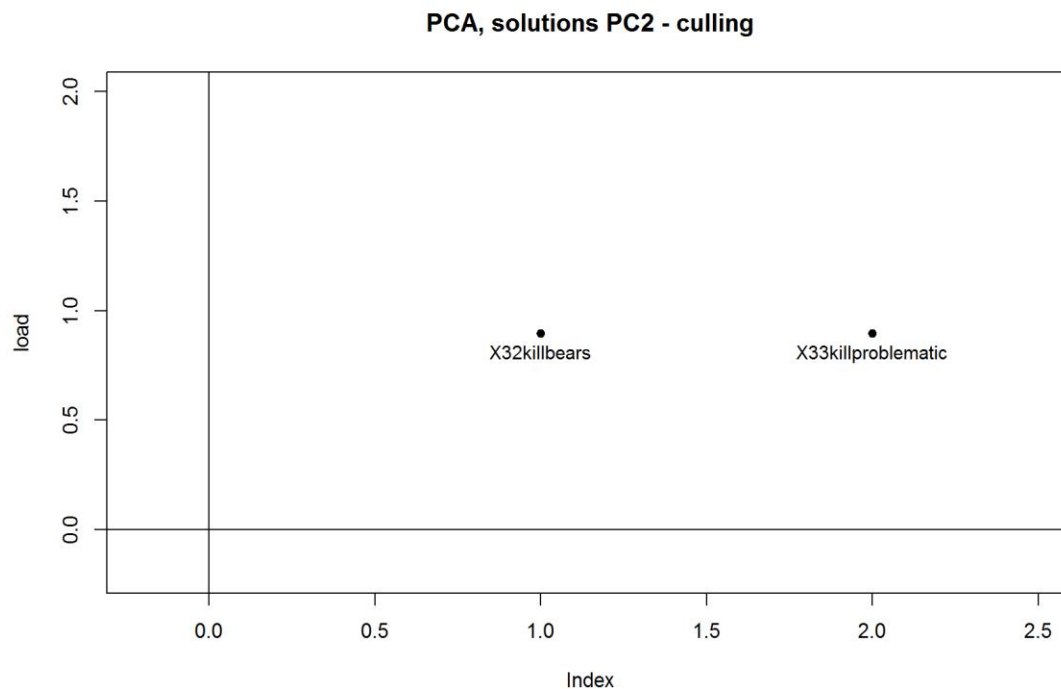
```
pca_cull

## Principal Components Analysis
## Call: principal(r = pcadata_sol[, c(5, 6)], nfactors = 1, rotate =
"varimax",
##     scores = T, missing = F)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                    PC1  h2  u2 com
## X32killbears        0.9 0.8 0.2   1
## X33killproblematic 0.9 0.8 0.2   1
##
##                PC1
## SS loadings    1.6
## Proportion Var 0.8
##
## Mean item complexity =  1
## Test of the hypothesis that 1 component is sufficient.
##
## The root mean square of the residuals (RMSR) is  0.2
##  with the empirical chi square  179.3  with prob <  NA
##
## Fit based upon off diagonal values = 0.89
```

To facilitate interpretation of PCA scores we need to find the "neutral" PCA score (all answers are 3).

```
JoeNeutral = pcadata_sol[1, c(5, 6)]
JoeNeutral[, 1:2] = rep(3, 2)
JoeCulling = predict(object = pca_cull, data = JoeNeutral, old.data =
pcadata_sol[,
    c(5, 6)])[1, 1]
```

Now for the "supplemental feeding" component.

```
pca_feed = principal(pcadata_sol[, c(1, 2)], rotate = "varimax", nfactors =
1, scores = T,
    missing = F)
plot(pca_feed, cex = 0.9, labels = names(pcadata_sol[, c(1, 2)]), title =
"PCA, solutions PC3 - supplemental feeding",
    xlim = c(-0.2, 3), ylim = c(0.6, 1))
```

PCA, solutions PC3 - supplemental feeding
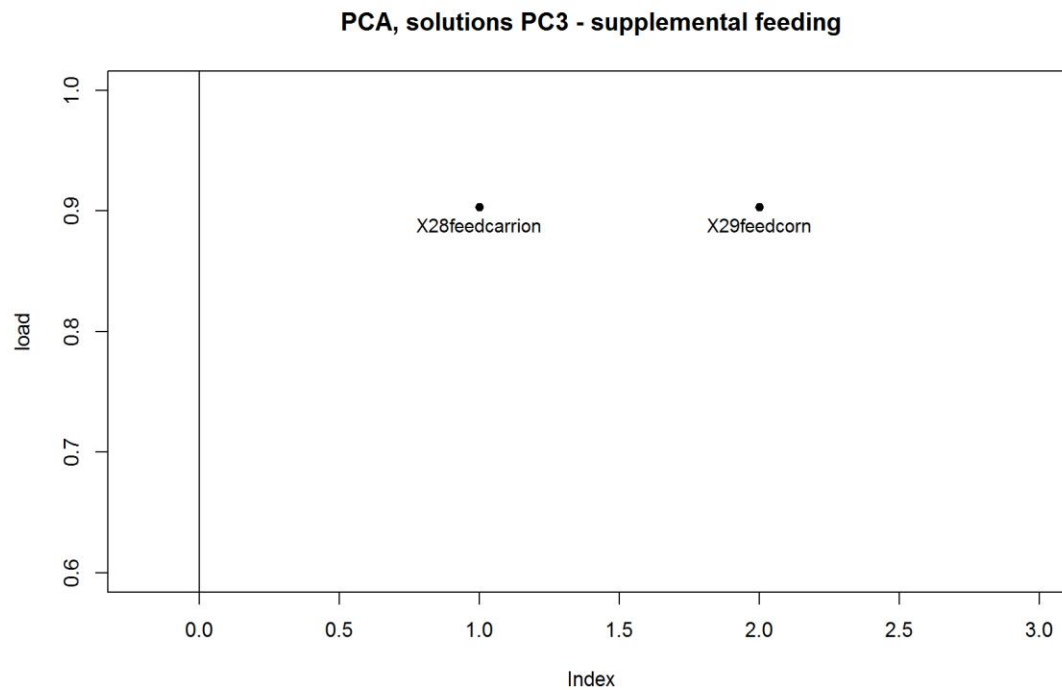

```
pca_feed

## Principal Components Analysis
## Call: principal(r = pcadata_sol[, c(1, 2)], nfactors = 1, rotate =
"varimax",
##      scores = T, missing = F)
## Standardized loadings (pattern matrix) based upon correlation matrix
##               PC1   h2   u2 com
## X28feedcarrion 0.9 0.82 0.18    1
## X29feedcorn    0.9 0.82 0.18    1
##
##                 PC1
## SS loadings    1.63
## Proportion Var 0.82
##
## Mean item complexity =  1
## Test of the hypothesis that 1 component is sufficient.
##
## The root mean square of the residuals (RMSR) is  0.18
##  with the empirical chi square  153.37  with prob <   NA
##
## Fit based upon off diagonal values = 0.92
```

To facilitate interpretation of PCA scores we need to find the "neutral" PCA score (all answers are 3).

```
JoeNeutral = pcadata_sol[1, c(1, 2)]
JoeNeutral[, 1:2] = rep(3, 2)
```

```
JoeFeeding = predict(object = pca_feed, data = JoeNeutral, old.data =
pcadata_sol[,
    c(1, 2)])[1, 1]
```

Now all PCA scores are going to be centered on "JoeNeutral" and re-scaled to -2 to +2, where 0 is neutral. This can be easily converted to Likert scale if need be just by adding 3. A new data frame with variables interesting for interpretation and PCA scores will be produced.

```
nonPCAvariables3 = names(modeldata2)[!names(modeldata2) %in%
PCAVariables_Solutions]  #the variables not included in PCA scores are
preserved
# Mitigation
sol_mitigation = scale(pca_mit$scores[, 1], center = JoeMitigation, scale =
F)
sol_mitigation = (sol_mitigation/max(abs(sol_mitigation), na.rm = T)) * 2
hist(sol_mitigation, xlab = "Mitigation measures support", main = "Histogram
of Support for Mitigation Measures",
    nclass = 50, xlim = c(-2, 2))
```


Histogram of Support for Mitigation Measures
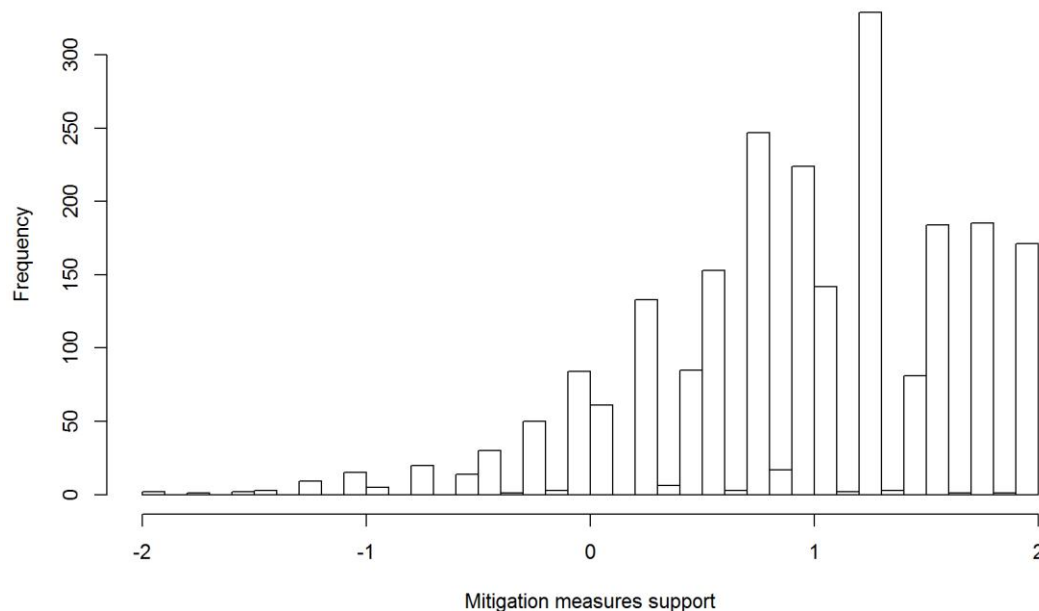
```
# Culling
sol_culling = scale(pca_cull$scores[, 1], center = JoeCulling, scale = F)
sol_culling = (sol_culling/max(abs(sol_culling), na.rm = T)) * 2
hist(sol_culling, xlab = "Culling support", main = "Histogram of Support for
Culling",
    nclass = 10, xlim = c(-2, 2))
```

Histogram of Support for Culling
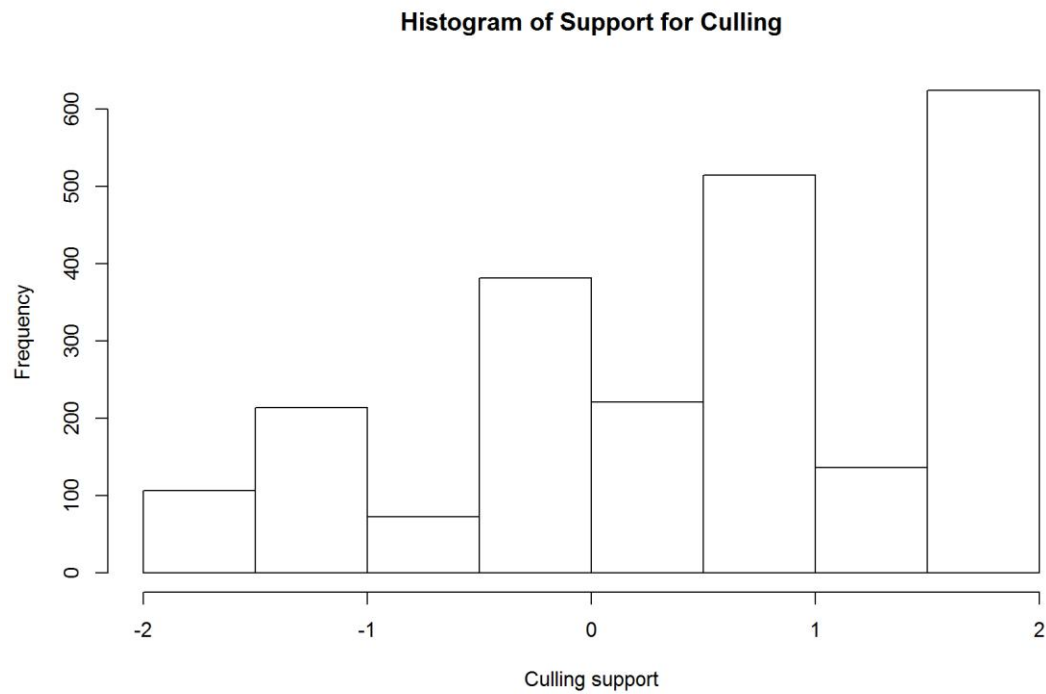

```r
# Supplemental feeding
sol_feeding = scale(pca_feed$scores[, 1], center = JoeFeeding, scale = F)
sol_feeding = (sol_feeding/max(abs(sol_feeding), na.rm = T)) * 2
hist(sol_feeding, xlab = "Sup. Feeding Support", main = "Histogram of Support
for Supplemental Feeding",
    nclass = 10, xlim = c(-2, 2))
```

Histogram of Support for Supplemental Feeding
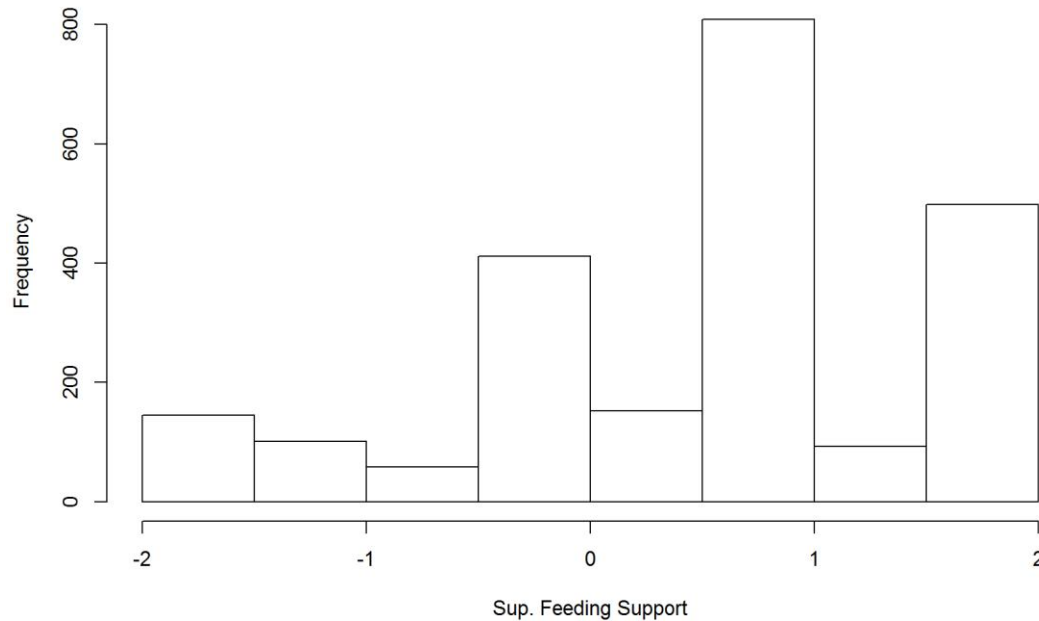

```
modeldata3 = data.frame(modeldata2[, nonPCAvariables3], sol_mitigation,
sol_culling,
     sol_feeding)
# View(data.frame(modeldata2[,c(6:14)],modeldata3[,46:48]))
```

This *concludes the PCA dimensionality reduction/Exploration*. Dataframe 'modeldata3' is the final thing - it includes all PCA factors and is without variables that were used in producing them. Factors were normalized -2 to 2, 0 is neutral, direction has been checked to be logical.

Export data:

```
# modeldata_out = cbind(qdata, modeldata3[,42:48])
# write.table(modeldata_out,'./DinAlpBearQData2016_Modelling.txt', sep='\t',
# row.names=F)
modeldata = modeldata3
save(modeldata, file = "./DinAlpBearQData2016_Modelling.Rdata")
qdata = cbind(qdata, modeldata3[, 23:29])
save(qdata, file = "./DinAlpBearAllQData2016.Rdata")
rm(list = ls())
```

PCA factors with explanation: *bear_conservation* - support for bear conservation. *bear_control* - support for bear control. *bear_value* - percieved value of bears. *conflict_tolerance* - how ready a person is to tolerate conflicts caused by bears. *sol_mitigation* - preference for 'mitigation measures' solutions for bear problems *sol_culling* - preference for culling as a solution for bear problems *sol_feeding* - preference of a person for supplemental feeding as a solution for bear problems.

Exploring data with statistical modelling

Re-load the data into a clean workspace.

```
load(".//DinAlpBearQData2016_Modelling.Rdata")  #all objects/data required
for the report
```

Exploring response and explanatory variables

Explore missing data, remove variables with a lot missing (to be explored separately):

```
apply(modeldata, 2, FUN = function(x) sum(is.na(x)))
```

```
##               ID             IdOld             Region
##                0                 0                  0
##     X43seencaptive     X44seennature  X45hadbeardamage
##                0                 0                 16
##           gender               age          education
##               11                 0                  0
##           hunter          beekeeper           dogowner
##                0                 0                  0
##          hassheep          hascattle          hashorses
##                0                 0                  0
##       heardproject      big_livestock     has_livestock
##                0                 0                  0
##        knowledge          georegion    seennatureyesno
##                0                 0                  0
##     ed_university  bear_conservation       bear_control
##               26                 0                  0
##       bear_value  conflict_tolerance     sol_mitigation
##                0                 0                  0
##      sol_culling        sol_feeding
##                0                 0
```

Let's look at distribution of these missing data

```
table(apply(modeldata, 1, FUN = function(x) sum(is.na(x))))
```

```
    0   1  2
 2217  47  3
```

Ok, this looks ok. The only one with possible problems is 'gender'. Hadbeardamage will be kicked out anyway since there are very small number of cases.

Variables to be used in modelling

Predictors

Region Yes. One of the primary things of interest.

X43seencaptive No. Almost everyone has seen a captive bear. *X44seennature* No, will use the 2-level seennatureyesno variable instead.

X45hadbeardamage No. Very few "yes" cases.

gender Yes *age* Yes *education* Yes

hunter No. Not enough cases. *beekeeper* No. Not enough cases. *dogowner* Yes.

hassheep No. Not enough cases. *hascattle* No. Not enough cases. *hashorses* No. Not enough cases. *heardproject* No *big_livestock* No. Not enough cases. *has_livestock* Yes, but low number of "yes" cases. *knowledge* Yes. Possibly also as RESPONSE? Sometime later. *georegion* Yes *seennatureyesno* Yes

Response vars

bear_conservation bear_control bear_value

Response/predictor variables

conflict_tolerance sol_mitigation sol_culling sol_feeding

Distribution of response variables:

```
par(mfrow = c(2, 2))
hist(modeldata$bear_conservation)
hist(modeldata$bear_control)
hist(modeldata$bear_value)
par(mfrow = c(1, 1))
```


Histogram of modeldata$bear_conservation

Histogram of modeldata$bear_control

Histogram of modeldata$bear_value

```
hist(modeldata$conflict_tolerance)
```
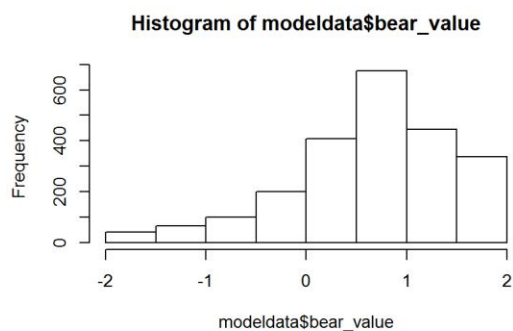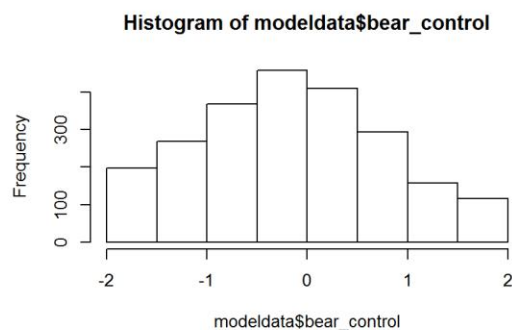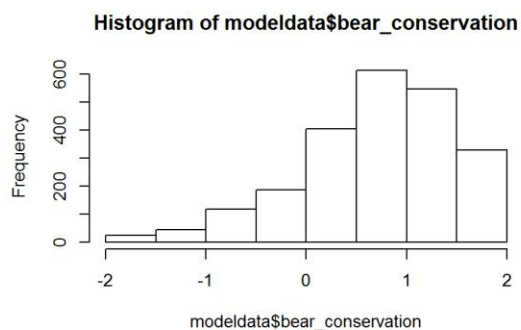
Histogram of modeldata$conflict_tolerance
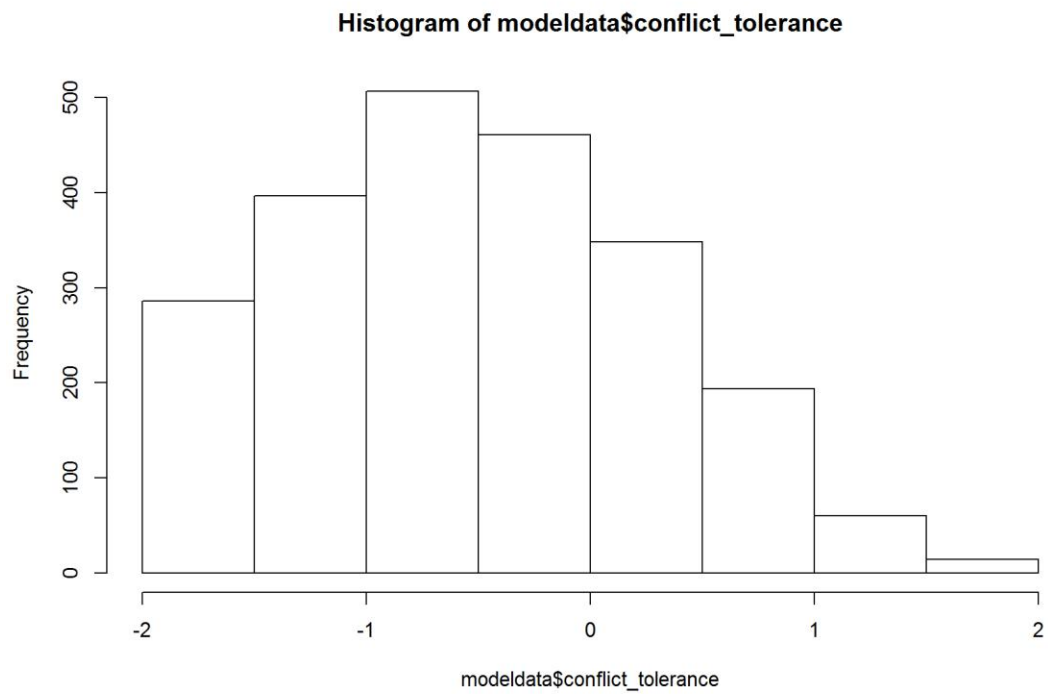

```
par(mfrow = c(2, 2))
hist(modeldata$sol_mitigation)
hist(modeldata$sol_culling)
hist(modeldata$sol_feeding)
par(mfrow = c(1, 1))
```

Histogram of modeldata$sol_mitigation

Histogram of modeldata$sol_culling

Histogram of modeldata$sol_feeding
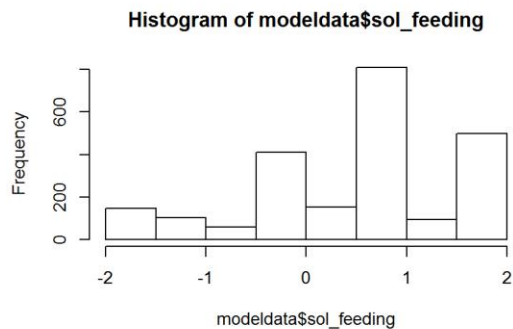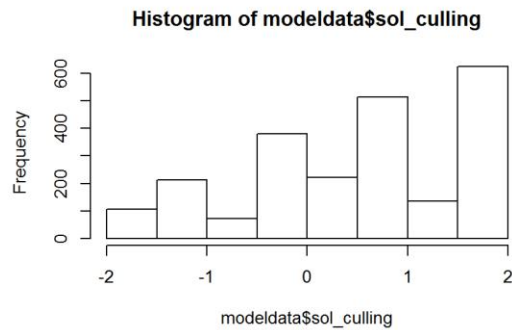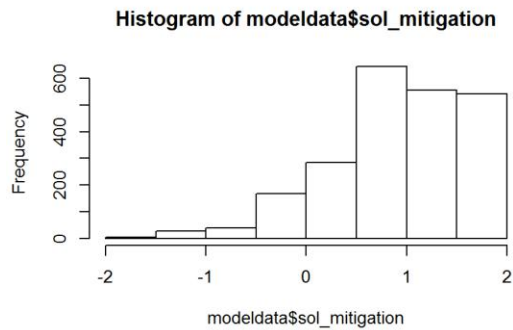
```
# to make some old code work
modeldata2 = modeldata
```

Not too bad, all are unimodal. Still, none are symtric and many are left-skewed, which means we'll need to do some transforming. Now let's see if we can fit a distribution to this, or apply a transformation to make the distributions near-normal.

Conflict Tolerance Exploration

Let's first fit a distribution to this response variable.

```
##      shape         rate
##   8.8253156    3.5506191
##  (0.2573289) (0.1065288)

##      shape         scale
##   3.35702810    2.77189013
##  (0.05442101) (0.01831579)

##      shape         rate
##    7.9752625    17.5511694
##  ( 0.2320972) ( 0.5271913)

## Estimated transformation parameters
## modeldata2$conflict_tolerance + 3
##                            0.573408
```
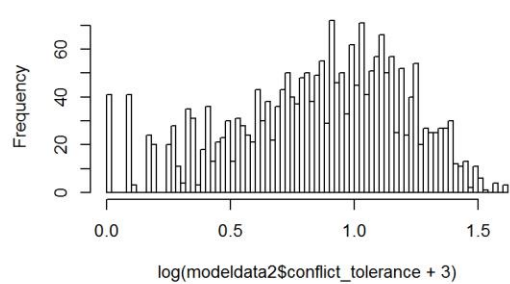
Both Wiebull and Gamma work, could use either. Box-Cox is not ok. However, the data look good enough even with a simple Gaussian.

Finding the model for Conflict Tolerance

We've fitted a generalized linear model (GLM) with gamma link function on moved by +3 (to get rid of values below zero) conflict_tolerance variable. The global model had a large set of predictors, but there is a very large data set to feed it.

For the global model, we fitted all variables we hypothesized (according to previous understanding of the problem) that they affect conflict tolerance.

Region and georegion are basically recoded, so only one of them could be kept at this stage.

```
table(apply(modeldata2, 1, FUN = function(x) sum(is.na(x))))
```

```
   0    1    2
2217   47    3
```

```
apply(modeldata2, 2, FUN = function(x) sum(is.na(x)))
```

```
##                ID            IdOld            Region
##                 0                0                 0
##     X43seencaptive     X44seennature    X45hadbeardamage
##                 0                0                16
##            gender              age         education
##                11                0                 0
##            hunter         beekeeper          dogowner
```

```
##                0                0                0
##           hassheep         hascattle         hashorses
##                0                0                0
##        heardproject     big_livestock     has_livestock
##                0                0                0
##          knowledge          georegion     seennatureyesno
##                0                0                0
##       ed_university  bear_conservation      bear_control
##               26                0                0
##         bear_value  conflict_tolerance     sol_mitigation
##                0                0                0
##         sol_culling        sol_feeding
##                0                0
```

```r
# sub-select variables to minimize the missing data problem.
modelVars = c("Region", "gender", "age", "education", "ed_university",
"dogowner",
    "has_livestock", "knowledge", "georegion", "seennatureyesno",
"bear_conservation",
    "bear_control", "bear_value", "conflict_tolerance", "sol_mitigation",
"sol_culling",
    "sol_feeding")
modeldata3 = modeldata2[, modelVars]
modeldata3NONA = modeldata3[complete.cases(modeldata3), ]
ConfFG = formula(I(conflict_tolerance + 3) ~ Region + gender + age +
education +
    knowledge + dogowner + has_livestock)  #+
# gender:age+gender:education+gender:knowledge+
# age:education+age:knowledge)#+georegion+
# Region
McGReg = glm(ConfFG, data = modeldata3NONA, family = gaussian(link =
"identity"),
    na.action = "na.fail")
McGGeo = update(McGReg, . ~ . - Region + georegion)
McGReg
```

```
##
## Call:  glm(formula = ConfFG, family = gaussian(link = "identity"), data =
modeldata3NONA,
##     na.action = "na.fail")
##
## Coefficients:
##           (Intercept)         RegionCroatia              RegionItaly
##              2.296227             -0.037199                 0.161581
##     RegionSlovenia Alps  RegionSlovenia Dinaric               gendermale
##             -0.016764             -0.144614                 0.179511
##                   age             education                knowledge
##             -0.002585             -0.022219                 0.133187
##           dogowneryes       has_livestockyes
##              0.083690             -0.042890
```

```
## 
## Degrees of Freedom: 2231 Total (i.e. Null);  2221 Residual
## Null Deviance:        1475
## Residual Deviance: 1376  AIC: 5278
```

McGGeo

```
## 
## Call:  glm(formula = I(conflict_tolerance + 3) ~ gender + age + education
+
##     knowledge + dogowner + has_livestock + georegion, family =
gaussian(link = "identity"),
##     data = modeldata3NONA, na.action = "na.fail")
## 
## Coefficients:
##      (Intercept)         gendermale                   age
##         2.372222           0.180117             -0.003956
##        education          knowledge           dogowneryes
##        -0.027320           0.126302              0.082476
##  has_livestockyes  georegionDinarics
##        -0.069726           0.007086
## 
## Degrees of Freedom: 2231 Total (i.e. Null);  2224 Residual
## Null Deviance:        1475
## Residual Deviance: 1398  AIC: 5308
```

```r
par(mfrow = c(2, 2))
plot(McGReg)
```
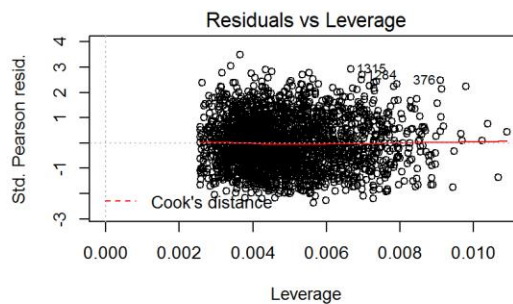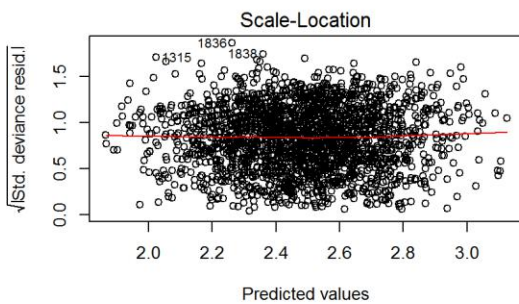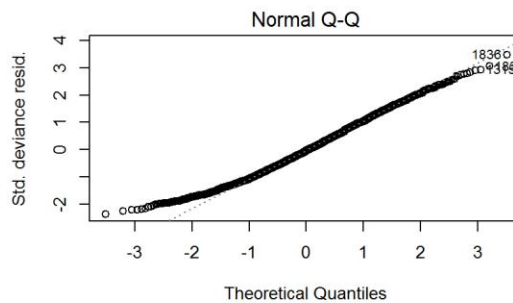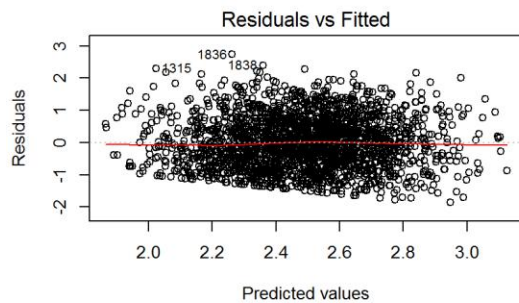
```
plot(McGGeo)
```
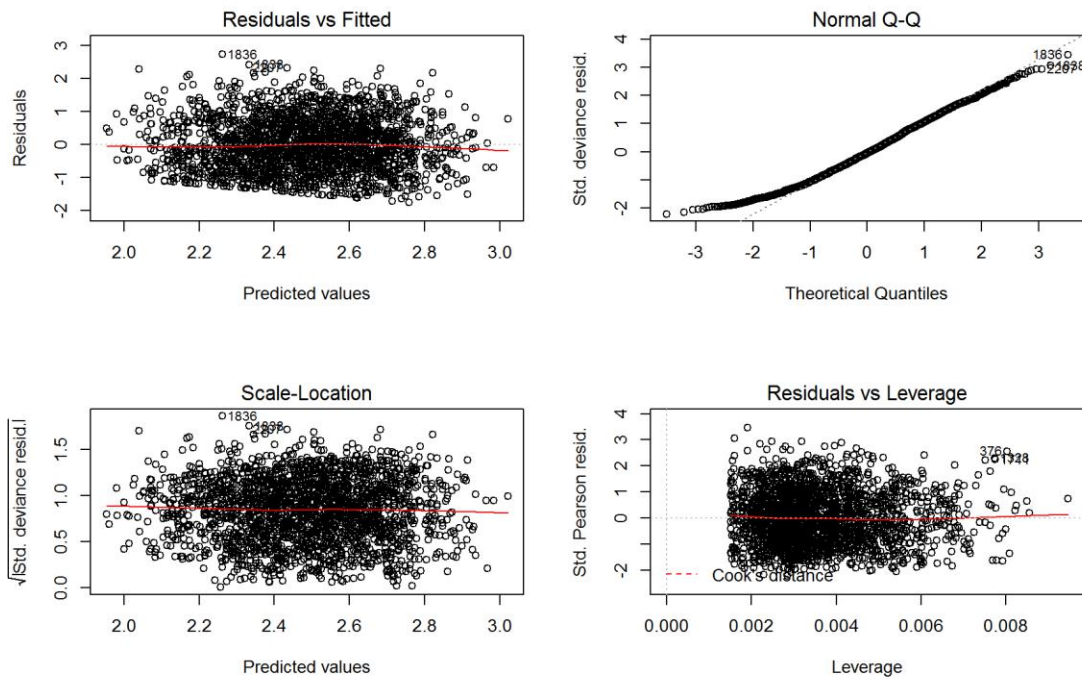


```
par(mfrow = c(1, 1))
```

Marginally acceptable, but the best I can do. The I can't get the bottom tail to fit better, but should be close enough.

Let's check multicollinearity (w/o interactions).

```
vif(McGReg)
```

	GVIF	Df	GVIF^(1/(2*Df))
Region	1.301932	4	1.033531
gender	1.055001	1	1.027132
age	1.188120	1	1.090009
education	1.146393	1	1.070698
knowledge	1.047654	1	1.023549
dogowner	1.117789	1	1.057255
has_livestock	1.081763	1	1.040078

```
vif(McGGeo)
```

```
##        gender           age     education     knowledge      dogowner
##      1.048528      1.110433      1.058212      1.031640      1.075173
## has_livestock     georegion
##      1.071526      1.061114
```

```
# vif(update(McGReg,.~.-gender:age-gender:education-gender:knowledge-
age:education-age:knowledge))
# vif(update(McGGeo,.~.-gender:age-gender:education-gender:knowledge-
age:education-age:knowledge))
```

There seems to be no multicolinearity problem.

```
clust = makeCluster(getOption("cl.cores", 4), type = "PSOCK")
clusterExport(clust, "modeldata3NONA")
# start=Sys.time()#report start time
DredgeGMConflictReg = pdredge(McGReg, cluster = clust, trace = F)  #Region

## Fixed term is "(Intercept)"

save(DredgeGMConflictReg, file = ".//conflict_dredgeGM_Reg.RData")
titi = pdredge(update(McGReg, . ~ . - education + ed_university), cluster =
clust,
    trace = F)  #TEMP

## Fixed term is "(Intercept)"

DredgeGMConflictGeo = pdredge(McGGeo, cluster = clust, trace = F)
#Geographic Region

## Fixed term is "(Intercept)"

save(DredgeGMConflictGeo, file = ".//conflict_dredgeGM_Geo.RData")
# end=Sys.time()#report end time end-start
```

Importance of parameters.

```
importance(DredgeGMConflictGeo)

##                      knowledge gender age  dogowner has_livestock
## Importance:          1.00      1.00   1.00 0.81     0.45
## N containing models: 64        64     64   64       64
##                      education georegion
## Importance:          0.37      0.27
## N containing models: 64        64

importance(titi)

##                      knowledge Region gender dogowner age  ed_university
## Importance:          1.00      1.00   1.00   0.85     0.84 0.36
## N containing models: 64        64     64     64       64   64
##                      has_livestock
## Importance:          0.33
## N containing models: 64

importance(DredgeGMConflictReg)

##                      knowledge Region gender dogowner age  has_livestock
## Importance:          1.00      1.00   1.00   0.85     0.84 0.33
```

```
## N containing models:    64          64       64      64        64    64
##                         education
## Importance:             0.33
## N containing models:    64
```

We ranked importance of each variable by checking in how many models it appeared weighted by Akaike's weights, and constructed the optimal model without interactions that retains all variables that had importance larger than 0.8. We checked AICc of models wihouth the variable with importance < 1.

Optimal model for Conflict Tolerance, by Region variable

We constructed the **optimal model for "Region"** without interactions. Variables *education* and *has_livestock* were removed.

excluded variables: education, has_livestock.

	df	AICc
McOptG	10	5275.742
McOptG2	11	5277.744
McOptG3	11	5277.579
McOptG4	11	5277.693
McOptG5	12	5279.697
McOptG6	13	5281.576
McOptG7	14	5278.066
McOptG8	18	5283.528
McOptG9	19	5285.558
McOptG10	14	5280.328
McOptG11	18	5283.528
McOptG12	19	5285.558
McOptG13	19	5285.558
McOptG14	13	5280.507

The only meaningful interaction to include seems to be between Region and Gender. Models with age are marginally better, so I'll keep it in.

edit In Italy gender was coded incorrectly, so the interaction flies out through the window.

The final model for conflict tolerance, by Region

```
# ModConflictTol_Reg =
#
glm(I(conflict_tolerance+3)~Region+gender+age+knowledge+dogowner+Region:gende
r,
# data=modeldata3NONA, family=gaussian(link='identity'), na.action='na.fail')
```

```
ModConflictTol_Reg = glm(I(conflict_tolerance + 3) ~ Region + gender + age +
knowledge +
    dogowner, data = modeldata3NONA, family = gaussian(link = "identity"),
na.action = "na.fail")
```

Optimal model for Conflict Tolerance, by georegion variable

We constructed the **optimal model for "georegion"** without interactions. Variables
education and *has_livestock* were removed. We decided to keep *age* for the time being and
check later with interactions.

excluded variables: education, has_livestock.

	df	AICc
McOptG	7	5306.948
McOptG2	8	5308.692
McOptG3	8	5308.186
McOptG4	8	5308.759
McOptG5	9	5310.512
McOptG6	10	5311.961
McOptG7	8	5308.955
McOptG8	9	5310.903
McOptG9	10	5312.883
McOptG10	8	5308.295
McOptG11	9	5310.903
McOptG12	10	5312.883
McOptG13	10	5312.883
McOptG14	7	5319.450

Again, the only meaningful interaction to include seems to be between georegion and
Gender. *edit* Gender interaction dissapears when Italian data was corrected, and is now
removed */edit* Age is a stronger predictore- maybe because it describes the difference
between regions where questionnaires were done via Internet?

The final model for conflict tolerance, by georegion

```
# ModConflictTol_Geo =
#
glm(I(conflict_tolerance+3)~georegion+gender+age+knowledge+dogowner+georegion
:gender,
# data=modeldata3NONA, family=gaussian(link='identity'), na.action='na.fail')
ModConflictTol_Geo = glm(I(conflict_tolerance + 3) ~ georegion + gender + age
+ knowledge +
    dogowner, data = modeldata3NONA, family = gaussian(link = "identity"),
na.action = "na.fail")
```

Exploration of drivers of conflict tolerance

Outliers

We checked for outliers - high influence points - with the optimal model and cook's distances. We re-fitted the model with outliers removed. We first used 4/N threshold (due to the large number of cases we ignored the number of parameters), however this seemed very drastic and completely destroyed model fit. I used Cook's original designated D<1, which didn't indicate any outliers at all.

