Using conjoint experiments to study preferences in multidimensional choice contexts

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Abstract

Conjoint experiments are a standard tool to measure (stated) preferences in the context of multidimensional choices on issues ranging from immigration to democratic innovations. This case study demonstrates how to design and effectively deploy a (survey embedded) conjoint experiment. Practical recommendations are offered along with the conjoint experiment checklist of steps to accomplish before executing a conjoint survey experiment, as well as steps to follow during the execution of the project itself.

Learning Outcomes

By the end of this case study, students should be able to:

- Identify a research question that qualifies for a conjoint experiment
- Assess how to effectively deploy a survey embedded conjoint experiment
- Analyze and interpret the results from conjoint experiments

Project Overview and Context

When people choose what product to buy, they typically form their preferences based on multiple criteria. For example, if they are looking to buy a computer, they consider variables such as price, look, reliability, processor speed, and quality of sound. They assign different degrees of importance to these various features and they are able to trade off some features for others. Such multidimensional choices go beyond shopping and can be easily identified in politics and public policy. Think, for instance, about electoral choices. Why does a person prefer Party X over Party Y, or why does he or she vote for Candidate A instead of for Candidate B? Here again, the choice is multidimensional since preferences for given candidates are formed based on not only their experience or position on various salient ideological issues but also their appearance or the way they talk. Conjoint experiments are the main analytical tool to capture such multidimensional preferences. This method is suitable for assessing people's preferences in multidimensional choice contexts; in other words, in situations where there are many attributes shaping preferences, such as in the contexts of choosing political candidates and supporting reforms. At a more general level, conjoint experiments are applied to test the explanatory power of multiple hypotheses within a single experimental study design.

In this case, I detail how to effectively apply a (survey embedded) conjoint experiment to study public preferences around a social benefit program and its reform. I do this by examining the study of preferences related to Poland's well-known "500 Plus" social program. With this study, I was interested in learning which reforms of the "500 Plus" program the public would welcome and which features of reform are most important to the public. In its 2021 version, the "500 Plus" program was an universal monthly cash transfer of 500 PLN (approximately 130 USD as of September 2021) for all children below 18 years of age in a family. Politicians and the media in Poland discuss the various reforms of the "500 Plus" program practically daily. Some of the most contentious issues revolve around the fact that the benefits are not means tested, have quite generous coverage (i.e., they apply to all children below 18 years of age), and lose their purchasing power due to a relatively high rate of inflation. With the conjoint (survey) experiment, I identified the most important design features of the "500 Plus" program and ascertained the public's most favored design for such a program.

Conjoint experiments gained popularity in the mid-2010s when the methodological foundations and estimation procedures for conjoint experiments were laid out by Hainmueller et al. (2014). Before conjoint experiments gained in popularity, factorial vignette experiments were the standard tool to capture the causal impact of various features on (stated) preferences toward political candidates, parties, and public policies, to name but a few. Standard vignette experiments use brief text describing a situation or person and randomly vary a part of the text that is related to a tested hypothesis. Because of their design features, which will be discussed later in this case study, conjoint experiments turn out to have several advantages over standard factorial vignette experiments. First, conjoint experiments have a potential to reduce social desirability bias and satisficing and, hence, have a higher internal and external validity (Hainmueller, Hangartner, et al., 2015). This is achieved by the fact that respondents do not need to explicitly declare which of the many attributes they are exposed to drives their decision. Second, these experiments are more easily able to deal with ordering effects when they are displayed in their traditional tabular form. Third, they allow the collection of much more data from respondents. In the conjoint experiments, there are many randomly varying attributes, and respondents cannot detect which attribute is of main interest for a researcher. Thus, respondents can be exposed to multiple conjoint tasks. Given these advantages, the conjoint experiments are widely applied in political science to capture multidimensional preferences toward, for instance, political candidates (e.g., Graham & Svolik, 2020), immigrants (e.g., Hainmueller & Hopkins, 2015), and institutional reforms (e.g., van der Does & Kantorowicz, 2021). Likewise, they are very popular in studying public preferences toward public policy changes such as social policies (e.g., Gallego & Marx, 2016), climate policies (e.g., Bechtel et al., 2017, Beiser-McGrath & Bernauer, 2019), economic policies (e.g., Bansak et al., 2021), foreign policies (e.g., Doherty et al., 2020), and counter-terrorism strategies (e.g., Kantorowicz-Reznichenko et al., 2021).

Section Summary

- Vignette experiments were the standard tool for measuring determinants of public preferences. However, they proved to have some limitations, in particular in studying preferences in the multidimensional choice contexts.
- Conjoint experiment has become a standard tool to measure preferences in the context multidimensional choices.
- Conjoint experiments are used by political science and public policy scholars to capture public preferences on issues ranging widely from immigration to democratic innovations.

