What really matters (and to whom): Investigating heterogeneous effects in high-dimensional conjoint analyses

Thomas Reiter   Philipp Sterner

Introduction

In the social sciences, conjoint analyses are a powerful research design to assess preferences in humans. Under the popular special case of *forced choice designs*, participants are presented with two options of choice from which they have to choose one, for example certain products in marketing research, or two potential candidates in political research on voting behavior. The two possible options are characterized by certain *attributes* (also: treatments), which can have different *attribute levels* (treatment levels), for example the attribute color of a car might have levels white, black, and blue. By randomly mixing the attribute levels and "forcing" participants to choose one of two options across multiple rounds, researchers are able to estimate the relative importance that participants give to certain attribute levels.

Arguably the most commonly estimated causal quantity in conjoint analyses is the *average marginal component effect* (AMCE). The AMCE is the effect of a specific attribute level of interest compared to another level of the same attribute, holding equal the joint distribution of all other attributes and averaged over this joint distribution as well as the sampling distribution from the population CITE. This quantity is estimable by regression models and provides us an effect of an attribute on the probability that a certain option (or profile) will be chosen. As the name AMCE suggests, this estimate is an average. That is, potential differences in effects among participants cannot be considered directly. However, this *effect heterogeneity* is often of interest, when trying to determine whether an attribute is equally important to all participants regardless of background covariates (e.g., age, gender, education, etc.) or whether there are subgroup differences. Ultimately, it is a question of generalization of results to the entire population and, even more advanced, of causal mechanisms in choice behavior.

The simplest approach to take into account potential effect heterogeneity in conjoint analyses is to estimate the AMCE-models in different subgroups, for example a model for all male and

1

female participants. Although appealing due to its simplicity, this approach quickly reaches its limits and has additional downsides. First, it is not clear how to a priori define the subgroups let alone how and where to include certain interactions. If a continuous covariate age is included in the data, arbitrary splits into distinct groups are necessary. Potential interaction effects would have to be included manually with the likely chance to miss important ones. Needless to say, sample sizes in the subgroups are always smaller than in the whole sample as well, increasing the uncertainty in estimations. This leads to a second issue: conjoint data can quickly become high-dimensional due to many different pairings of different attribute levels (across attributes). Consequently, there are more combinations of attribute levels (and thus, possible options) that should be presented to participants than there are actual rounds of choosing per participant. This leads to some kind of "double high-dimensionality issue": there are many different attribute (level) combinations *and* many potential covariates characterizing the participants. This results in a number of possible interactions that are intractable for classical methods (these interactions correspond to the effect heterogeneity mentioned above).

New Approaches to Handle Effect Heterogeneity under High-Dimensionality

To remedy the downsides of the "naive" subgroup approach outlined above, researchers developed more advanced methods based on machine learning. Most notable in this regard are (a) an approach based on *Bayesian additive regression trees* (in the following called *cjbart* CITE), (b) an approach based on Bayesian mixture of regularized logistic regressions (*FactorHet* CITE), and (c) a testing approach based on conditional randomization tests (*CRT* CITE). In this article, we focus on the explanation and demonstration of cjbart. At the end of this section, we briefly delineate similarities and differences in these three approaches.

cjbart

The premise of cjbart as introduced by CITE is that there are several *nested causal quantities* underlying the AMCE. Specifically, the AMCE can be decomposed into an individual-level (i.e., participant-level), round-level, and observation-level marginal component effect (IMCE, RMCE, and OMCE, respectively). Let us consider N individuals choosing between J profiles across K rounds (where in the simplest case of binary choices $J = 2$). In each round, an individual i is presented with J profiles in which the attribute levels of L attributes are assigned randomly. In the final data set, there are $N \times J \times K$ rows and $L + X$ columns (with X being the covariates characterizing the individuals). From these data we now want to estimate the causal parameters of interest, that is, AMCE, IMCE, RMCE, and OMCE. Nested in the AMCE described above, the IMCE is the change in probability that subject i choses a profile given a specific attribute level (compared to a reference level of the same attribute), again averaged over the effects of all other attributes. This corresponds to subgroup analyses of