I tried refitting with the 'robust statistics' methods, but the tools are unfortunately quite underdeveloped. So, sticking with GLM.

Results were the same with the georegion model.

```
cook = cooks.distance(ModConflictTol_Reg)
plot(1:nrow(modeldata3NONA), cook)
abline(h = 4/nrow(modeldata3NONA), col = "red")
```
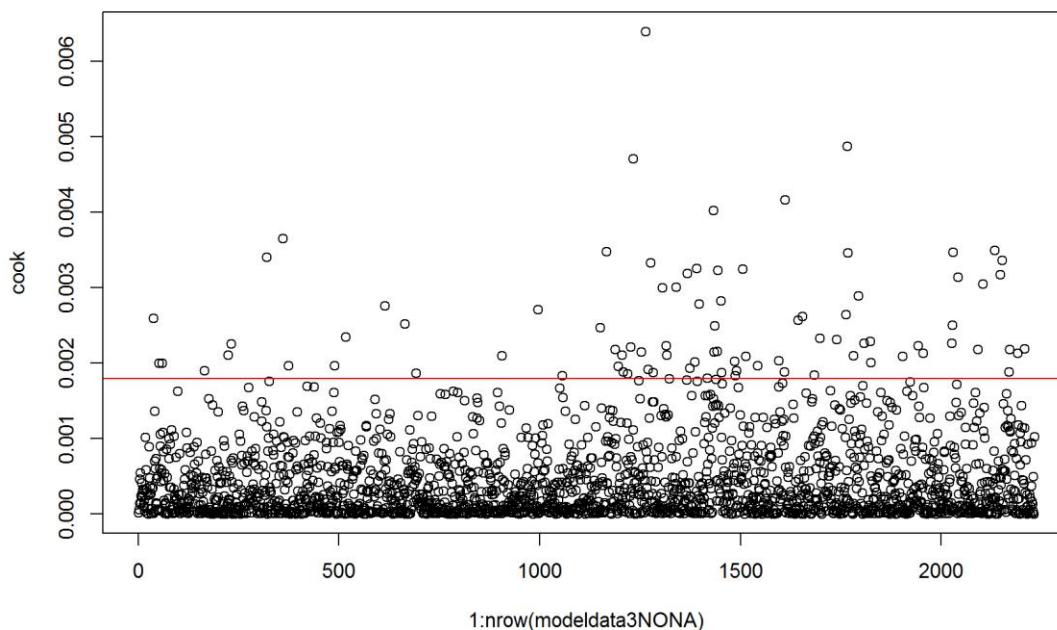


```
# explore if there are many outliers in certain combinations of parameters.
coplot(cook ~ modeldata3NONA$knowledge | modeldata3NONA$Region)
```
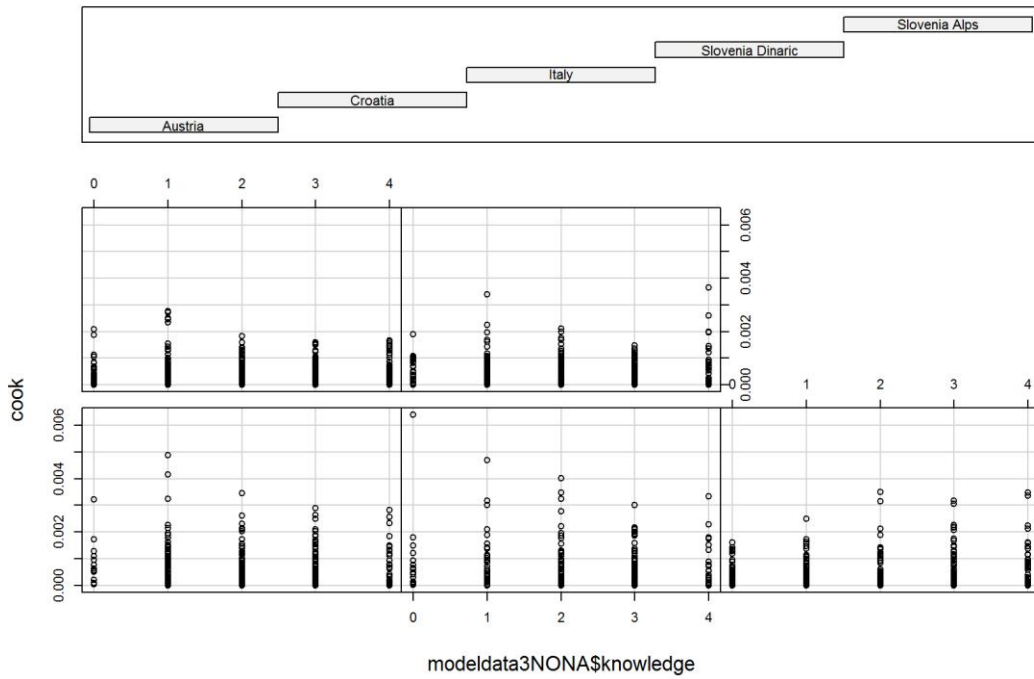
Given : modeldata3NONA$Region

coplot(cook ~ modeldata3NONA$education | modeldata3NONA$Region)

Given : modeldata3NONA$Region
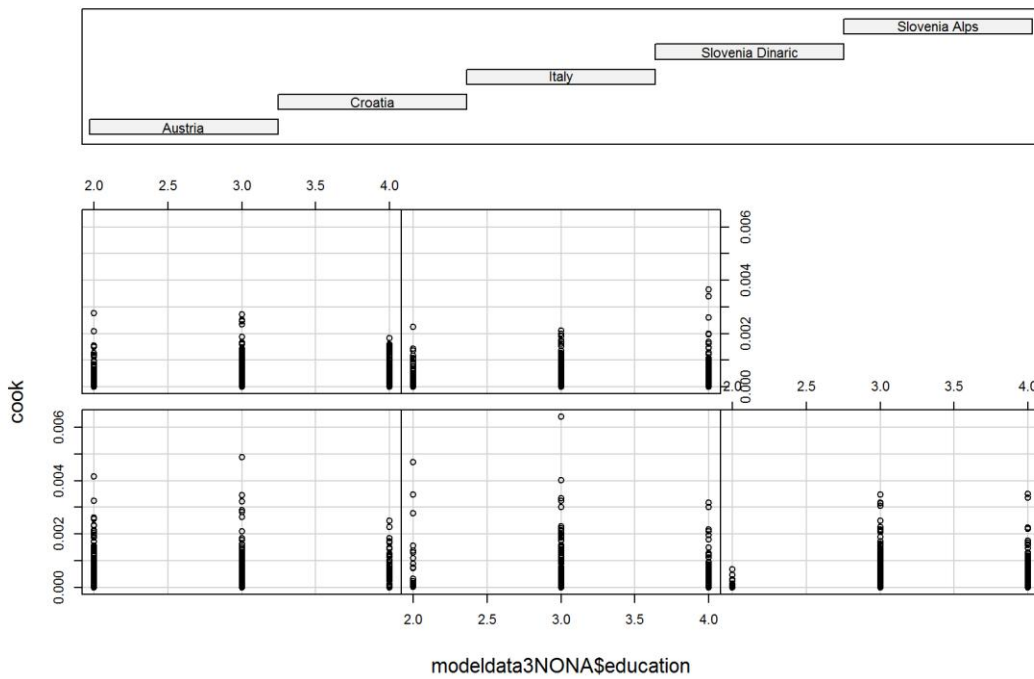
coplot(cook ~ modeldata3NONA$knowledge | modeldata3NONA$gender)
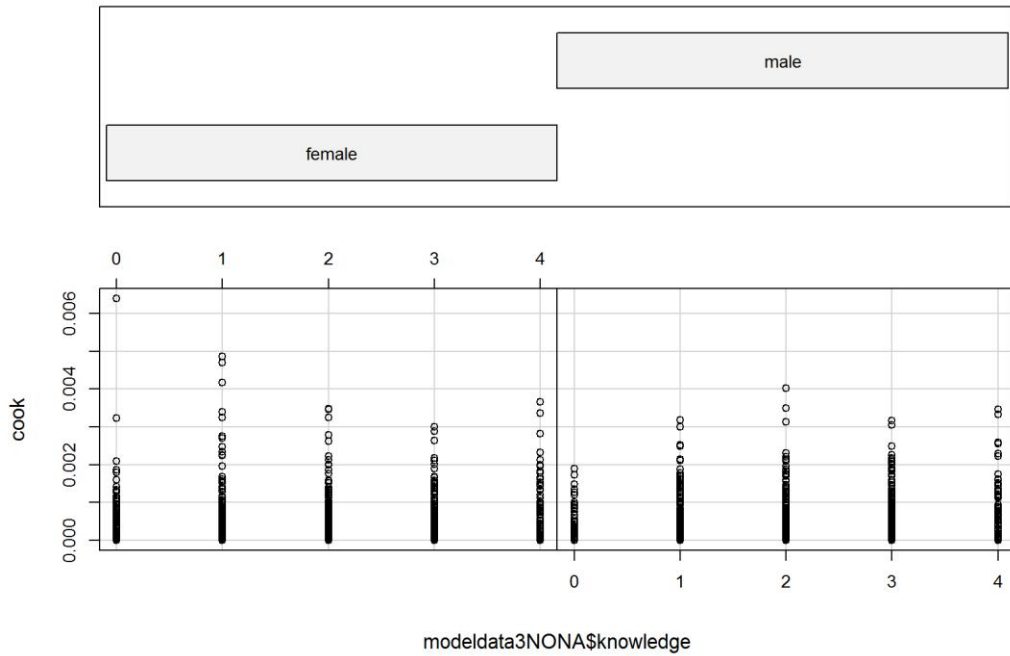
Given : modeldata3NONA$gender

```
coplot(cook ~ modeldata3NONA$education | modeldata3NONA$gender)
```


Given : modeldata3NONA$gender
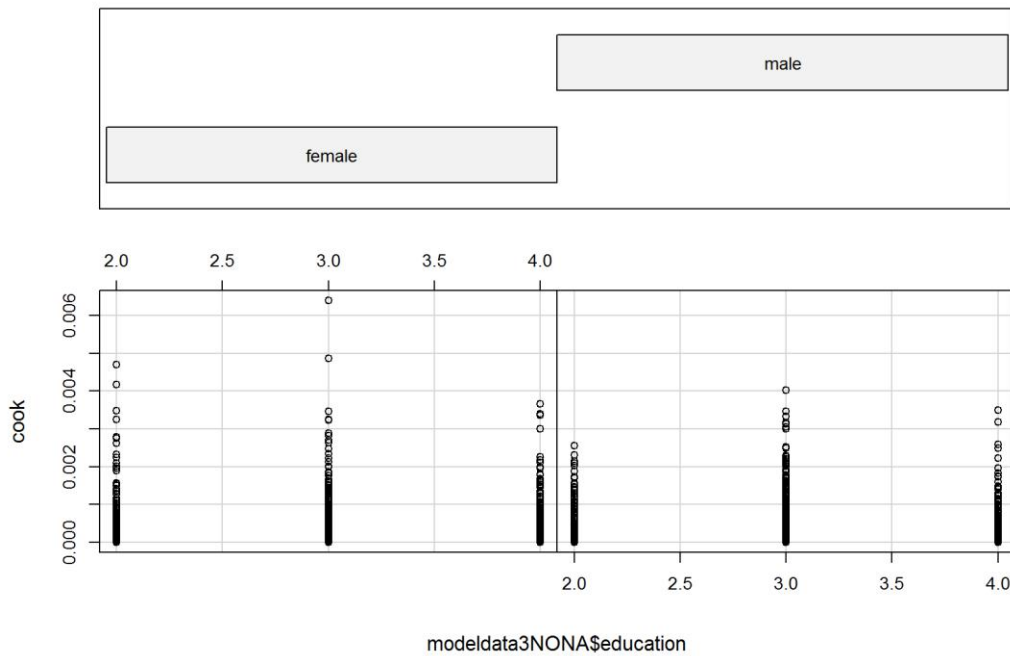
```
# remove model outliers
modeldata3.NO = modeldata3NONA[which(cook <= 4/nrow(modeldata3NONA)), ]
# re-evalute the model with outlier-fee data
```

```
ModConflictTol_Reg2 = glm(I(conflict_tolerance + 3) ~ Region + gender + age +
knowledge +
    dogowner + Region:gender, data = modeldata3.NO, family = gaussian(link =
"identity"),
    na.action = "na.fail")
par(mfrow = c(2, 2))
plot(ModConflictTol_Reg2)
```
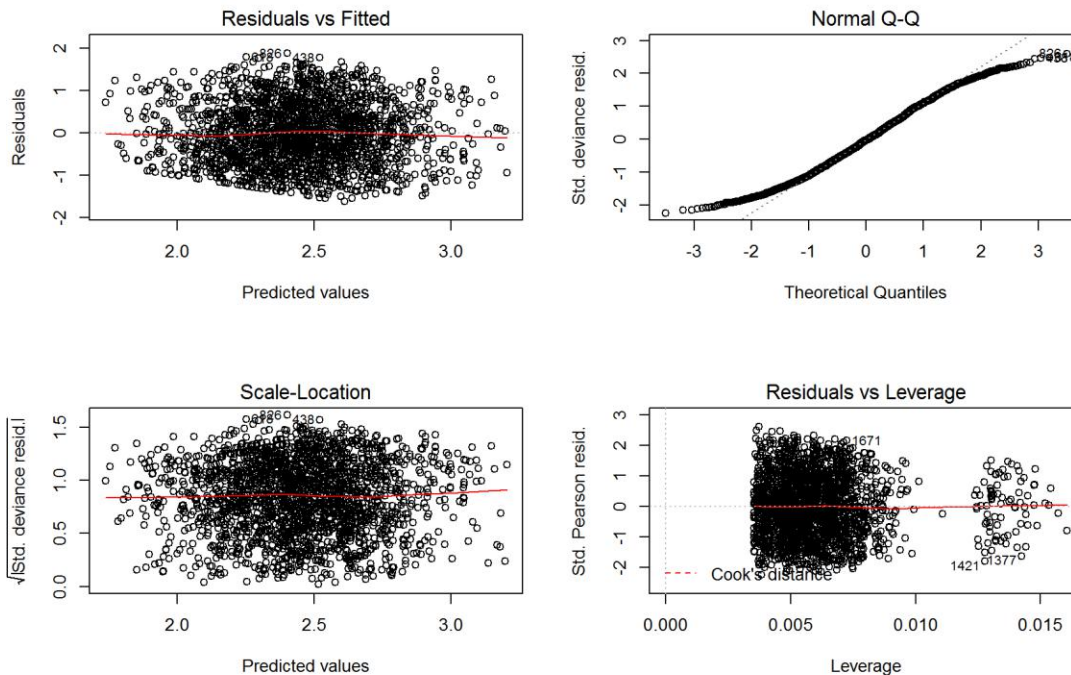


```
par(mfrow = c(1, 1))
```

Residuals vs. fitted plot looks reasonable, Q-Q plot is a bit off, but the rest seems ok.

A plotting function to make life easier.

Exploring Effects - Bear Conflict Tolerance

Using the constructed model of Bear Conflict Toelrance, we can explore the effect of a single variable or a combination of variables while controlling for the effect of other variables. In this manner we can understand the effect of i.e. Region where the respondent lives (or any other parameter we wish to explore) withouth the confounding effects of other characteristics of the respondent (e.g. gender, age etc.)

Effect of Region

Let's explore the effect of Region on Conflict Tolerance.

```
bwplot(Region ~ (conflict_tolerance), data = modeldata3NONA, main = "Effect
of Region on Bear Conflict Tolerance - Raw Data",
    xlab = "Tolerance of bear conflicts")
```

Effect of Region on Bear Conflict Tolerance - Raw Data
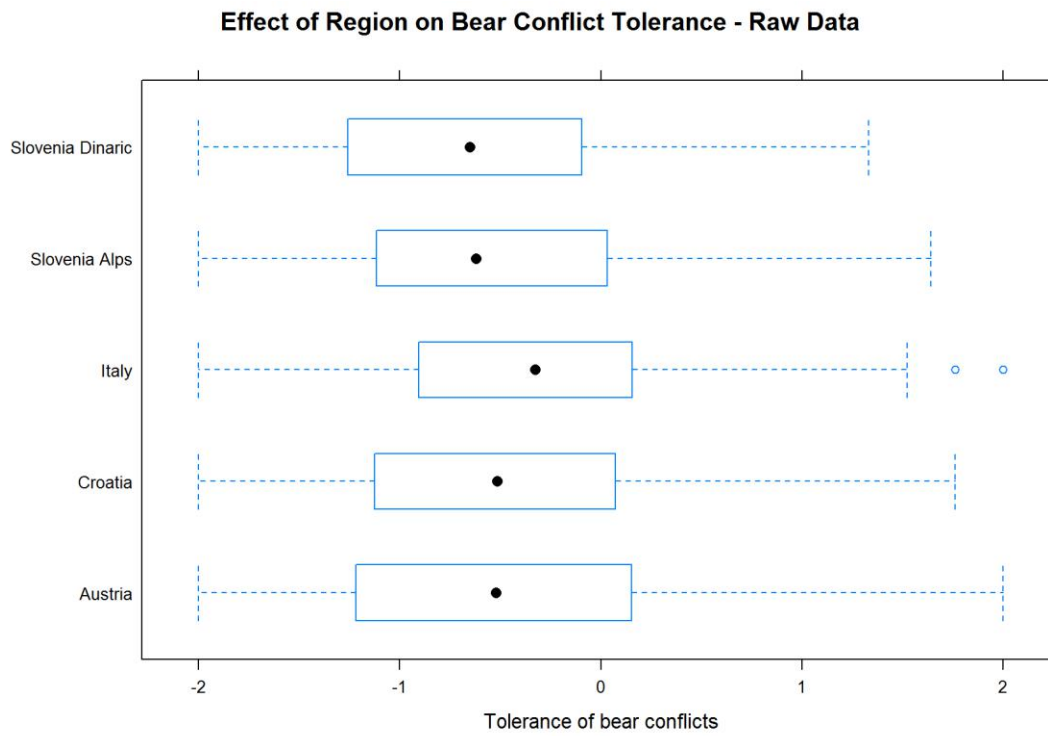

```
PlotEffectsConflict("Region", ModConflictTol_Reg2, main = "Effect of Region
on Bear Conflict Tolerance",
    ylim = c(-1, 0.2))
```

Effect of Region on Bear Conflict Tolerance
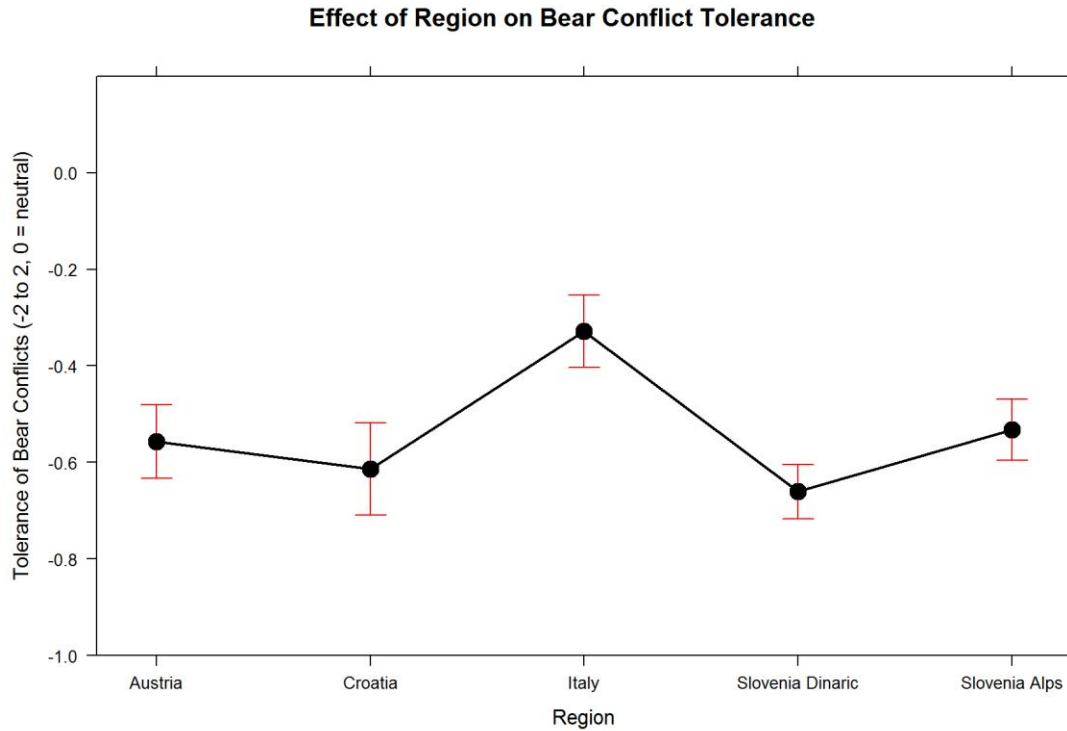
Italy seems more conflict tolerant, and Dinaric part of Slovenia the least. CI's overlap though.

How about geographic area?

```
bwplot(georegion ~ (conflict_tolerance), data = modeldata3NONA, main =
"Effect of Geographic Area on Bear Conflict Tolerance - Raw Data",
    xlab = "Tolerance of bear conflicts")
```

Effect of Geographic Area on Bear Conflict Tolerance - Raw Data
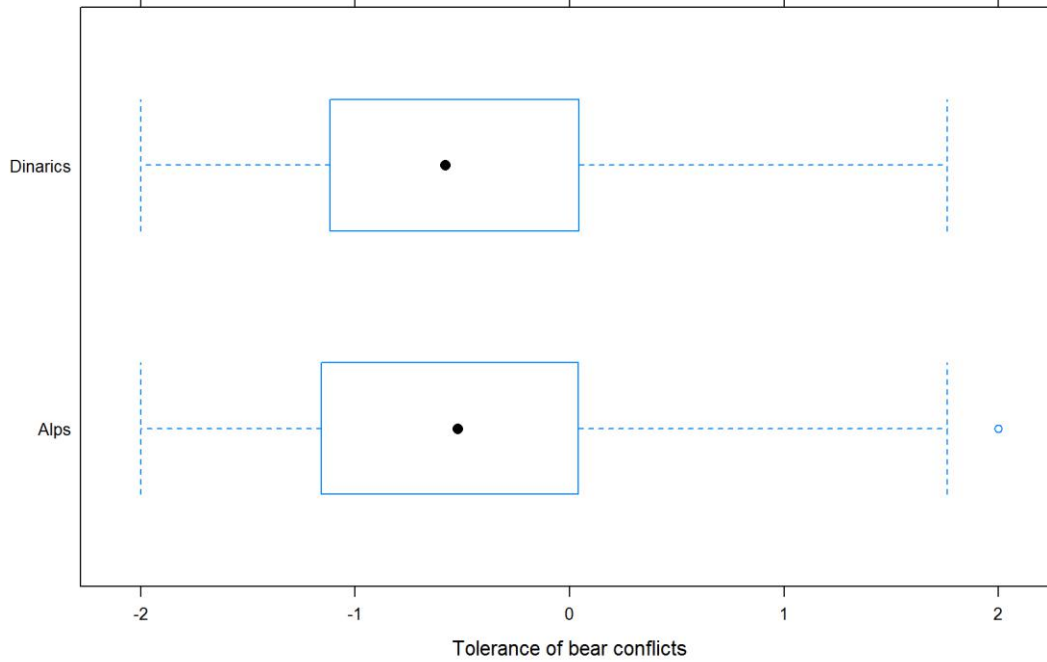

```
PlotEffectsConflict("georegion", ModConflictTol_Geo, main = "Effect of Geo-
Region on Bear Conflict Tolerance",
    ylim = c(-1, 0.2))
```

Effect of Geo-Region on Bear Conflict Tolerance

Tolerance for bear conflicts seems lower in Dinarics.

Effects of gender of the respondent?

```
bwplot(gender ~ (conflict_tolerance), data = modeldata3NONA, main = "Effect
of Gender on Bear Conflict Tolerance - Raw Data",
    xlab = "Tolerance of bear conflicts")
```

Effect of Gender on Bear Conflict Tolerance - Raw Data
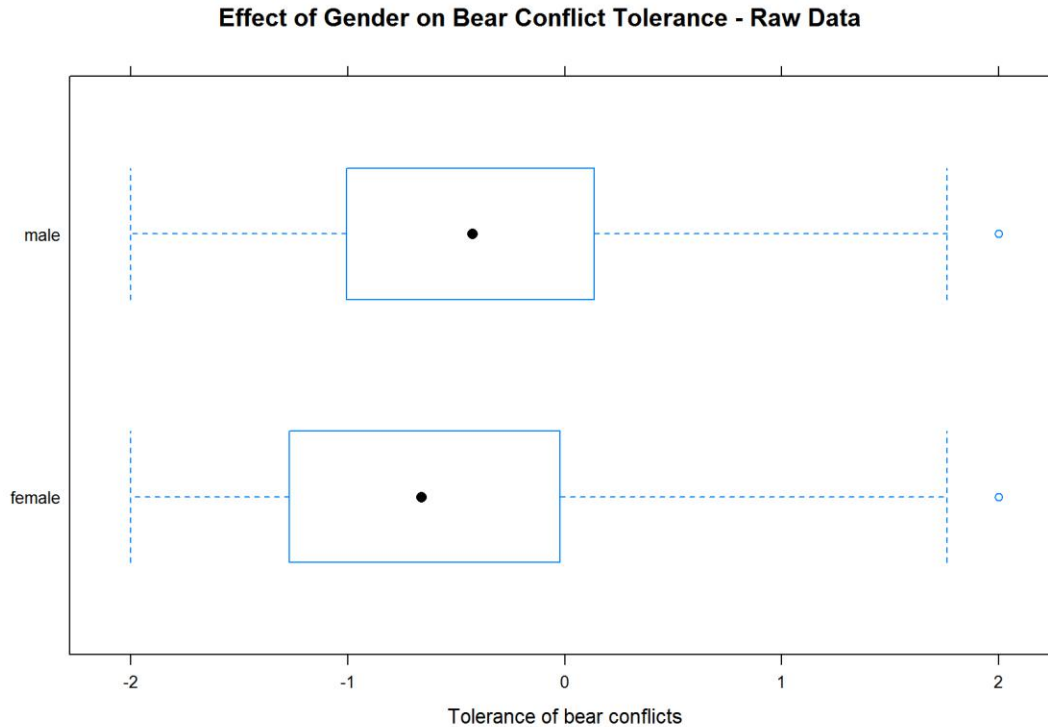

```
PlotEffectsConflict("gender", ModConflictTol_Reg2, main = "Effect of Gender
on Bear Conflict Tolerance",
    ylim = c(-1, 0.2))
```

Effect of Gender on Bear Conflict Tolerance
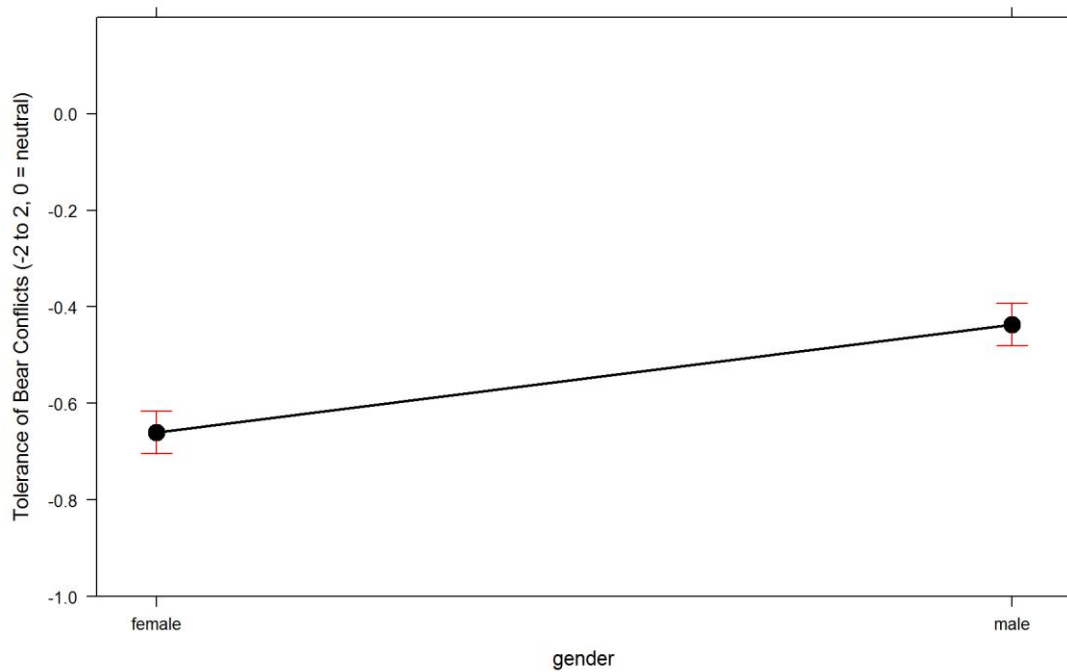
Women seem less tolerant. There also seems to be an interaction with Region. *edit* there is no interaction, Italian data was coded incorrectly. Now all good.

```
PlotEffectsConflict(c("gender", "Region"), ModConflictTol_Reg2, main =
"Effect of Gender*Region on Bear Conflict Tolerance",
    ylim = c(-1, 0.2))
```

Effect of Gender*Region on Bear Conflict Tolerance
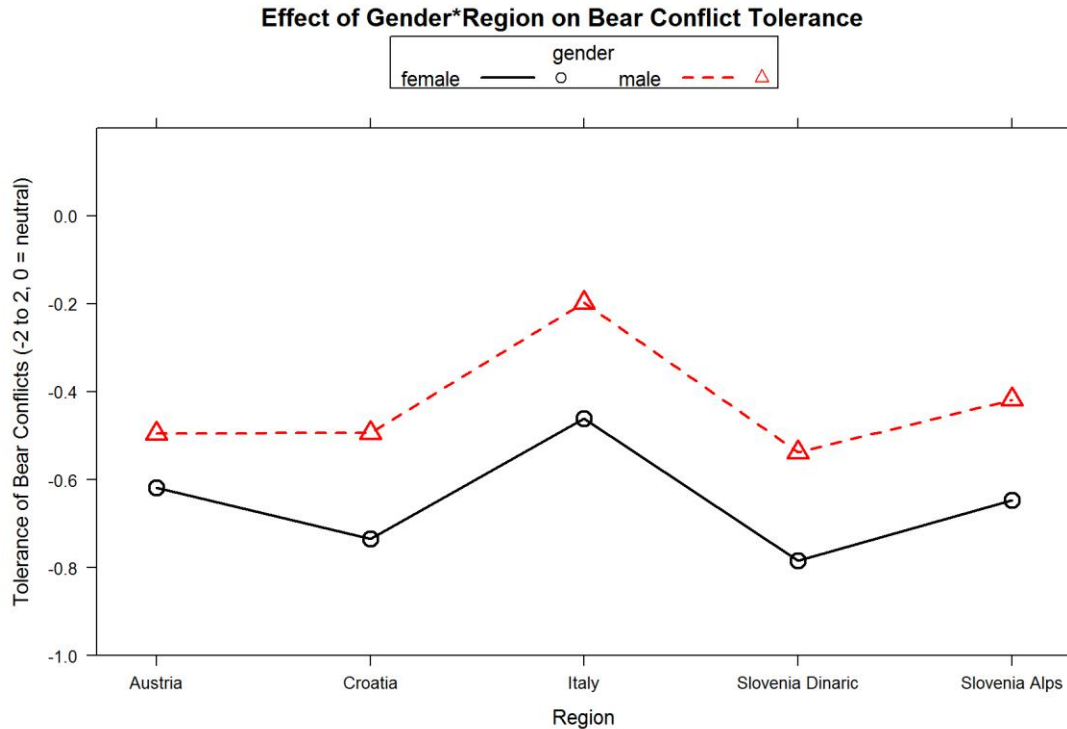
Interesting. In Slovenia Women seem to have a considerably less tolerance to bear conflicts - may be the effect of perceived danger of bears. In Italy we may be seeing the "teddy bear" effect since we have a younger population and low bear presence.

```
modeldata3 %>% group_by(Region) %>% summarize(medianAge = median(age))
```

Region	medianAge
Austria	44
Croatia	57
Italy	37
Slovenia Alps	50
Slovenia Dinaric	51

What is the general effect of age?

```
PlotEffectsConflict("age", ModConflictTol_Reg, main = "Effect of Age on Bear
Conflict Tolerance",
    ylim = c(-1, 0.2))
```

Effect of Age on Bear Conflict Tolerance
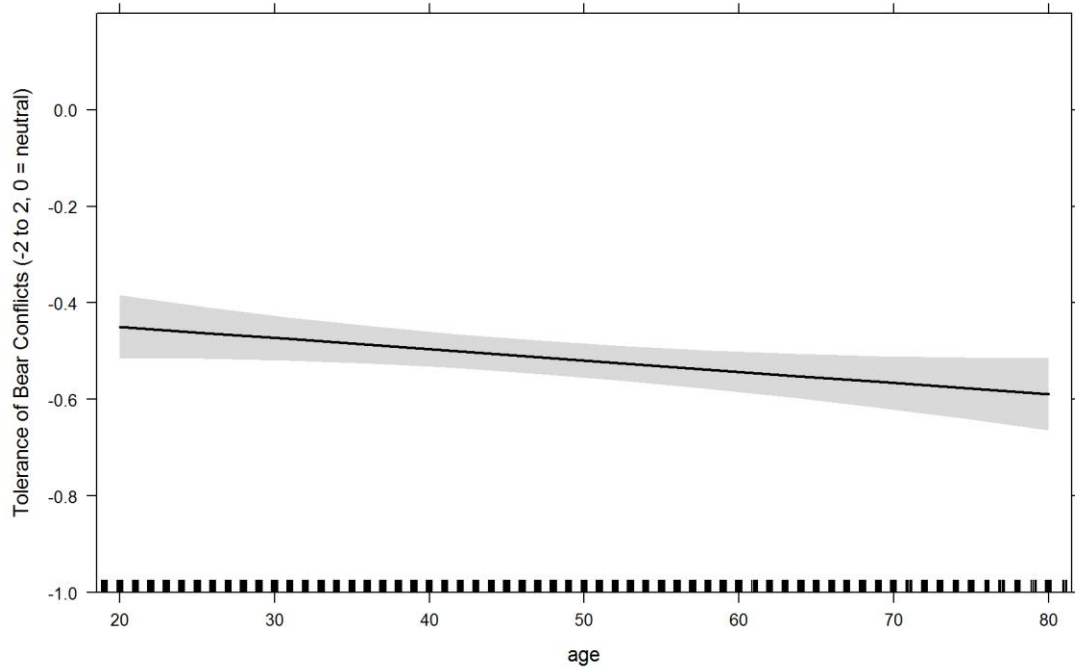
Does knowledge help?

```
PlotEffectsConflict("knowledge", ModConflictTol_Reg2, main = "Effect of
Knowledge on Bear Conflict Tolerance",
    ylim = c(-1, 0.2))
```

Effect of Knowledge on Bear Conflict Tolerance
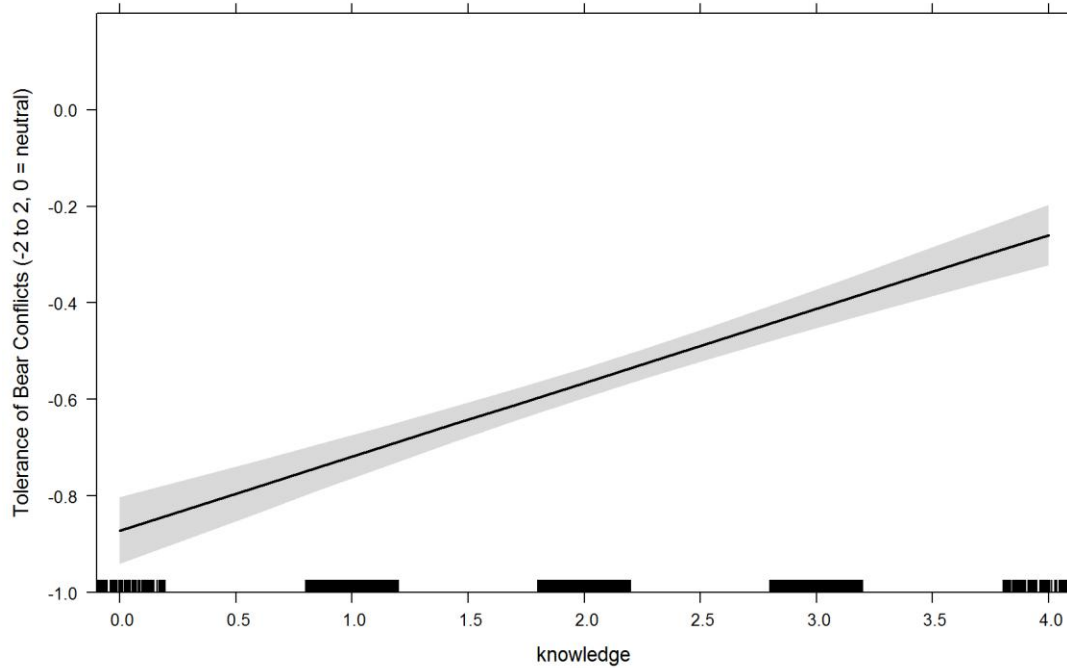
Yes! It seems it does!

Let's see if dog owners tolerate bears more.

```
PlotEffectsConflict("dogowner", ModConflictTol_Reg2, main = "Effect of Owning
a Dog on Bear Conflict Tolerance",
    ylim = c(-1, 0.2))
```

Effect of Owning a Dog on Bear Conflict Tolerance
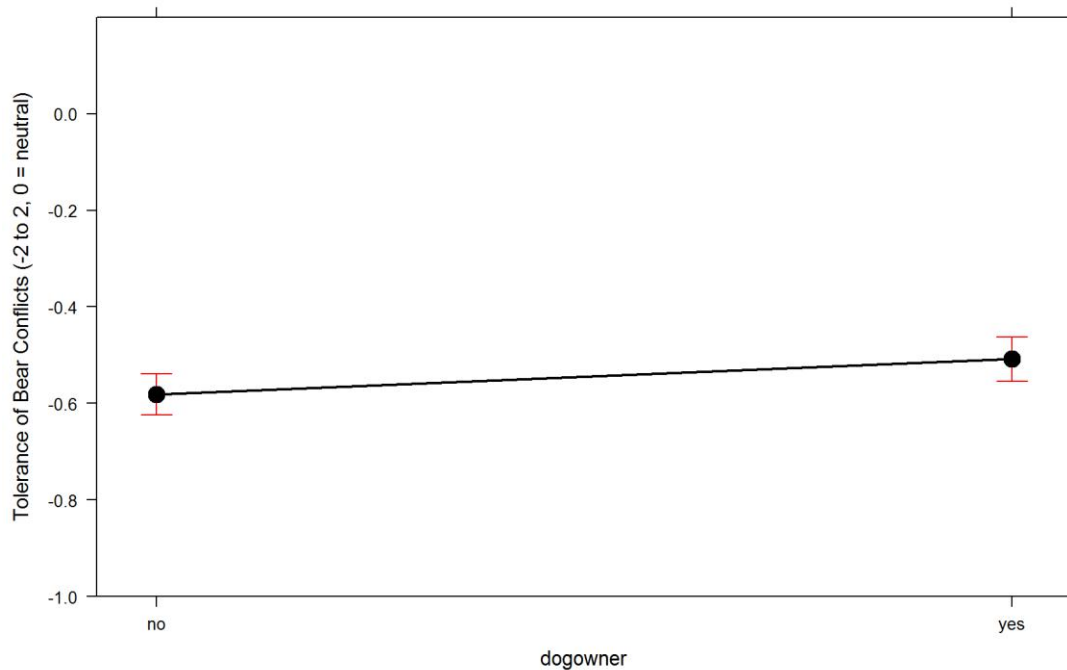
Well, marginally. Still, delta AIC >3 if this variable is removed.