Research Design

In a conjoint experiment, respondents are presented with multiple attributes to evaluate (e.g., gender, age, education, political affiliation, and so forth, in the context of choosing a political candidate). These attributes are typically organized within a table and their order is random. Importantly, each attribute must have at least two levels (e.g., the gender attribute typically contains two levels: female and male) and these levels must be randomly assigned for each of the tasks performed by a respondent (often respondents perform multiple evaluations).

When deploying a survey embedded conjoint experiment, one needs to make several fundamental decisions. Some decisions simply consider the design of the conjoint experiment and some others relate to the contextual choice (e.g., in which country to perform a survey) and sampling strategy (e.g., should the sample be nationally representative?). When it comes to the design of the conjoint experiment itself, the major decisions pertain to (1) what and how many attributes should be included in the conjoint table, (2) what and how many levels should each attribute contain, (3) how many different profiles should appear in any given task, (4) how many different tasks should each respondent perform, and, finally (5) what are the outcome variables.

The policy dimensions of the “500 Plus” program were used to choose the survey attributes for the study. Specifically, the attributes selected for the conjoint table included:

- generosity (the size of the benefit),
- its scope (first, in terms of the number of children covered by the program per family and, second, the eligible age of children),
- eligibility criteria (in terms of both income and nationality),
- the source of financing, and,
- lastly, the indexation of benefits.

These attributes were selected based on the review of media debates discussing the reforms of the “500 Plus” program. Overall, for this study, seven attributes were chosen. Though, if given an opportunity to run this experiment once again, I would have added one more attribute, namely the employment criterion, on top of the income and nationality criteria. While there are no clear guidelines on what the optimal number of attributes is, the research shows that respondents can handle quite a large number of them (Bansak et al., 2021). This can vary depending on how familiar respondents are with the choices under investigation, but seven attributes did not seem excessive for this reform study, particularly given the fact that respondents could be expected to be familiar with the well-known “500 Plus” program. In conjoint tables, the attributes are typically displayed in a random order to deal with the ordering effect. The order is randomized for each respondent but is kept constant within the respondents. As discussed later, every respondent performs several tasks, and to limit their cognitive burden, the order of attributes is the same.

After deciding on the substance and the number of attributes, the next step was to design the levels of each attribute, that is, to list the categories that randomly varied within attributes. These categories needed to be substantively informative, feasible, and concise to minimize the cognitive burden on respondents. Besides this, the number of levels (the attribute with the greatest number of levels) is decisive in deriving the desired sample size (for power analysis in conjoint experiments, see Schuessler & Freitag, 2020 and Stefanelli & Lukac, 2020). For that reason, the general advice is to minimize the number of levels, but of course, not at the expense of compromising the validity of the study. In the context of this study, apart from one attribute, which has two levels, all the remaining attributes contained three levels. All the attributes and levels of the "500 Plus" reform experiment are displayed in Table 1.

Table 1. Attributes and levels of the "500 Plus" program reform

No	Attributes	Levels
1	Size of benefits	300 PLN 500 PLN* 700 PLN
2	Source of financing	Income tax Public debt Savings in other public spending
3	Indexation of benefits	No* Yes, for inflation
4	Income criterion	Income below the national average Income below the poverty line Irrespective of income*
5	Nationality criterion	Polish families Polish families taxed in Poland All families taxed in Poland*
6	Number of children eligible	All children in the family* Second and each subsequent child in the family Third and each subsequent child in the family
7	Eligible age of children	Up to 18 years of age* Up to 12 years of age

No	Attributes	Levels
		Up to 6 years of age

*Denotes the features of the “500 Plus” program that were currently in place as of September 2021.

A standard approach in conjoint experiments is to display two (candidate or policy) profiles side-by-side. This particular design is then called a paired-profile conjoint experiment. Other types of design, such as displaying one or more than two profiles at the same time, are also feasible. The multiple profile design is especially suitable when ultimately one candidate or one policy is being chosen from a set of alternative candidates or policies. Unlike the single profile conjoint, the multiple profile set-up forces respondents to more carefully consider the trade-offs between the displayed profiles. On the other hand, displaying multiple profiles at the same time may impose an excessive cognitive burden on respondents. For that reason, a paired-profile design (displaying two profiles side-by-side) is typically considered an optimal solution. Given its benefits, this reform study opted for the paired-profile design for my research into the “500 Plus” program. An example of a randomly generated conjoint table is shown in Table 2.