the AMCE with the convenient addition that the IMCE considers conditional effects based on all possible individual-level covariates. By inspecting the IMCE, effect heterogeneity due to non-randomized characteristics (i.e., the covariates) can be identified. The IMCE further contains the two lower-level quantities RMCE and OMCE. Because for each participant, there are usually multiple rounds of observations (i.e., choices), the RMCE can be obtained as the effect of an attribute within a specific round k of the experiment for a given individual i. Lastly, the OMCE is estimated by additionally conditioning on a specific profile-level (i.e., if $J = 2$, by conditioning on one of the two profiles). As CITE note, the OMCE does not contain too much substantial information. It is, however, of statistical importance: assuming the OMCE is an independent random draw from an individual-level distribution, we can aggregate the OMCEs to estimate the IMCEs.

In the following, we explain how the IMCEs are estimated. IMCEs can be considered the most important quantity for our purpose of investigating effect heterogeneity because it allows us to analyze how attribute importances differ depending on participant covariates. CITE propose a three-step estimation procedure.

Step 1: Modeling Potential Heterogeneity

In a first step, potential effect heterogeneity is modeled. Specifically, some function is estimated that relates the attribute levels of the L attributes that were shown to subject i in the kth round in profile j and the covariate vector X_i to the observed binary outcome Y_{ijk} (which is equal to 1 if the profile was chosen and equal to 0 if it was not chosen). CITE detail this estimation procedure using Bayesian additive regression trees (BART) but other appropriate models that can estimate this potentially complex functional relationship could be used as well. BART is a supervised learning model based on a boosting procedure: many small decision trees are trained subsequently, each one aiming to explain the residual variance of the outcome variable which was not explained by all previous trees. The "Bayesian part" in BART is that parameters are seen as random variables (instead of constants, as would be the case in frequentist approaches). An advantage of BART is its robustness to the choice of hyperparameters (e.g., the number of individual trees) but they could be tuned if necessary, for example by cross-validation. The data that is used to train the BART are the data resulting from the conjoint experiment; that is, the different choices of profiles as well as the covariates, which are invariant at the individual-level.

Step 2: Predicting Counterfactual Outcomes

In a second step, the estimated function from step 1 (i.e., the trained BART model) is used to predict counterfactual outcomes by changing the values of attribute levels. These predictions are counterfactual because they did not happen — but we assess what would have been chosen had a certain attribute level been set to a different attribute level of the same attribute. This is done repeatedly by drawing multiple times from a predicted posterior distribution, once

with the altered attribute level and once with the reference level of the same attribute. By subtracting these results and averaging them over the multiple draws of the posterior, we arrive at a parameter estimate of the OMCE (i.e., observation-level effects).

Step 3: Calculating IMCEs

Following the nested causal quantities structure outlines above, IMCEs are calculated by averaging the OMCEs for each individual. Specifically, the OMCE estimates from step 2 are summed and divided by $J \times K$, that is, the number of profiles times the number of rounds (which is the number of total observations).

Identification of Heterogeneity

As mentioned, the main reason why we employ these complicated procedures is because we want to estimate heterogeneous treatment effects. More specifically, we want to assess whether the effects of certain attribute levels on choice behavior are different across individuals. CITE provide two methods that yield information about which covariates are associated with heterogeneity in effects of attribute levels. Both methods are tree-based which is especially suitable to investigate heterogeneity because trees partition a data set into increasingly homogeneous groups. Thereby, they can reveal covariates that drive the heterogeneity as these covariates will be used for splitting the data.

Tool 1: Random Forest Variable Importance

The first tool uses random forests, an ensemble of decision trees, to investigate which covariates are the important ones in the prediction of differences in the IMCE distributions for all attribute levels (i.e., the effect heterogeneity). Specifically, for each attribute level, a random forest is trained where the covariates X_i are used as predictors. Subsequently, variable importance measures (VIMPs) are derived to assess which covariates are driving the data partitioning. Briefly, the VIMPs are calculated by permuting the covariates (i.e., by introducing random noise to its values). If predictions change noticeably, this is an indication that the covariate is important for predicting the outcome (i.e., IMCE distributions). Of note, this is done separately for every combination of covariate and attribute level because the importance of a certain covariate may differ with respect to different attribute levels. This results in a comprehensive VIMP-heatmap, which we show as an example in the results section.