This concludes the first analysis. Housekeeping.

```
rm(list = ls()[-grep("modeldata3", ls())])
rm(modeldata3.NO)
```

Support for mitigation measures

Let's first fit a distribution to this response variable.

```
##       shape        rate
##    9.1487895    4.4359321
##   (0.2669314) (0.1330406)

##       shape       scale
##    3.16542035   2.30254316
##   (0.04884935) (0.01618210)

##       shape        rate
##    23.077357    87.341432
##   ( 0.680554) ( 2.603861)

## Estimated transformation parameters
## modeldata3$sol_mitigation * -1 + 4
##                            -0.1879194
```

red=Gamma, blue=Wiebull

Gamma, 1/X
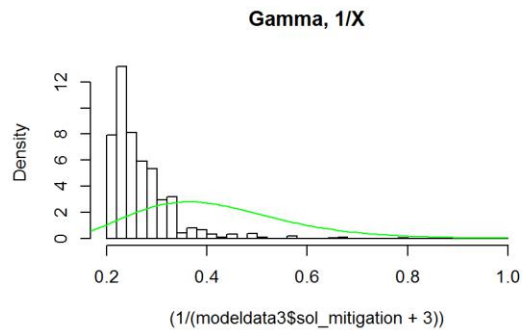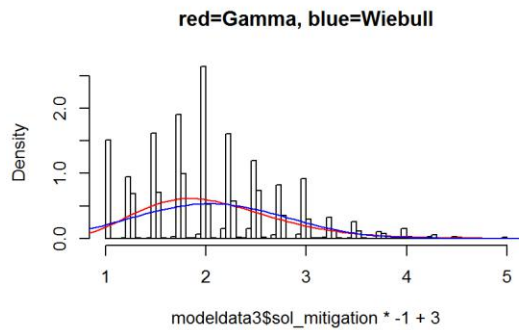
ogram of bcPower(modeldata3$sol_mitigation * -1 + 4, -0.1
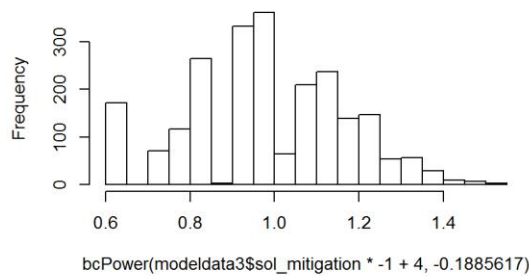
Histogram of log(modeldata3$sol_mitigation * -1 + 3)
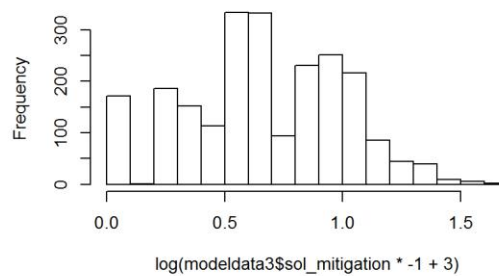
Both Wiebull and Gamma work, could use either. However, the data look reasonable even with a simple Gaussian when switched around (*-1). Will play to see what works.

Finding the model for mitigation solutions.

We've fitted a generalized linear model (GLM) with different links link multiplied by -1 and moved by +3 (to get rid of values below zero) and sol_mitigation variable as response.

For the global model, we fitted all variables we hypothesized (according to previous understanding of the problem) that they would affect this respnse.

We'll only make models for Region, georegion we'll explore if it seems neccessary.

```
mitFG = formula(I((sol_mitigation * -1) + 3) ~ Region + gender + age +
education +
    knowledge + dogowner + has_livestock)  #+
# Region
McGReg = glm(mitFG, data = modeldata3NONA, family = Gamma(link = "identity"),
na.action = "na.fail")
McGReg

##
## Call:  glm(formula = mitFG, family = Gamma(link = "identity"), data =
modeldata3NONA,
##     na.action = "na.fail")
##
## Coefficients:
##          (Intercept)              RegionCroatia              RegionItaly
```

```
##              2.4408495                -0.1815184                  0.0390187
##    RegionSlovenia Alps  RegionSlovenia Dinaric                 gendermale
##             -0.0805389                -0.0251124                  0.0311899
##                    age                 education                  knowledge
##             -0.0002183                -0.0484374                 -0.0803122
##            dogowneryes          has_livestockyes
##             -0.0897688                 0.1486535
##
## Degrees of Freedom: 2231 Total (i.e. Null);  2221 Residual
## Null Deviance:       247.8
## Residual Deviance: 238.1     AIC: 4383
```

```
par(mfrow = c(2, 2))
plot(McGReg)
```
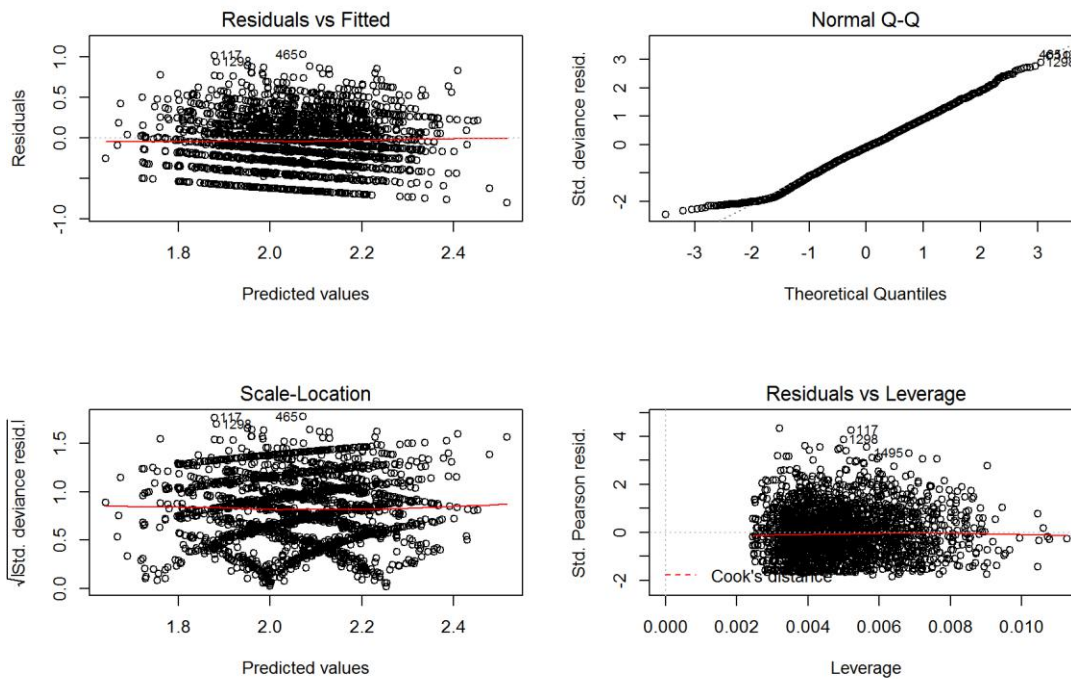


```
par(mfrow = c(1, 1))
```

Reasonably acceptable with Gamma link, the best I can do. The I can't get the bottom tail to fit better, but should be close enough.

Let's check multicollinearity (w/o interactions).

```
vif(McGReg)
```

	GVIF	Df	GVIF^(1/(2*Df))
Region	1.281122	4	1.031451
gender	1.056980	1	1.028095

age	1.182591	1	1.087470
education	1.136912	1	1.066261
knowledge	1.045756	1	1.022622
dogowner	1.112273	1	1.054644
has_livestock	1.072922	1	1.035819

There seems to be no multicolinearity problem.

```
clust = makeCluster(getOption("cl.cores", 4), type = "PSOCK")
clusterExport(clust, "modeldata3NONA")
# start=Sys.time()#report start time
DredgeGMmitigationReg = pdredge(McGReg, cluster = clust, trace = F)  #Region

## Fixed term is "(Intercept)"

save(DredgeGMmitigationReg, file = ".//mitigation_dredgeGM_Reg.RData")
# end=Sys.time()#report end time end-start
```

Importance of parameters.

```
importance(DredgeGMmitigationReg)

##                       knowledge Region has_livestock dogowner education
## Importance:           1.00      1.00   1.00          0.97     0.80
## N containing models:  64        64     64            64       64
##                       gender age
## Importance:           0.40   0.27
## N containing models:  64     64
```

We ranked importance of each variable by checking in how many models it appeared weighted by Akaike's weights, and constructed the optimal model without interactions that retains all variables that had importance larger than 0.8.

Optimal model for mitigation support

We constructed the **optimal model** without interactions. Variables *gender* and *age* were removed. We decided to keep *education* for the time being and check later with interactions.

excluded variables: gender, age

	df	AICc
McOptG	10	4379.993
McOptG2	14	4375.464
McOptG3	14	4385.521
McOptG4	14	4383.076
McOptG5	11	4374.568

McOptG6   11   4381.897
McOptG7   9   4387.138
McOptG8   9   4382.953
McOptG9   11   4380.893
McOptG10   14   4378.402
McOptG11   15   4371.010
McOptG12   19   4370.731
McOptG13   20   4393.249
McOptG14   17   4374.208

Meaningful interactions are Region:education and knowledge:has_livestock

*The final model for mitigation support

```
ModmitigationTol_Reg = glm(I((sol_mitigation * -1) + 3) ~ Region + education
+ knowledge +
    dogowner + has_livestock + +Region:education + knowledge:has_livestock,
data = modeldata3NONA,
    family = Gamma(link = "identity"), na.action = "na.fail")
```

Exploration of drivers of mitigation support

Outliers

We checked for outliers - high influence points - with the optimal model and cook's distances. We re-fitted the model with outliers removed.

```
cook = cooks.distance(ModmitigationTol_Reg)
plot(1:nrow(modeldata3NONA), cook)
abline(h = 4/nrow(modeldata3NONA), col = "red")
```
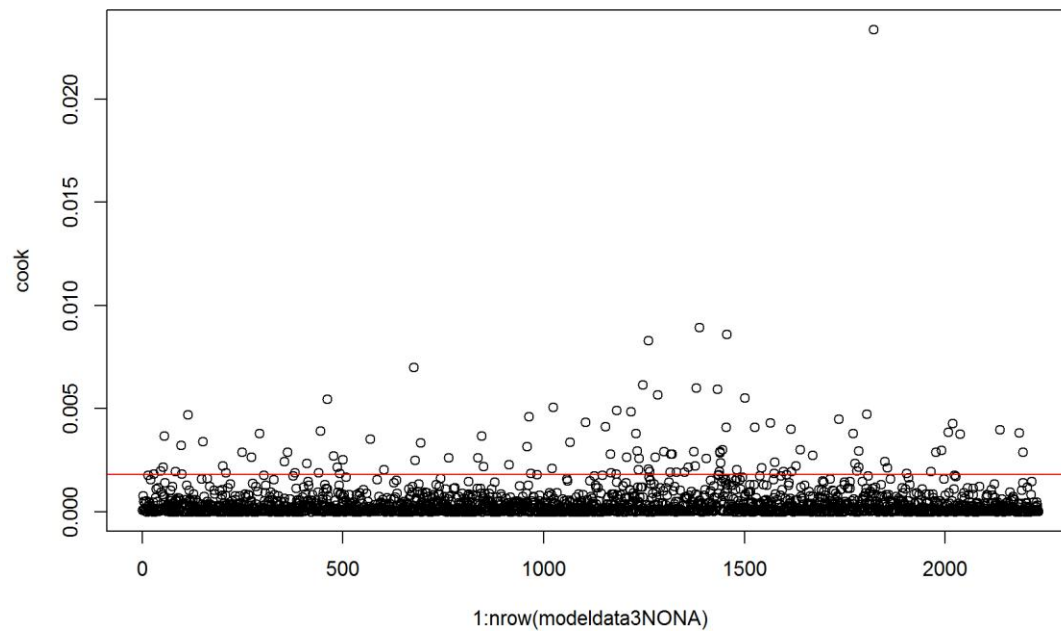
```
modeldata3.NO = modeldata3NONA[which(cook <= 4/nrow(modeldata3NONA)), ]
# re-evalute the model with outlier-fee data
ModmitigationTol_Reg2 = glm(I((sol_mitigation * -1) + 3) ~ Region + education
+ knowledge +
    dogowner + has_livestock + +Region:education + knowledge:has_livestock,
data = modeldata3.NO,
    family = Gamma(link = "identity"), na.action = "na.fail")
par(mfrow = c(2, 2))
plot(ModmitigationTol_Reg2)
```
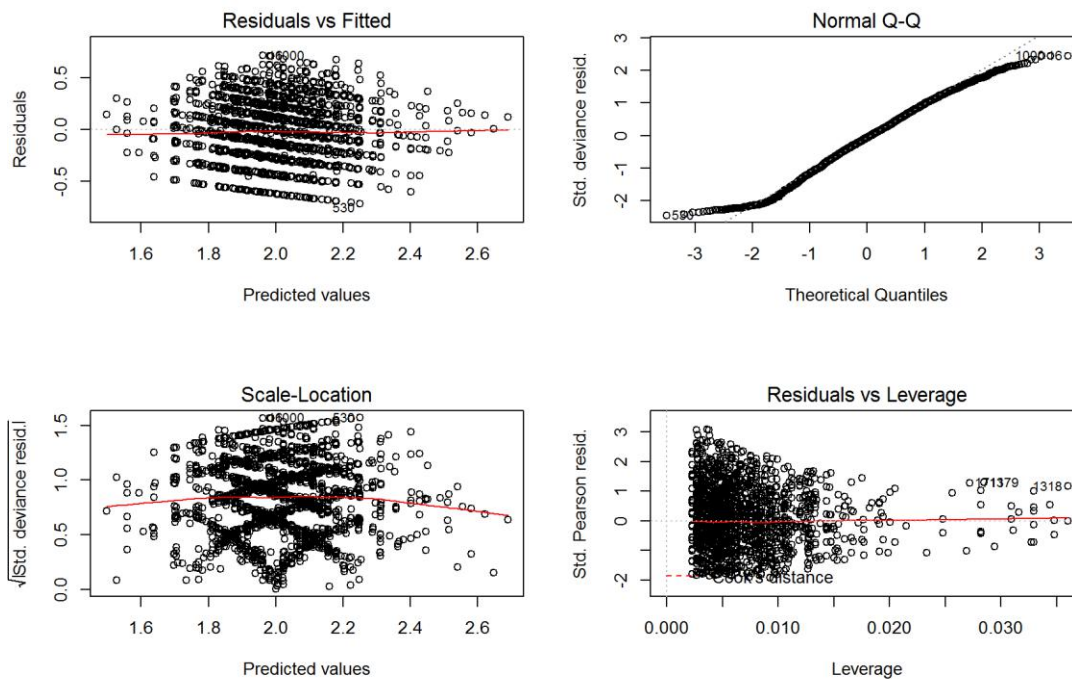
```
# plot(ModmitigationTol_Reg)
par(mfrow = c(1, 1))
```

Diagnostics is not grand, but not too bad. Q-Q plot is a bit off at low values.

A plotting function to make life easier.

Exploring Effects - Bear mitigation Tolerance

Using the constructed model of Bear mitigation support we can explore the effect of a single variable or a combination of variables while controlling for the effect of other variables. In this manner we can understand the effect of i.e. Region where the respondent lives (or any other parameter we wish to explore) withouth the confounding effects of other characteristics of the respondent (e.g. education, having livestock etc.)

Let's explore the effect of Region on mitigation support.

```
bwplot(Region ~ (sol_mitigation), data = modeldata3NONA, main = "Effect of
Region on Bear Conflict Mitigation Support - Raw Data",
    xlab = "Support for Mitigation Measures")
```

Effect of Region on Bear Conflict Mitigation Support - Raw Data
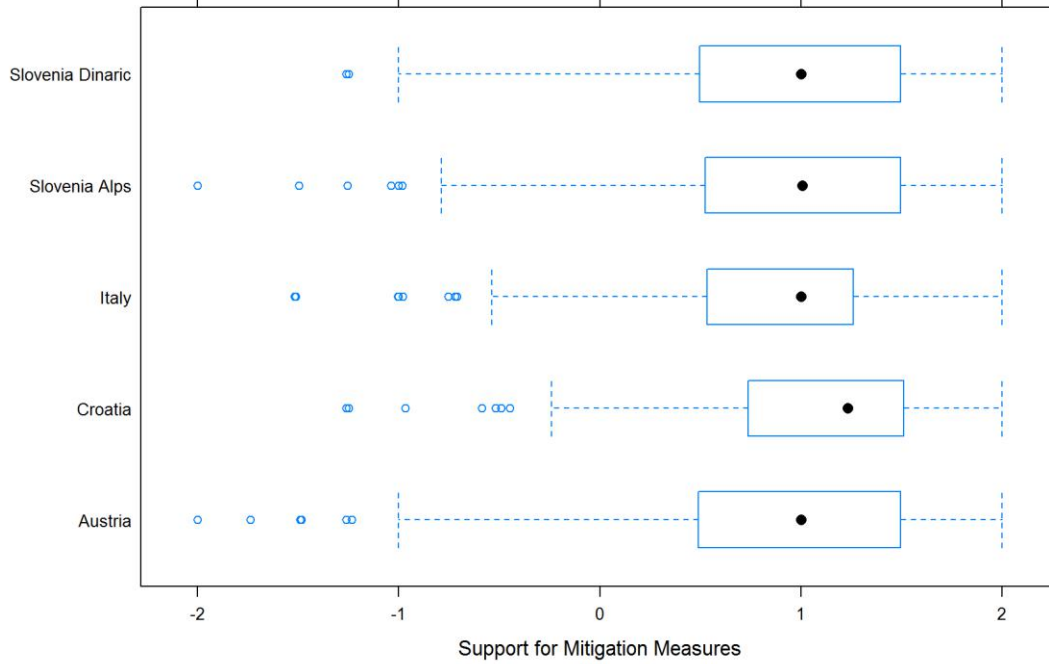

```
PlotEffectsmitigation("Region", ModmitigationTol_Reg2, main = "Effect of
Region Mitigation Measures Support",
    ylim = c(0.3, 1.5))
```

Effect of Region Mitigation Measures Support
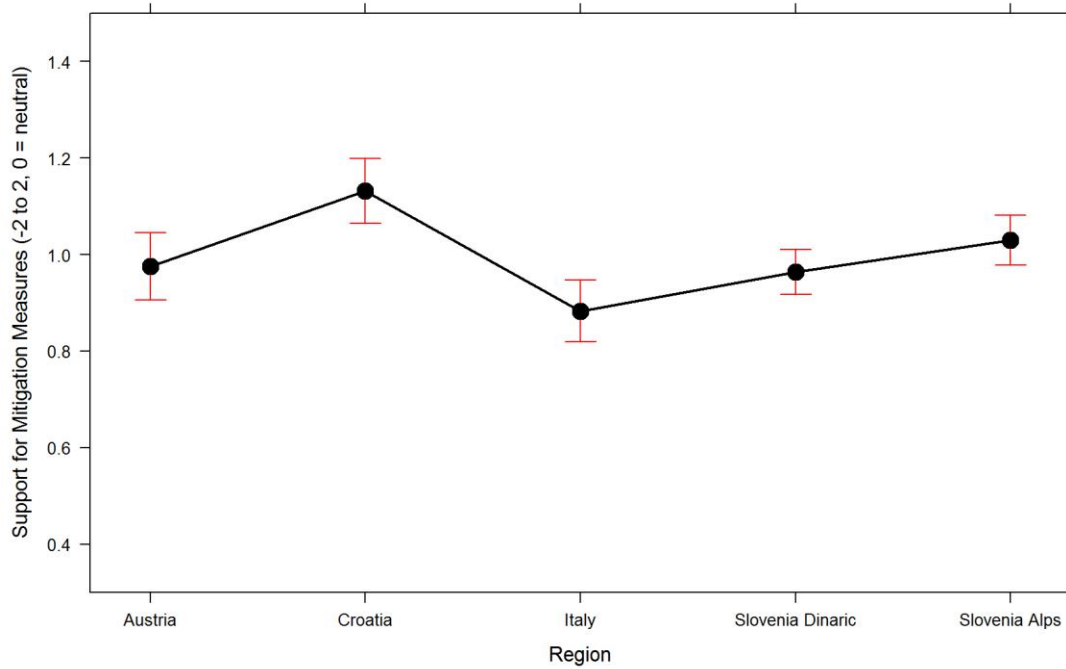
Overall, everyone seems quite supportive of mitigation measures. Croatia is even more supportive of mitigation measures then others, and Italy a bit less.

How does having livestock affect this?

```
bwplot(has_livestock ~ (sol_mitigation), data = modeldata3NONA, main =
"Effect of Having Livestock on Support for Mitigation Measures - Raw Data",
    xlab = "Mitigation Measures Support")
```


Effect of Having Livestock on Support for Mitigation Measures - Raw Data
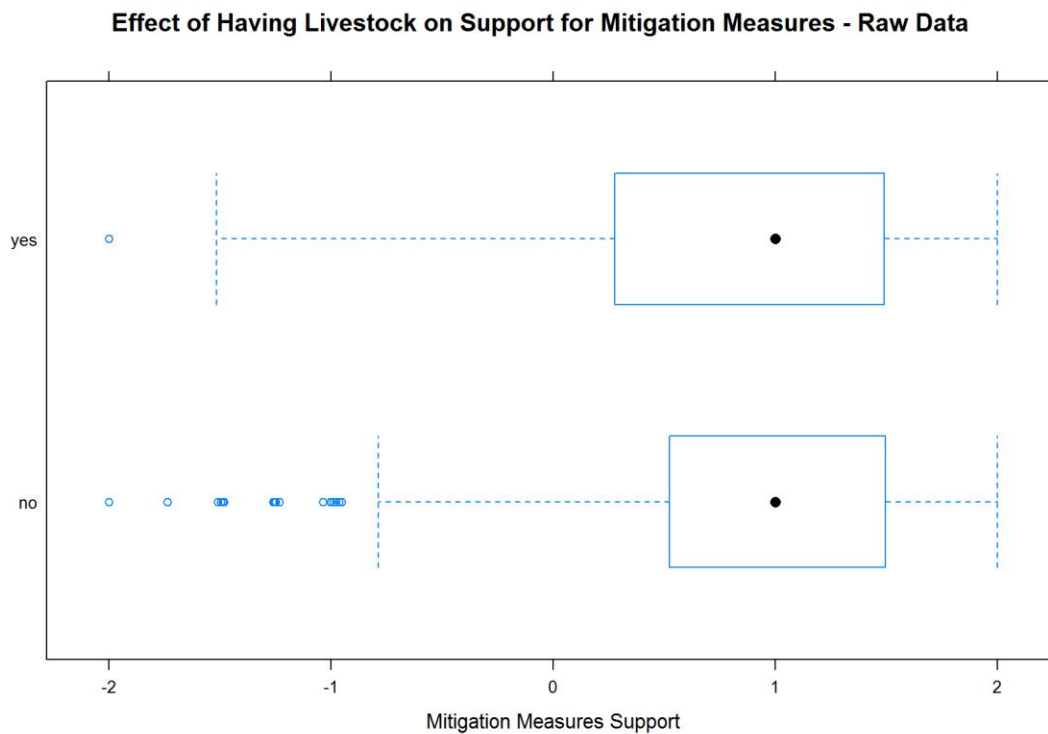
```
PlotEffectsmitigation("has_livestock", ModmitigationTol_Reg2, main = "Effect
of Having Livestock on Mitigation Measures Support",
    ylim = c(0.3, 1.5))
```

Effect of Having Livestock on Mitigation Measures Support
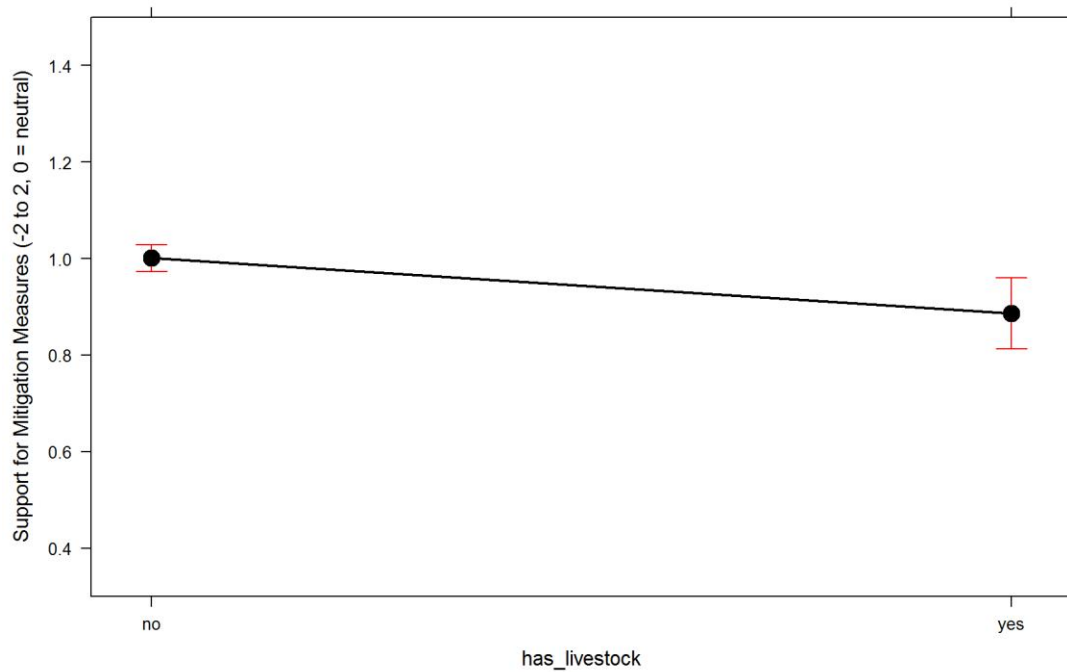
Having livestock seems to negatively impact support for mitigation measures. However, there was a supported interaction with knowledge.

```
PlotEffectsmitigation(c("has_livestock", "knowledge"), ModmitigationTol_Reg2,
main = "Effect of knowledge*has_livestock on Support for Mitigation
Measures",
    ylim = c(0.3, 1.5))
```

Effect of knowledge*has_livestock on Support for Mitigation Measures
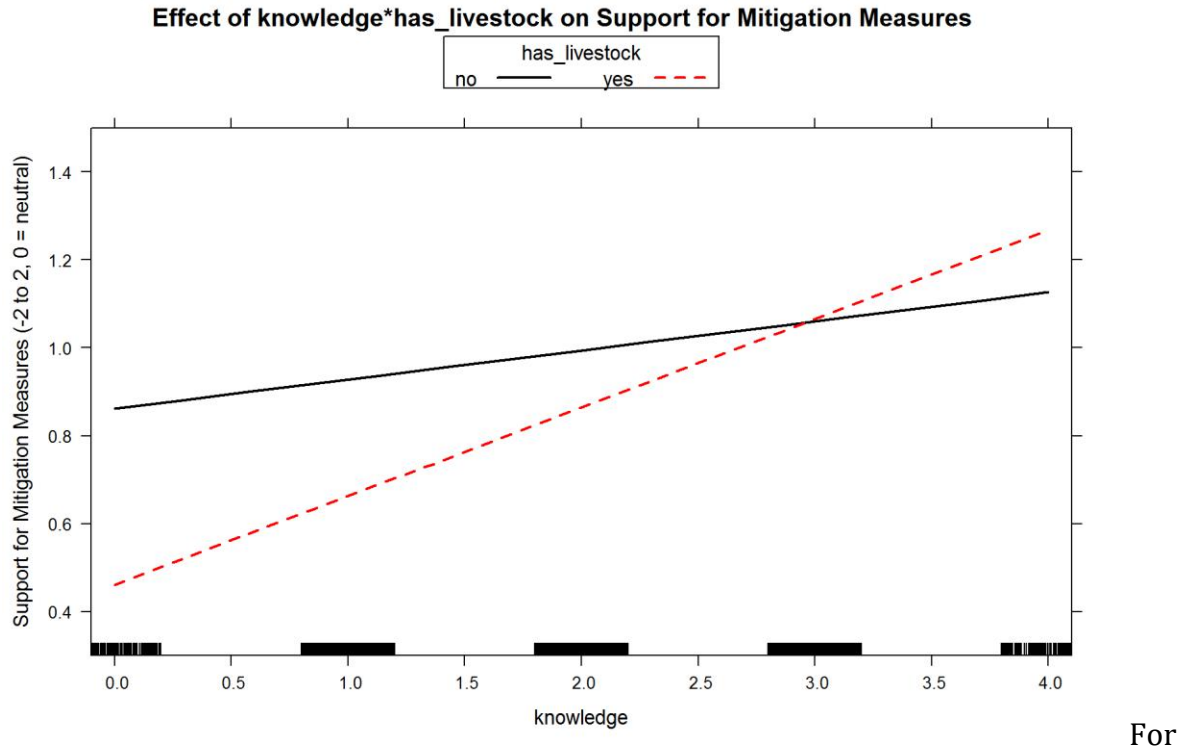
For people that do have livestock, their support of mitigation measures seems to be quite dependent on how much they know about bears.

How does knowledge affect this response on its own?

```
PlotEffectsmitigation("knowledge", ModmitigationTol_Reg2, main = "Effect of
Knowledge on Support for Mitigation Measures",
    ylim = c(0.3, 1.5))
```

Effect of Knowledge on Support for Mitigation Measures
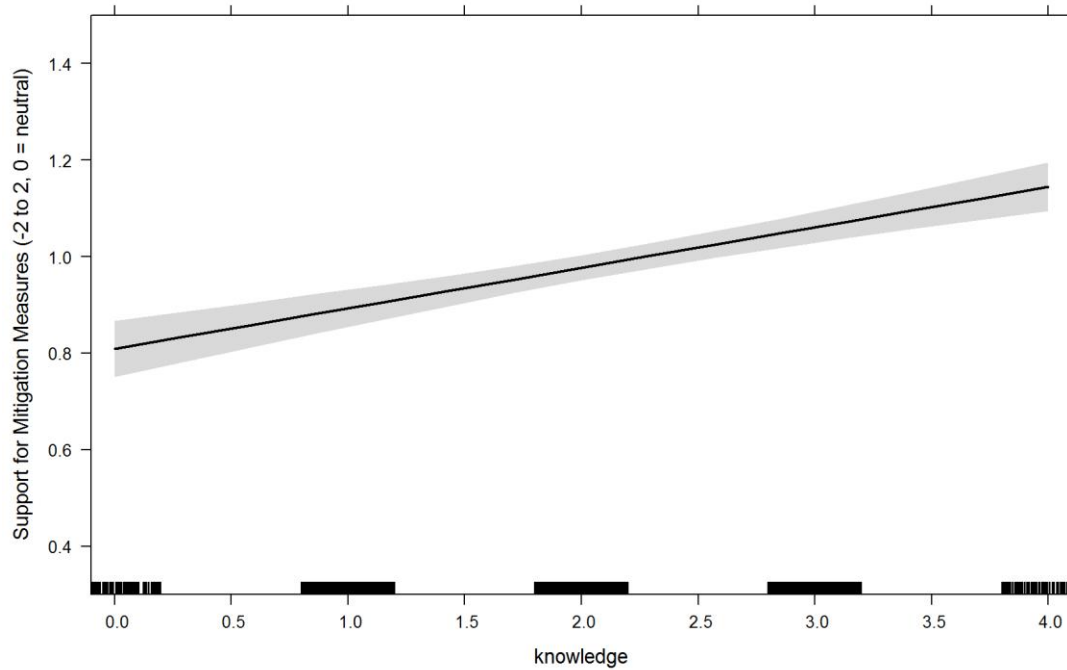
Some effect, but more drastic for livestock owners.

How about education?

```
PlotEffectsmitigation("education", ModmitigationTol_Reg2, main = "Effect of
Education on Support for Mitigation Measures",
    ylim = c(0.3, 1.5))
```

Effect of Education on Support for Mitigation Measures
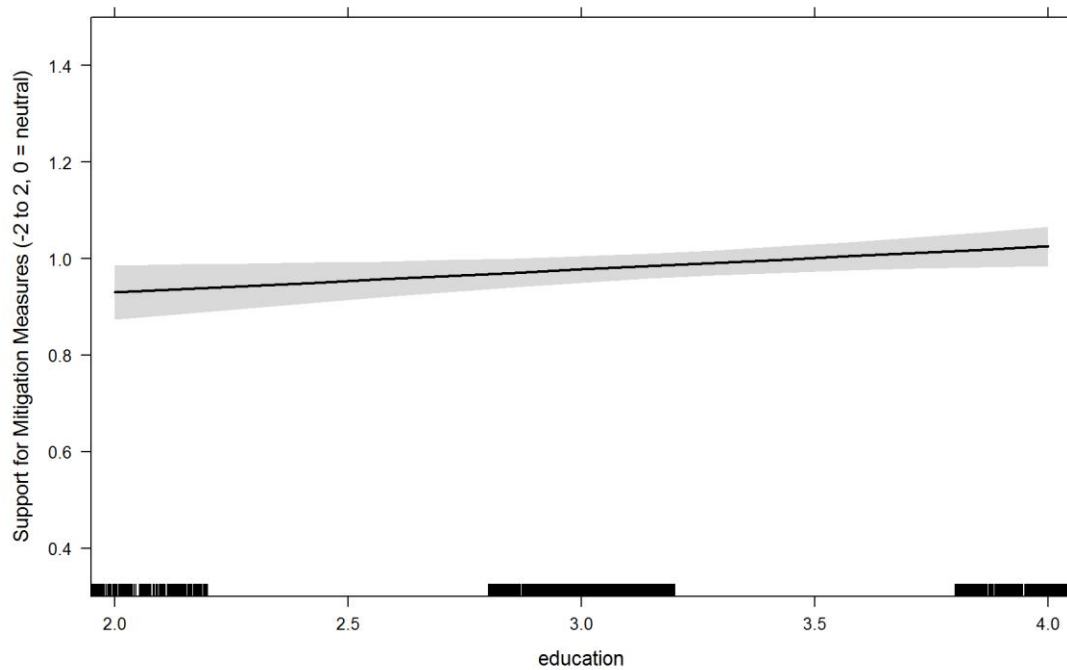
Slight positive effect, but not radical. However, there is an interaction between education and region:

```
PlotEffectsmitigation(c("education", "Region"), ModmitigationTol_Reg2, main =
"Effect of region*education on Support for Mitigation Measures",
    ylim = c(0.3, 1.5))
```

Effect of region*education on Support for Mitigation Measures
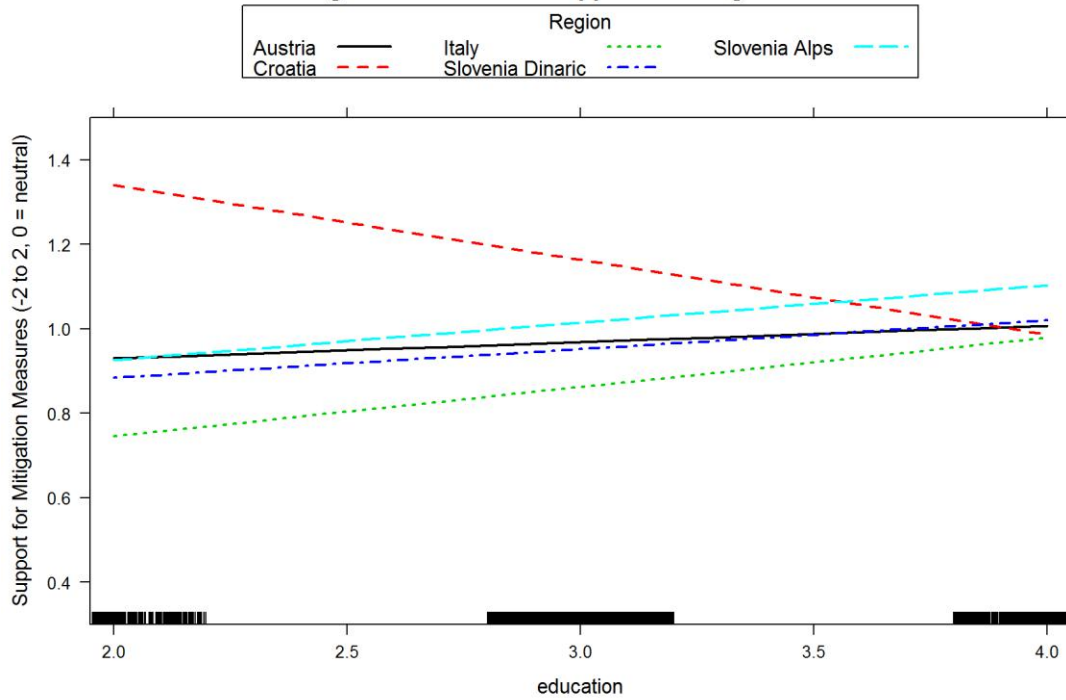
Croatia
is strange. Is everything coded correctly?

```
modeldata3NONA %>% group_by(as.factor(education), Region) %>% summarize(num =
length(education),
    meanage = median(age))
```

as.factor(education)	Region	num	meanage
2	Austria	164	48.5
2	Croatia	25	68.0
2	Italy	13	51.0
2	Slovenia Alps	64	60.5
2	Slovenia Dinaric	79	64.0
3	Austria	139	37.0
3	Croatia	176	56.0
3	Italy	247	38.0
3	Slovenia Alps	266	51.0
3	Slovenia Dinaric	330	51.0
4	Austria	85	42.0
4	Croatia	77	55.0

4	Italy	141	35.0
4	Slovenia Alps	185	43.0
4	Slovenia Dinaric	241	44.0
Distribution by differe	nt education levels	in Cr	oatia seems reasonably the same as in Slovenia. There is a discrepancy in Austria with a lot of people that seem to have only primary school - but this is probably down to the differences in education system since people that got vocation training were not considered as high-school graduates.

Now just the key question... "do you own a dog?!?"

```
PlotEffectsmitigation("dogowner", ModmitigationTol_Reg2, main = "Effect of
Owning a Dog on Support for Mitigation Measures",
    ylim = c(0.3, 1.5))
```


Effect of Owning a Dog on Support for Mitigation Measures
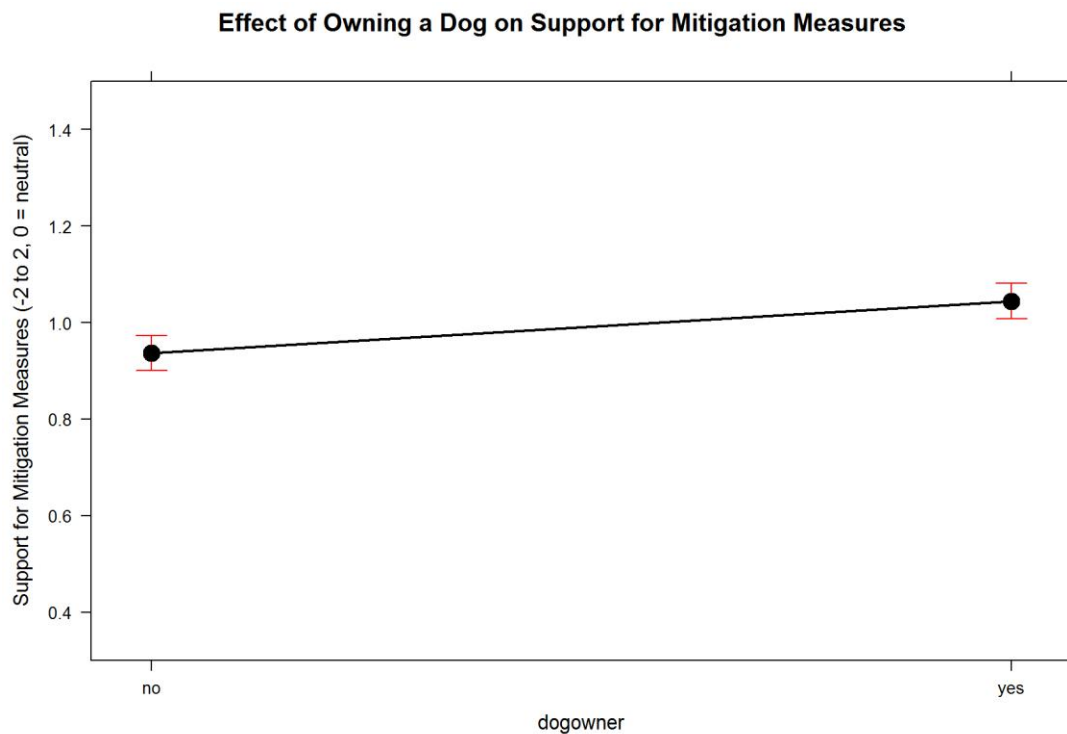
And yes, dogowners have a slightly higher support for mitigation measures. Using the model inference this is actually not too low:

```
nodog = update(ModmitigationTol_Reg2, . ~ . - dogowner)
nodogAIC = AIC(ModmitigationTol_Reg2, nodog)
nodogAIC
```

	df	AIC
ModmitigationTol_Reg2	15	3693.876
nodog	14	3707.995
Delta AIC = 14.1186961,	meani	ng that 'dogowner' variable considerably improves the model.

This concludes the analysis of support for mitigation measures. Housekeeping.

```
rm(list = ls()[-grep("modeldata3", ls())])
rm(modeldata3.NO)
```

Support for Culling of Bears

Let's first fit a distribution to this response variable.

```
##       shape         rate
##    5.08979414    2.02534414
##   (0.14649212) (0.06126599)

##       shape         scale
##    2.50435597    2.84162982
##   (0.04096196) (0.02518075)

##       shape         rate
##    4.6671205    9.4844976
##   (0.1339636) (0.2874314)

## Estimated transformation parameters
## modeldata3$sol_culling * -1 + 3
##                       0.345346
```
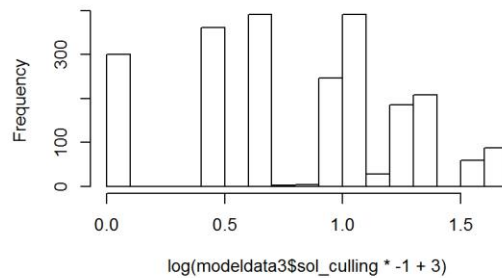
Gamma and Box-Cox about the same, gamma easier to use.