Table 2. An example of a paired-profile conjoint experiment

	Reform 1	**Reform 2**
Number of children eligible	Second and each subsequent child in the family	All children in the family
Eligible age of children	Up to 18 years of age	Up to 12 years of age
Indexation of benefits	No	No
Nationality criterion	All families taxed in Poland	Polish families taxed in Poland
Source of financing	Public debt	Savings in other public spending
Size of benefits	500 PLN	500 PLN
Income criterion	Income below the national average	Income below the national average

After designing the attributes and levels of the conjoint table, the reform study then had to choose the number of tasks each respondent would encounter. It is typical in conjoint experiments to let each respondent perform 5–10 tasks, hence, to be exposed to up to 10–20 different (candidate or policy) profiles in case the paired-profile conjoint experiment was chosen. The research shows that there is a limited increase in survey satisfaction even if respondents have as many as 30 tasks to perform (Bansak et al., 2018). Yet, the overall choice of the number of tasks should take into account the entire survey design, which typically comes with a battery of pre- and post-treatment questions, and then conform to the agreed length of the survey. Therefore, the typical choice is to select between 5 and 10 tasks per respondent. Given the overall survey design for this study, six conjoint tasks were chosen.

Lastly, I needed to decide on the types of questions that would capture respondent's (stated) preferences and constitute the outcome variables in my conjoint experiment. There are two common ways to measure preferences in these types of experiments: (1) forced choice questions whereby respondents declare which of the displayed choices they prefer, and (2) rating questions whereby displayed profiles are rated on a Likert scale (typically 1–7 or 0–10 scale) with larger numbers indicating greater approval. Note that whereas the rating questions allow equal rating between the profiles, forced choices do not leave room for it, and thus encourage the respondents to put more effort into trading off different attributes and their levels. Given this knowledge, for the "500 Plus" study I chose to employ a forced choice question in order to "push" respondents to consider the trade-offs more carefully. The general recommendations for conjoint experiments, permitting the time constraints for the survey, is to use various types of outcome variables. It typically means employing both forced choices and rating questions together and ordering them randomly. Due to a survey time constraint, I left the rating questions out. However, if more time for the survey was permitted, I would definitely add the rating questions.

Section Summary

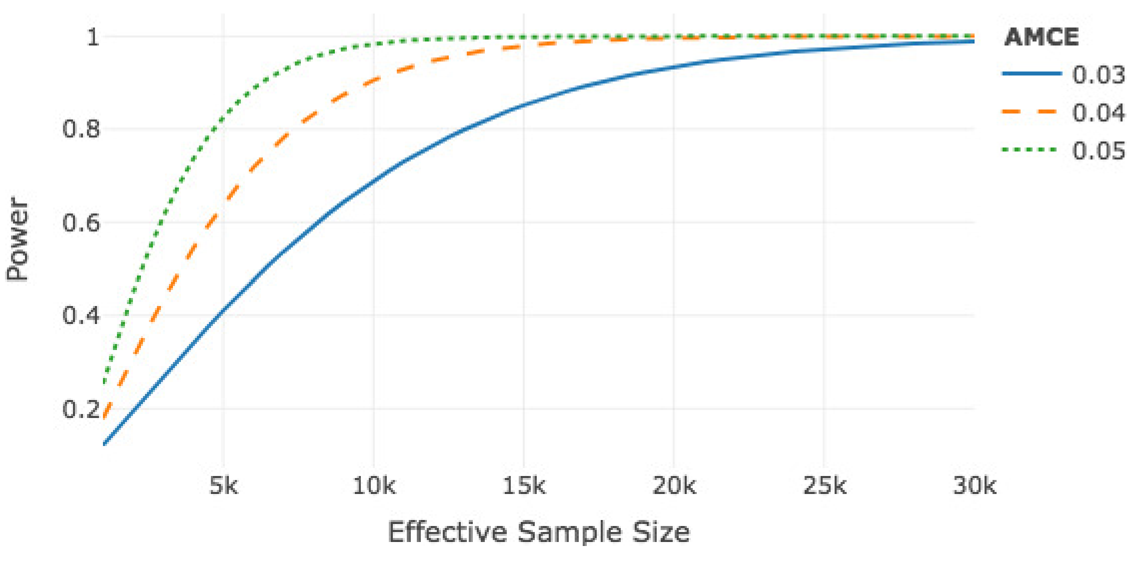
- There are at least five crucial steps in designing a conjoint experiment, choosing (1) the substance and number of attributes, (2) levels that vary within attributes, (3) the number of profiles to display, (4) the number of tasks each respondent performs, and (5) the outcome variables.
- The most typical designs have between 3 and 8 attributes, which contain between 2 and 6 levels. The most common design is a paired-profile conjoint experiment with forced choice and rating questions capturing outcome variables. The standard number of tasks per respondent varies between 5 and 10.
- While these seem to be the most common design choices, the recommendation is always to consider all of them carefully against the background of each particular research question.