Tool 2: Single Decision Tree Partitioning

By combining many weak decision trees, random forest have the advantage of increased predictive performance. However, this advantage comes at the cost of interpretability. Each tree only considers a random subset of predictor variables (in our case: subject-level covariates) and is trained on a bootstrap sample. Thus, CITE suggest a complementary analysis with single decision trees which are grown for a specific attribute level. In this analysis, a decision tree predicts IMCEs for this specific attribute level, again using subject-level covariates as predictors. The partitions within the tree can be readily investigated and interpreted as heterogeneity in IMCEs because only one model is fit to the data set and all predictor variables are considered for splitting. Importantly, to keep decision trees interpretable (i.e., to not let them grow too deep), they have to be pruned by setting a complexity parameter controlling the depth. CITE suggest to set this parameter such that the tree only continues to split the data if the increase in explained variance of the IMCE (i.e., R^2) is at least 0.02 to 0.04. The predictions in the terminal nodes of the tree correspond to conditional AMCEs, which would normally be assessed by estimating AMCEs in subgroups. However, by using decision trees, which are an exploratory tool by design, no subgroups have to be specified in advance. Even further, trees might even identify interaction effects between multiple covariates, for example by splitting twice on two different variables (e.g., Germans older than 30 years).

Data and Research Question

In the following, we showcase the application of cjbart to data provided by Prof. Dr. Paul Thurner and Fabian Haggerty from the Geschwister-Scholl-Institute of Political Science, LMU Munich. The data were first described in CITE. In their work, CITE aimed at investigating which attributes citizens from five different NATO-member countries (United States [US], United Kingdom [UK], Germany, Italy, and France) deem important when deciding whether Ukraine should be supported economically and militarily against the Russian aggression. For this, CITE conducted a conjoint experiment where $N = 10,011$ participants from the five countries chose one of two possible profiles. In these profiles, nine different attributes with varying attribute levels were manipulated randomly to indicate the consequences that a support of Ukraine would entail if the profile was chosen. The different attributes, their corresponding levels, and the reference categories we used for our analyses are shown in Table 1. Additionally, subject-level covariates were assessed, for example, participants' age, gender, political orientation, or their country of origin (of the five countries mentioned above).

Table 1: Attributes, attribute levels, and reference categories used in the analyses.

Attribute	Attribute Levels	Reference Category
Number of Ukrainian soldiers killed?	1. 12,500 2. 25,000 3. 50,000	12,500
Number of Russian soldiers killed?	1. 25,000 2. 50,000 3. 100,000	25,000
Number of Ukrainian civilians killed?	1. 4,000 2. 8,000 3. 16,000	4,000
Value of destroyed infrastructure in Ukraine?	1. $50B 2. $100B 3. $200B	$50B
[Country] contribution to military aid to Ukraine?	1. X bn (0.1% of [Country] GDP) 2. X bn (0.2% of [Country] GDP) 3. X bn (0.3% of [Country] GDP)	0.1% of GDP
[Country] contribution to economic aid to Ukraine?	1. X bn (0.1% of [Country] GDP) 2. X bn (0.2% of [Country] GDP) 3. X bn (0.3% of [Country] GDP)	0.1% of GDP
Risk of a Russian nuclear strike on Ukraine?	1. Not present (0%) 2. Low (5%) 3. Moderate (10%)	Not present (0%)
How much political self-determination of Ukraine?	1. Full self-determination 2. No NATO/EU membership 3. Russian influence over Ukr. gov.	Full self-determination

Table 1: Attributes, attribute levels, and reference categories used in the analyses.