Finding the model for Culling Support.

We've fitted a generalized linear model (GLM) with different links link multiplied by -1 and moved by +3 (to get rid of values below zero) and sol_culling variable as response. Gamma is the first thing to try.

For the global model, we fitted all variables we hypothesized (according to previous understanding of the problem) that they would affect this response.

We'll only make models for Region, georegion we'll explore if it seems neccessary.

```
cullFG = formula(I(((sol_culling * -1) + 3)) ~ Region + gender + education +
knowledge +
    dogowner + has_livestock)  #+
# Region
McGReg = glm(cullFG, data = modeldata3NONA, family = Gamma, na.action =
"na.fail")
McGReg

##
## Call:  glm(formula = cullFG, family = Gamma, data = modeldata3NONA,
##     na.action = "na.fail")
##
## Coefficients:
##          (Intercept)            RegionCroatia              RegionItaly
##             0.384606                 0.092338                -0.049890
```

```
##     RegionSlovenia Alps  RegionSlovenia Dinaric                gendermale
##               0.025855                 0.064602                  0.061197
##              education                knowledge               dogowneryes
##              -0.009149                -0.003185                 -0.013379
##       has_livestockyes
##               0.042863
##
## Degrees of Freedom: 2231 Total (i.e. Null);  2222 Residual
## Null Deviance:      450.3
## Residual Deviance: 395.4      AIC: 6230

par(mfrow = c(2, 2))
plot(McGReg)
```
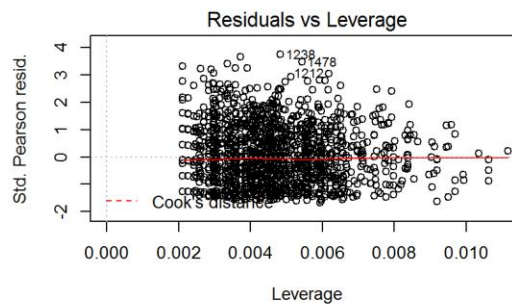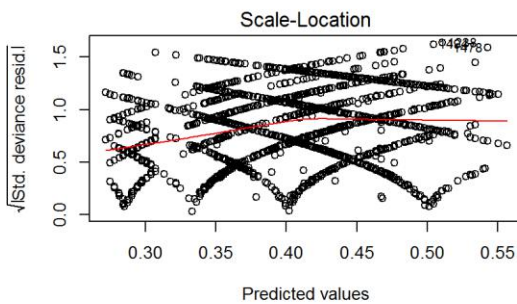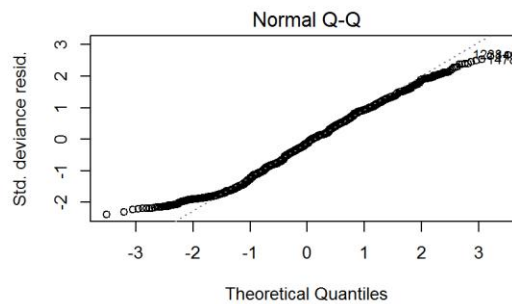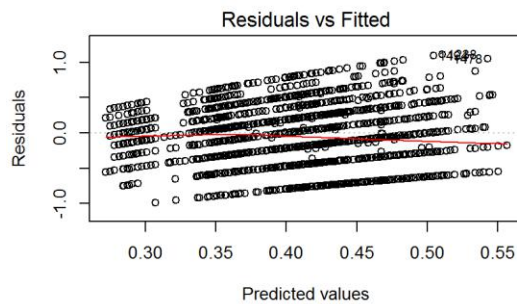


```
par(mfrow = c(1, 1))
hist(resid(McGReg))
```

Histogram of resid(McGReg)
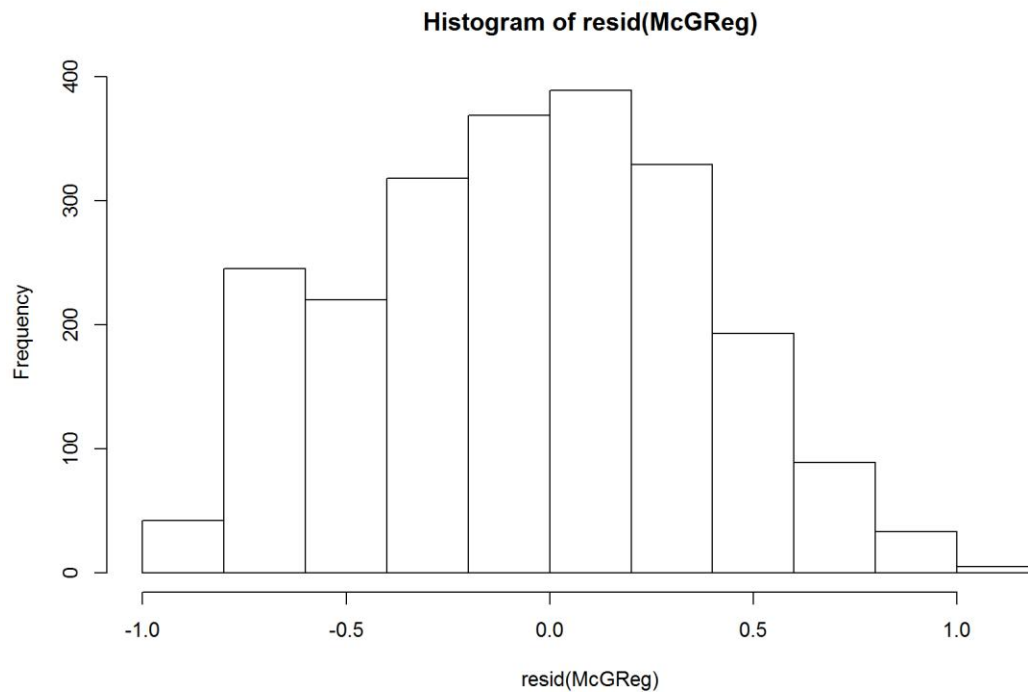
I've been playing with this for a long time now... can't get residuals to become random. So, it seems homoscedastic, but a bit biased. I don't know how to approach this, but with gamma family the bias is the smallest. It shouldn't be that bad, and residuals seem relatively normal. Ah, these damn real-life data.

Let's check multicollinearity (w/o interactions).

```
vif(McGReg)
```

	GVIF	Df	GVIF^(1/(2*Df))
Region	1.183571	4	1.021291
gender	1.044792	1	1.022151
education	1.090013	1	1.044037
knowledge	1.049321	1	1.024363
dogowner	1.097788	1	1.047754
has_livestock	1.062243	1	1.030652

There seems to be no multicolinearity problem.

```
clust = makeCluster(getOption("cl.cores", 4), type = "PSOCK")
clusterExport(clust, "modeldata3NONA")
# start=Sys.time()#report start time
DredgeGMcullingReg = pdredge(McGReg, cluster = clust, trace = F)  #Region

## Fixed term is "(Intercept)"
```

```
save(DredgeGMcullingReg, file = ".//culling_dredgeGM_Reg.RData")
# end=Sys.time()#report end time end-start
```

Importance of parameters.

```
importance(DredgeGMcullingReg)

##                         Region gender has_livestock dogowner education
## Importance:              1.00   1.00   1.00                  0.69      0.63
## N containing models:      32     32     32                    32        32
##                         knowledge
## Importance:              0.40
## N containing models:      32
```

We ranked importance of each variable by checking in how many models it appeared weighted by Akaike's weights, and constructed the optimal model without interactions that retains all variables that had importance larger than 0.8.

Optimal model for culling support

We constructed the **optimal model** without interactions. Variables *education* and *knowledge* were removed.

excluded variables: knowledge, educatoin, dogowner

	df	AICc
McOptG	8	6232.127
McOptG2	12	6223.211
McOptG3	12	6236.541

The only meaningful interaction seems to be Region:gender

*The final model for culling support

```
ModcullingTol_Reg = glm(I((sol_culling * -1) + 3) ~ Region + gender +
has_livestock +
    Region:gender, data = modeldata3NONA, family = Gamma, na.action =
"na.fail")
```

Exploration of drivers of culling support

Outliers

We checked for outliers - high influence points - with the optimal model and cook's distances. We re-fitted the model with outliers removed.

```
cook = cooks.distance(ModcullingTol_Reg)
plot(1:nrow(modeldata3NONA), cook)
abline(h = 4/nrow(modeldata3NONA), col = "red")
```
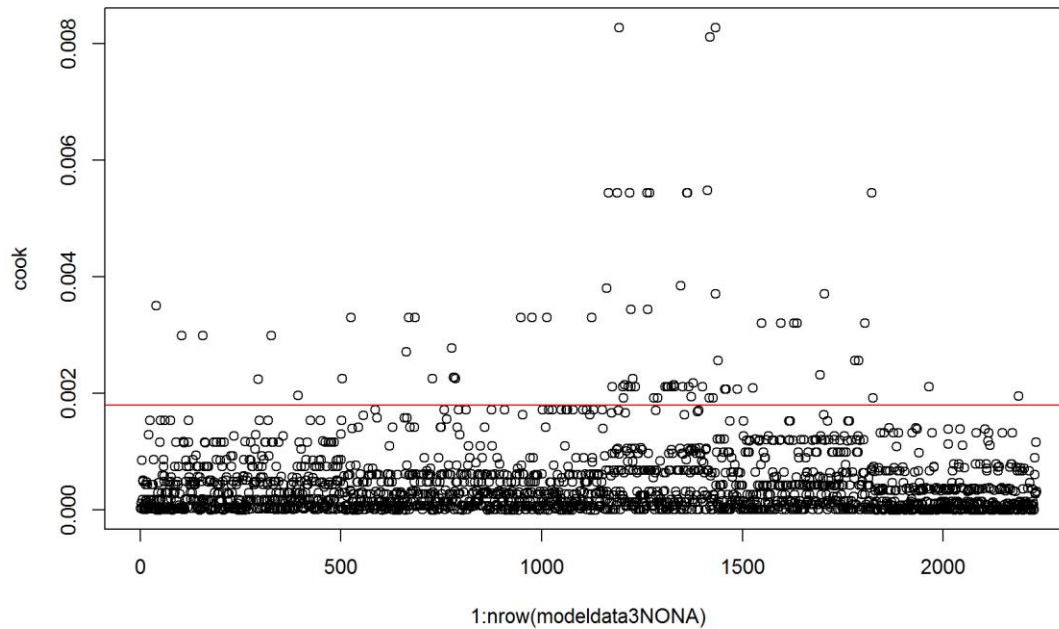
```
modeldata3.NO = modeldata3NONA[which(cook <= 4/nrow(modeldata3NONA)), ]
# re-evalute the model with outlier-fee data
ModcullingTol_Reg2 = glm(I((sol_culling * -1) + 3) ~ Region + gender +
has_livestock +
    Region:gender, data = modeldata3.NO, family = Gamma, na.action =
"na.fail")

## Warning: closing unused connection 12 (<-BingPadX:11626)

## Warning: closing unused connection 11 (<-BingPadX:11626)

## Warning: closing unused connection 10 (<-BingPadX:11626)

## Warning: closing unused connection 9 (<-BingPadX:11626)

par(mfrow = c(2, 2))
plot(ModcullingTol_Reg2)
```
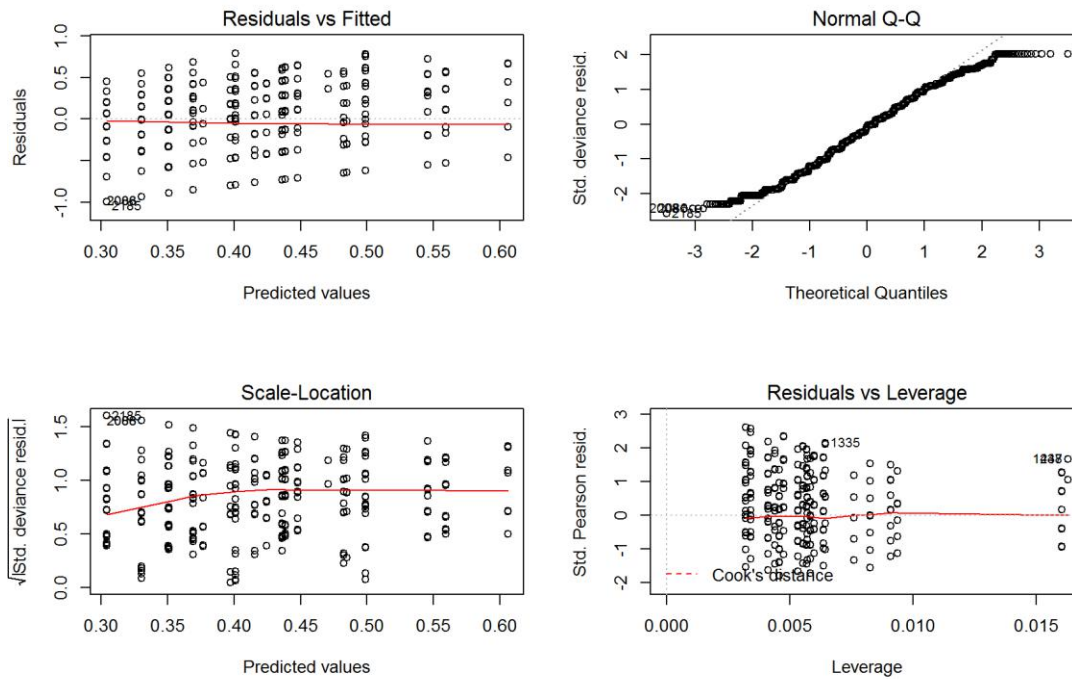
```
par(mfrow = c(1, 1))
```

Not grand - but this comes from having low number of integer variables aggregated into PCA. Not too bad.

A plotting function to make life easier.

Exploring Effects - Support for Culling of Bears

Using the constructed model of bear culling support we can explore the effect of a single variable or a combination of variables while controlling for the effect of other variables. In this manner we can understand the effect of i.e. Region where the respondent lives (or any other parameter we wish to explore) withouth the confounding effects of other characteristics of the respondent (e.g. gender, having livestock etc.)

Let's explore the effect of Region on culling support.

```
bwplot(Region ~ (sol_culling), data = modeldata3NONA, main = "Effect of
Region on Culling Support - Raw Data",
    xlab = "Support for Culling")
```

Effect of Region on Culling Support - Raw Data
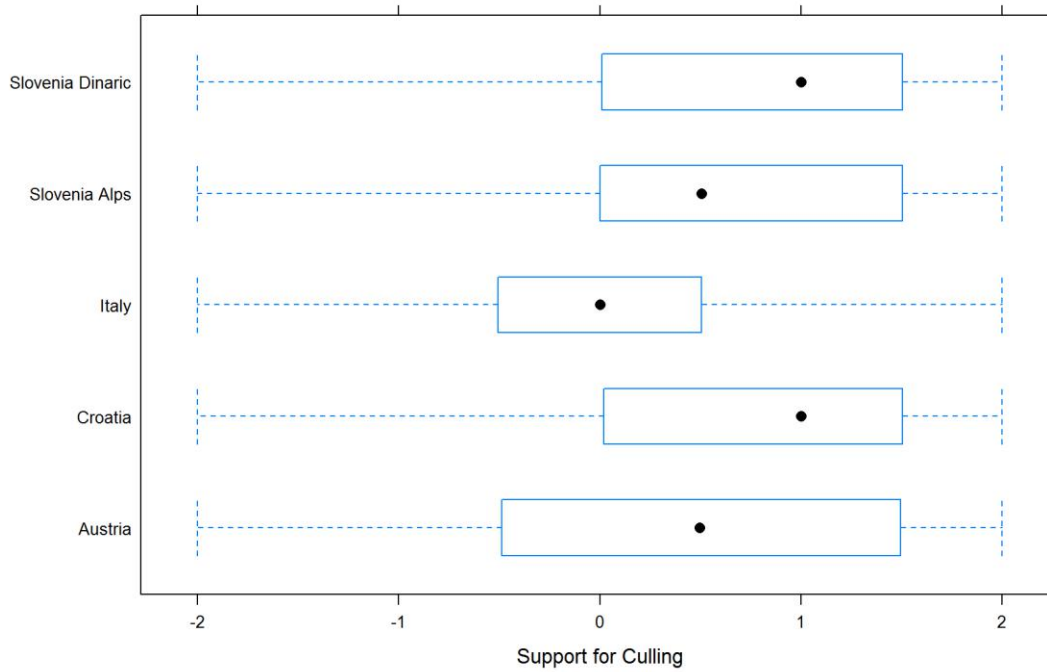

```
PlotEffectsculling("Region", ModcullingTol_Reg2, main = "Effect of Region
Support for Culling",
    ylim = c(0.2, 0.6))
```

Effect of Region Support for Culling
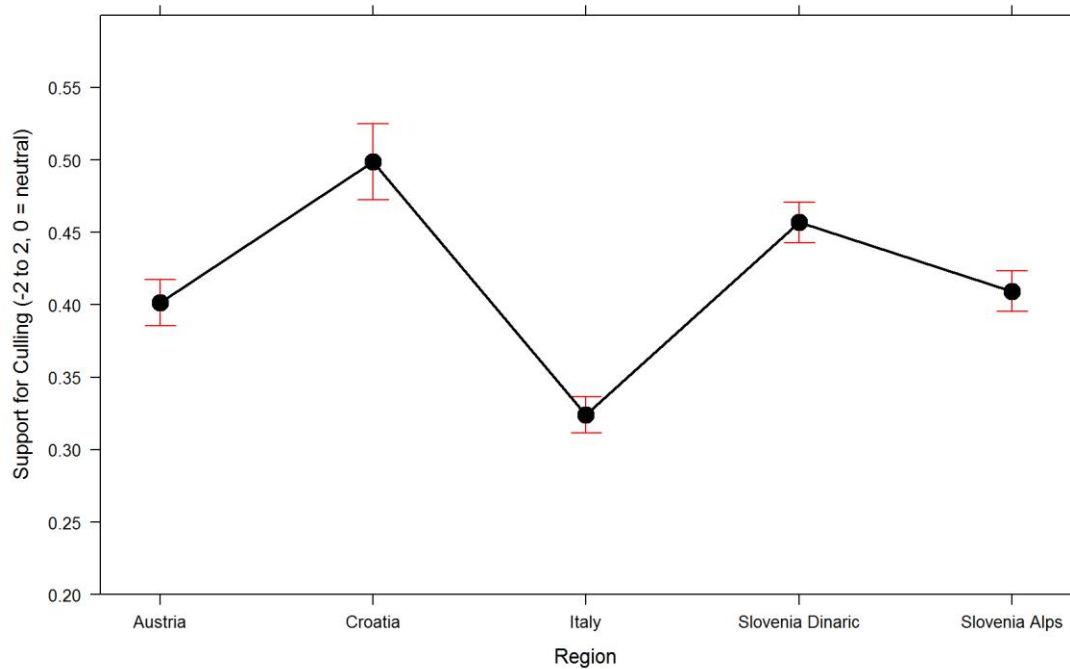
Overall, everyone seems quite supportive of bear culling (0 = neutral). Culling seems to be more acceptable where bears are actually present.

How does having livestock affect this?

```
bwplot(has_livestock ~ (sol_culling), data = modeldata3NONA, main = "Effect
of Having Livestock on Support Bear Culling - Raw Data",
    xlab = "Bear Culling Support")
```

Effect of Having Livestock on Support Bear Culling - Raw Data
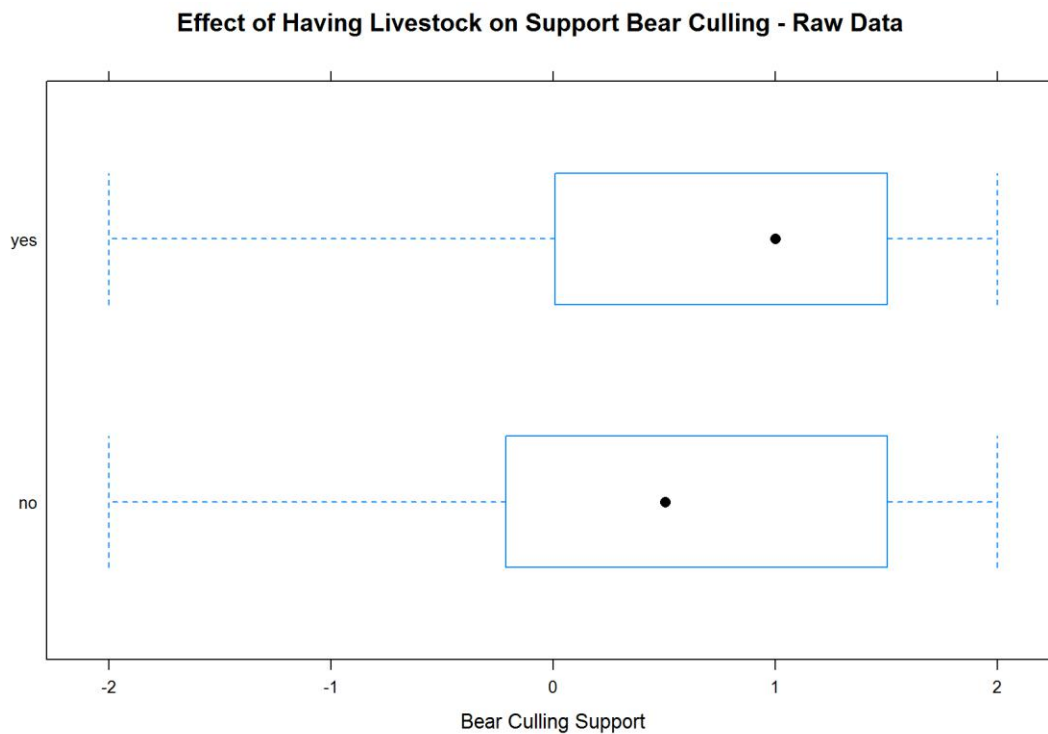

```
PlotEffectsculling("has_livestock", ModcullingTol_Reg2, main = "Effect of
Having Livestock on Support for Culling",
    ylim = c(0.2, 0.6))
```

Effect of Having Livestock on Support for Culling
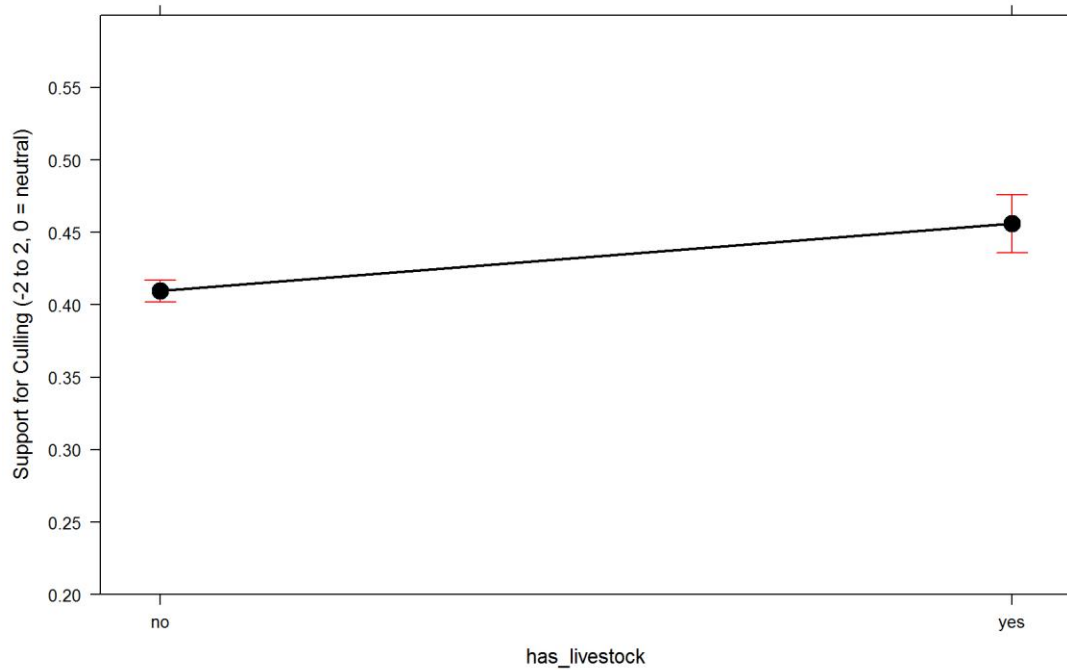
A very small effect.

Gender?

```
PlotEffectsculling("gender", ModcullingTol_Reg2, main = "Effect of Gender on
Support for Culling",
    ylim = c(0.2, 0.6))
```

Effect of Gender on Support for Culling
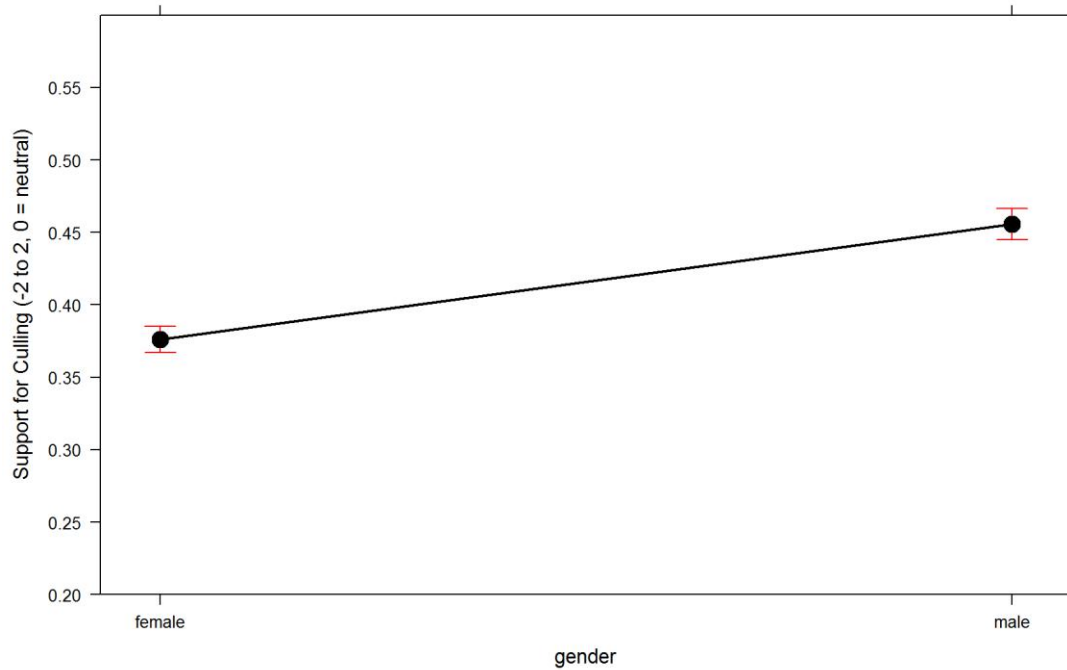
Ok, small but visible. There is interection with region, let's explore.

```
PlotEffectsculling(c("Region", "gender"), ModcullingTol_Reg2, main = "Effect
of Region*Gender for Culling Support",
    ylim = c(0.2, 0.6))
```

Effect of Region*Gender for Culling Support
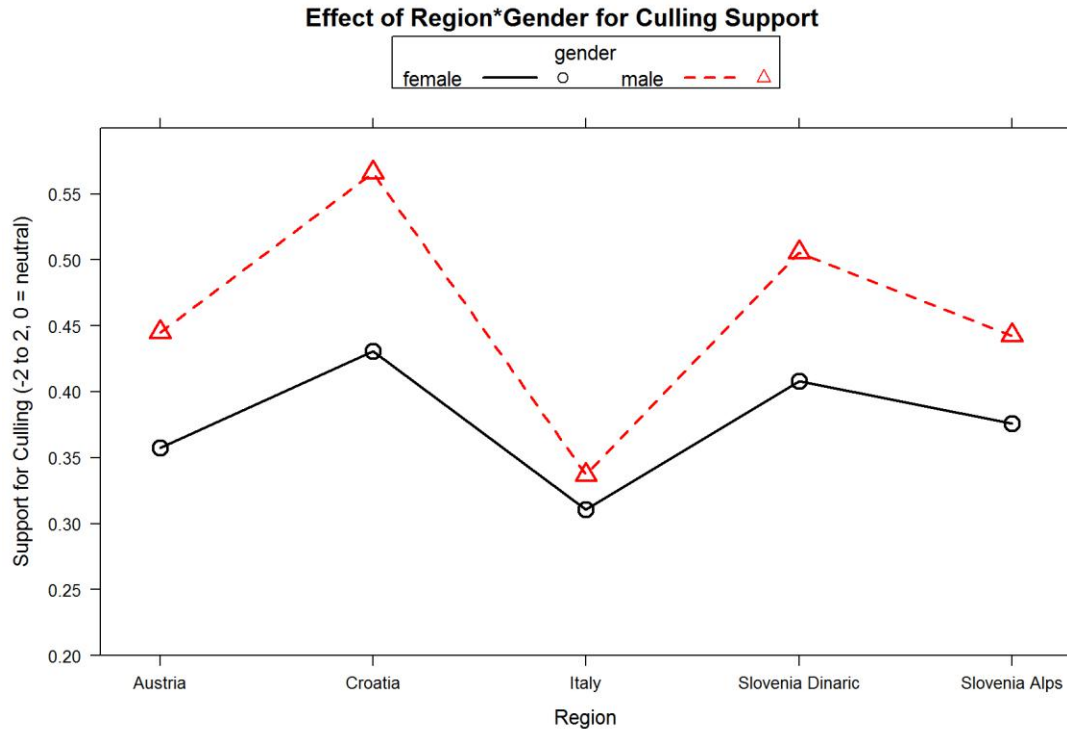
Italy the same, the others different.

This concludes the analysis of support for bear culling. Housekeeping.

```
rm(list = ls()[-grep("modeldata3", ls())])
rm(modeldata3.NO)
```

Support for bear conservation

In the first iteration of this analysis, I fitted support for mitigation measures, tolerance of conflicts and support for culling as predictors. That doesn't really make sense and there is not much useful to be learned from that, so I re-did the analysis without this.

Ok, this is now becoming important. First thing first - let's fit a distribution to this response variable.

```
##       shape         rate
##    9.2580221    4.0301003
##   (0.2701741) (0.1208544)

##       shape         scale
##    3.12604001    2.56658042
##   (0.04805998) (0.01828385)
```

red=Gamma, blue=Wiebull
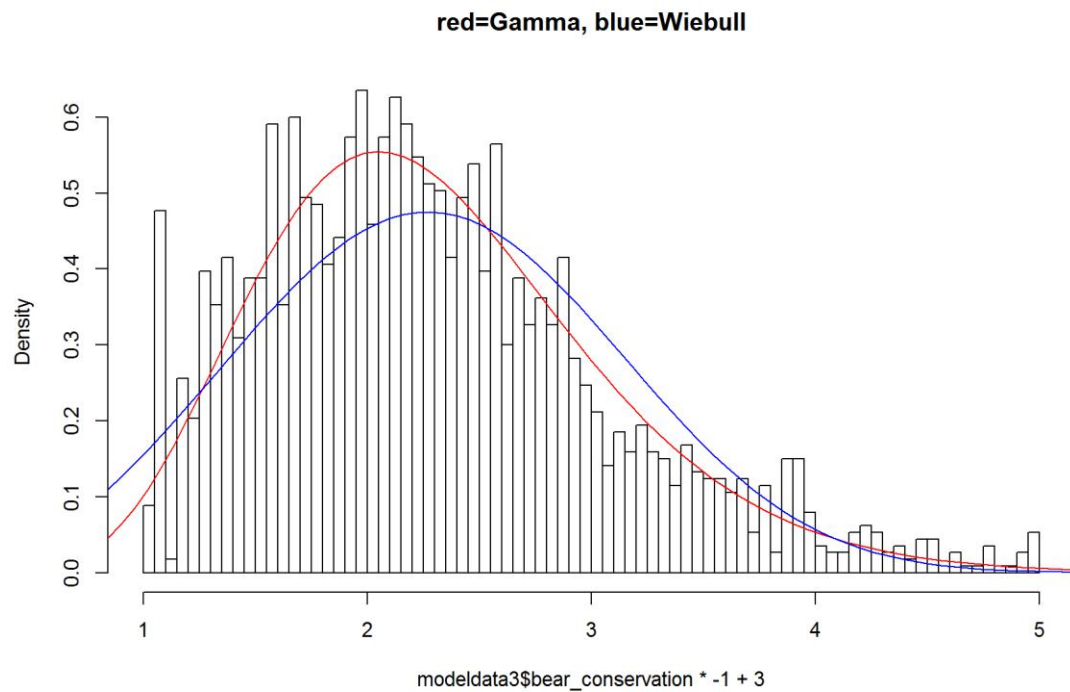
Gamma, no question. Happy about that. :)

Finding the model for conservation support.

We've fitted a generalized linear model (GLM) with different links link multiplied by -1 and moved by +3 (to get rid of values below zero) and bear_conservation variable as response.

For the global model, we fitted all variables we hypothesized (according to previous understanding of the problem) that they would affect this respnse.

We'll only make models for Region, georegion we'll explore if it seems neccessary.

```
# consFG = formula (I((bear_conservation*-1)+3)~Region+gender+age+education+
#
knowledge+dogowner+has_livestock+conflict_tolerance+sol_mitigation+sol_cullin
g)#+
# I tried this analysis, didn't make much sense...
consFG = formula(I((bear_conservation * -1) + 3) ~ Region + gender + age +
education +
    knowledge + dogowner + has_livestock + seennatureyesno)
MGcons = glm(consFG, data = modeldata3NONA, family = Gamma(link = "inverse"),
na.action = "na.fail")
MGcons

##
## Call:  glm(formula = consFG, family = Gamma(link = "inverse"), data =
modeldata3NONA,
##      na.action = "na.fail")
```

```
## 
## Coefficients:
##         (Intercept)         RegionCroatia              RegionItaly
##            0.385841             -0.014188                -0.046304
##   RegionSlovenia Alps  RegionSlovenia Dinaric           gendermale
##           -0.011112             -0.038378                 0.008713
##                 age             education                knowledge
##           -0.001076              0.021195                 0.029886
##         dogowneryes       has_livestockyes       seennatureyesnoyes
##            0.011511             -0.057668                -0.004772
## 
## Degrees of Freedom: 2231 Total (i.e. Null);  2220 Residual
## Null Deviance:       245.4
## Residual Deviance: 216.4     AIC: 4650

par(mfrow = c(2, 2))
plot(MGcons)
```
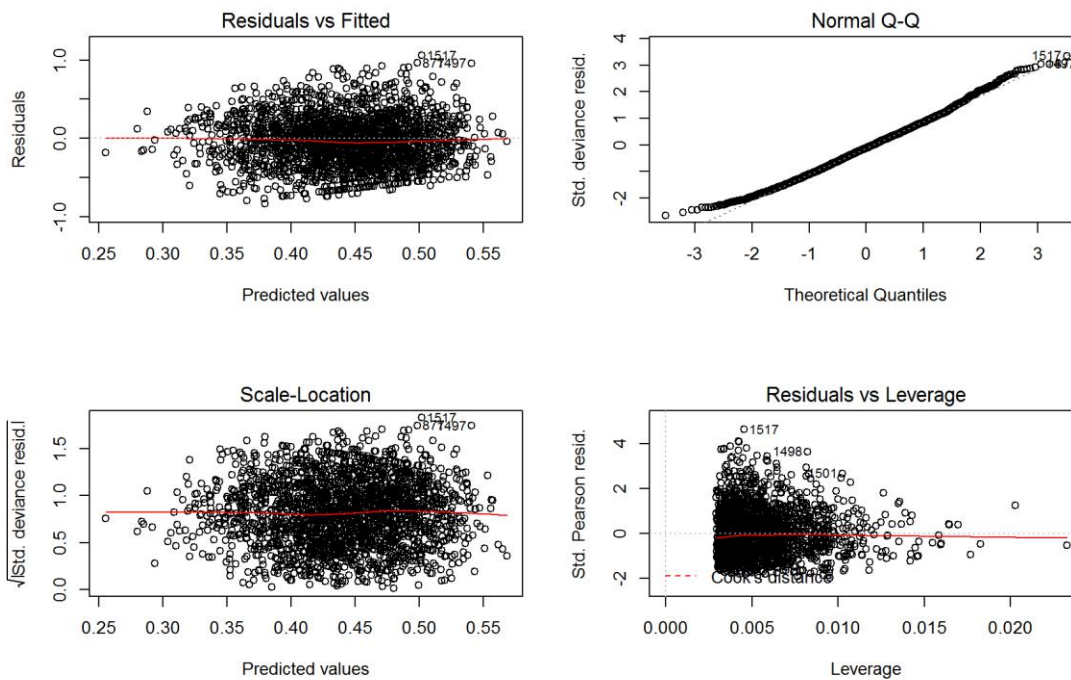


```
par(mfrow = c(1, 1))
```

Gamma quite ok. Happy.

Let's check multicollinearity (w/o interactions).

```
vif(MGcons)
```

                    GVIF   Df   GVIF^(1/(2*Df))

Region	1.540116	4	1.055466
gender	1.081831	1	1.040111
age	1.225920	1	1.107213
education	1.165098	1	1.079397
knowledge	1.067265	1	1.033085
dogowner	1.123815	1	1.060101
has_livestock	1.125674	1	1.060978
seennatureyesno	1.265747	1	1.125054

```
modeldata3NONA.b = modeldata3NONA
```

There seems to be no multicolinearity problem.

```
# MGcons=MGcons2
clust = makeCluster(getOption("cl.cores", 4), type = "PSOCK")
clusterExport(clust, "modeldata3NONA")
# start=Sys.time()#report start time
DredgeGMconservationReg = pdredge(MGcons, cluster = clust, trace = F)
#Region

## Fixed term is "(Intercept)"

save(DredgeGMconservationReg, file = ".//conservation_dredgeGM_Reg.RData")
# end=Sys.time()#report end time end-start
```

Importance of parameters.

```
importance(DredgeGMconservationReg)

##                          knowledge has_livestock age  Region education
## Importance:              1.00          1.00      1.00 1.00   1.00
## N containing models:     128           128       128  128    128
##                          dogowner gender seennatureyesno
## Importance:              0.68     0.49   0.30
## N containing models:     128      128    128
```

We ranked importance of each variable by checking in how many models it appeared weighted by Akaike's weights, and constructed the optimal model without interactions that retains all variables that had importance larger than 0.8.

Optimal model for conservation support

We constructed the **optimal model** without interactions.

excluded variables: seennatureyesno, dogowner, gender.

```
## Warning: closing unused connection 12 (<-BingPadX:11149)

## Warning: closing unused connection 11 (<-BingPadX:11149)
```

```
## Warning: closing unused connection 10 (<-BingPadX:11149)

## Warning: closing unused connection 9 (<-BingPadX:11149)

## Warning: closing unused connection 8 (<-BingPadX:11149)

## Warning: closing unused connection 7 (<-BingPadX:11149)

## Warning: closing unused connection 6 (<-BingPadX:11149)

## Warning: closing unused connection 5 (<-BingPadX:11149)
```

	df	AICc
McOptG	10	4649.511
McOptG2	14	4655.428
McOptG3	14	4649.145
McOptG4	14	4656.725
McOptG5	11	4647.863
McOptG6	11	4648.883
McOptG7	11	4649.711
McOptG8	12	4651.347
McOptG9	14	4648.307
McOptG10	15	4646.601
McOptG11	11	4649.711
McOptG12	16	4647.052
McOptG13	13	4653.322
McOptG14	17	4649.777

Meaningful interactions are +knowledge:has_livestock+Region:age. 'gender' actually lowers support for the best model, so there is no justification to keep the variable.

*The final model for conservation support

```
ModconservationTol_Reg = glm(I((bear_conservation * -1) + 3) ~ Region + age +
education +
    knowledge + has_livestock + knowledge:has_livestock + Region:age, data =
modeldata3NONA,
    family = Gamma(link = "inverse"), na.action = "na.fail")
```

Exploration of drivers of conservation support

Outliers

We checked for outliers - high influence points - with the optimal model and cook's distances. We re-fitted the model with outliers removed.

```
cook = cooks.distance(ModconservationTol_Reg)
plot(1:nrow(modeldata3NONA), cook)
abline(h = 4/nrow(modeldata3NONA), col = "red")
```



```
modeldata3.NO = modeldata3NONA[which(cook <= 4/nrow(modeldata3NONA)), ]
# re-evalute the model with outlier-fee data
ModconservationTol_Reg2 = glm(I((bear_conservation * -1) + 3) ~ Region + age
+ education +
    knowledge + has_livestock + knowledge:has_livestock + Region:age, data =
modeldata3.NO,
    family = Gamma(link = "inverse"), na.action = "na.fail")
par(mfrow = c(2, 2))
plot(ModconservationTol_Reg2)
```

```
par(mfrow = c(1, 1))
```

Removing outliers (about 5%) in this case actually improves model fit a bit (better-looking residuals). This actually looks good.