Research Practicalities

While a standard vignette experiment can be relatively easily administered, for example, as a pen-and-pencil survey, a conjoint experiment requires software for proper deployment because respondents perform several tasks with randomly ordered attributes and randomly assigned attribute levels. Among researchers, Qualtrics has become one of the main platforms for administering surveys, including conjoint experiments. While the commercial version of Qualtrics does contain a module for creating conjoint experiments in an interactive way, a standard version of Qualtrics, which researchers typically have access to, does not have it. Nonetheless, Strezhnev et al. (2014) have created an easy to navigate software package called "Conjoint Survey Design Tool" (SDT), which greatly facilitates the implementation of conjoint experiments in Qualtrics. This is exactly the tool I used to design the "500 Plus" conjoint experiment. The end product generated by this software is a php file that contains all the design features of the conjoint, such as the number of attributes, levels, profiles, and tasks. After loading the php file onto a server and after allowing Qualtrics to extract contents from it via a web service, one is able then to fill in the conjoint tables created in Qualtrics with randomly ordered attributes and randomly assigned levels.

Before collecting the data, the sample size (i.e., the number of respondents taking part in the survey) was chosen for the "500 Plus" study. To arrive at this number, I conducted an *ex ante* power analysis. Figure 1 displays the level of statistical power for the main quantity of interest, AMCE (average marginal component effect), at three different effect sizes, 0.03, 0.04, and 0.05, respectively. It is of note that these calculations were made for a conjoint design with a maximum of three attribute levels and forced choice outcome, reflecting the design features of my "500 Plus" conjoint experiment. It can be read from Figure 1 that with an effective sample size of 17,500 roughly 90% statistical power was achieved for the small effect of 0.03. Dividing the effective sample size (17,500) by 12 (the number of profiles displayed per task multiplied by the number of tasks: 2 × 6 = 12) gave an optimal number of respondents equal to 1459. The final sample size drawn for this study, in terms of number of the respondents recruited, amounted to 1587, thus meeting the minimum sample size for detecting relatively small effects.

Figure 1. power calculations for forced-choice conjoint experiment with a maximum of three attribute levels.



Since the goal of the "500 Plus" reform experiment was to provide a nationally representative result, the respondents were recruited by a professional survey company. The quota sampling applied in my study was supposed to reflect the general population in terms of age, gender, and education. Naturally, the exact composition of a sample depends on the particular research question at hand. In some cases, the researchers might be interested in gathering data from politicians or street bureaucrats (e.g., Jankowski et al., 2020) or from convenience samples obtained through Facebook or other social media platforms (e.g., Zhang et al., 2018).

While the estimation of the main parameters of interest in the conjoint experiment (AMCE) could have been performed with any statistical software, there were at least two dedicated packages for me to choose from for the conjoint experiment analysis in R (i.e., *cjoint* by Barari et al., 2018 and *cregg* by Thomas Leeper). They facilitate analysis in several ways. For instance, they enabled me a fast transformation of data retrieved from Qualtrics. To be more precise, they transform data from a wide format to a long format in such a way that each row corresponds to one particular policy profile. With the dedicated functions from these packages, I was able to quickly estimate the AMCEs. Even though it was not needed in the context of my study, these packages would also have made it easier to handle more complex conjoint designs, such as when some attribute levels cannot appear together in a conjoint table (due to the fact that they would, for instance, create an impossible policy mix) or when the probability of random assignment of some levels is not equal.