Attribute	Attribute Levels	Reference Category
Territorial cessions of Ukraine to Russia?	1. No cessions of territory 2. Crimea (ca. 4% of land) 3. 2014 Line of Conflict (ca. 8%) 4. 2023 Line of Conflict (ca. 16%)	No cessions of territory

To investigate which attributes and attribute levels matter when people decide whether Ukraine should be supported in their defense endeavors, CITE estimated AMCEs as well as marginal means for subgroup analyses. The results of their analyses will be outlined below, where we compare them to the results of our analyses using cjbart. As described above, the "classical" approach of estimating AMCEs and conducting subgroup analyses comes with the disadvantage that the potentially complex heterogeneity of attribute effects cannot be assessed. Additionally, subgroup analyses can only be carried out for a priori defined groups. If covariates have many different levels, it quickly becomes unfeasible to carry out all subgroup analyses. If covariates are continuous, it might even be impossible, unless arbitrarily chosen splits to discretize the data are performed.

Thus, the goal of this project is to complement the existing results reported by CITE with an exploratory analysis. Using cjbart, we are able to scrutinize the data for heterogeneity of attribute effects. Additionally, using the decision tree approach described above, we perform exploratory subgroup analyses. The goal of these analyses is to identify which groups differ in their preferences regarding specific attribute levels.

Method

Data of the above conjoint experiment was modeled by the previously described cjbart approach. For this, we used the R package *cjbart* described in CITE. We fitted a BART model containing the profile attributes and various subject-level covariates: age, country, gender, and political orientation, and subjects' agreement on different statements regarding political statements (e.g., EXAMPLE). A list of all covariates, including their type, can be found in Table 2. This resulted in a trained BART model that was used to make the (counterfactual) predictions needed for calculating the quantities of interest, such as IMCEs or AMCEs.

Table 2: Covariates and corresponding scale levels used in the analyses.

Covariates	Scale Level
Country	Categorical with 5 levels: Germany, UK, USA, France, Italy
Age	Continuous
Gender	Categorical with 2 levels: male and female
Political Orientation	Categorical with 3 levels: left, middle, right
The political agenda should focus on the war against Ukraine.	Categorical: 6-point Likert scale
How scared are you by the Russian war against Ukraine?	Categorical: 7-point Likert scale (*not scared at all* to *very scared*)
Does military support of [country] matter regarding your current voting intention?	Categorical: 4-point Likert scale (*matters a lot* to *does not matter at all*)
The US-American imperialism is the real threat to world peace.	Categorical: 7-point Likert scale (*do not agree at all* to *completely agree*)
I can see why Russia feels threatened by the West.	Categorical: 7-point Likert scale (*do not agree at all* to *completely agree*)
Would you say that your general opinion of the NATO is very positive, slightly positive, neither positive nor negative, slightly negative, or very negative?	Categorical: 5-point Likert scale (*very positive* to *very negative*)
Ukraine should waive a NATO membership if this would bring peace.	Categorical with 2 levels: yes and no
Ukraine should not make any concessions to achieve peace.	Categorical with 2 levels: yes and no
Trading or deliveries of weapons between countries should be prohibited.	Categorical: 7-point Likert scale (*do not agree at all* to *completely agree*)
If a country is being attacked and the aggressor is targeting civilians, [country] should provide military support.	Categorical: 7-point Likert scale (*do not agree at all* to *completely agree*)

Table 2: Covariates and corresponding scale levels used in the analyses.

Covariates	Scale Level
If a country is being attacked and the aggressor is targeting critical infrastructure (e.g., hospitals or electricity and water supply), [country] should provide military support.	Categorical: 7-point Likert scale (*do not agree at all* to *completely agree*)
If a country is being attacked (without actual fault) and the aggressor is taking away its land, [country] should provide military support.	Categorical: 7-point Likert scale (*do not agree at all* to *completely agree*)

In the next step, these (counterfactual) predictions were used to calculate OMCEs. These were aggregated to the different individual- and attribute-specific IMCEs.