A plotting function to make life easier.

Exploring Effects - Support for Bear Conservation

Using the constructed model of Bear conservation support we can explore the effect of a single variable or a combination of variables while controlling for the effect of other variables. In this manner we can understand the effect of i.e. Region where the respondent lives (or any other parameter we wish to explore) withouth the confounding effects of other characteristics of the respondent (e.g. education, having livestock etc.)

Let's explore the effect of Region on conservation support.

```
bwplot(Region ~ (bear_conservation), data = modeldata3.NO, main = "Effect of
Region on Support for Bear Conservation - Raw Data",
    xlab = "Support for Bear Conservation")
```

Effect of Region on Support for Bear Conservation - Raw Data


```
PlotEffectsconservation("Region", ModconservationTol_Reg2, main = "Effect of
Region Conservation Support",
    ylim = c(0.2, 1.3))
```

Effect of Region Conservation Support

Overall, everyone seems quite supportive of bear conservation, but there are differences between regions.

There is an interaction between region and age.

```
PlotEffectsconservation(c("age", "Region"), ModconservationTol_Reg2, main =
"Effect of age*region on Support for Conservation",
    ylim = c(0.2, 1.3))
```
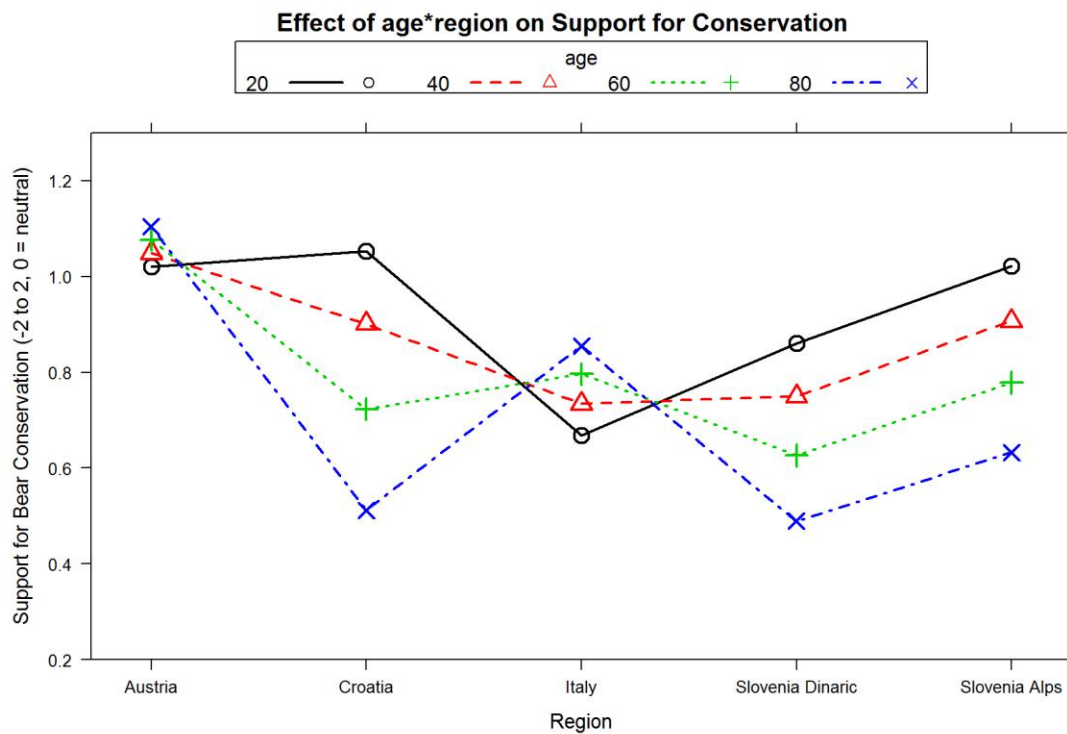

Eeee... ok? How about only age?

```
PlotEffectsconservation("age", ModconservationTol_Reg2, main = "Effect of Age
on Conservation Support",
    ylim = c(0.2, 1.3))
```

Effect of Age on Conservation Support
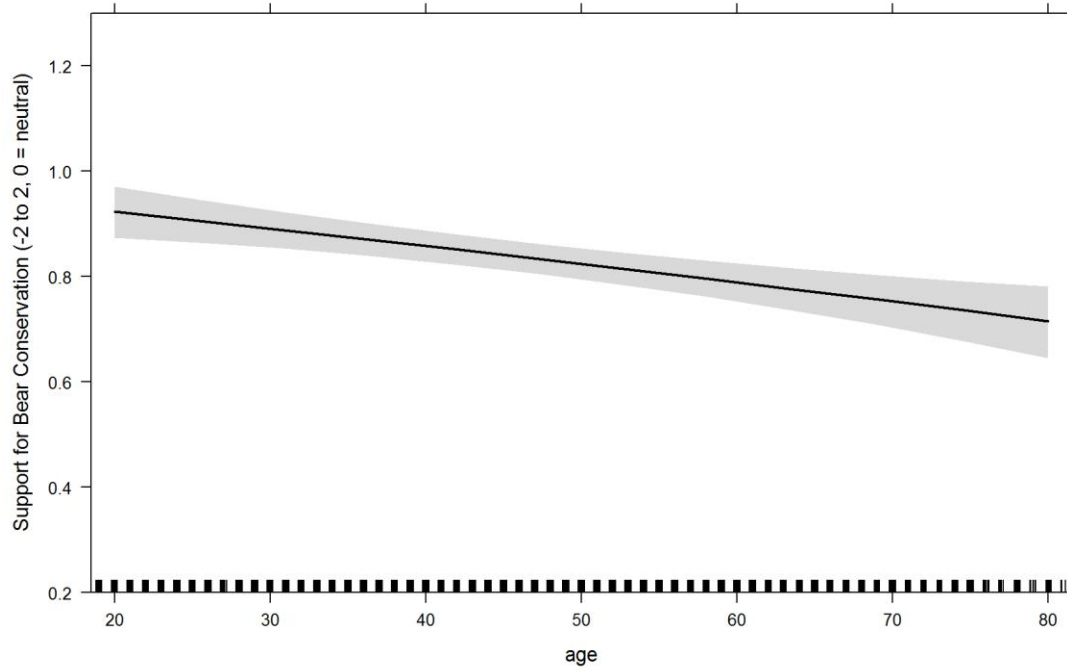
Education?

```
PlotEffectsconservation("education", ModconservationTol_Reg2, main = "Effect
of Education on Conservation Support",
    ylim = c(0.2, 1.3))
```

Effect of Education on Conservation Support

Knowledge?

```
PlotEffectsconservation("knowledge", ModconservationTol_Reg2, main = "Effect
of Knowledge on Conservation Support",
    ylim = c(0.2, 1.3))
```
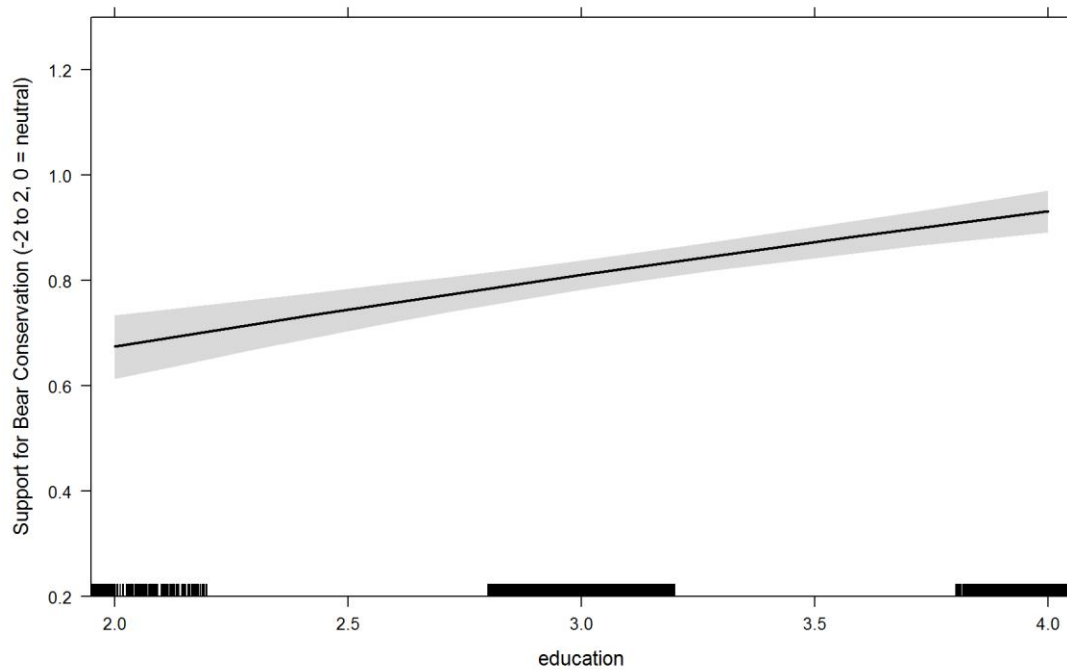

Effect of Knowledge on Conservation Support
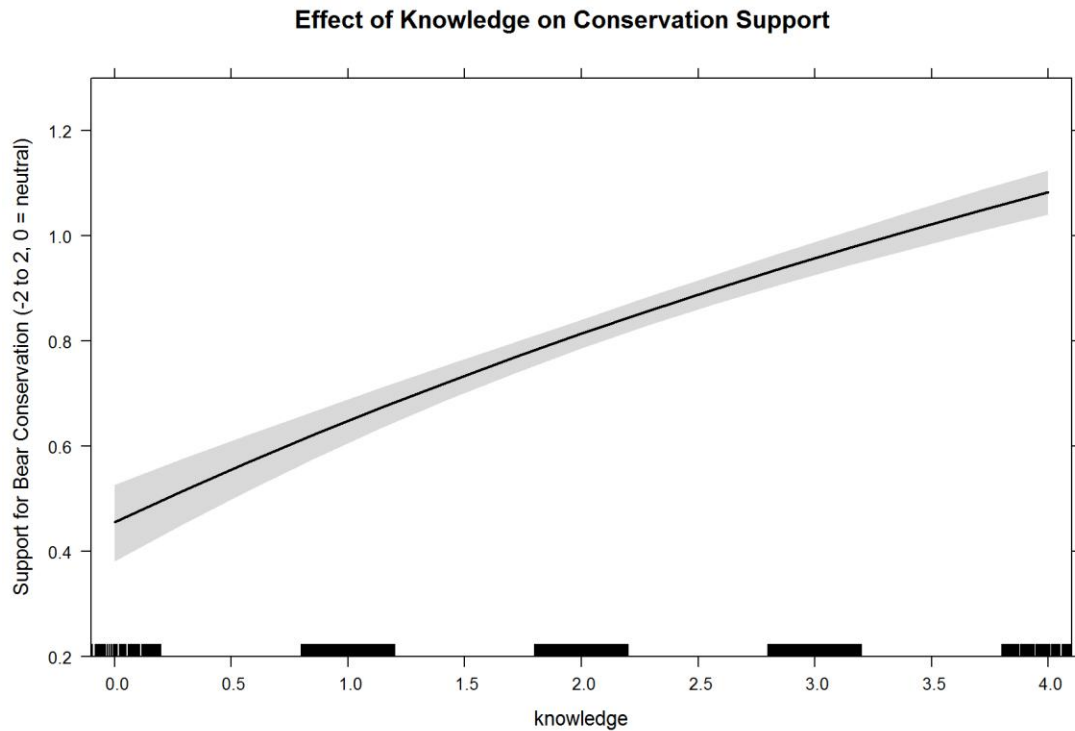
Huge effect. Knowledge also interacts with has_livestock. Let's first look at this parameter.

```
PlotEffectsconservation("has_livestock", ModconservationTol_Reg2, main =
"Effect Having Livestock on Conservation Support",
    ylim = c(0.2, 1.3))
```

Effect Having Livestock on Conservation Support
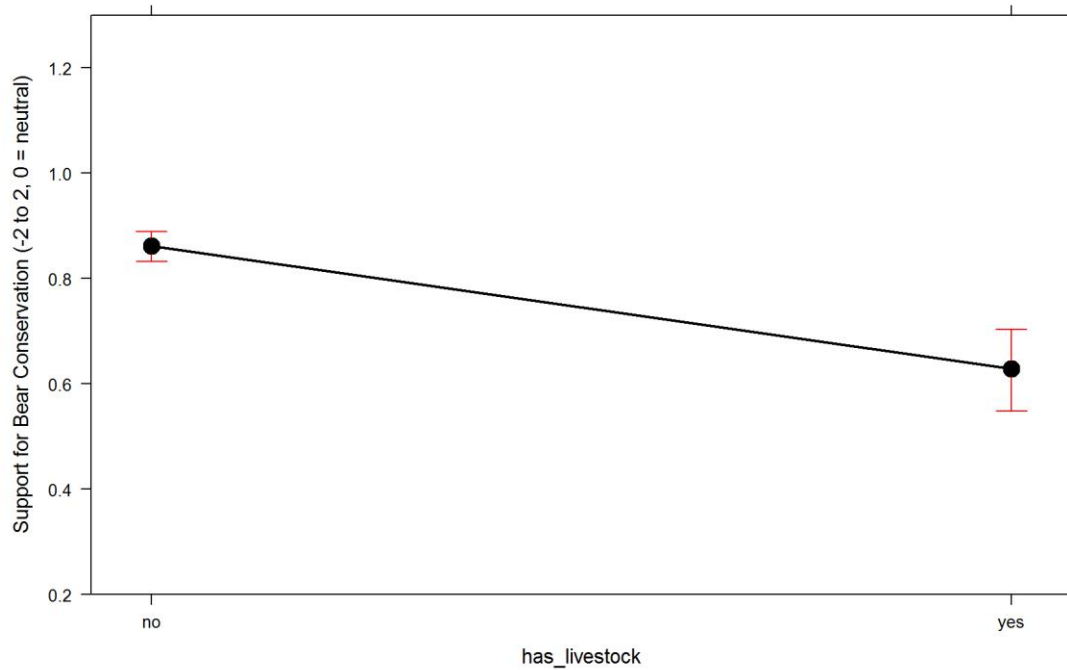
And now interaction.

```
PlotEffectsconservation(c("knowledge", "has_livestock"),
ModconservationTol_Reg2,
    main = "Effect of knowledge*has_livestock on Support for Conservation",
ylim = c(-0.5,
        1.3))
```

Effect of knowledge*has_livestock on Support for Conservation
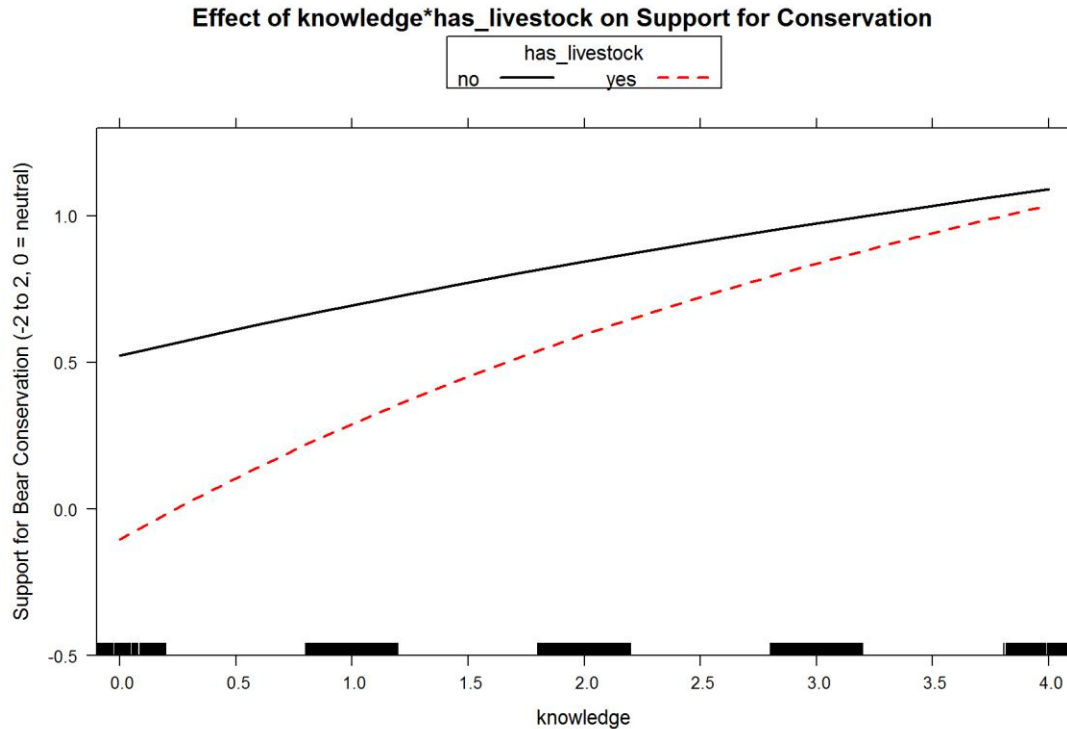
Knowledge has a huge effect in livestock breeders. Had to change the scale to draw this.

This concludes the analysis of support for bear conservation. Housekeeping.

```r
rm(list = ls()[-grep("modeldata3", ls())])
rm(modeldata3.NO)
```

Support for Control of Bear Population

First thing first - let's fit a distribution to this response variable.

```
##        shape          rate
##     9.63564094    3.06773577
##    (0.28138430)  (0.09195851)
```

```
##        shape          scale
##     3.77391078    3.48104977
##    (0.06296938)  (0.02038802)
```

red=Gamma, blue=Wiebull
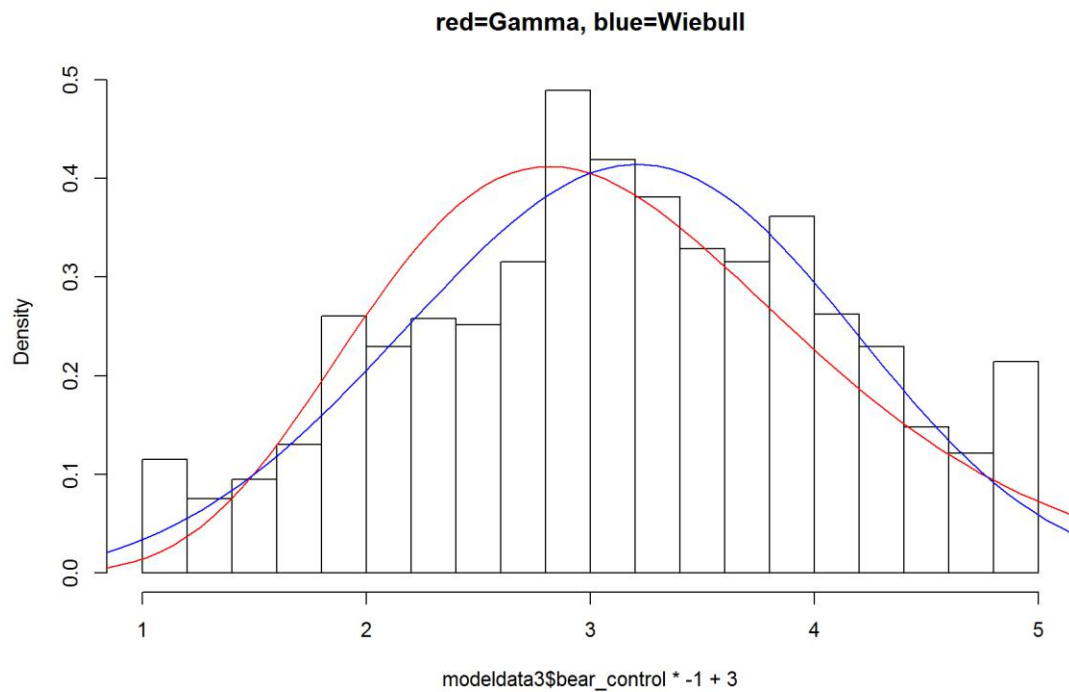
Ok, this actually looks normal out of the box. Will play with different links in moswla.

Finding the model for support for population control.

We've fitted a generalized linear model (GLM) with different links link multiplied by -1 and moved by +3 (to get rid of values below zero) and bear_control variable as response.

For the global model, we fitted all variables we hypothesized (according to previous understanding of the problem) that they would affect this response.

```
consFG = formula(I((bear_control * -1) + 3) ~ Region + gender + age +
education +
    knowledge + dogowner + has_livestock + seennatureyesno)
MGcons = glm(consFG, data = modeldata3NONA, family = gaussian(link =
"inverse"),
    na.action = "na.fail")
MGcons

##
## Call:  glm(formula = consFG, family = gaussian(link = "inverse"), data =
modeldata3NONA,
##      na.action = "na.fail")
##
## Coefficients:
##           (Intercept)              RegionCroatia                 RegionItaly
##             0.2615222                  0.0337251                   0.0088903
##      RegionSlovenia Alps   RegionSlovenia Dinaric                  gendermale
##             0.0504521                  0.0876697                   0.0137462
```

```
##                  age                education                knowledge
##            0.0009331               -0.0064783               -0.0084378
##          dogowneryes          has_livestockyes       seennatureyesnoyes
##           -0.0037853                0.0327756                0.0127666
##
## Degrees of Freedom: 2231 Total (i.e. Null);  2220 Residual
## Null Deviance:      1977
## Residual Deviance: 1508  AIC: 5484
```

```
par(mfrow = c(2, 2))
plot(MGcons)
```
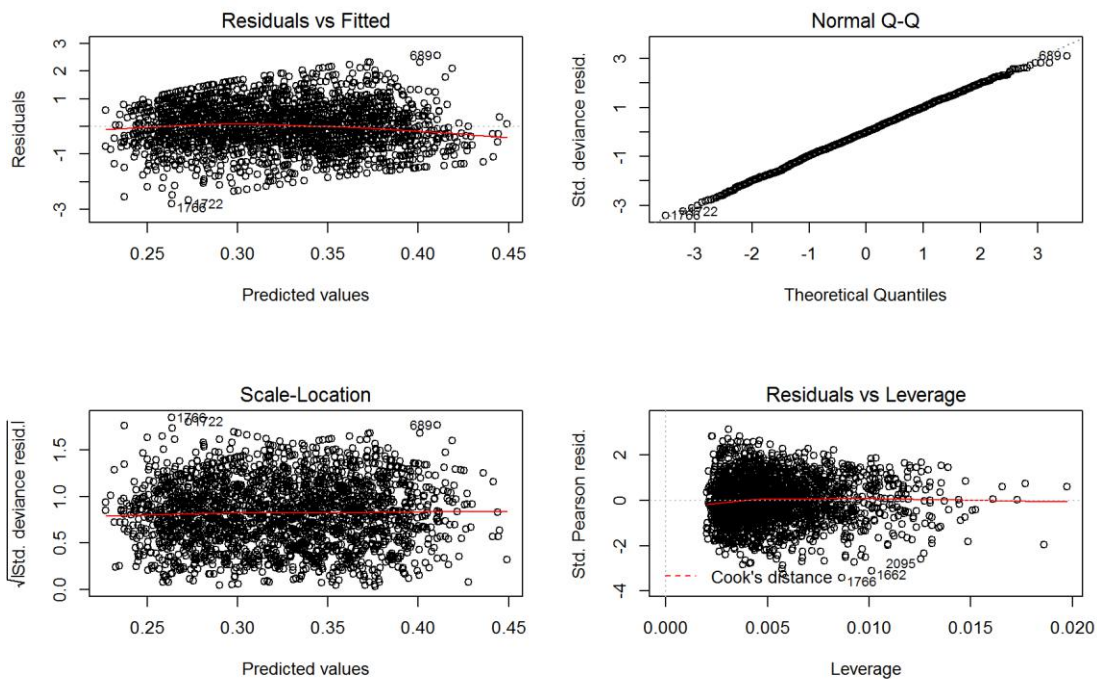


```
par(mfrow = c(1, 1))
```

Gaussian w/inverse link is ok. A bit of bias, no heteroscedascity and linear - not perfect, but generally ok.

Let's check multicollinearity (w/o interactions).

```
vif(MGcons)
```

	GVIF	Df	GVIF^(1/(2*Df))
Region	1.599993	4	1.060510
gender	1.081828	1	1.040109
age	1.175989	1	1.084430
education	1.144171	1	1.069659

knowledge	1.051621	1	1.025486
dogowner	1.130810	1	1.063396
has_livestock	1.065459	1	1.032210
seennatureyesno	1.259915	1	1.122459

There seems to be no multicolinearity problem.

```
clust = makeCluster(getOption("cl.cores", 4), type = "PSOCK")
clusterExport(clust, "modeldata3NONA")
# start=Sys.time()#report start time
DredgeGMcontrolReg = pdredge(MGcons, cluster = clust, trace = F)  #Region

## Fixed term is "(Intercept)"

save(DredgeGMcontrolReg, file = ".//control_dredgeGM_Reg.RData")
# end=Sys.time()#report end time end-start
```

Importance of parameters.

```
importance(DredgeGMcontrolReg)

##                       Region age  has_livestock knowledge gender
## Importance:             1.00    1.00 1.00              1.00      1.00
## N containing models:     128     128  128               128       128
##                       seennatureyesno education dogowner
## Importance:             0.95                0.88      0.39
## N containing models:     128                 128       128
```

We ranked importance of each variable by checking in how many models it appeared weighted by Akaike's weights, and constructed the optimal model without interactions that retains all variables that had importance larger than 0.8.

Optimal model for control support

We constructed the **optimal model** without interactions. Variable *dogowner* was removed.

excluded variables: dogowner

	df	AICc
McOptG	12	5483.757
McOptG2	16	5482.352
McOptG3	16	5486.492
McOptG4	16	5485.440
McOptG5	13	5484.130
McOptG6	13	5485.763
McOptG7	16	5489.260
McOptG8	13	5484.954

McOptG9   16   5441.613

McOptG10   17   5441.982

McOptG11   13   5485.151

McOptG12   13   5485.780

McOptG13   20   5445.462

McOptG14   11   5487.693

Meaningful interaction is +Region:age.

*The final model for control support

```
ModcontrolTol_Reg = glm(I((bear_control * -1) + 3) ~ Region + gender + age +
education +
    knowledge + has_livestock + seennatureyesno + Region:age, data =
modeldata3NONA,
    family = gaussian(link = "inverse"), na.action = "na.fail")
```

Exploration of drivers of control support

Outliers

We checked for outliers - high influence points - with the optimal model and cook's distances. We re-fitted the model with outliers removed.

```
cook = cooks.distance(ModcontrolTol_Reg)
plot(1:nrow(modeldata3NONA), cook)
abline(h = 4/nrow(modeldata3NONA), col = "red")
```
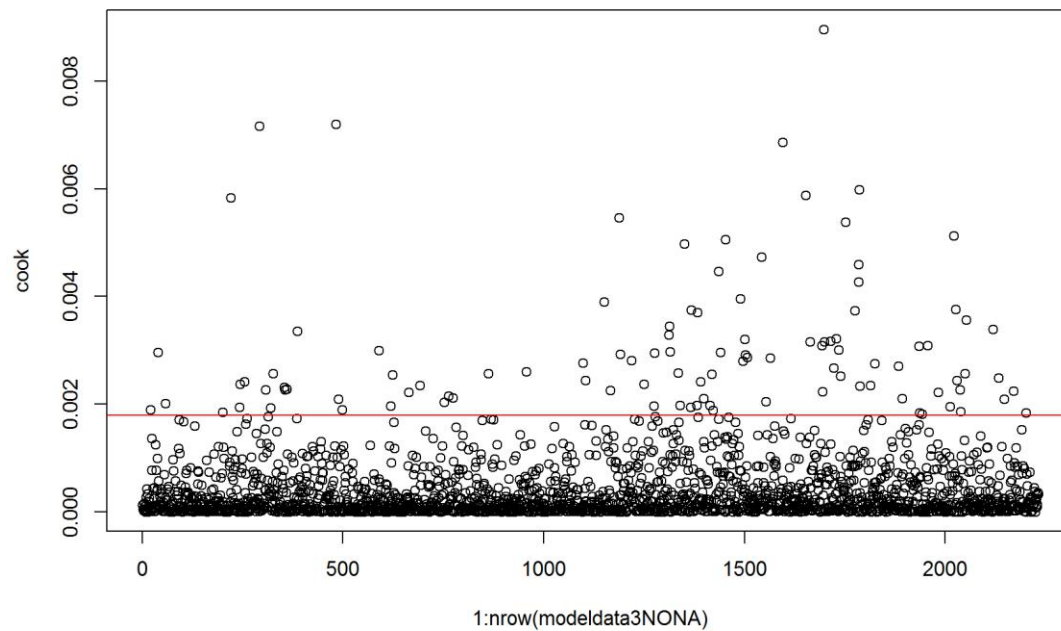
```
modeldata3.NO = modeldata3NONA[which(cook <= 4/nrow(modeldata3NONA)), ]
# re-evalute the model with outlier-fee data
ModcontrolTol_Reg2 = glm(I((bear_control * -1) + 3) ~ Region + gender + age +
education +
    knowledge + has_livestock + seennatureyesno + Region:age, data =
modeldata3.NO,
    family = gaussian(link = "inverse"), na.action = "na.fail")
par(mfrow = c(2, 2))
plot(ModcontrolTol_Reg2)
```

```r
par(mfrow = c(1, 1))
```
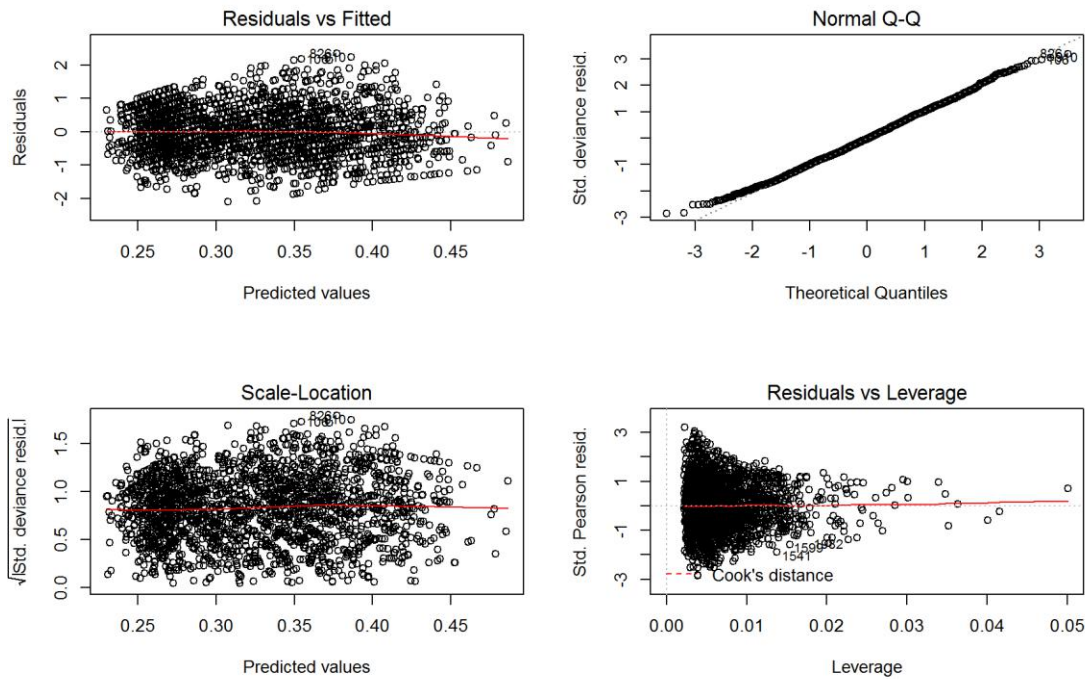
Removing outliers (about 5%) in this cases actually improves model fit quite a bit (better-looking residuals), so I decided to go with it. Will check final results of both models.

A plotting function to make life easier.

Exploring Effects - Support for Bear control

Using the constructed model of population control support we can explore the effect of a single variable or a combination of variables while controlling for the effect of other variables. In this manner we can understand the effect of i.e. Region where the respondent lives (or any other parameter we wish to explore) withouth the confounding effects of other characteristics of the respondent (e.g. education, having livestock etc.)

Let's explore the effect of Region on control support.

```r
bwplot(Region ~ (bear_control), data = modeldata3.NO, main = "Effect of
Region on Support for Population Control - Raw Data",
    xlab = "Support for Population Control")
```

Effect of Region on Support for Population Control - Raw Data
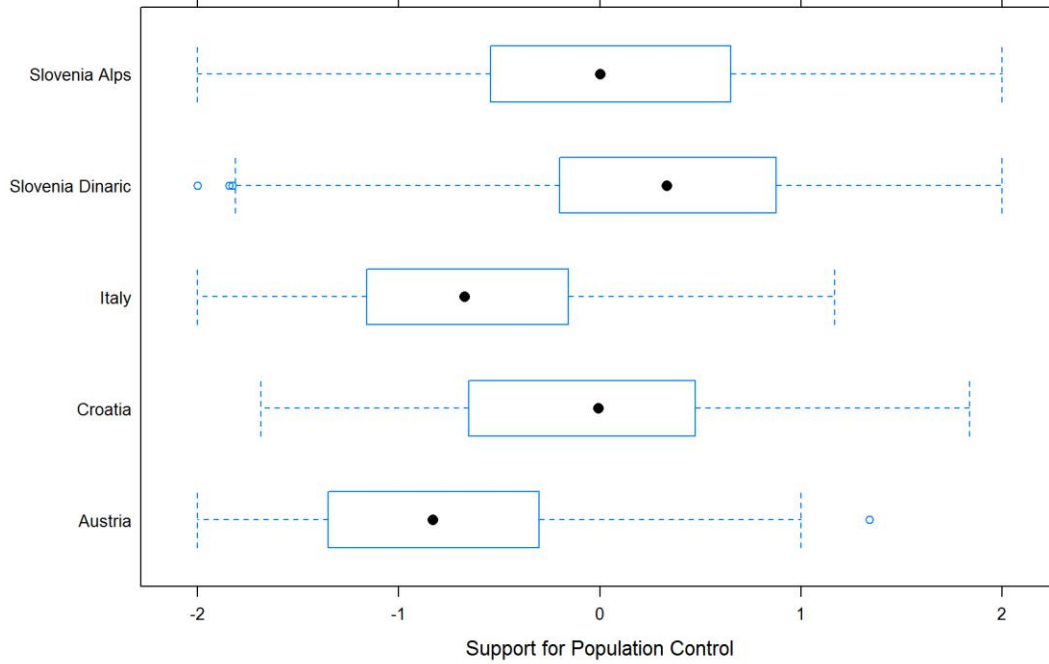

```
PlotEffectscontrol("Region", ModcontrolTol_Reg2, main = "Effect of Region on
Pop. Control Support",
    ylim = c(-1, 1))
```

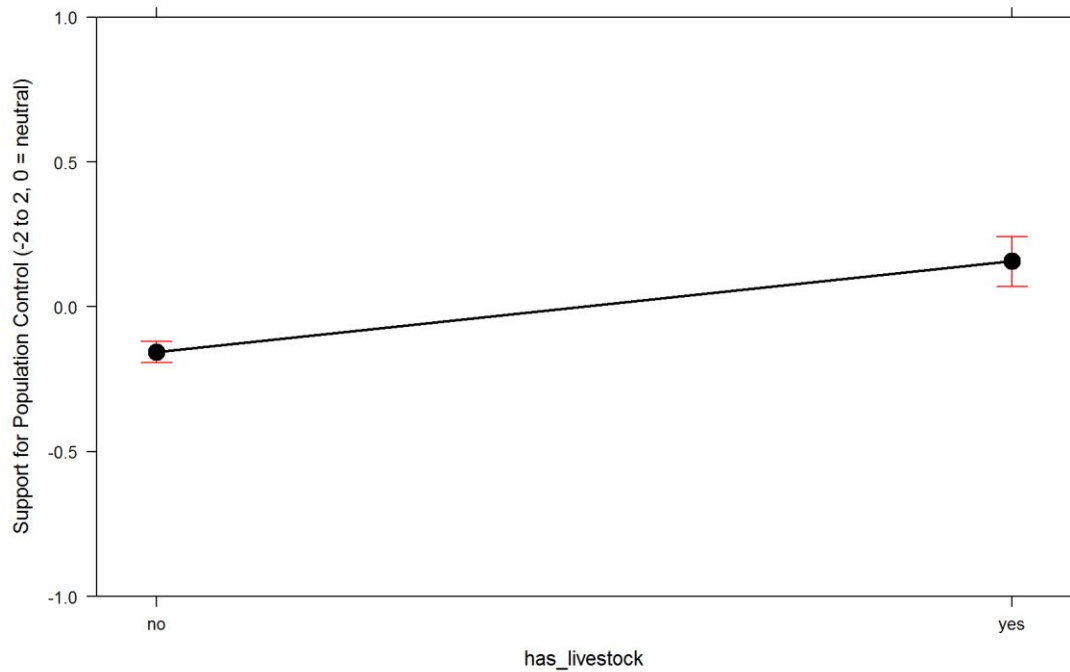**Effect of Region on Pop. Control Support**
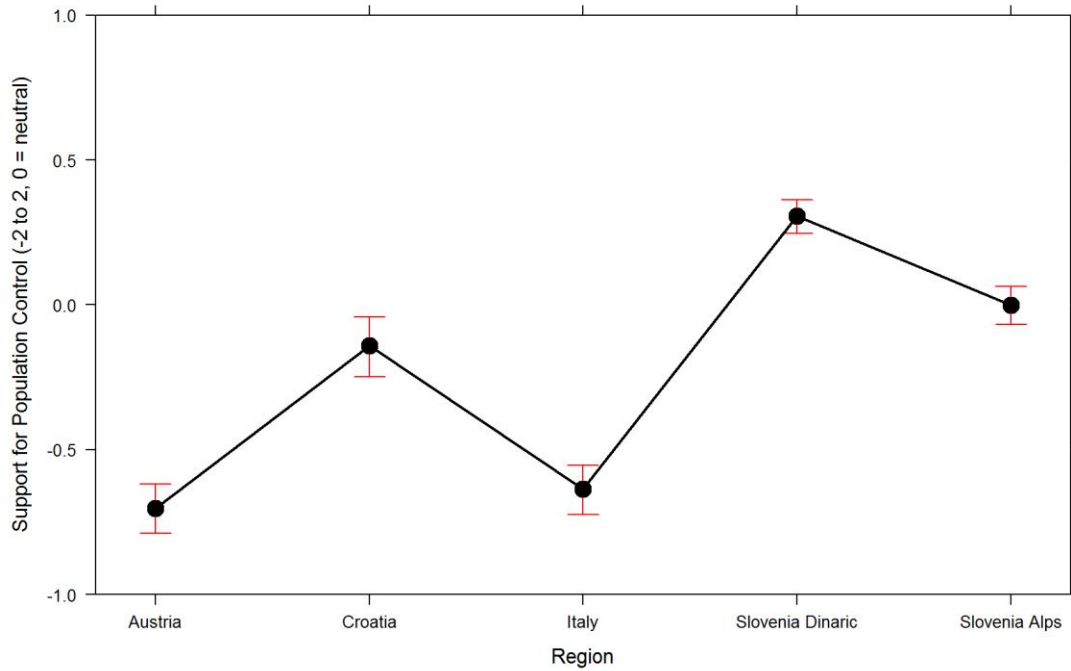
With outliers. Very similar, less clear.

```
bwplot(Region ~ (bear_control), data = modeldata3NONA, main = "Effect of
Region on Support for Population Control - Raw Data (OL)",
    xlab = "Support for Population Control")
PlotEffectscontrol("Region", ModcontrolTol_Reg, main = "Effect of Region on
Pop. Control Support (OL, DO NOT USE)",
    ylim = c(-1, 1))
```

General public doesn't seem much in favor of control of bear population, even more so in
Italy and Austria. Slovenia in bear areas is the most supportive of culling bears.