Section Summary

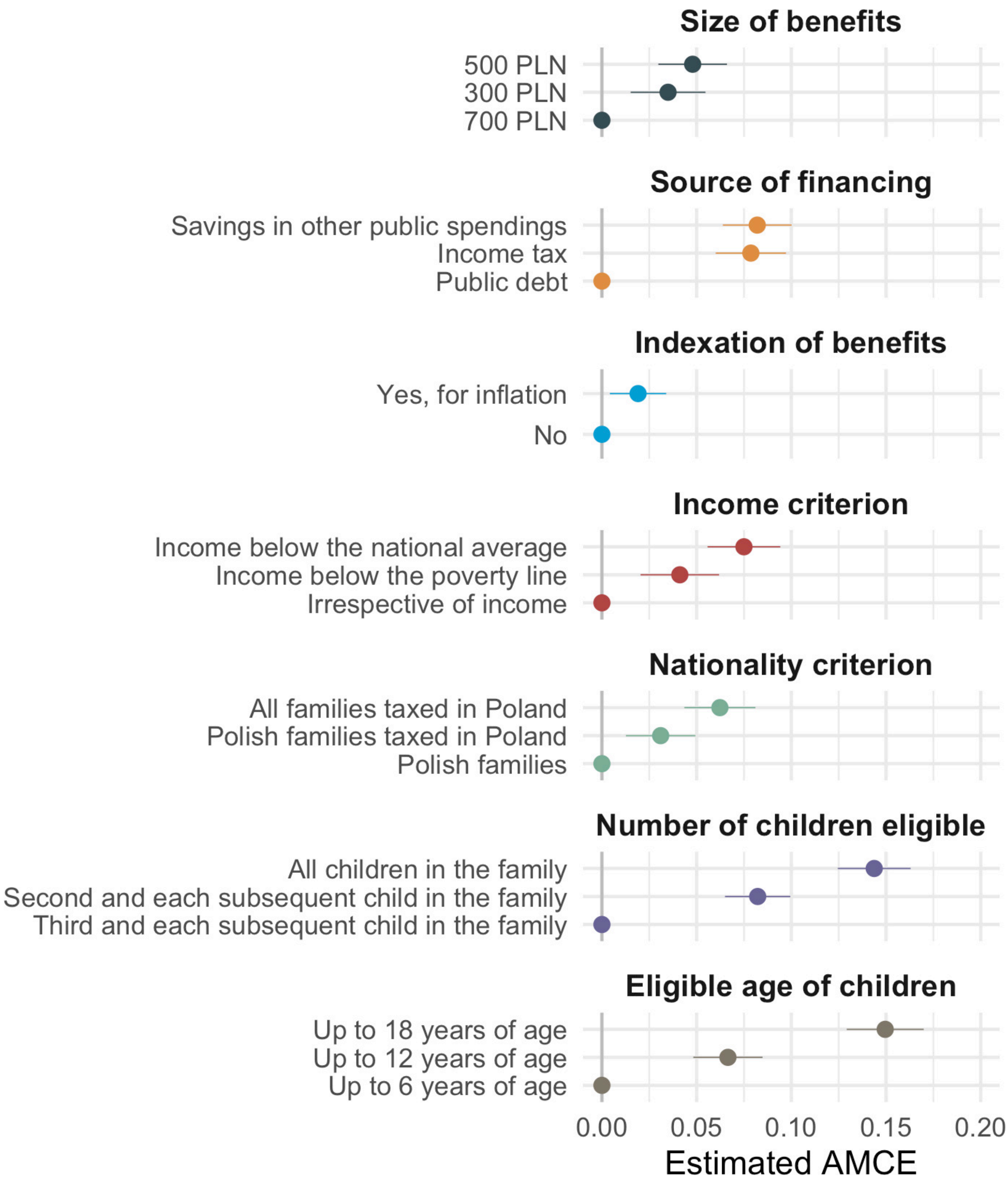
- Conjoint experiments are more difficult to deploy than standard vignette experiments.
- Before launching conjoint experiments, it is strongly advisable to perform power analysis, which will inform the decision about the desired sample size.
- Several packages exist for R that greatly facilitate the analysis of conjoint experiments.

Method in Action

The AMCE is the core estimated causal parameter of interest in conjoint experiments. The AMCE captures the effect of a particular attribute level averaged across all other attributes that appear in the conjoint table. What that in practice means is that AMCE can be obtained by running a multiple OLS (ordinary least square) regression model where all variables are entered as covariates without their interactions. This is different from typical factorial vignette experiments whereby authors are, by and large, interested in conditional effects, which require an interaction between constitutive terms. These interaction models commonly require a large sample size for detection of such interaction (moderating) effects. While conjoint experiments also require large sample sizes, if these models were to be calculated in a traditional way, (i.e., with interaction terms), these types of experiments would require a sample size which would be far too large, making these experiments cost ineffective.

Figure 2 presents the results from the “500 Plus” conjoint experiment where the respondents were asked to state their preferences over various reform proposals of this program. The horizontal axis captures the direction and size of AMCEs estimated for the forced choice (binary) outcome variable. Since the outcome variable is binary, the results can be interpreted as a change in probability of choosing a given profile. Thus, looking at the first estimated causal effect next to the “500 PLN” attribute, one should conclude that the probability of choosing the reform proposals with the size of benefits at 500 PLN was 5 percentage points higher than the probability of choosing the reform offering 700 PLN averaged across the other six attributes that appear in the conjoint table. Overall, one can conclude that respondents preferred smaller rather than larger benefits.

Figure 2. The main results from the “500 Plus” reform conjoint experiment.