To better understand the associations of different subject-level covariates and individual effects of specific attributes (i.e., IMCEs), we used the two tree-based approaches proposed by CITE. For this, a random forest model was first fit, predicting the IMCEs using the respective individuals' subject-level covariates. We then used decision trees to more thoroughly investigate the relationships of specific IMCEs and covariates for which the previous step suggested relevant contribution to the prediction. As already proposed in CITE, we found complexity parameter values (cp) between 0.02 and 0.04 to yield useful results. Usage of larger cp values resulted in overly simplified trees often consisting of only a single root node. Smaller cp values, on the other hand, often resulted in overly deep trees with little differentiation across many terminal nodes, making the interpretation of substantive differences too difficult. In the next section, we present the results of these analyses, followed by a discussion and comparison to the results reported by CITE.

Results

In Figure 1 we present the AMCEs estimated by averaging the IMCEs calculated using the cjbart model.

Figure 2 displays the variable importance measures for the subject-level covariates as extracted from the cjbart model. Variable Importances are colorized using heatmap-like colorcoding with stronger red (vs. white) color indicating larger importance measures.
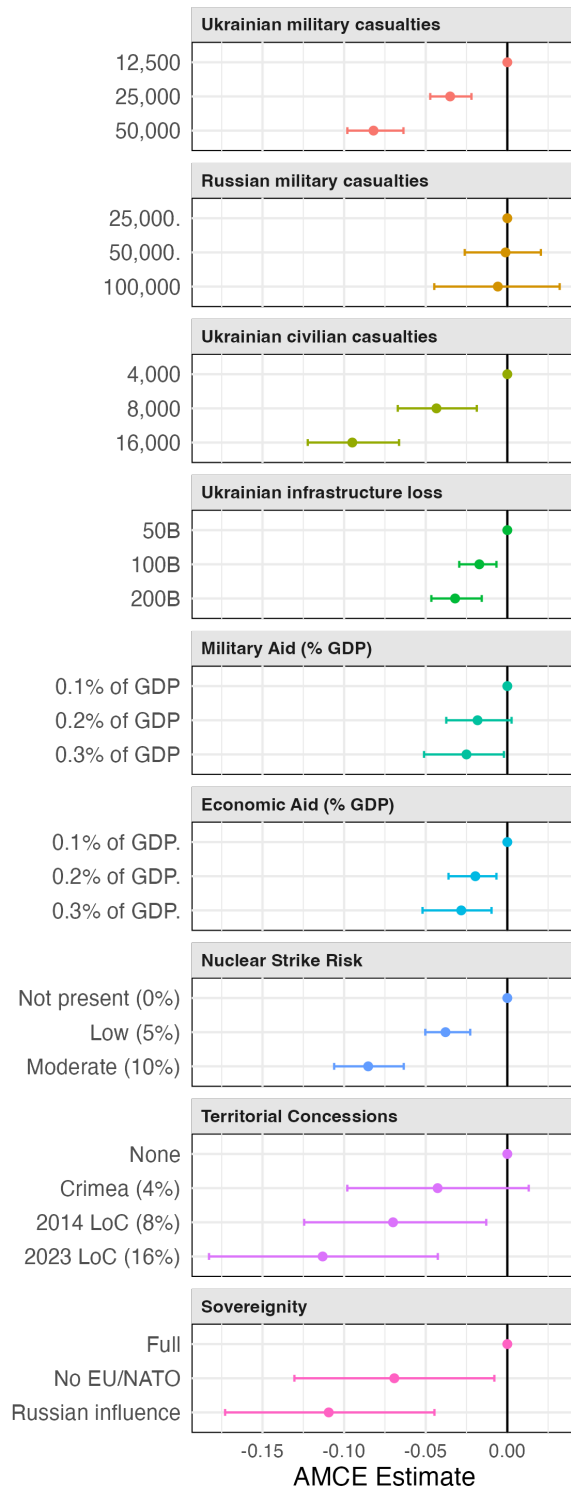
AMCE Estimates with 95% C

Ukrainian military casualties
- 12,500
- 25,000
- 50,000

Russian military casualties
- 25,000.
- 50,000.
- 100,000

Ukrainian civilian casualties
- 4,000
- 8,000
- 16,000

Ukrainian infrastructure loss
- 50B
- 100B
- 200B

Military Aid (% GDP)
- 0.1% of GDP
- 0.2% of GDP
- 0.3% of GDP

Economic Aid (% GDP)
- 0.1% of GDP.
- 0.2% of GDP.
- 0.3% of GDP.