There is an interaction between region and age.

```
PlotEffectscontrol(c("age", "Region"), ModcontrolTol_Reg2, main = "Effect of
age*region on Pop. Control Support",
    ylim = c(-1, 1))
```
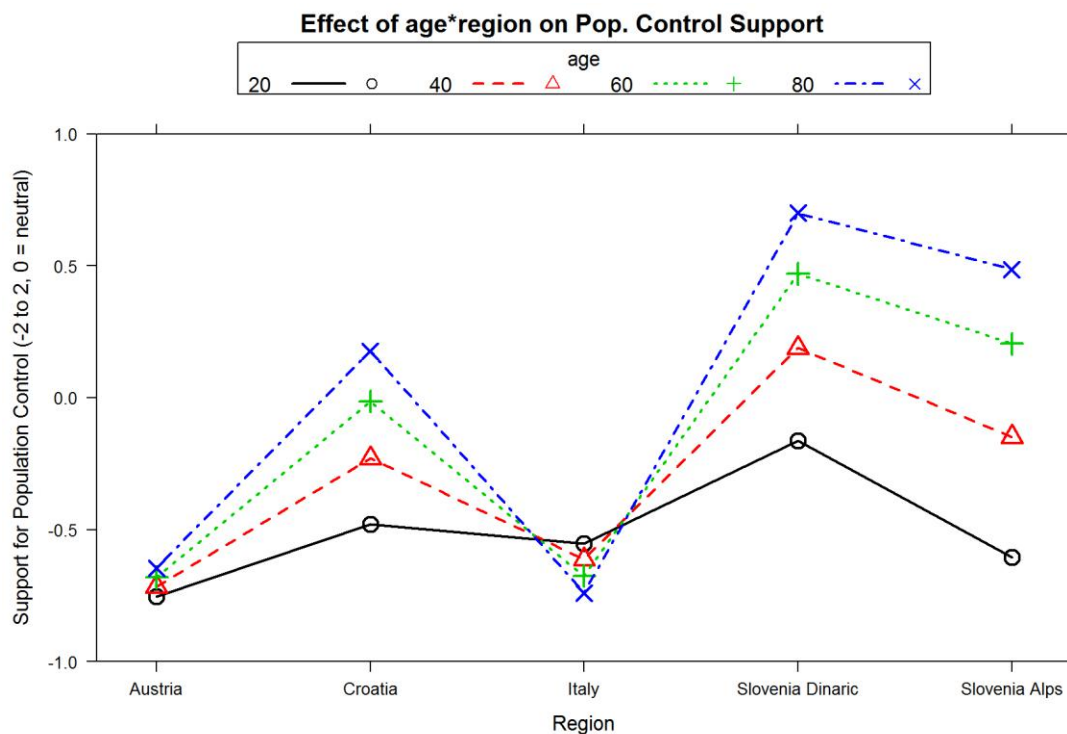

Interesting. Only age?

```
PlotEffectscontrol("age", ModcontrolTol_Reg2, main = "Effect of Age on Pop.
Control Support",
    ylim = c(-1, 1))
```

Effect of Age on Pop. Control Support
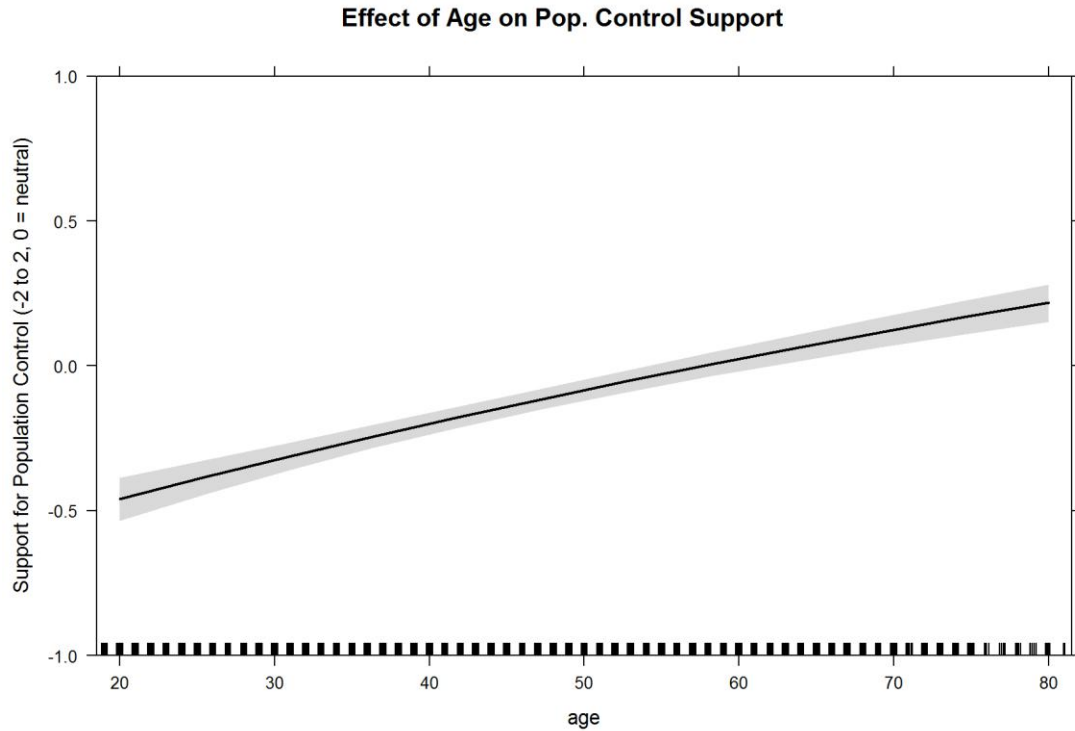
The older you are, more you want to shoot bears. Unless you're Italian.

How does gender affect this?

```
bwplot(gender ~ (bear_control), data = modeldata3.NO, main = "Effect of
Gender on Pop. Control Support - Raw Data",
    xlab = "Pop. Control Support")
```

Effect of Gender on Pop. Control Support - Raw Data
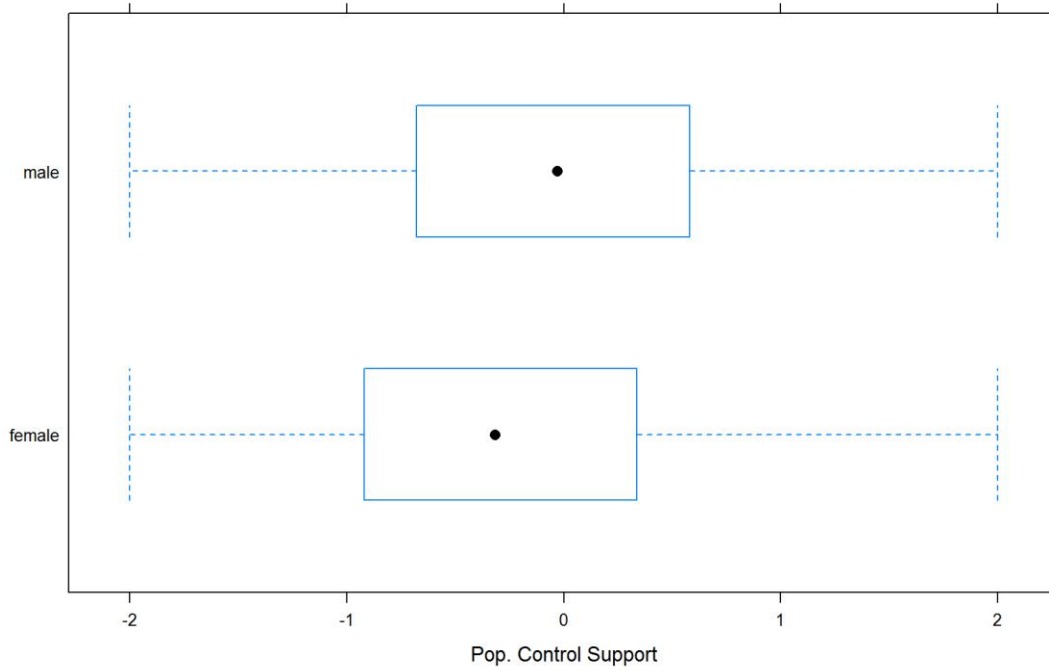

```
PlotEffectscontrol("gender", ModcontrolTol_Reg2, main = "Effect of Gender on
Pop. Control Support",
    ylim = c(-1, 1))
```

Effect of Gender on Pop. Control Support
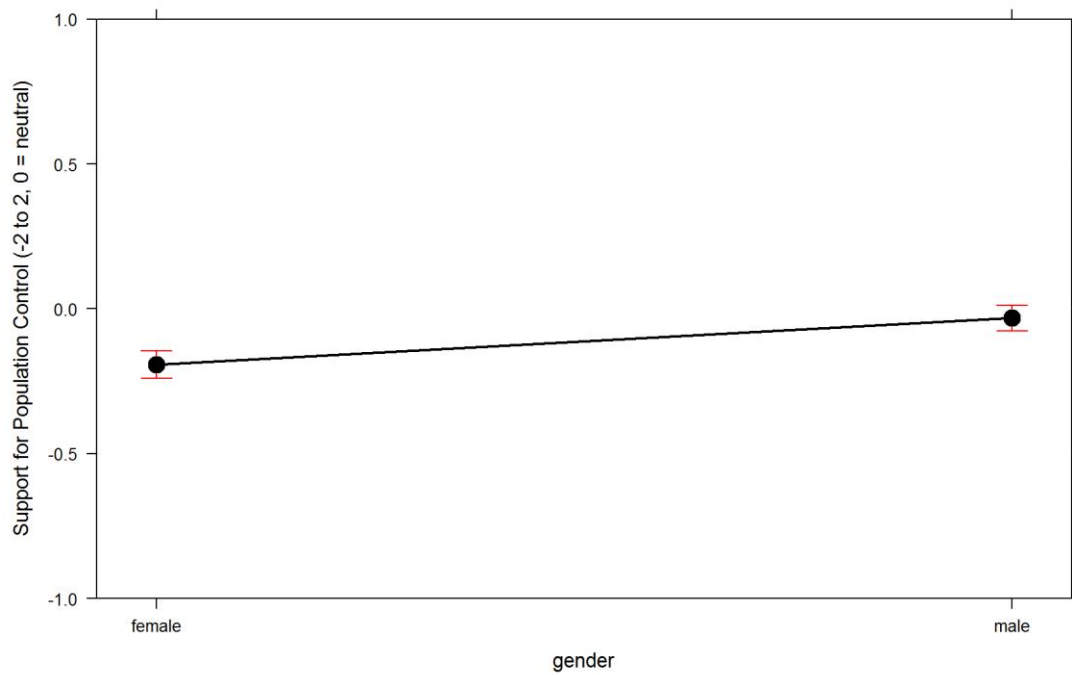
A small difference.

Education?

```
PlotEffectscontrol("education", ModcontrolTol_Reg2, main = "Effect of
Education on Pop. Control Support",
    ylim = c(-1, 1))
```

Effect of Education on Pop. Control Support
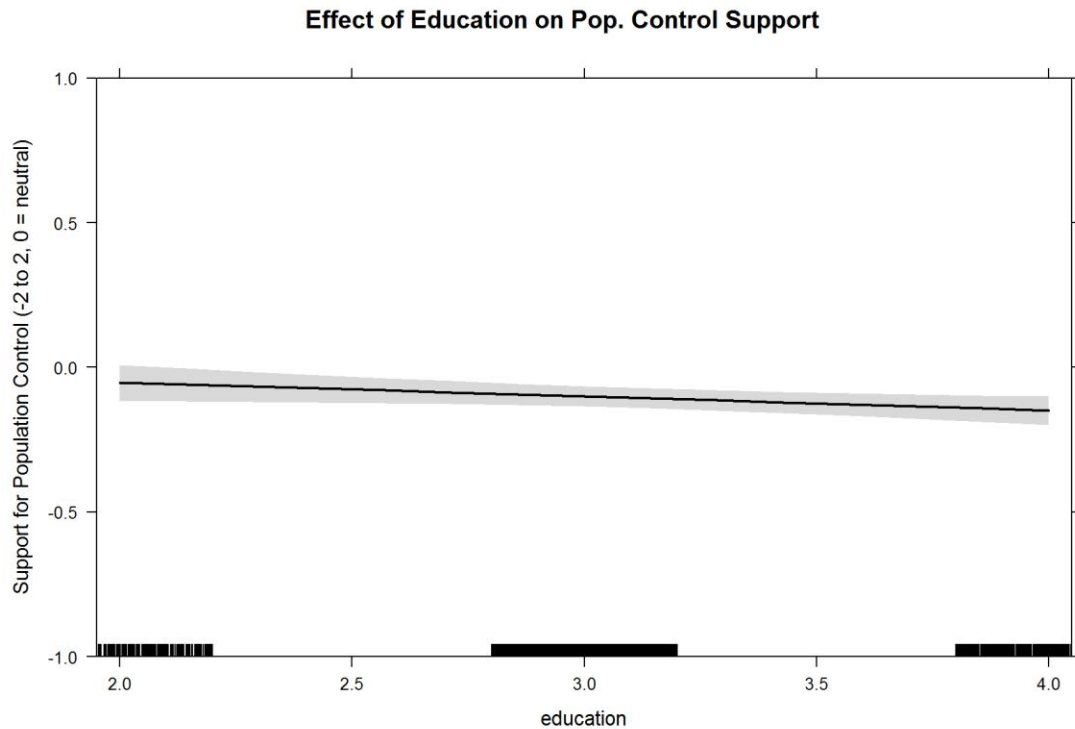
Knowledge?

```
PlotEffectscontrol("knowledge", ModcontrolTol_Reg2, main = "Effect of
Knowledge on Pop. Control Support",
    ylim = c(-1, 1))
```

Effect of Knowledge on Pop. Control Support
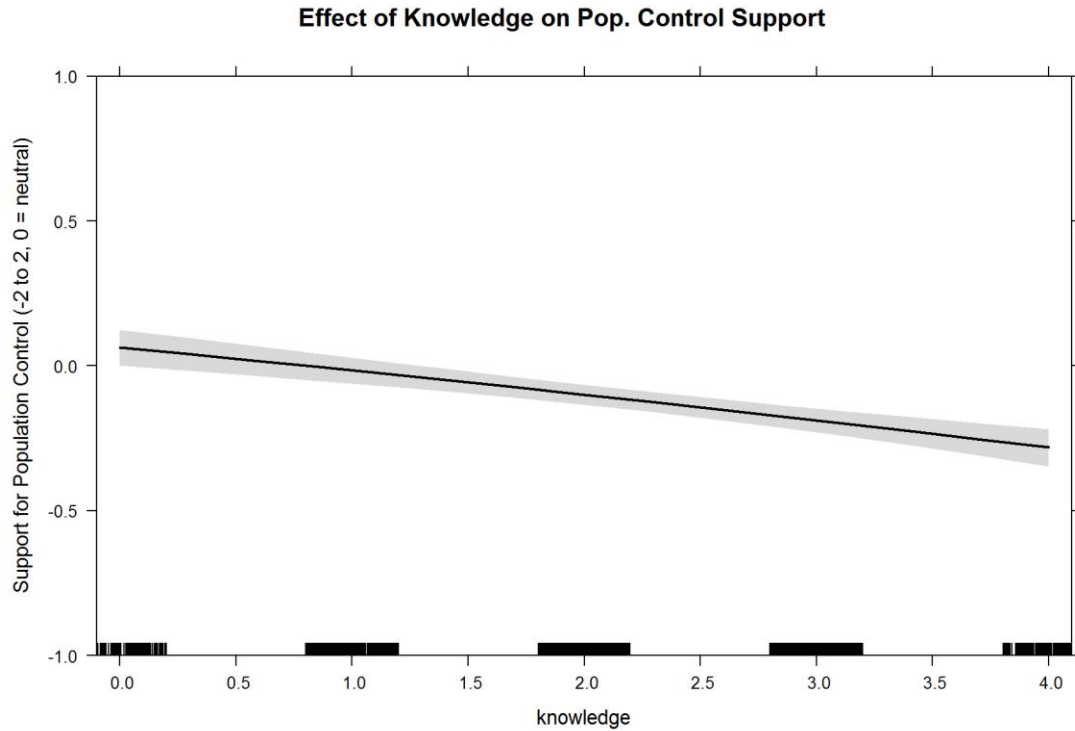
Huge effect. How about having livestock?

```
PlotEffectscontrol("has_livestock", ModcontrolTol_Reg2, main = "Effect Having
Livestock on Pop. Control Support",
    ylim = c(-1, 1))
```

Effect Having Livestock on Pop. Control Support

Ok, considerable

Last but not least, seeing bear in nature?

```
PlotEffectscontrol("seennatureyesno", ModcontrolTol_Reg2, main = "Effect of
Seeing a Bear in Nature on Pop. Control Support",
    ylim = c(-1, 1))
```

Effect of Seeing a Bear in Nature on Pop. Control Support
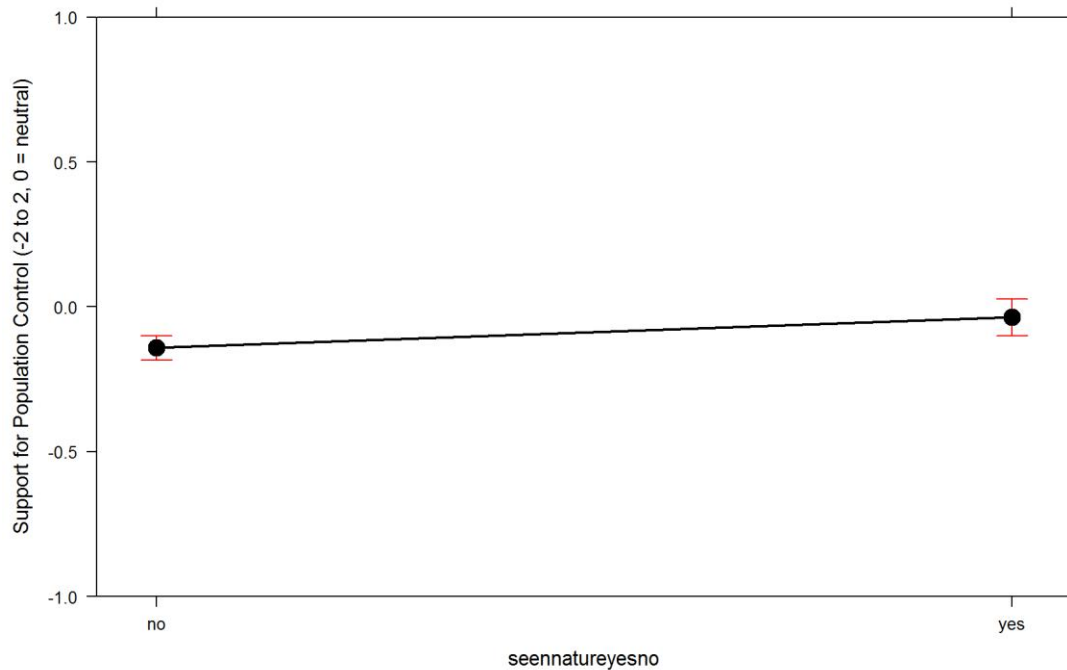
You've seen a bear, you wanna shoot it. Ok, this also has to do with areas in which they see bears. The parameter should possibly be excluded as there may not be enough cases.

This concludes the analysis of support for bear control. Housekeeping.

```
rm(list = ls()[-grep("modeldata3", ls())])
rm(modeldata3.NO)
```

Perception of bear value

First thing first - let's fit a distribution to this response variable.

```
##        shape        rate
##     8.5415870    3.6578783
##    (0.2489067)  (0.1097861)

##        shape        scale
##     3.03893690    2.61219029
##    (0.04675890)  (0.01912805)
```

red=Gamma, blue=Wiebull
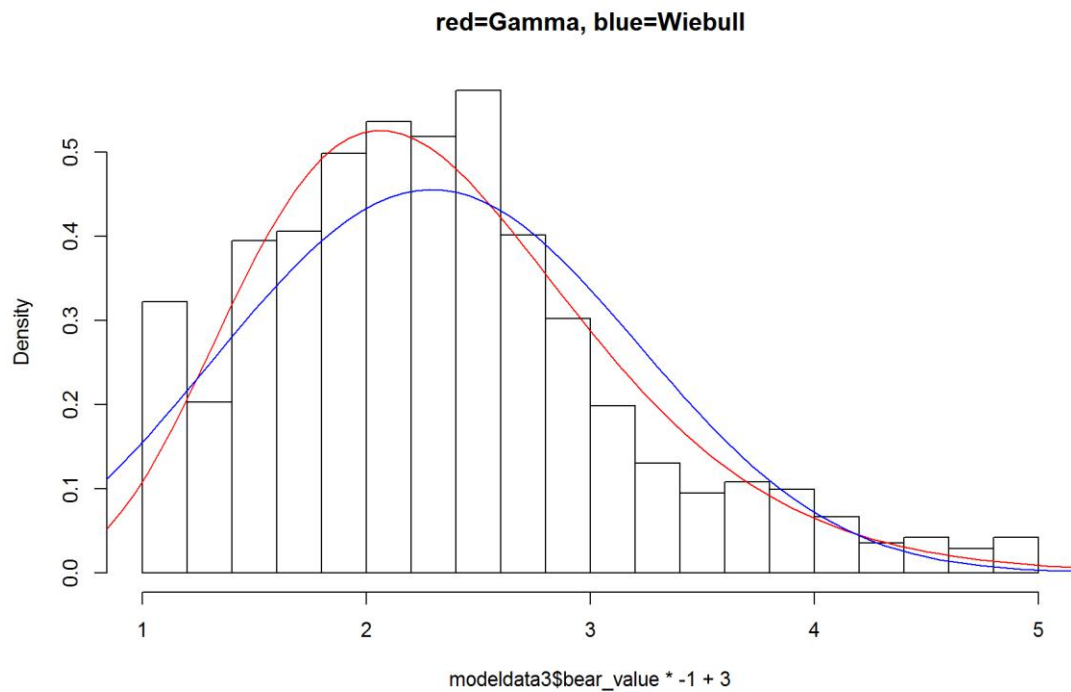
Gamma

ok.

Finding the model for support for population value.

We've fitted a generalized linear model (GLM) with different links link multiplied by -1 and moved by +3 (to get rid of values below zero) and bear_value variable as response.

For the global model, we fitted all variables we hypothesized (according to previous understanding of the problem) that they would affect this response.

```
consFG = formula(I((bear_value * -1) + 3) ~ Region + gender + age + education
+ knowledge +
    dogowner + has_livestock + seennatureyesno)
MGcons = glm(consFG, data = modeldata3NONA, family = Gamma(link = "inverse"),
na.action = "na.fail")
MGcons

##
## Call:  glm(formula = consFG, family = Gamma(link = "inverse"), data =
modeldata3NONA,
##      na.action = "na.fail")
##
## Coefficients:
##           (Intercept)            RegionCroatia                 RegionItaly
##             0.3573615                0.0336551                   0.0080044
##     RegionSlovenia Alps  RegionSlovenia Dinaric                  gendermale
##             0.0285511               -0.0072757                   0.0102729
##                   age                education                   knowledge
```

```
##              -0.0009851                0.0179256                0.0249831
##             dogowneryes           has_livestockyes          seennatureyesnoyes
##               0.0115698               -0.0558812                0.0018852
##
## Degrees of Freedom: 2231 Total (i.e. Null);  2220 Residual
## Null Deviance:       266.3
## Residual Deviance: 242.5      AIC: 4958
```

```r
par(mfrow = c(2, 2))
plot(MGcons)
```
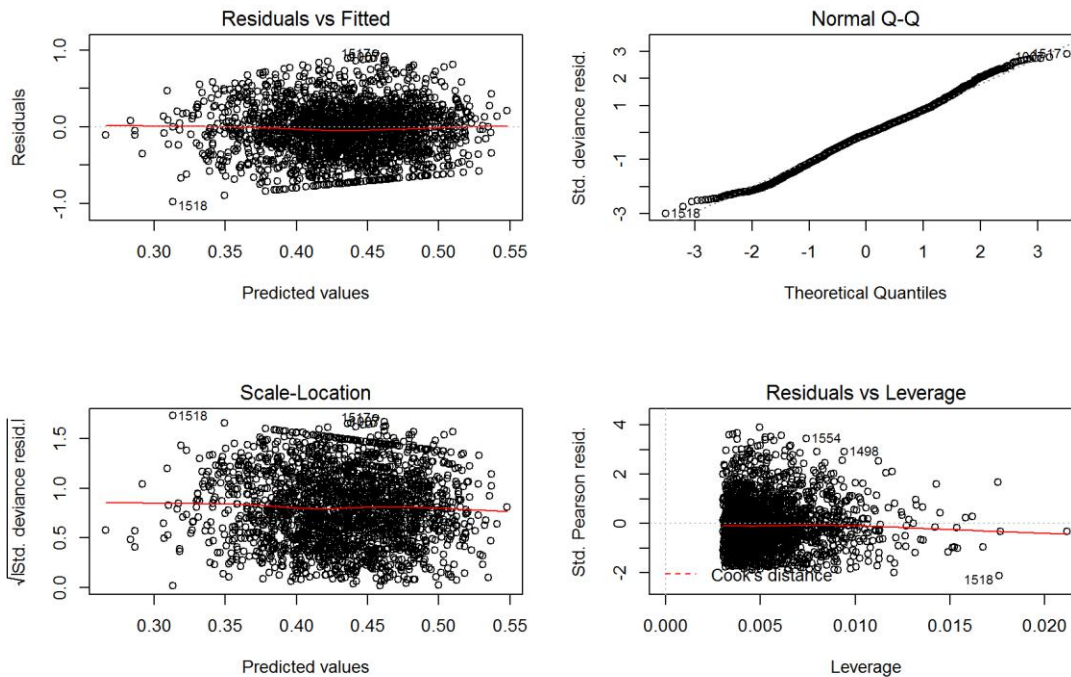


```r
par(mfrow = c(1, 1))
```

Reasonable fit.

Let's check multicollinearity (w/o interactions).

```r
vif(MGcons)
```

	GVIF	Df	GVIF^(1/(2*Df))
Region	1.546353	4	1.055999
gender	1.078089	1	1.038311
age	1.214476	1	1.102033
education	1.168852	1	1.081135
knowledge	1.062877	1	1.030959
dogowner	1.128567	1	1.062341

has_livestock	1.120908	1	1.058729
seennatureyesno	1.260736	1	1.122825

There seems to be no multicolinearity problem.

```
clust = makeCluster(getOption("cl.cores", 4), type = "PSOCK")
clusterExport(clust, "modeldata3NONA")
# start=Sys.time()#report start time
DredgeGMvalueReg = pdredge(MGcons, cluster = clust, trace = F)  #Region

## Fixed term is "(Intercept)"

save(DredgeGMvalueReg, file = ".//value_dredgeGM_Reg.RData")
# end=Sys.time()#report end time end-start
```

Importance of parameters.

```
importance(DredgeGMvalueReg)

##                    knowledge has_livestock age  Region education
## Importance:           1.00        1.00      1.00 1.00    1.00
## N containing models:  128         128        128  128     128
##                    dogowner gender seennatureyesno
## Importance:           0.66     0.61    0.28
## N containing models:  128      128     128
```

We ranked importance of each variable by checking in how many models it appeared weighted by Akaike's weights, and constructed the optimal model without interactions that retains all variables that had importance larger than 0.8.

Optimal model for value support

We constructed the **optimal model** without interactions. Variable *dogowner, gender, seennatureyesno* was removed.

excluded variables: dogowner, gender, seennatureyesno

```
## Warning: closing unused connection 8 (<-BingPadX:11149)

## Warning: closing unused connection 7 (<-BingPadX:11149)

## Warning: closing unused connection 6 (<-BingPadX:11149)

## Warning: closing unused connection 5 (<-BingPadX:11149)

## Warning: closing unused connection 16 (<-BingPadX:11149)

## Warning: closing unused connection 15 (<-BingPadX:11149)

## Warning: closing unused connection 14 (<-BingPadX:11149)

## Warning: closing unused connection 13 (<-BingPadX:11149)
```

	df	AICc
McOptG	10	4966.827
McOptG2	14	4972.919
McOptG3	14	4974.091
McOptG4	14	4966.406
McOptG5	11	4965.384
McOptG6	11	4968.195
McOptG7	15	4970.594
McOptG8	11	4966.823
McOptG9	14	4972.714
McOptG10	15	4971.278
McOptG11	11	4965.568
McOptG12	12	4967.047
McOptG13	12	4964.057
McOptG14	9	4978.725

Meaningful interaction is +knowledge:has_livestock. It doesn't improve the model much, but I decided to keep it in since it's interesting.

*The final model for value support

```
ModvalueTol_Reg = glm(I((bear_value * -1) + 3) ~ Region + age + education +
knowledge +
    has_livestock + knowledge:has_livestock, data = modeldata3NONA, family =
Gamma(link = "inverse"),
    na.action = "na.fail")
```

Exploration of drivers of Perception of Bear Value

Outliers

We checked for outliers - high influence points - with the optimal model and cook's distances. We re-fitted the model with outliers removed.

```
cook = cooks.distance(ModvalueTol_Reg)
plot(1:nrow(modeldata3NONA), cook)
abline(h = 4/nrow(modeldata3NONA), col = "red")
```
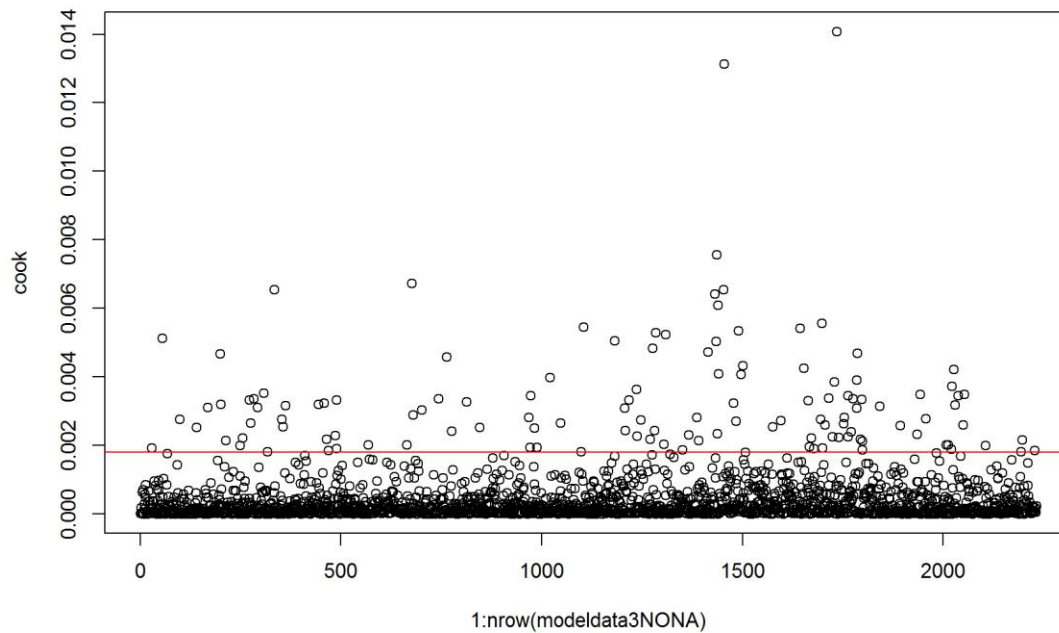
```
modeldata3.NO = modeldata3NONA[which(cook <= 4/nrow(modeldata3NONA)), ]
# re-evalute the model with outlier-fee data
ModvalueTol_Reg2 = glm(I((bear_value * -1) + 3) ~ Region + age + education +
knowledge +
    has_livestock + knowledge:has_livestock, data = modeldata3.NO, family =
Gamma(link = "inverse"),
    na.action = "na.fail")
par(mfrow = c(2, 2))
plot(ModvalueTol_Reg2)

## Warning: closing unused connection 16 (<-BingPadX:11626)

## Warning: closing unused connection 15 (<-BingPadX:11626)

## Warning: closing unused connection 14 (<-BingPadX:11626)

## Warning: closing unused connection 13 (<-BingPadX:11626)
```

```
par(mfrow = c(1, 1))
```
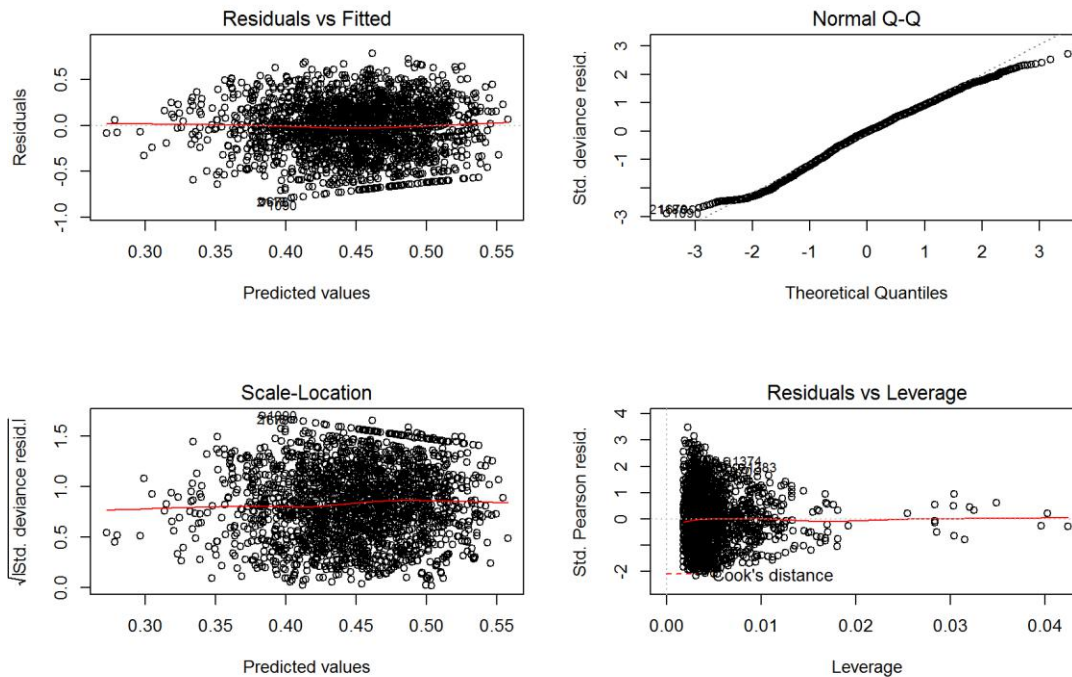
Removing outliers (about 5%) in this cases seems to make fit worse. Will check final results of both models.

A plotting function to make life easier.

Exploring Effects - Perception of Bear Value

Using the constructed model of Perception of Bear Value we can explore the effect of a single variable or a combination of variables while valueling for the effect of other variables. In this manner we can understand the effect of i.e. Region where the respondent lives (or any other parameter we wish to explore) withouth the confounding effects of other characteristics of the respondent (e.g. education, having livestock etc.)

Let's explore the effect of Region on value support.

```
bwplot(Region ~ (bear_value), data = modeldata3.NO, main = "Effect of Region
on Perception of Bear Value - Raw Data",
    xlab = "Perception of Bear Value")
```

Effect of Region on Perception of Bear Value - Raw Data
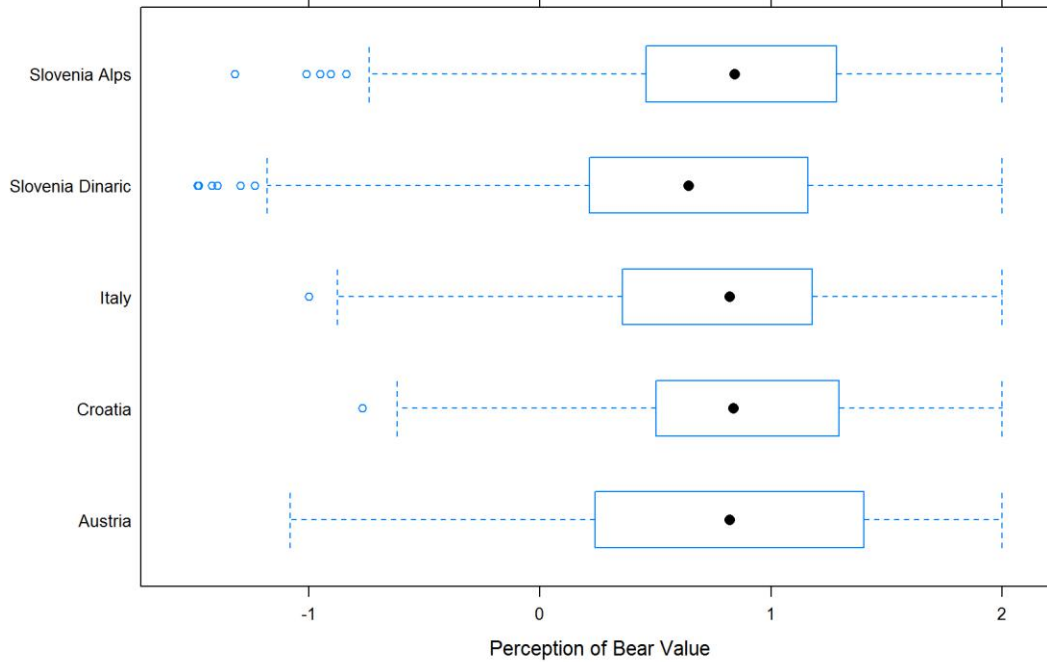

```
PlotEffectsvalue("Region", ModvalueTol_Reg2, main = "Effect of Region on
Perception of Bear Value (NO)",
    ylim = c(0.5, 1))
```

Effect of Region on Perception of Bear Value (NO)
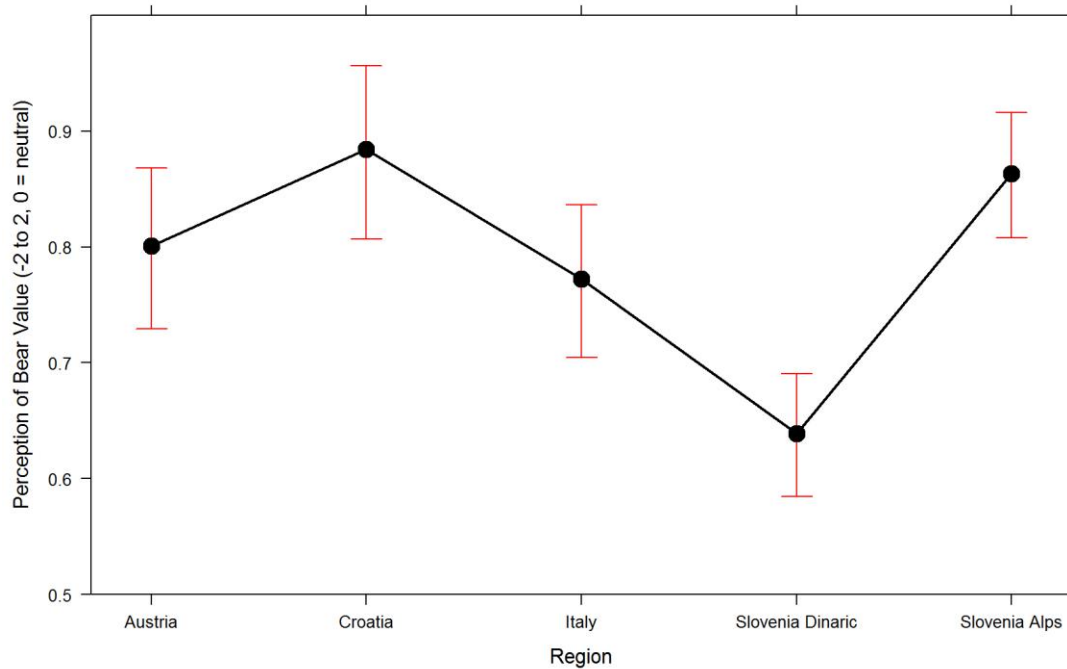
Quite high in general. Interesting is this low valuation of bears in Dinaric Mts in Slo?