In a similar vein, the AMCEs can be interpreted for the income criterion attribute. It is evident that the probability of choosing a profile increases by some 7.5 percentage points if the income criterion is introduced (benefits for families with an income below the national average) as compared to the situation where there are no income criteria. Hence, the reform study found that the public was strongly in favor of introducing reforms that limit access to benefits via means testing.

Besides interpreting the AMCEs for particular attributes, by looking at the magnitude of AMCEs across attributes, their overall importance can also be gauged. In other words, the reform study showed the weight that respondents assigned to the various attributes when making their decisions. In the forced choice set-up, as the one analyzed here, the importance can be compared directly with only these attributes, which have the same number of levels. Thus, here, six out of seven attributes, which include three levels, are directly comparable (the indexation of benefits attribute has two levels, but its AMCE is nonetheless relatively low). By looking at the magnitude of AMCEs for the six three-level attributes, we conclude that the scope of benefits, captured by the number of children eligible and the eligible age of children, were the most important reform features. The source of financing and the income criterion scored in the middle in terms of importance. Lastly, based on these results, one could argue that the reform which would be the most preferred by the public would include the following components: (1) size of benefit: 500 PLN, (2) source of financing: either from income taxes or from savings in other budgetary areas, (3) indexation of benefits to keep up with the rate of inflation, (4) means tested benefits for families with income below the national average, (5) benefits available to all families taxed in Poland, (6) benefits available for all children in the family, and (7) benefits should be available for every child up to 18 years of age.

Investigating AMCEs for all attributes and comparing their importance constituted the main analysis for my reform study. Researchers are often interested in even more complex analysis, such as examining the effects of one attribute conditional on another attribute, though. For example, in the context of the “500 Plus” reform experiment, one could hypothesize that the effect of the generosity of benefits depends on the scope of benefits. To be more precise, respondents might prefer larger benefits if the scope of benefits is small, and vice versa. Yet another question could be about the comparison of AMCEs across various (sub)groups of respondents, say, respondents leaning toward left and right ideologies. In line with a common perception, one could expect that respondents with more progressive views support more generous and extensive benefits as opposed to conservative respondents who are typically supportive of small and well-targeted benefits. If these are the types of research questions that the researcher is interested in, then the estimated parameters are called conditional AMCEs. It should be stressed that these types of analysis require large sample sizes. Leeper et al. (2019) give an account of the pitfalls of this type of analysis and offers a standard solution to comparing subgroups in the context of conjoint experiments. Even though these types of questions could be asked and answered in the context of my study, this was not my primary interest. Nonetheless, in my future work, I aim to tackle these questions and more advanced types of analysis as well.

Section Summary

- The main causal parameter of interest in the conjoint experiments is called the AMCE. In the forced choice conjoint design, it captures the change in probability of choosing a profile containing a given level of attribute as compared to some baseline level while holding equal the joint distribution of other attributes.

- The comparison of AMCEs across attributes enables the assessment of the relative importance of attributes in driving the choice.
- More complex types of analysis, which imply an interaction between attributes and comparisons across subgroups of respondents, are possible too but they require larger sample sizes.

Practical Lessons Learned

This section offers a checklist of steps one could/should accomplish before executing a conjoint survey experiment, as well as steps to follow during the execution of the project. This checklist is derived based on the “500 Plus” reform experiment

Conjoint experiment checklist:

1. Make sure that your study/research question qualifies for a conjoint experiment. In general, that means that your research goal is to capture and analyze multidimensional preferences. This was the case with my conjoint experiment study: I was interested in examining which dimensions of the “500 Plus” program the public believed should be reformed.
2. Think carefully about the design of your conjoint experiment in terms of the substance and number of attributes and levels, and the number of tasks each respondent performs. At this stage, you also need to decide whether respondents assess one or more profiles per task. As in my “500 Plus” study, those choices require a deep knowledge of the contexts under investigation. If I was given an opportunity to rerun this experiment and the survey could be longer, I would definitely add one more attribute (the “employment” criterion) to the conjoint table and would add rating questions.
3. Conduct a power analysis. Derive a desired sample size for detecting effect sizes of interest based on power analysis tools created by Schuessler and Freitag (2020) and Stefanelli & Lukac (2020). Note that this point is related to point 2, as power analysis largely depends on the conjoint experiment design choices. In my study, I used the above-mentioned tools for conducting power analysis and found them useful.
4. If required at your institute, obtain an ethics (internal review) board approval for conducting your study. From my experience in submitting applications to the ethics board, I would recommend to reserve at minimum 6 weeks for getting an ethical approval.
5. If you aim to publish your research in an academic journal, pre-register your study on one of the commonly used platforms, for example, Open Science Framework (https://osf.io/), As Predicted (https://aspredicted.org/), Evidence in Governance and Politics (https://egap.org/registry/) and AEA RCT Registry (https://www.socialscienceregistry.org/). This study was not preregistered, but I aim to follow this step in any of my future work on public perceptions toward the “500 Plus” program.
6. If you aim to gather data on a representative sample of the population, contact a survey company and ask for a quote. In most cases, this step is only feasible if your research acquires some external funding. This was precisely the procedure I followed in my study.
7. Build your survey in Qualtrics. Follow guidelines prepared by Strezhnev et al. (2014) for embedding

a conjoint experiment within Qualtrics. I found these guidelines extremely helpful in my study.