Nuclear Strike Risk
- Not present (0%)
- Low (5%)
- Moderate (10%)

Territorial Concessions
- None
- Crimea (4%)
- 2014 LoC (8%)
- 2023 LoC (16%)

Sovereignty
- Full
- No EU/NATO
- Russian influence

AMCE Estimate

Figure 1: AMCEs

10

Figure 2: Ext VarImps

Figure 3 depicts 4 exemplary decision trees that were fitted to better understand how different subject level covariates contribute to effect heterogeneity. These decision trees were selected based on content-related and interpretational criteria and to highlight how single decision tress can be utilized for model interpretation.

Discussion

Integration of Results

For AMCEs, theoretically most favorable events served as baseline. As can be seen, increased attribute levels (i.e., less favourable events) were usually linked to significantly decreased levels of support. For example, increasing the risk of a nuclear strike from the reference level 'Not present (0%)' to 'Moderate (10%)' decreased the average probability of a participant choosing the latter profile by about 8.5 percentage points. The AMCE point estimates were in line with the AMCEs reported in CITE, which is why we refrain from an in-depth discussion here and refer the interested reader to CITE. HIER WAS DAZU SCHREIBEN DAS WIR HÖHERE SEs HABEN? DAZU SCHREIBEN DIE HALT IN IHREM PAPER EH GAR NIX

As a next step, we predicted the subject-level IMCEs using the subject-level covariates. Based on this random forest model, we then calculated variable importance measures which served
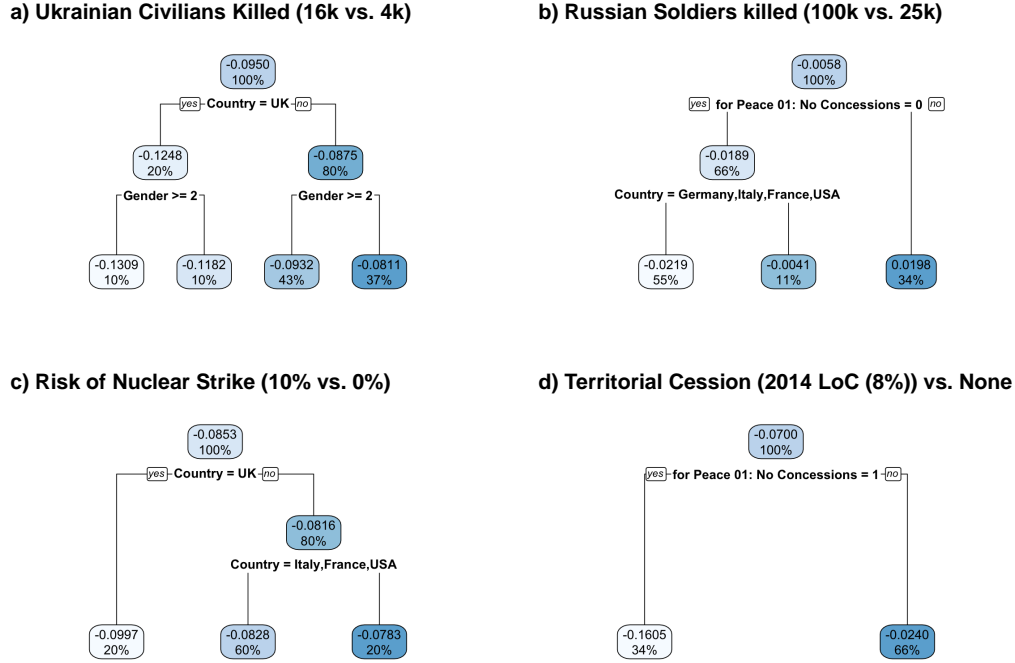
11

a) Ukrainian Civilians Killed (16k vs. 4k)

b) Russian Soldiers killed (100k vs. 25k)

c) Risk of Nuclear Strike (10% vs. 0%)

d) Territorial Cession (2014 LoC (8%)) vs. None

Figure 3: Exemplary deicision trees for predicting IMCEs based on Covariates.