Age?

```
PlotEffectsvalue("age", ModvalueTol_Reg2, main = "Effect of Age on Perception
of Bear Value",
    ylim = c(0.5, 1))
```

Effect of Age on Perception of Bear Value
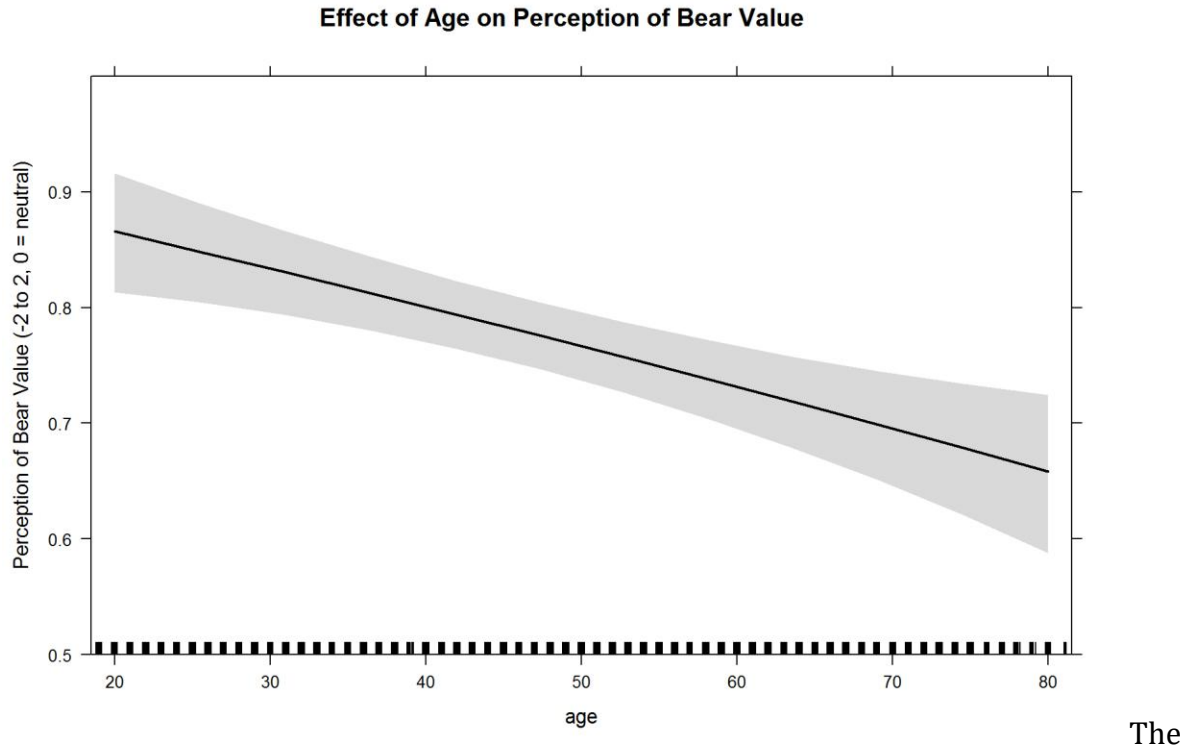
The older you are, the less you value bears.

Education?

```
PlotEffectsvalue("education", ModvalueTol_Reg2, main = "Effect of Education
on Perception of Bear Value",
    ylim = c(0.5, 1))
```

Effect of Education on Perception of Bear Value
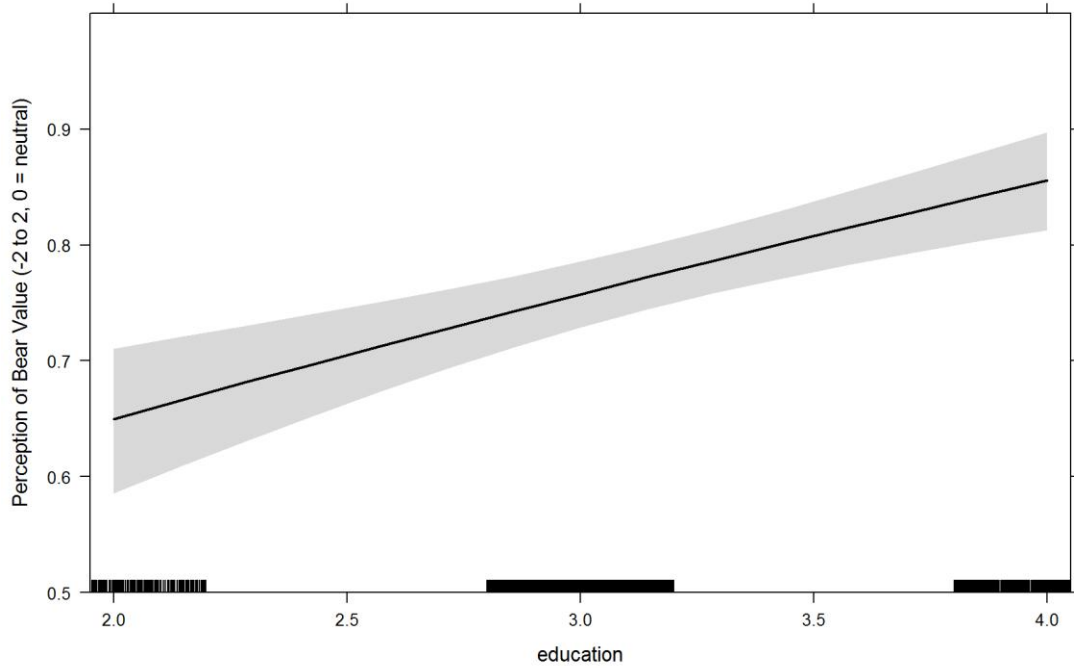
Knowledge?

```
PlotEffectsvalue("knowledge", ModvalueTol_Reg2, main = "Effect of Knowledge
on Perception of Bear Value",
    ylim = c(0.5, 1))
```

Effect of Knowledge on Perception of Bear Value
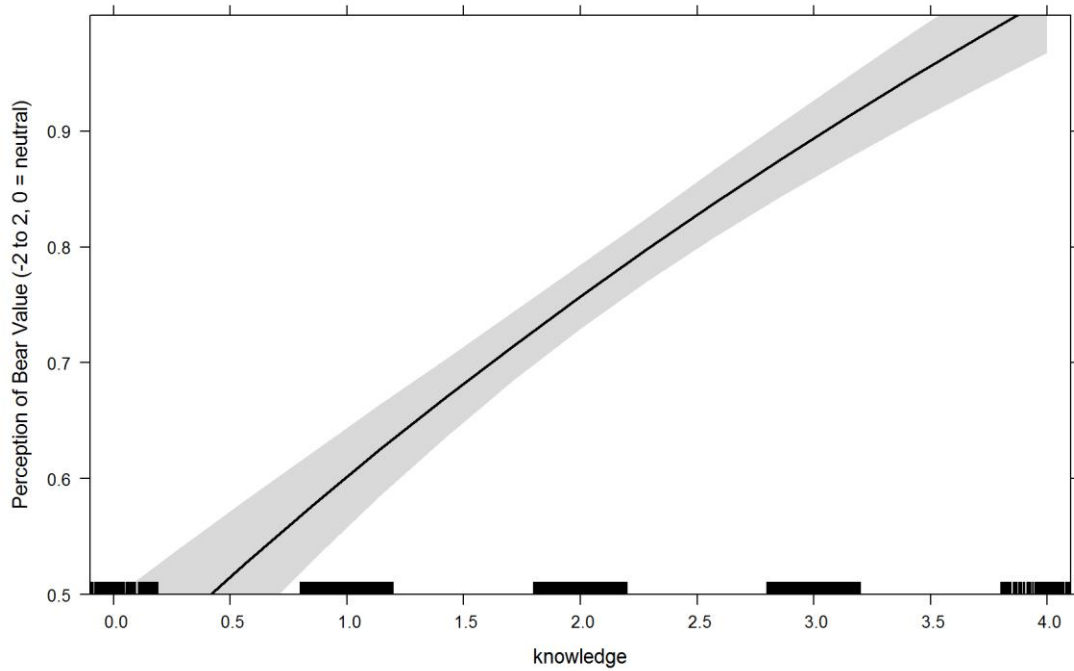
```
PlotEffectsvalue("knowledge", ModvalueTol_Reg2, main = "Effect of Knowledge
on Perception of Bear Value - Zoom",
    ylim = c(0.2, 1.2))
```

Effect of Knowledge on Perception of Bear Value - Zoom
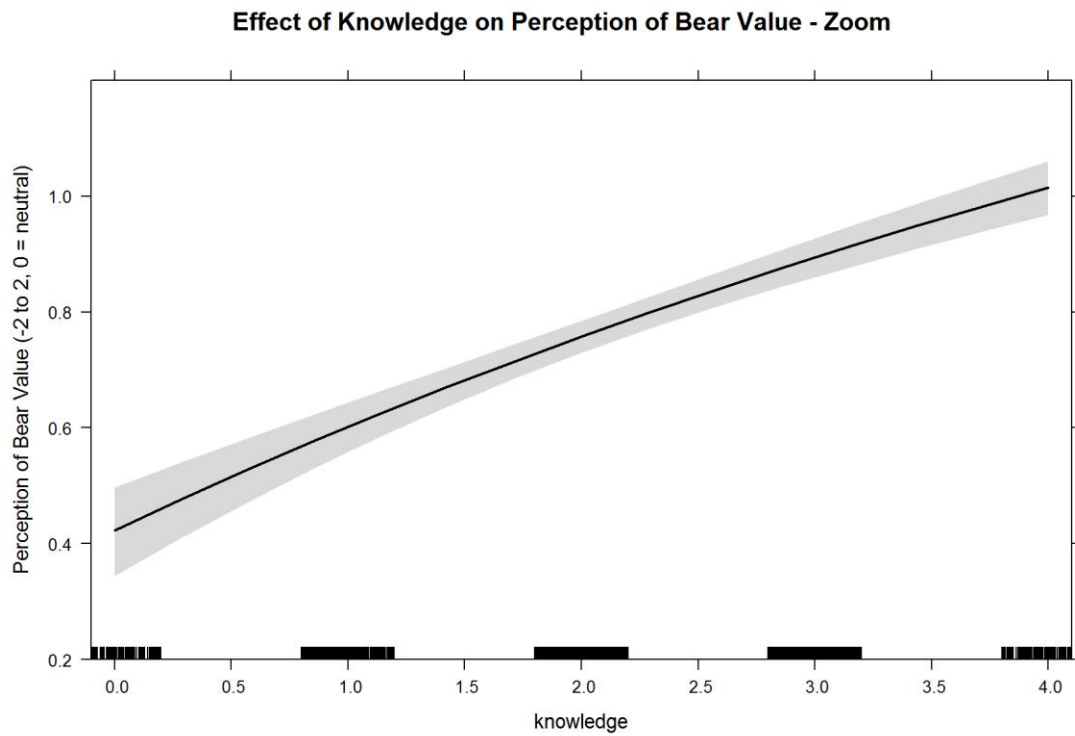
Huge effect, had to rescale the graph! Knowledge also interacts with has_livestock. Let's first look at this parameter.

```
PlotEffectsvalue("has_livestock", ModvalueTol_Reg2, main = "Effect Having
Livestock on Perception of Bear Value",
    ylim = c(0.4, 1))
```

Effect Having Livestock on Perception of Bear Value
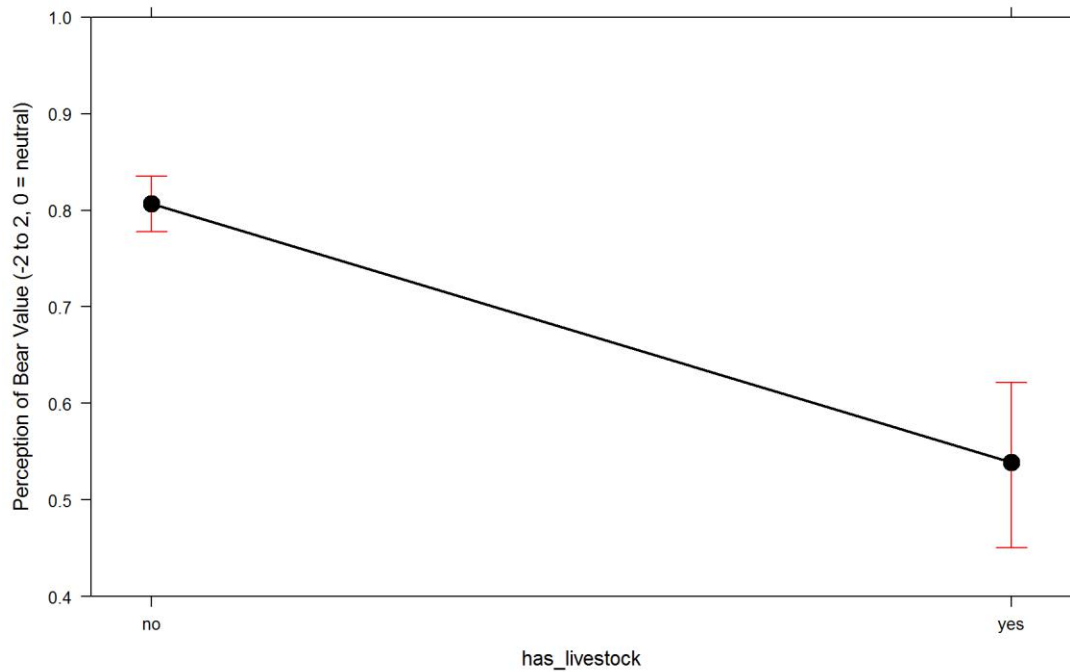
Ok, considerable effect, also had to rescale.

And now interaction.

```
PlotEffectsvalue(c("knowledge", "has_livestock"), ModvalueTol_Reg2, main =
"Effect of knowledge*has_livestock on Perception of Bear Value",
    ylim = c(0, 1.2))
```

Effect of knowledge*has_livestock on Perception of Bear Value
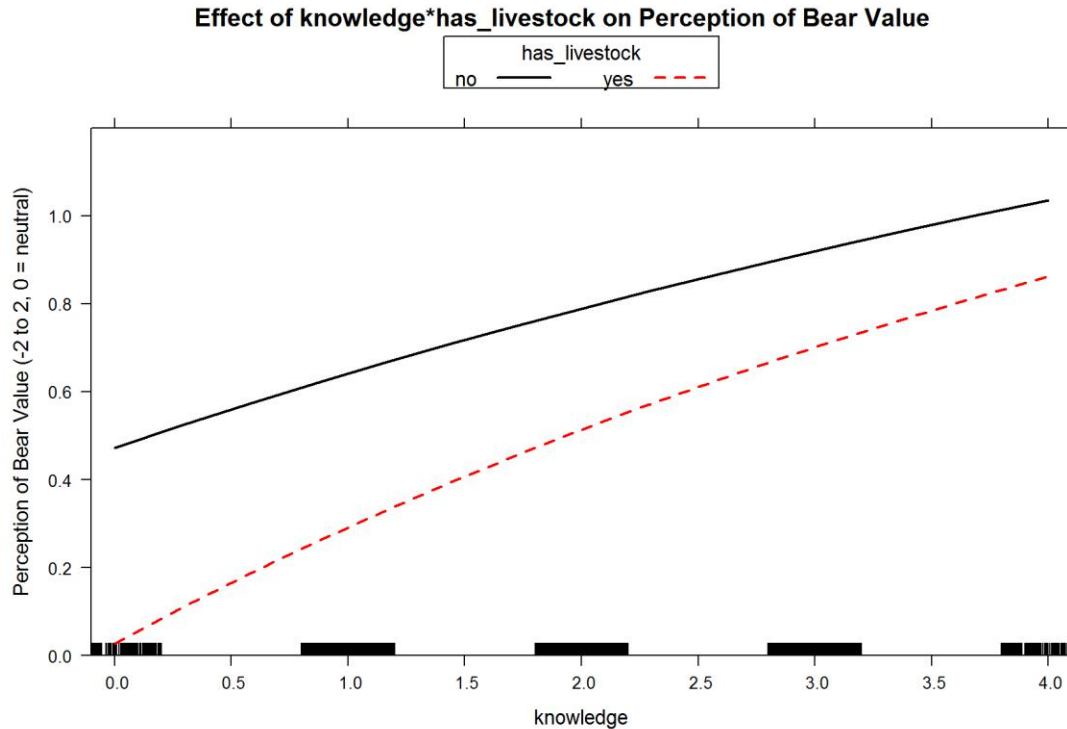
Knowledge has a slightly bigger effect in livestock breeders on perception of bears as valuable as in others... but also because they start lower.

Ok, that's it.

```
rm(list = ls()[-grep("modeldata3", ls())])
rm(modeldata3.NO)
```

Support for bear conservation - Revisited

In this iteration I'll include support for mitigation measures, tolerance of conflicts, support for culling and feeding of bears as predictors. They correlate very much with conservation support, but obfuscate the other variables and were excluded before.

Finding the model for conservation support.

For the global model, we included the "extra" variables.

We'll only make models for Region, georegion we'll explore if it seems neccessary.

```
consFG = formula(I((bear_conservation * -1) + 3) ~ Region + gender + age +
education +
    knowledge + seennatureyesno + dogowner + has_livestock +
conflict_tolerance +
    sol_mitigation + sol_culling + sol_feeding)   #+
MGcons = glm(consFG, data = modeldata3NONA, family = Gamma(link = "log"),
```

```
na.action = "na.fail")
MGcons

##
## Call:  glm(formula = consFG, family = Gamma(link = "log"), data =
modeldata3NONA,
##     na.action = "na.fail")
##
## Coefficients:
##          (Intercept)          RegionCroatia              RegionItaly
##            0.9102925               0.0520228                0.2000049
##    RegionSlovenia Alps  RegionSlovenia Dinaric               gendermale
##            0.0624570               0.0773351               -0.0216182
##                  age               education                knowledge
##            0.0004996              -0.0505030               -0.0323717
##    seennatureyesnoyes           dogowneryes         has_livestockyes
##            0.0048884               0.0017223                0.0754592
##     conflict_tolerance          sol_mitigation              sol_culling
##           -0.1790103              -0.1184021                0.0888283
##          sol_feeding
##           -0.0187079
##
## Degrees of Freedom: 2231 Total (i.e. Null);  2216 Residual
## Null Deviance:          245.4
## Residual Deviance: 104.9      AIC: 3023

par(mfrow = c(2, 2))
plot(MGcons)
```
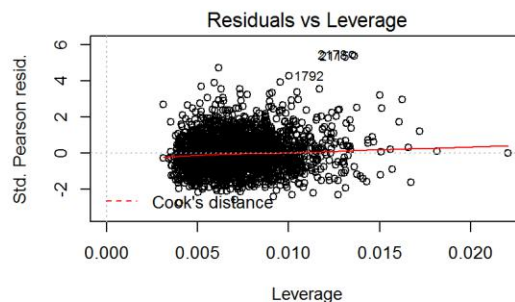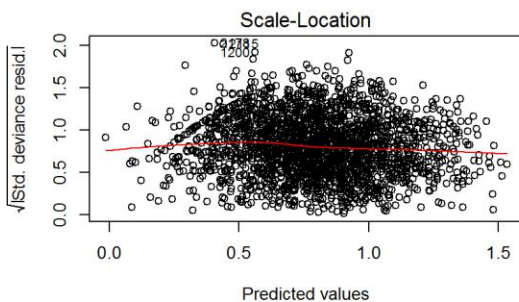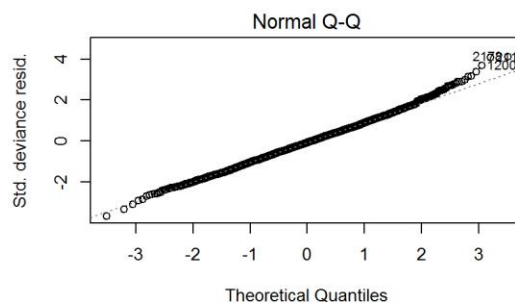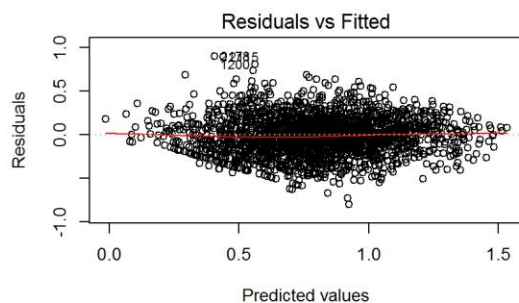
```
par(mfrow = c(1, 1))
```

Gamma quite ok with log and inverse link, not so good with identity

Let's check multicollinearity (w/o interactions).

```
vif(MGcons)
```

	GVIF	Df	GVIF^(1/(2*Df))
Region	1.762115	4	1.073382
gender	1.139977	1	1.067697
age	1.259213	1	1.122147
education	1.151332	1	1.073002
knowledge	1.099266	1	1.048459
seennatureyesno	1.300545	1	1.140414
dogowner	1.124580	1	1.060462
has_livestock	1.112694	1	1.054843
conflict_tolerance	1.330635	1	1.153532
sol_mitigation	1.165726	1	1.079688
sol_culling	1.430699	1	1.196118
sol_feeding	1.201664	1	1.096205

```
modeldata3NONA.b = modeldata3NONA
```

There seems to be no multicolinearity problem.

```
# MGcons=MGcons2
clust = makeCluster(getOption("cl.cores", 4), type = "PSOCK")
clusterExport(clust, "modeldata3NONA")
# start=Sys.time()#report start time
DredgeGMconservationReg = pdredge(MGcons, cluster = clust, trace = F)
#Region

## Fixed term is "(Intercept)"

save(DredgeGMconservationReg, file = ".//conservation_dredgeGM_Reg.RData")
# end=Sys.time()#report end time end-start
```

Removing "outliers" is not very well justified here - there is enough data that outliers are not much of a problem, and removing by an automated procedure at this stage actually makes fit worse.

Importance of parameters.

```
importance(DredgeGMconservationReg)

##                      conflict_tolerance Region sol_culling sol_mitigation
## Importance:          1.00                      1.00   1.00        1.00
```

```
## N containing models: 2048                     2048   2048         2048
##                       knowledge education has_livestock sol_feeding gender
## Importance:           1.00      1.00      1.00          1.00        0.78
## N containing models: 2048      2048      2048          2048        2048
##                       age   seennatureyesno dogowner
## Importance:           0.56 0.28            0.27
## N containing models: 2048 2048            2048
```

As expected, the "new" variables are quite important as predictors.

We ranked importance of each variable by checking in how many models it appeared weighted by Akaike's weights, and constructed the optimal model without interactions that retains all variables that had importance larger than 0.8.

Optimal model for conservation support - 2ND ROUND

We constructed the **optimal model** without interactions.

excluded variables: age, dogowner,seennatureyesno Gender is marginal, but we'll keep it in.

```
## Warning: closing unused connection 12 (<-BingPadX:11149)

## Warning: closing unused connection 11 (<-BingPadX:11149)

## Warning: closing unused connection 10 (<-BingPadX:11149)

## Warning: closing unused connection 9 (<-BingPadX:11149)
```

	df	AICc
McOptG	14	3019.755
McOptG2	18	3026.074
McOptG3	18	3011.268
McOptG4	18	3026.755
McOptG5	15	3020.320
McOptG6	15	3021.710
McOptG7	18	3012.881
McOptG8	15	3019.840
McOptG9	18	3017.354
McOptG10	18	3017.321
McOptG11	15	3020.836
McOptG12	22	3009.658
McOptG13	26	3006.293
McOptG14	25	3009.315

Meaningful interactions seem *+Region:knowledge+Region:sol_feeding+Region:sol_culling*. However, the interactions to be explored should be re-thought. Removing gender from the best model increases AIC by 3.1, so I'll keep it in.

*The final model for conservation support

```
ModconservationTol_Reg = glm(I((bear_conservation * -1) + 3) ~ Region +
gender +
    education + knowledge + has_livestock + conflict_tolerance +
sol_mitigation +
    sol_culling + sol_feeding + Region:knowledge + Region:sol_feeding +
Region:sol_culling,
    data = modeldata3NONA, family = Gamma(link = "log"), na.action =
"na.fail")
```

Exploration of drivers of conservation support - REVISITED

Outliers

We checked for outliers - high influence points - with the optimal model and cook's distances. We re-fitted the model with outliers removed.

```
cook = cooks.distance(ModconservationTol_Reg)
plot(1:nrow(modeldata3NONA), cook)
abline(h = 4/nrow(modeldata3NONA), col = "red")
```



```
modeldata3.NO = modeldata3NONA[which(cook <= 4/nrow(modeldata3NONA)), ]
# re-evalute the model with outlier-fee data
```

```
ModconservationTol_Reg2 = glm(I((bear_conservation * -1) + 3) ~ Region +
gender +
    education + knowledge + has_livestock + conflict_tolerance +
sol_mitigation +
    sol_culling + sol_feeding + Region:knowledge + Region:sol_feeding +
Region:sol_culling,
    data = modeldata3.NO, family = Gamma(link = "log"), na.action =
"na.fail")
par(mfrow = c(2, 2))
plot(ModconservationTol_Reg2)
```



```
par(mfrow = c(1, 1))
```

Removing outliers (about 5%) in this cases actually improves model fit a bit (better-looking residuals), so I decided to go with it.

A plotting function to make life easier.

Exploring Effects - Support for Bear Conservation REVISITED

Using the constructed model of Bear conservation support we can explore the effect of a single variable or a combination of variables while controlling for the effect of other variables. In this manner we can understand the effect of i.e. Region where the respondent lives (or any other parameter we wish to explore) withouth the confounding effects of other characteristics of the respondent (e.g. education, having livestock etc.)

Let's explore the effect of Region on conservation support.

```
bwplot(Region ~ (bear_conservation), data = modeldata3.NO, main = "Effect of
Region on Support for Bear Conservation - Raw Data",
    xlab = "Support for Bear Conservation")
```

Effect of Region on Support for Bear Conservation - Raw Data


```
PlotEffectsconservation("Region", ModconservationTol_Reg2, main = "Effect of
Region Conservation Support",
    ylim = c(0.2, 1.3))
```
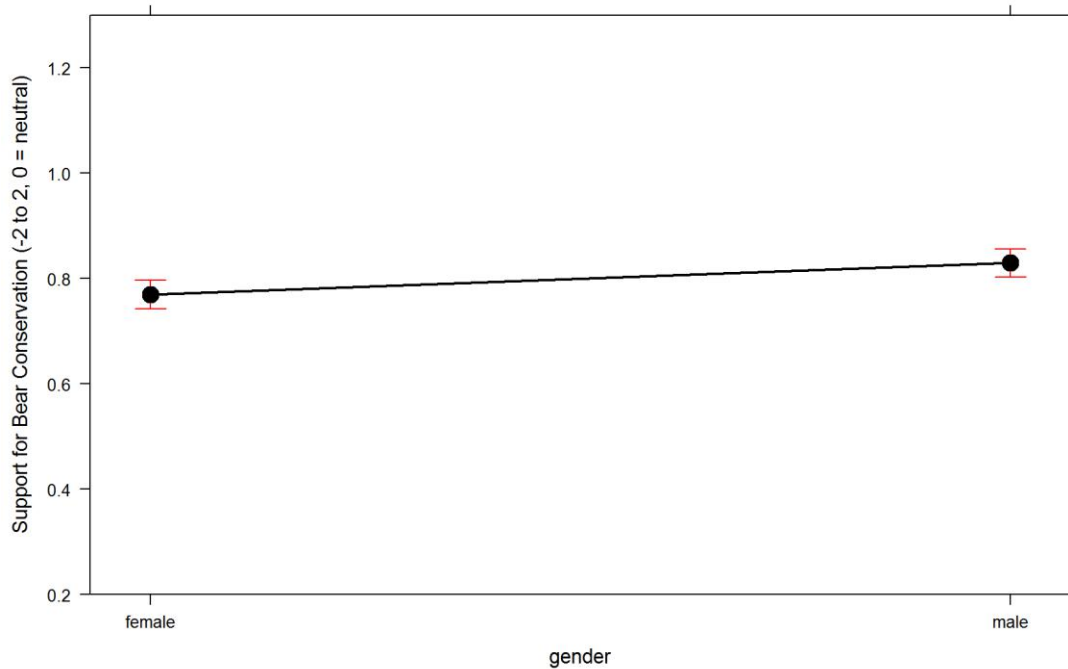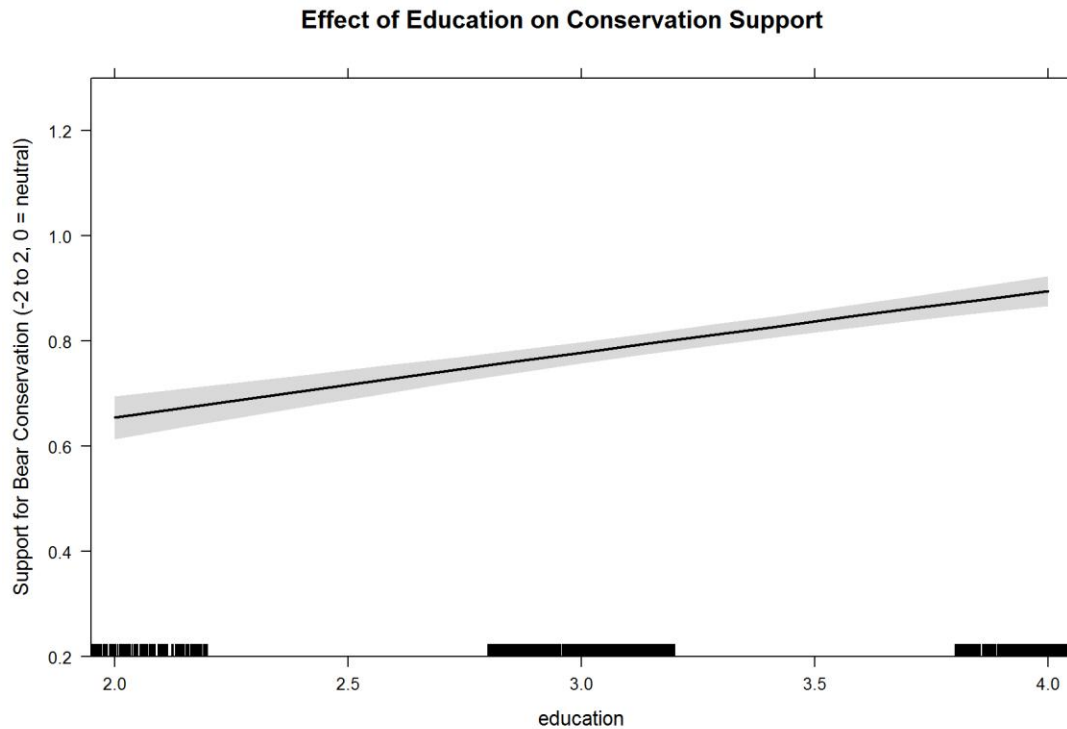
Effect of Region Conservation Support

Overall, everyone seems quite supportive of bear conservation, but there are differences between regions.

There is an interaction between region and knowledge. Let's look first at knowledge.

```
PlotEffectsconservation("knowledge", ModconservationTol_Reg2, main = "Effect
of Knowledge on Conservation Support",
    ylim = c(0.2, 1.3))
```

Effect of Knowledge on Conservation Support
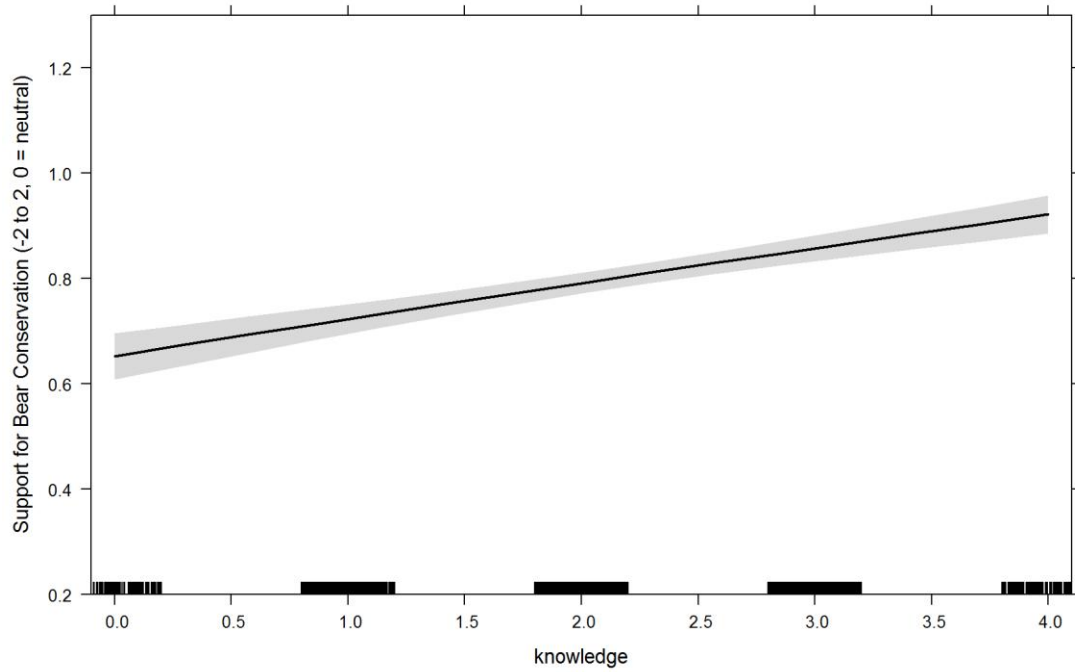
Now interaction.

```
PlotEffectsconservation(c("knowledge", "Region"), ModconservationTol_Reg2,
main = "Effect of knowledge*region on Support for Conservation",
    ylim = c(0.2, 1.3))
```

Effect of knowledge*region on Support for Conservation
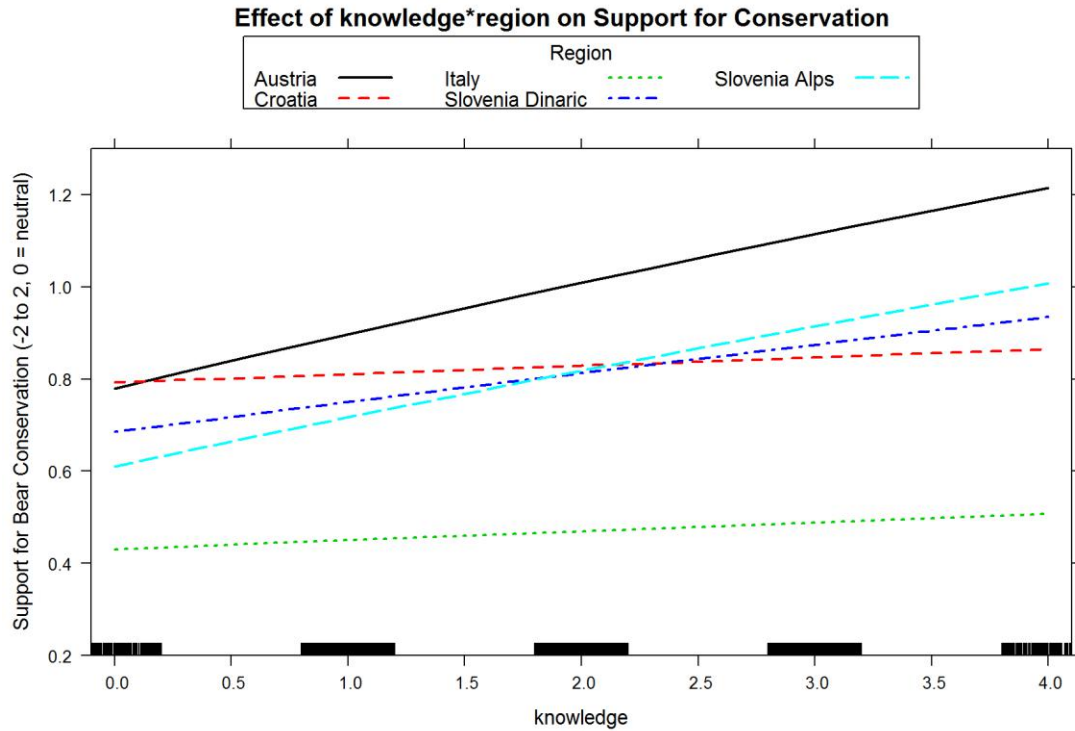
Hm... ok? This may be driven by age, but age got kicked out. I'd trust the previous model wihtout the extra predictors more on this.

How does gender affect this?

```
bwplot(gender ~ (bear_conservation), data = modeldata3.NO, main = "Effect of
Gender on Support for Bear Conservation - Raw Data",
    xlab = "conservation Support")
```

Effect of Gender on Support for Bear Conservation - Raw Data
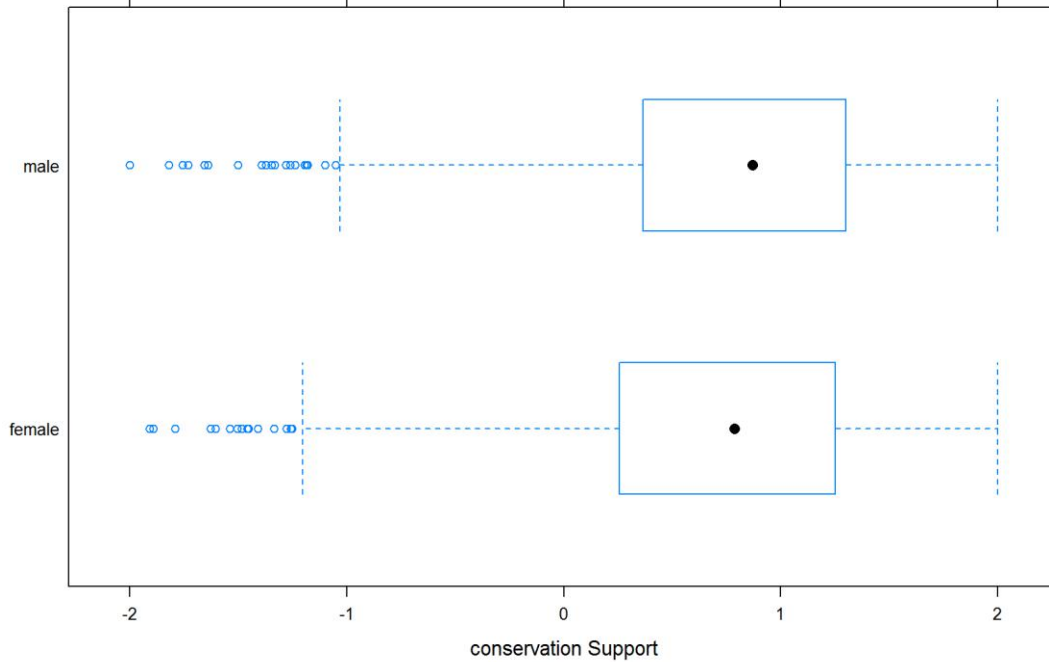

```
PlotEffectsconservation("gender", ModconservationTol_Reg2, main = "Effect of
Gender on Conservation Support",
    ylim = c(0.2, 1.3))
```

Effect of Gender on Conservation Support

A small difference, but there's no overlap in CI.

Education?

```
PlotEffectsconservation("education", ModconservationTol_Reg2, main = "Effect
of Education on Conservation Support",
    ylim = c(0.2, 1.3))
```

Effect of Education on Conservation Support

Having livestock?

```
PlotEffectsconservation("has_livestock", ModconservationTol_Reg2, main =
"Effect Having Livestock on Conservation Support",
    ylim = c(0.2, 1.3))
```

Effect Having Livestock on Conservation Support
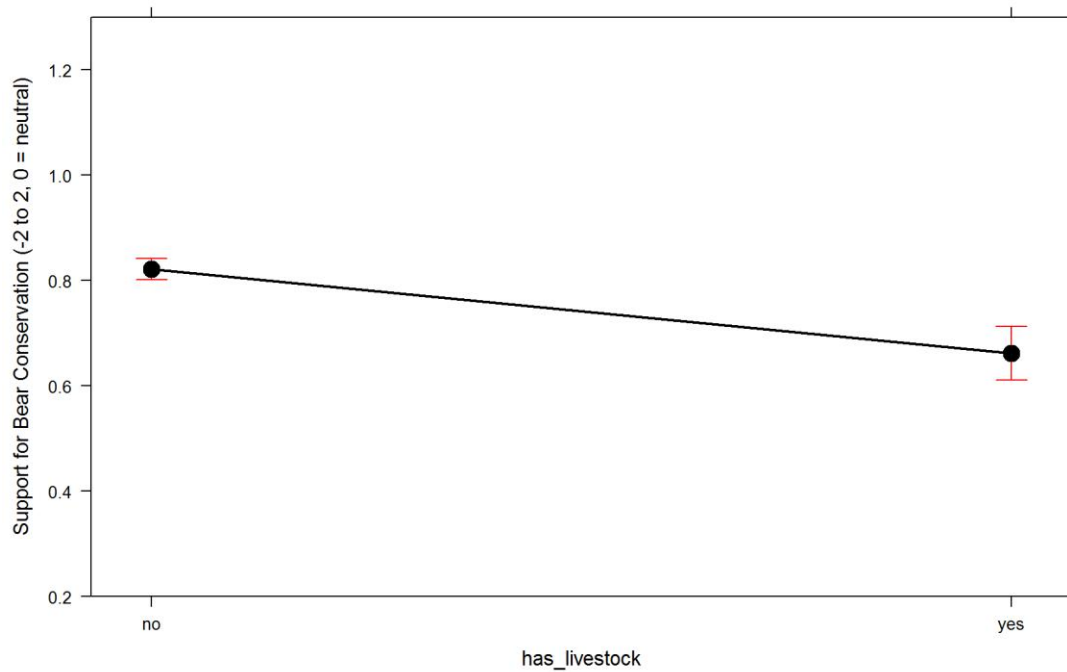
Ok, these were the direct characteristics of respondents. Now *derived characteristics*.