8. Run a pilot study to check if the randomization of attributes and levels works correctly and whether all the tasks are clear and understandable for respondents. Give an opportunity to the respondents to express their opinion about the survey through an open-ended question embedded at the end of the survey. After running the pilot, some refinement of the survey might be necessary. Even though I very much recommend running pilots, I was not able to run it for the "500 Plus" study due to budget constraints.
9. Based on the pilot data, write a code, for example in R, that will include all steps of your analysis, that is, diagnostic tests (such as, for example, carryover effect) and estimation of AMCE and/or conditional AMCE. Using off-the-shelf packages for loading and analyzing conjoint experiment data, such as *cjoint* and *cregg*, should be helpful. Given that I had not run the pilot, I was not able to write the code before the main launch. Should I run the study again, however, I would definitely follow this recommendation.
10. Launch the final version of the survey.
11. Use the code written in step 9 to analyze the full dataset. If necessary, extend the code to provide some additional analyses. As I was not able to run a pilot study for the "500 Plus" study, I wrote the code and analyzed the results only after the full launch. If given an opportunity to run this study again, I would definitely perform the pilot first.

Section Summary

- To robustly execute a survey experiment, a lot of steps need to be accomplished before the study is actually launched.
- A checklist of steps to follow can help in the careful and robust implementation of (survey embedded) conjoint experiments.

Conclusions

Conjoint experiments are well-suited to study preferences in the context multidimensional choice architecture. In the political and public policy contexts, these kinds of choices are ubiquitous. This case study demonstrated how a conjoint experiment can elicit which design features of a social policy reform are the most favored and important to the general public. With this information at hand, straightforward recommendations can be made on how to modify national policies so that they are in line with public preferences. Since conjoint experiments constitute a relatively novel methodology, there is a wide range of possibilities to apply them in various contexts. However, the novelty of conjoint experiments also implies that some of the methodological issues are still being worked out and thus applied researchers should stay alert and constantly follow the latest developments. One such issue considers the fact that randomization of attributes and their levels may lead to profiles that are highly unlikely in the real-life setups. Another and arguably more serious limitation—as it touches upon external validity—is the fact that typically people form their preferences via visual and audio modes, whereas in the conjoint experiments the attributes are written and presented in a tabular form. This mode of presentation may lead respondents to evaluate relevant choices differently than it would be otherwise done in the real-life context (Bansak et al., 2021).

Section Summary

- Because of the novelty of conjoint experiments, there is a wide range are areas where they can be successfully applied.
- Applied researchers are recommended to stay alert and look for the most recent developments pertaining to conjoint experiments.

Classroom Discussion Questions

1. What is the difference between a standard factorial vignette experiment and a conjoint experiment?
2. Conjoint experiment questions are typically displayed in tables. What potential problems might arise with such a presentation? What solutions might there be?
3. The most common design in conjoint experiment is a paired-profile design (i.e., two profiles are presented side-by-side). What study or context when presenting a single profile do you think would be a better option? Why?

Further Reading

Bansak, K., **Hainmueller, J.**, **Hopkins, D. J.**, & **Yamamoto, T.** (2021). Conjoint survey experiments. In **J. N.Druckman** & **D. P.Green** (Eds.), *Cambridge handbook of advances in experimental political science*. Cambridge University Press.

Diaz, G., **Grady, C.**, & **Kuklinski, J. H.** (2020). Survey experiments and the quest for valid interpretation. In **L.Curini** & **R.Franzese** (Eds.), *The SAGE handbook of research methods in political science and international relations*. SAGE Publications Ltd.

Knudsen, E., & **Johannesson, M. P.** (2019). Beyond the limits of survey experiments: how conjoint designs advance causal inference in political communication research. *Political Communication*, 36(2), 259–271.