as indicators for variables associated with effect heterogeneity. We found the highest variable importance values for the subject-level covariates country, gender, and the items asking participants about whether they generally support supply of weapons to countries defending themselves against other country's invasions (Q10_10) and whether Ukraine should make any concessions in order to achieve peace (Q15_7).

These variable importance measures do not provide any more interpretability than which covariates in general seem to matter, which is why we further substantiated the previous analysis by fitting single decision trees to different IMCEs. IMCEs for this were selected due to content-related purposes and to highlight how decision trees facilitate interpretation of effect heterogeneity. As can be seen in @image-panel (upper left panel), for participants from countries different to the UK the probability to select a given profile decreased by -12.5% if the respective profile was associated with 16,000 (vs. 4,000) Ukrainian civilian casualties. For participants from the UK, the larger number of civilian casualties was also linked to a lower profile selection probability, although, the attribute level was less influential for their decision. In general, we saw the UK vs other countries split in many different trees possibly indicating slight differences in attitudes towards weapon supplies across these countries. Moreover, whether participants were female (within both UK and Non-UK subgroups) predicted

Apart from this, participants' attitude about whether the Ukraine should make any concessions to Russia if this would lead to a peace agreement predicted some level of effect heterogeneity to an interesting extent. For example, with regard to Russian soldiers killed, people who

responded that Ukraine should not make any concessions, on average were more likely to select profiles with a larger number of Russian military casualties (100,000 vs. 25,000). Interestingly, out of the investigated IMCE decision trees this was the only case for which we observed splits resulting in nodes with different signs meaning that the probability of profile selection decreased in one child node and increased in the other. These results have, however, to be interpreted with caution as the split cannot be interpreted as a sign of statistically significant differences. As for this result, though having different signs, the differences in probability are still small (less than 2 percentage points) and close to zero. Lastly, for the attribute of how much cession of Ukrainian territory a selected profile would result in, we once again found the general attitude towards Ukrainian concessions to predict effect heterogeneity. People who responded that Ukraine should make no concessions were 16 percentage points less likely to select profiles with the 'comparably moderate negative outcome' of Ukraine loosing 8% of their territory (resembling the 2014 Line of Conflict) (vs. reference level 'None (0%)'). For people that did not select the no concessions option, profile selection probabilities for the same attribute level decreased by only 2.4 percentage points.

However, as already outlined in many other papers, these AMCEs cannot be used to reason about absolute profile selection probabilities but are relative in nature. Accordingly a given AMCE has always to be interpreted as change in profile selection probability *relative to a given reference level* of the same attribute. This still holds when comparing IMCEs across different subsets of participants, no matter whether these partitions were or are said-to-be defined theory-based or were generated by data (as in the previous approach). Accordingly the average IMCEs in the different terminal nodes of the decision trees always are relative to the baseline profile selection probability taking into account the reference level *and* the subgroups of participants. The often applied approach of calculating Marginal Means, on the other hand, provides marginalized profile selection probabilities for different attribute levels. This allows for straightforward reading off the absolute profile selection probabilities. However, as marginal means are solely descriptive, they do not allow for any causal interpretation. Accordingly, whether AMCEs or MMs are used should be guided by the kind of conclusions that shall be made. As in the present case, the goal was to understand how different subject-level covariates affect decisions-making among different weapon supply attributes, AMCEs provide the right choice for answering this question.

-Vergleich mit "normaler" Subgruppen Analyse –> aka vergleich mit deren paper

Methodological Discussion

The methodological advantages of cjbart over existing methods to estimate AMCEs and conduct subgroup analyses have been discussed above. To briefly recap, cjbart can estimate complex relations regarding attribute level importances, thereby taking potential effect heterogeneity into account. Using tree-based follow up analyses, variable importance measures (i.e., which covariates matter for which attribute level) can be calculated. Additionally, users

can calculate IMCE differences predicted by person-level covariates to investigate heterogeneity in an exploratory manner. In closing, we now discuss some important methodological points and potential limitations that should be kept in mind when applying cjbart to conjoint designs.