Exploring effects of various attitude (derived) variables

First, let's explore each of the added variables.

Tolerance of conflicts caused by bears

```
PlotEffectsconservation("conflict_tolerance", ModconservationTol_Reg2, main =
"How does tolerance of conflicts caused by bears reflect on Conservation
Support",
    ylim = c(-0.2, 1.5))
```

How does tolerance of conflicts caused by bears reflect on Conservation Support
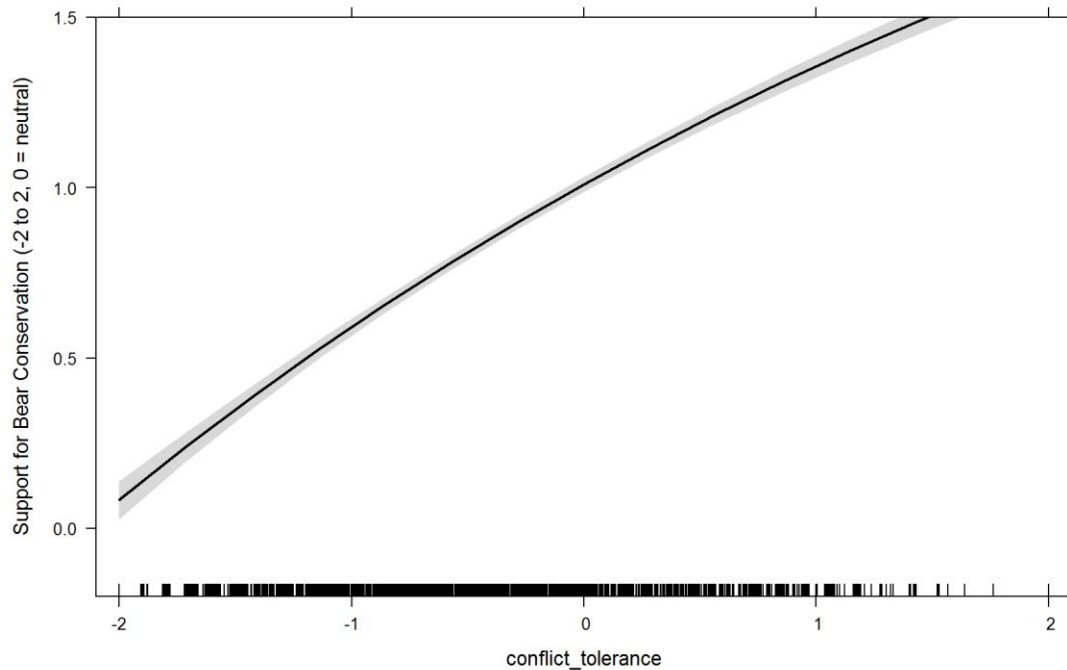
Interesting. People considered to have extremely low tolerance of conflicts caused by bears are about neutral on bear conservation. Warning - there are very few extreme cases (see "rug" of cases on the bottom).

Preference of mitigation solutions

```
PlotEffectsconservation("sol_mitigation", ModconservationTol_Reg2, main =
"How does support of mitigation activities reflect on Conservation Support",
    ylim = c(-0.2, 1.5))
```

How does support of mitigation activities reflect on Conservation Support
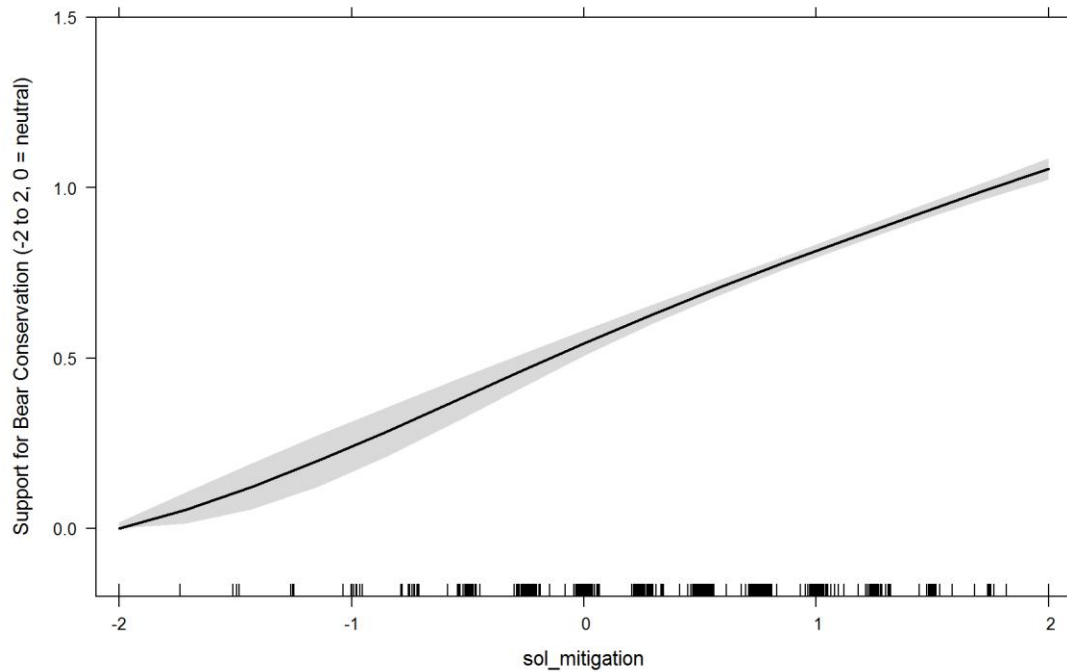
Expected

How about support for culling?

```
PlotEffectsconservation("sol_culling", ModconservationTol_Reg2, main = "How
does support for culling reflect on Conservation Support",
    ylim = c(-0.2, 1.5))
```

How does support for culling reflect on Conservation Support
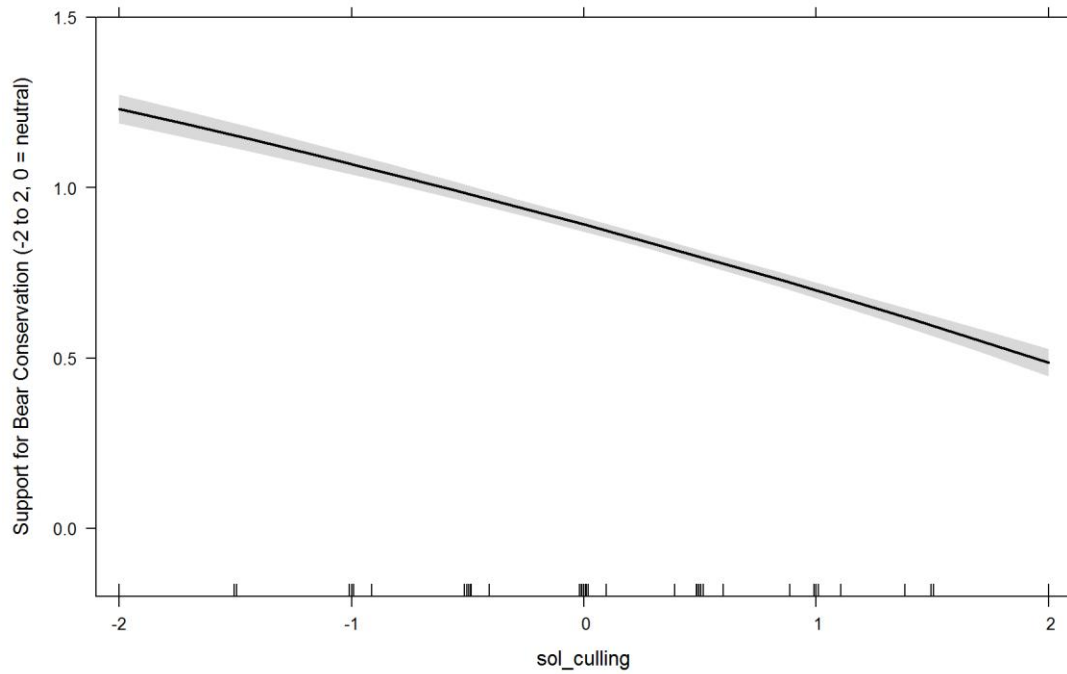
Expected.

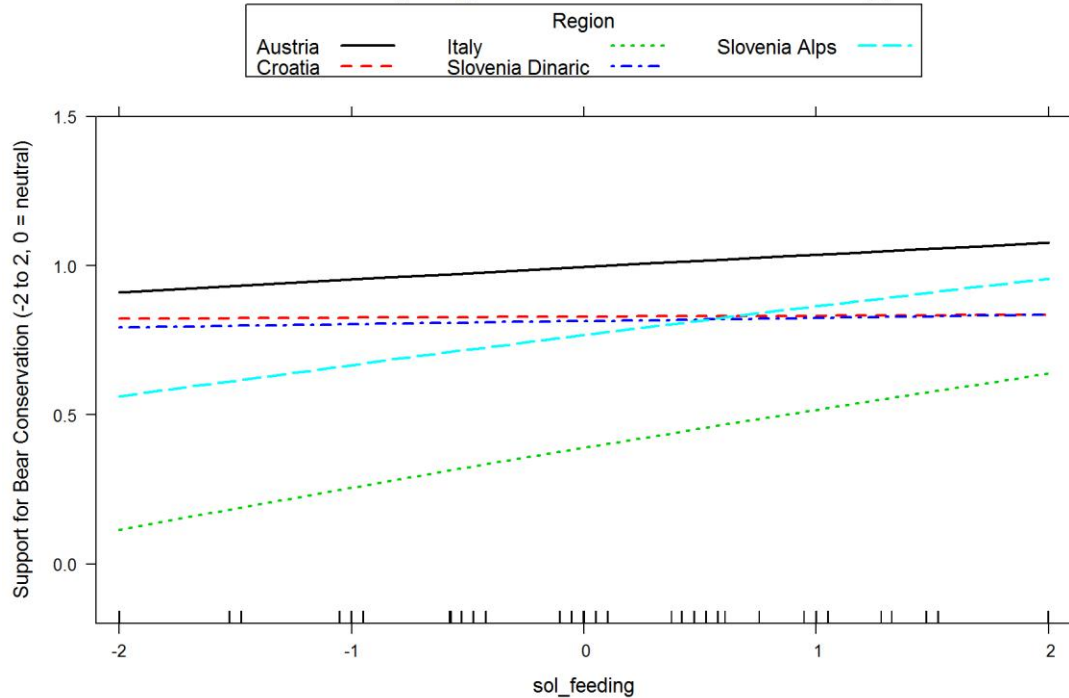Feeding?

```
PlotEffectsconservation("sol_feeding", ModconservationTol_Reg2, main = "How
does support for supplemental feeding reflect on Conservation Support",
    ylim = c(-0.2, 1.5))
```

How does support for supplemental feeding reflect on Conservation Support
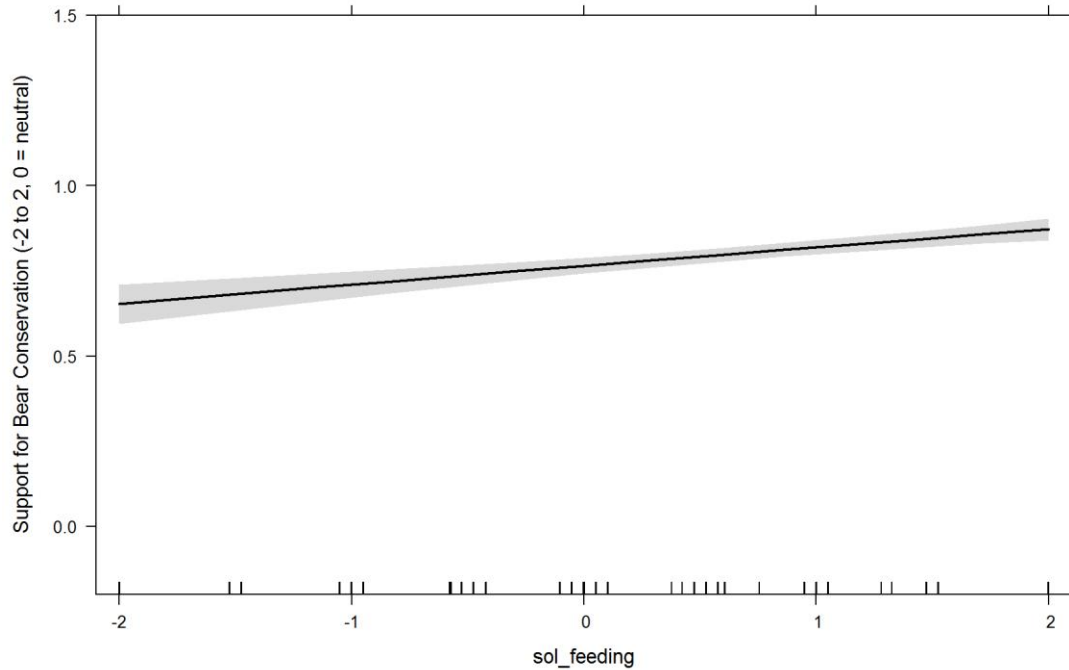
A little, but positively. There are also regional differences?

```
PlotEffectsconservation(c("sol_feeding", "Region"), ModconservationTol_Reg2,
main = "Interaction feeding * region and effect on Conservation Support",
    ylim = c(-0.2, 1.5))
```


Interaction feeding * region and effect on Conservation Support

This concludes the analysis of support for bear conservation. Housekeeping.

```
rm(list = ls()[-grep("modeldata3", ls())])
rm(modeldata3.NO)
```

Support for Supplemental Feeding

First thing first - let's fit a distribution to this response variable.

```
##       shape          rate
##    4.98813623    2.08512492
##   (0.14347842) (0.06310028)

##       shape         scale
##    2.37670730    2.70743490
##   (0.03768169) (0.02532473)
```


red=Gamma, blue=Wiebull
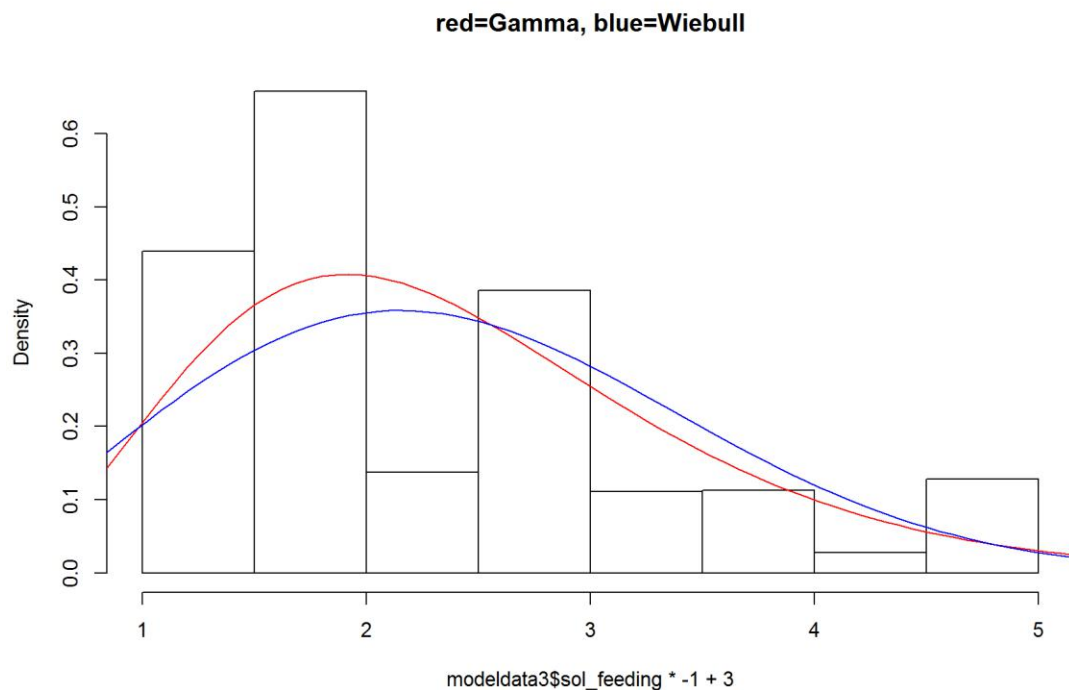
Hm.
Gamma?

Finding the model for support for population feeding.

We've fitted a generalized linear model (GLM) with different links link multiplied by -1 and moved by +3 (to get rid of values below zero) and sol_feeding variable as response.

For the global model, we fitted all variables we hypothesized (according to previous understanding of the problem) that they would affect this response.

```r
feedFG = formula(I((sol_feeding * -1) + 3) ~ Region + gender + age +
education +
    knowledge + dogowner + has_livestock + seennatureyesno)
MGfeed = glm(feedFG, data = modeldata3NONA, family = Gamma(link =
"identity"), na.action = "na.fail")
MGfeed

##
## Call:  glm(formula = feedFG, family = Gamma(link = "identity"), data =
modeldata3NONA,
##      na.action = "na.fail")
##
## Coefficients:
##          (Intercept)          RegionCroatia            RegionItaly
##             2.890247               -0.090006              -0.524824
##     RegionSlovenia Alps  RegionSlovenia Dinaric             gendermale
##            -0.736918               -0.718365              -0.019480
##                  age              education              knowledge
##             0.002984                0.035037              -0.094397
##          dogowneryes        has_livestockyes      seennatureyesnoyes
##            -0.050068                0.017189              -0.116625
##
## Degrees of Freedom: 2231 Total (i.e. Null);  2220 Residual
## Null Deviance:          461.2
## Residual Deviance: 421.9      AIC: 6143

par(mfrow = c(2, 2))
plot(MGfeed)
```
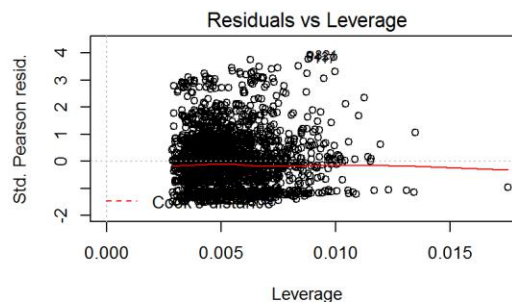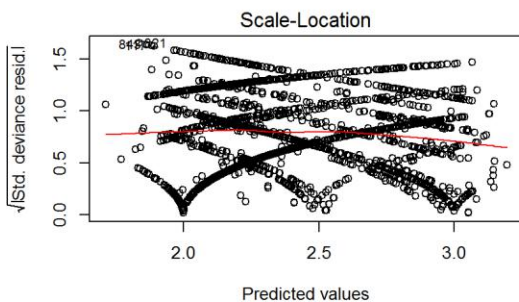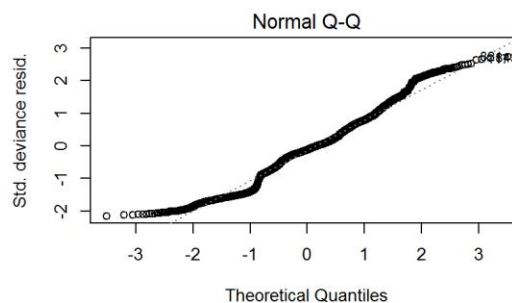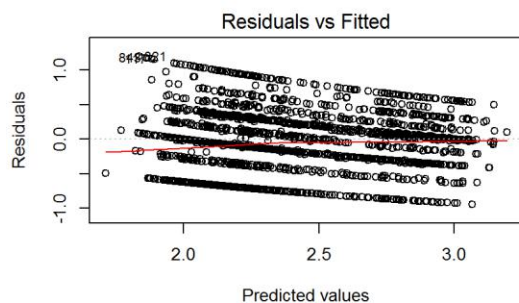
```
par(mfrow = c(1, 1))
```

A bit of bias, no heteroscedascity and relatively linear - not perfect, but generally ok.

Let's check multicollinearity (w/o interactions).

```
vif(MGfeed)
```

	GVIF	Df	GVIF^(1/(2*Df))
Region	1.420004	4	1.044807
gender	1.078509	1	1.038513
age	1.166108	1	1.079865
education	1.131074	1	1.063520
knowledge	1.051638	1	1.025494
dogowner	1.105613	1	1.051481
has_livestock	1.093996	1	1.045942
seennatureyesno	1.245339	1	1.115948

There seems to be no multicolinearity problem.

```
clust = makeCluster(getOption("cl.cores", 4), type = "PSOCK")
clusterExport(clust, "modeldata3NONA")
# start=Sys.time()#report start time
DredgeGMfeedingReg = pdredge(MGfeed, cluster = clust, trace = F)  #Region

## Fixed term is "(Intercept)"

save(DredgeGMfeedingReg, file = ".//feeding_dredgeGM_Reg.RData")
# end=Sys.time()#report end time end-start
```

Importance of parameters.

```
importance(DredgeGMfeedingReg)

##                        Region knowledge seennatureyesno age   dogowner
## Importance:            1.00   1.00      0.87            0.78  0.43
## N containing models:   128    128       128             128   128
##                        education gender has_livestock
## Importance:            0.37      0.29   0.27
## N containing models:   128       128    128
```

We ranked importance of each variable by checking in how many models it appeared weighted by Akaike's weights, and constructed the optimal model without interactions that retains all variables that had importance larger than 0.8.

Optimal model for feeding support

We constructed the **optimal model** without interactions. Interesting, only region, knowledge and seeing bear in nature are supported. Age is marginally supported so I'll include it and check AIC during model selection.

excluded variables: dogowner, education, gender, has_livestock

	df	AICc
McOptG	9	6138.529
McOptG2	13	6142.293
McOptG3	13	6138.247
McOptG4	13	6142.004
McOptG5	10	6139.775
McOptG6	10	6139.409
McOptG7	8	6142.347

No interactions. Removal of age is not supported (dAIC~4)

*The final model for feeding support

```
ModfeedingTol_Reg = glm(I((sol_feeding * -1) + 3) ~ Region + age + knowledge
+ seennatureyesno,
    data = modeldata3NONA, family = Gamma(link = "log"), na.action =
"na.fail")
```

Exploration of drivers of feeding support

Outliers

We checked for outliers - high influence points - with the optimal model and cook's distances. We re-fitted the model with outliers removed.

```
cook = cooks.distance(ModfeedingTol_Reg)
plot(1:nrow(modeldata3NONA), cook)
abline(h = 4/nrow(modeldata3NONA), col = "red")
```
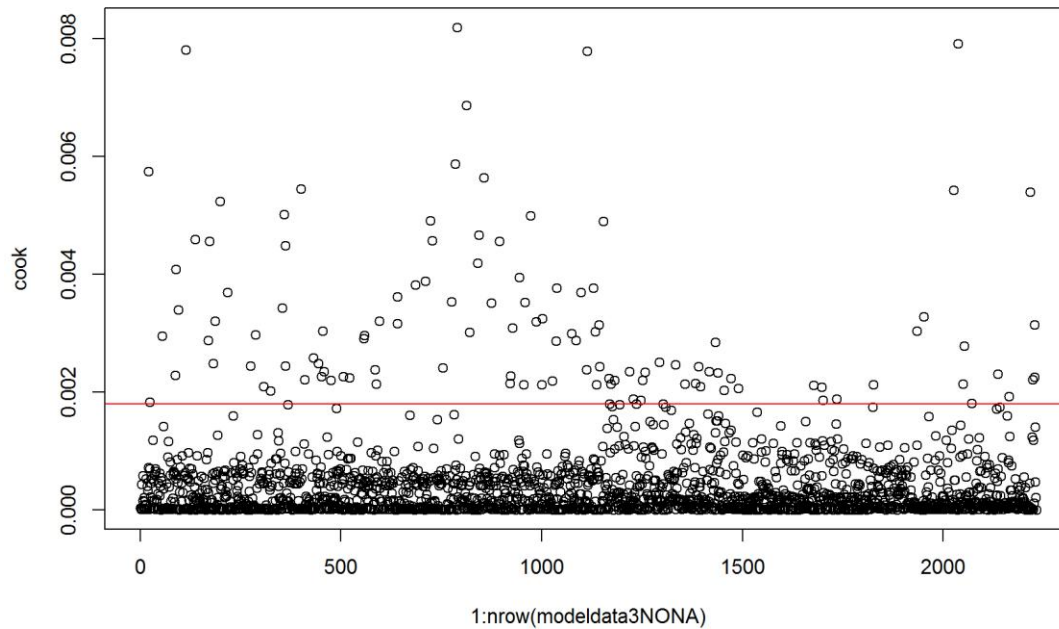
```
modeldata3.NO = modeldata3NONA[which(cook <= 4/nrow(modeldata3NONA)), ]
# re-evalute the model with outlier-fee data
ModfeedingTol_Reg2 = glm(I((sol_feeding * -1) + 3) ~ Region + age + knowledge
+ seennatureyesno,
    data = modeldata3.NO, family = Gamma(link = "log"), na.action =
"na.fail")
par(mfrow = c(2, 2))
plot(ModfeedingTol_Reg2)
```
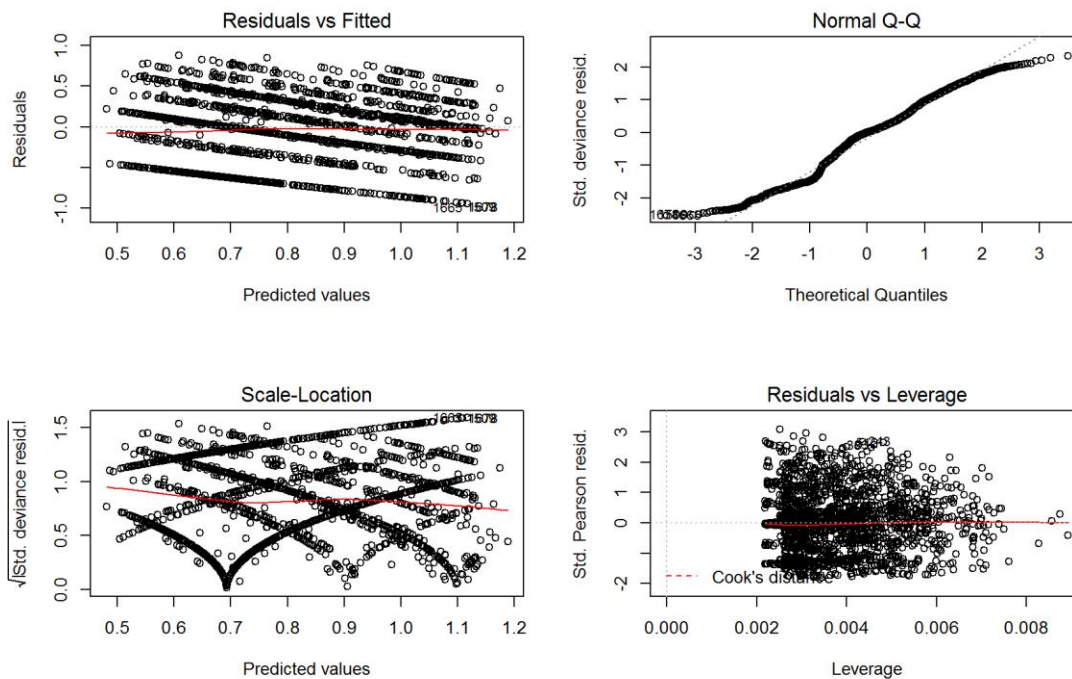
```
par(mfrow = c(1, 1))
```

Not grand, but ok.

A plotting function to make life easier.

Exploring Effects - Support for Supplemental Feeding

Using the constructed model of supplemental feeding support we can explore the effect of a single variable or a combination of variables while controling for the effect of other variables. In this manner we can understand the effect of i.e. Region where the respondent lives (or any other parameter we wish to explore) withouth the confounding effects of other characteristics of the respondent (e.g. knowledge etc.)

Let's explore the effect of Region on supplemental feeding support.

```
bwplot(Region ~ (sol_feeding), data = modeldata3.NO, main = "Effect of Region
on Support for Supplemental Feeeding - Raw Data",
    xlab = "Support for Suplemental Feeding")
```

Effect of Region on Support for Supplemental Feeeding - Raw Data
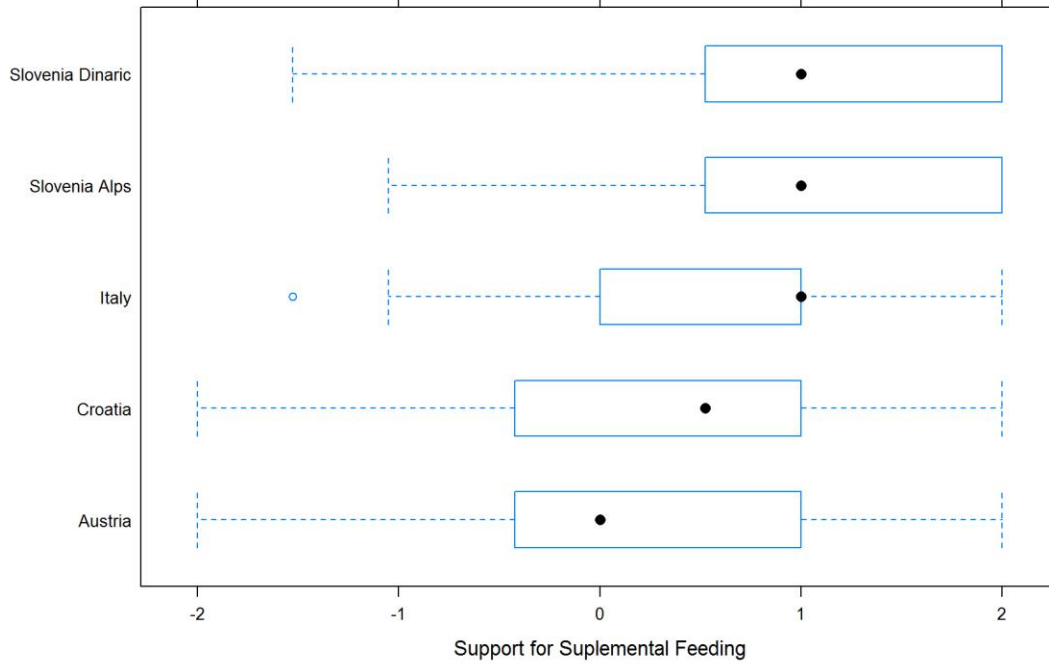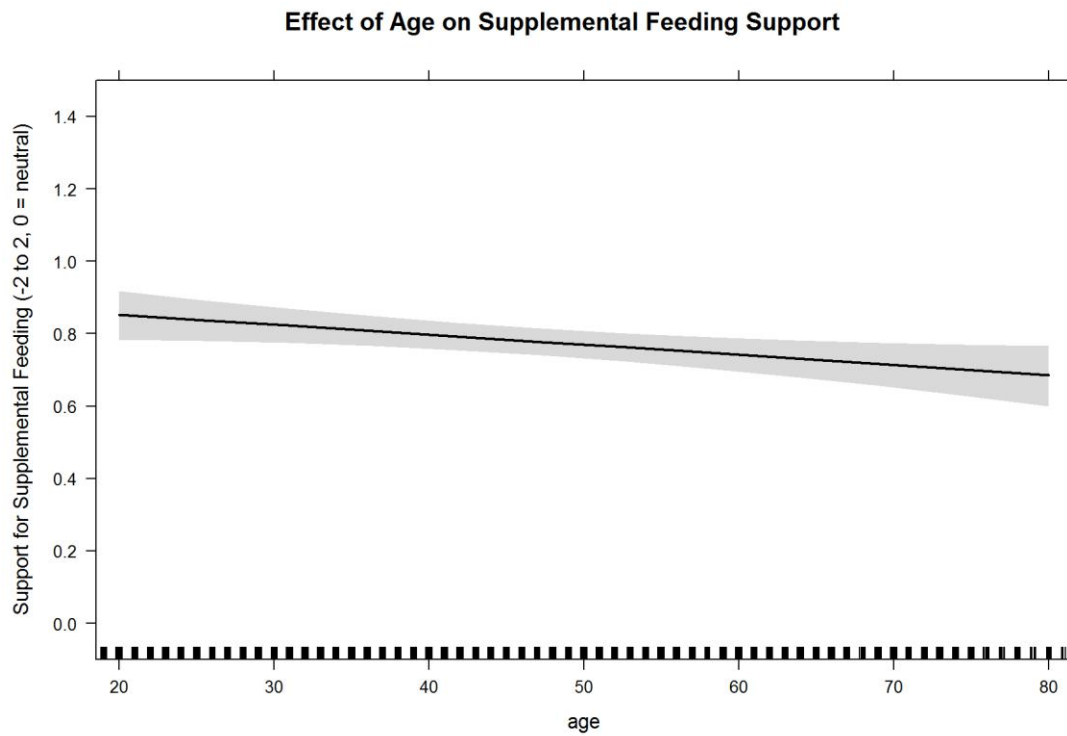


```
PlotEffectsfeeding("Region", ModfeedingTol_Reg2, main = "Effect of Region on
Pop. feeding Support",
    ylim = c(-0.1, 1.5))
```

Effect of Region on Pop. feeding Support
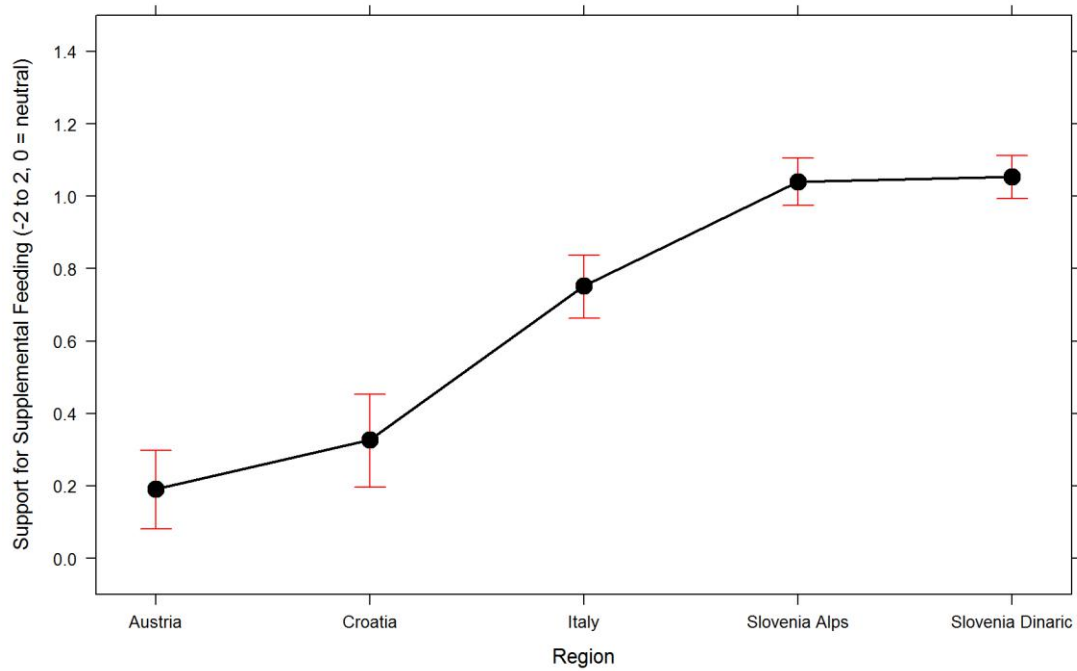
Age?

```
PlotEffectsfeeding("age", ModfeedingTol_Reg2, main = "Effect of Age on
Supplemental Feeding Support",
    ylim = c(-0.1, 1.5))
```

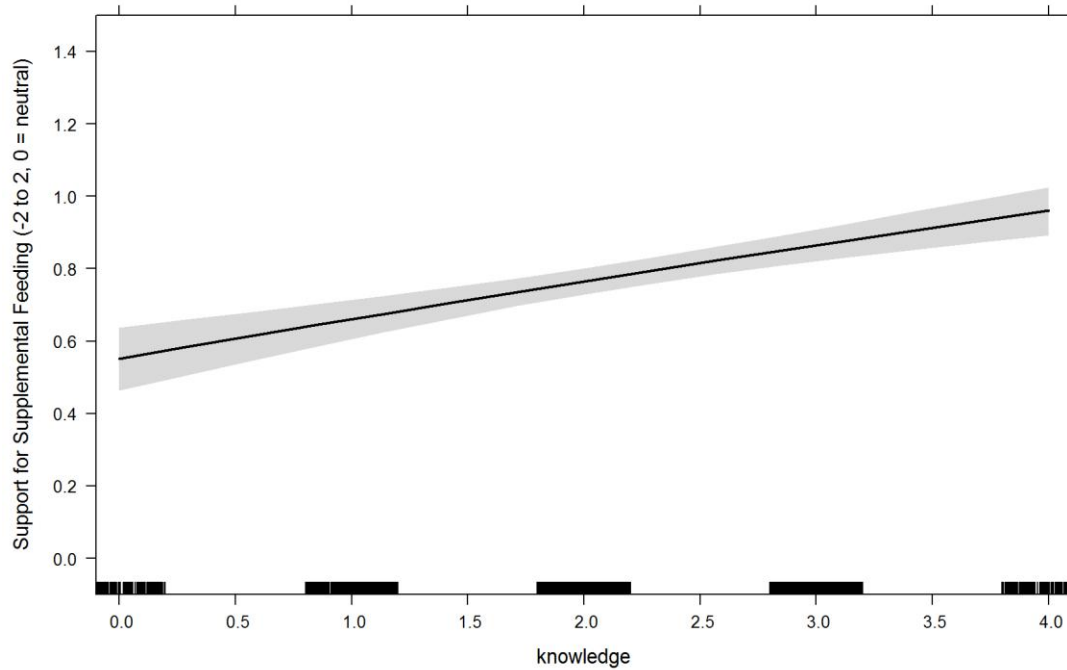**Effect of Age on Supplemental Feeding Support**

This is a bit counterintuitive. This parameter should possibly be excluded, but does improve model fit.

Knowledge?

```
PlotEffectsfeeding("knowledge", ModfeedingTol_Reg2, main = "Effect of
Knowledge on Supplemental Feeding Support",
    ylim = c(-0.1, 1.5))
```

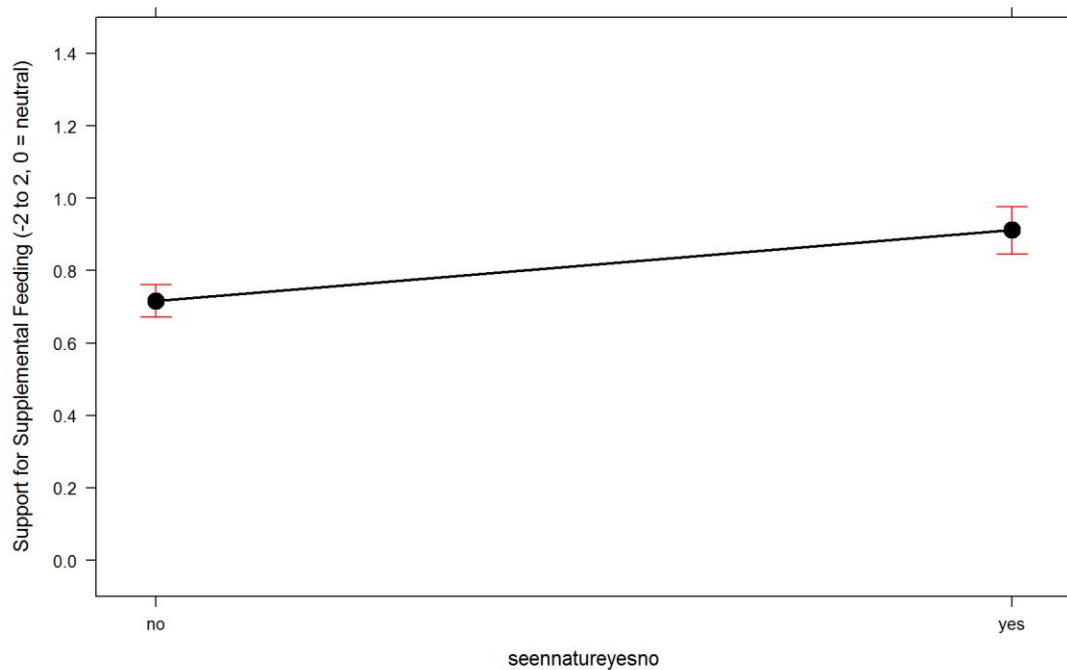**Effect of Knowledge on Supplemental Feeding Support**

Considerable.

Last but not least, seeing bear in nature?

```
PlotEffectsfeeding("seennatureyesno", ModfeedingTol_Reg2, main = "Effect of
Seeing a Bear in Nature on Supplemental Feeding Support",
    ylim = c(-0.1, 1.5))
```

Effect of Seeing a Bear in Nature on Supplemental Feeding Support

You've seen a bear, you wanna feed it. Yay. Bears are cute, so quite an understandable reaction.

```
rm(list = ls()[-grep("modeldata3", ls())])
rm(modeldata3.NO)
```

THE END