Web Resources

Lukac, M., & Stefanelli, A. (2020). *Conjoint experiments: Power analysis tool*. https://mblukac.shinyapps.io/conjoints-power-shiny/

References

Bansak, K., **Bechtel, M. M.**, & **Margalit, Y**. (2021). Why austerity? The mass politics of a contested policy. *American Political Science Review*, 115(2), 486–505. 10.1017/S0003055420001136

Bansak, K., **Hainmueller, J.**, **Hopkins, D. J.**, & **Yamamoto, T**. (2018). The number of choice tasks and survey satisficing in conjoint experiments. *Political Analysis*, 26(1), 112–119. 10.1017/pan.2017.40

Bansak, K., **Hainmueller, J.**, **Hopkins, D. J.**, & **Yamamoto, T**. (2019). Beyond the breaking point? Survey satisficing in conjoint experiments. *Political Science Research and Methods*, 9(1), 53–71. 10.1017/psrm.2019.13

Barari, S., **Berwick, E.**, **Hainmueller, J.**, **Hopkins, D.**, **Liu, S.**, **Strezhnev, A.**, & **Yamamoto, T**. (2018). *cjoint: AMCE Estimator for Conjoint Experiments*. https://cran.r-project.org/web/packages/cjoint/index.html

Bechtel, M. M., **Genovese, F.**, & **Scheve, K. F**. (2017). Interests, norms and support for the provision of global public goods: The case of climate co-operation. *British Journal of Political Science*, 49(4), 1333–1355. 10.1017/S0007123417000205

Beiser-McGrath, L. F., & **Bernauer, T**. (2019). Could revenue recycling make effective carbon taxation politically feasible?*Science Advances*, 5(9), eaax3323. 10.1126/sciadv.aax3323

Doherty, D., **Bryan, A. C.**, **Hanania, D.**, & **Pajor, M**. (2020). The public's foreign aid priorities: Evidence from a conjoint experiment. *American Politics Research*, 48(5), 635–648. 10.1177/1532673X20939925

Gallego, A., & **Marx, P**. (2016). Multi-dimensional preferences for labour market reforms: a conjoint experiment. *Journal of European Public Policy*, 24(7), 1027–1047. 10.1080/13501763.2016.1170191

Graham, M. H., & **Svolik, M. W**. (2020). Democracy in America? Partisanship, polarization, and the robustness of support for democracy in the United States. *American Political Science Review*, 114(2), 392–409. 10.1017/S0003055420000052

Hainmueller, J., **Hangartner, D.**, & **Yamamoto, T**. (2015). Validating vignette and conjoint survey experiments against real-world behavior. *Proceedings of the National Academy of Sciences of the United States of America*, 112(8), 2395–2400. 10.1073/pnas.1416587112

Hainmueller, J., & **Hopkins, D. J**. (2015). The hidden American immigration consensus: A conjoint analysis of attitudes toward immigrants. *American Journal of Political Science*, 59(3), 529–548. 10.1111/ajps.12138

Hainmueller, J., **Hopkins, D. J.**, & **Yamamoto, T**. (2014). Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments. *Political Analysis*, 22(1), 1–30. 10.1093/pan/mpt024

Jankowski, M., **Prokop, C.**, & **Tepe, M**. (2020). Representative bureaucracy and public hiring preferences: Evidence from a conjoint experiment among German municipal civil servants and private sector employees. *Journal of Public Administration Research and Theory*, 30(4), 596–618. 10.1093/jopart/muaa012

Kantorowicz-Reznichenko, E., **Kantorowicz, J.**, & **de Vries, G**. (2021). *Public perception and counter-terrorism measures: A conjoint experiment*. Working Paper.

Leeper, T. J., **Hobolt, S. B.**, & **Tilley, J**. (2019). Measuring subgroup preferences in conjoint experiments. *Political Analysis*, 28(2), 207–221. 10.1017/pan.2019.30

Schuessler, J., & **Freitag, M**. (2020). *Power analysis for conjoint experiments [SocArXiv]*. 10.31235/osf.io/9yuhp

Stefanelli, A., & **Lukac, M**. (2020). Subjects, Trials, and Levels: Statistical Power in Conjoint Experiments. *SocArXiv*. 10.31235/osf.io/spkcy

Strezhnev, A., **Hainmueller, J.**, **Hopkins, D. J.**, & **Yamamoto, T**. (2014). *Conjoint Survey Design Tool*. https://github.com/astrezhnev/conjointsdt

van der Does, R., & **Kantorowicz, J**. (2021). Why do citizens (not) support democratic innovations? The role of instrumental motivations in support for participatory budgeting. *Research & Politics*, 8(2). 10.1177/20531680211024011

Zhang, B., **Mildenberger, M.**, **Howe, P. D.**, **Marlon, J.**, **Rosenthal, S. A.**, & **Leiserowitz, A**. (2018). Quota sampling using Facebook advertisements. *Political Science Research and Methods*, 8(3), 558–564. 10.1017/psrm.2018.49