First, cjbart is, like all tree-based methods, a rather exploratory method. This allows for a data-driven investigation of effect heterogeneity without a priori specification of subgroups (when combined with follow-up analyses). However, it also impedes a confirmatory approach to answering hypotheses about underlying theories. For the follow-up analyses using single decision trees, any reasoning from effects of covariates on IMCEs (e.g., people who oppose concessions for peace agreement favor larger territory cessions less) must be done with caution. That is, they cannot readily be interpreted as directed nor as a causal effect of covariates on IMCEs. The "naive" approach of investigating attribute levels that stand out in the variable importance heatmap (like we did above), is useful for *hypothesis generation*. Effects that were found and that seem to align with political theory could now be investigated in more detail. Using appropriate study designs (e.g., experimental settings) or modeling strategies (e.g., confounder adjustment) would now be necessary to investigate the direction of effects and to approach the hypotheses in a more causal manner.

Second, and closely related, while the decision trees offer an easy interpretation of subgroup differences, they do not provide information on whether these differences are statistically significant. This is because decision trees as implemented by CITE and also in our article base their split decision on a maximal reduction of *impurity*. That is, the goal of decision trees is to partition the data so that observations in the resulting nodes are as homogeneous as possible (in the sense of reduced variance in nodes). These splitting decisions are, however, not based on statistical inference. Consequently, any two given terminal nodes that show differences (in IMCEs, in our case) do not necessarily show statistically significant differences. Domain expertise when interpreting the results is needed to reason about whether the differences are practically meaningful. For example, for the result of changed signs in IMCEs reported above, it is a theoretical and content related question whether the difference of around 2 percentage points is relevant. A possible extension would be to use a different decision tree algorithm, for example conditional inference trees CITE. These types of trees base their split decisions on non-parametric hypotheses tests. Nonetheless, domain expertise would still be needed to assess whether a statistically significant split is substantially meaningful.

Third, more simulated and empirical research on cjbart is needed to properly assess the stability of its solutions. Internally, the *cjbart()* function as implemented by CITE calls the *mc-pbart()* function from the *BART* package CITE. This function estimates complex relations using the BART model described above and uses a seed (which defaults to 99). Thus, when repeatedly used on the same data, users should always receive the same results (of AMCEs). Simulation studies should be conducted to assess the variability in results when seeds are changed. Additional variance in results is then introduced when using random forests to assess variable importances. This step should be included in these simulations to investigate whether, and if yes, how strongly changes in BART results are perpetuated in the variable importance results.

Other factors that might influence cjbarts results are the specific settings of hyperparameters. Hyperparameters are second-order parameters that cannot be estimated by the data but that have to be set prior to estimating the model. Examples of hyperparameters of the cjbart model are the number of individual trees that are grown sequentially and the number of cut points that are investigated (i.e., the number of "segments" of, for example, age for which a split is considered). In our analyses, we used the default values of these hyperparameters (50 trees and 100 cut points). However, it would also be possible to tune these values, that is, to try out different settings and choose the most optimal values (with respect to some evaluation metric). Because tuning hyperparameters can be computationally expensive, it is an interesting topic of future methodological research to assess whether tuning in the case of cjbart is worth the additional computational burden. Tuning hyperparameters would also be possible for the random forest when calculating variable importances. However, random forests have been shown to have good performance with default values of its hyperparameters (CITE), so we believe the focus should be on the hyperparameters of the upstream BART model.

HIER NOCH EIN PAAR SÄTZE ZU ANDEREN BEIDEN METHODEN; VORTEILE; NACHTEILE; WARUM BEI UNS CJBART

-weitere Modelle: -factorHet + idee kurz -CRT + idee kurz Warum cjBart
das Modell stark machen

Conclusion