Experimental Methods Lecture 5

Discrete Choice Experiments

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Overview

- Road Map
  - Conjoint
  - Causal Inference with “Text”
- References and Data
  - https://www.pnas.org/doi/full/10.1073/pnas.2026382118
  - https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/PMV0TG

Conjoint Experiments

Conjoint Experiments

- Typical survey experiments test uni-dimensional causal effect
  - Treatment versus Control
- Typical vignette experiments: immigration, candidate, racial cue
- But what components of manipulation produce observed effect?
  - Why does immigration status matter?

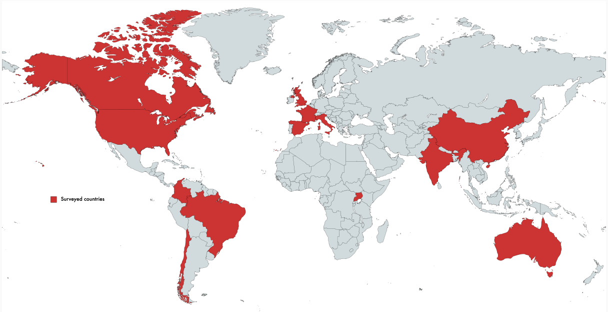
Hainmueller et al

- Political Analysis 2013 Causal Inference in Conjoint Analysis
- Understanding Multidimensional Choices via State Preference Experiments
- The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes towards Immigrants
- Validating Vignette and Conjoint Survey Experiments Against Real-World Behaviour

Conjoint Example: The CANDOUR project

The CANDOUR project jseeks to understand public opinion on Covid-19 vaccinations globally

- Fielded surveys in 13 countries across all continents (Nov.-Dec. 2020)
- Focused on understanding what strategies national publics think are equitable and fair



COVID-19 Vaccine Allocation Priorities

	COVID-19			Occupation		
	Age	Transmission	Vulnerability	Essential infrastructure	Health/ social care	Education/ child care
Australia	x	x	x	x	x	
Brazil	x		x	x	x	x
Canada	x	x	x	x	x	
Chile				x	x	x
China	x	x	x	x	x	
Colombia	x		x		x	
France	x	x	x	x	x	
India	x			x	x	
Italy	x		x		x	
Spain			x		x	
Uganda			x		x	
UK	x		x		x	
USA	x		x	x	x	

Table 1. Criteria proposed or used to prioritize COVID-19 vaccine allocation by country as of early December 2020

Example: Vaccine Priorities

- Respondents chose between 2 potential vaccine recipients
  - J=2 (choices)
  - K=8 choices/evaluations
- Each potential recipient has a profile
  - Each profile has a set of L discretely valued attributes, or a treatment composed of L components
  - D denotes the total number of levels for attribute L
  - L=5 (vaccine candidate attributes, D(1)= 4 D(2)=3 D(3)=8 D(4)=3 D(5)=3

Profile Attributes and Levels

Vulnerability
- Average (risk of death)
- Moderate (risk of death)
- High (risk of death)

Transmission
- Average risk (of transmission)
- Moderate risk (of transmission)
- High risk (of transmission)

Income
- Lowest 20% income level
- Average income level
- Highest 20% income level

Occupation
- Not Working
- Non-Key worker: Can work at home
- Non-Key worker: Cannot work at home
- Key worker: Education and childcare
- Key worker: Factory worker
- Key worker: Water and electricity service
- Key worker: Police and fire-fighting
- Key worker: Health and social care

Age Category
- 25 years old
- 40 years old
- 65 years old
- 79 years old

Conjoint Choice Profile Scenarios

Q5.1. As you can see each of the persons (Person A and Person B) differs on our five characteristics: **risk of COVID-19 related death**, **risk of catching and transmitting the COVID-19 virus**, **income level**, **occupation status**, and **age category**.

This vaccine could be given to one of these persons (Person A or Person B) immediately. Please indicate the person you think should get the vaccine immediately.

Q5.2.

	Person A	**Person B**
Risk of COVID-19 related death	High (Five times the average risk of COVID death)	Low (Average risk of COVID death)
Risk of catching and transmitting the COVID-19 virus	Average risk of catching and transmitting the COVID-19 virus	Average risk of catching and transmitting the COVID-19 virus
Income level	Average income level	Average income level
Occupation status	Key worker: Education and childcare	Non-Key worker: Can work at home
Age category	25 years old	65 years old

Conjoint Discrete Choice Questions

Q5.3.
Which of the Persons do you think should get the vaccine immediately? Select one of them.

- ○ Person A
- ○ Person B

Q5.5. **Person A:** On a scale from 1 to 7, where 1 indicates that you think **Person A** should get **Very Low Priority** for the vaccine and 7 indicates that you think **Person A** should get **Very High Priority** for the vaccine**,** what vaccine priority would you give **Person A**?

	1	2	3	4	5	6	7	
Very Low Priority	○	○	○	○	○	○	○	Very High Priority

Respondent's JK Profiles

$$\sum_{j=1}^{J} Y_{ijk}(\bar{\mathbf{t}}) = 1$$

Stability Assumption

- Potential outcomes always take on the same value as long as all the profiles in the same choice task have identical sets of attributes

$$Y_{ijk}(\bar{T}_i) = Y_{ijk'}(\bar{T}_i)$$
$$\text{if } \bar{T}_{ik} = \bar{T}_{ik'}$$
$$\text{for any } j, k, k^{'}$$

No Profile Order Effect

$$Y_{ij}(T_{ik}) = Y_{ij'}(T'_{ik})$$

$$\text{if } T_{ijk} = T'_{ij'k}$$

$$\text{and } T_{ij'k} = T'_{ijk}$$

$$\text{for any } i, j, j', k$$

Randomization of Profiles

$$Y_i(\mathbf{t}) \perp T_{ijkl} \text{ for any } i, j, k, l$$

- Pairwise independence between all elements of $Y_i(t)$ and T_{ijkl} and $0 < p(t) = p(T_{ik} = t) < 1)$

Qualtrics Illustration

https://fenuchile.qualtrics.com/jfe/form/SV_
6yReW6csGdDX3XD

Programming the Conjoint Experiment

- Details in Lab Module 2
- For each discrete choice profile that the respondents sees, the attributes of each vaccine candidate are randomly assigned;
- The order of the attributes are constant across choice sets for any particular respondent
- The order of the attributes though are randomly assigned to each respondent – so respondents will see ordering of attributes that are different than what other respondents see

Basic Profile Effects

$$\pi(t_1, t_0) = Y_i(t_1) - Y_i(t_0)$$

Profiles	Candidate	Service	Income	Eduction
t_0	1	military	rich	college
	2	no service	poor	college
t_1	1	military	rich	college
	2	military	poor	college

Estimate Profile Effects

- Unit-level causal effects are difficult to identify
    - Involve counterfactuals and hence fundamental problem of causal inference
- Average Treatment Effects (ATE)?
    - If there are a large number of attributes with multiple levels the number of observations in each conditioning set will be virtually zero rendering estimation difficult if not impossible

Average Marginal Component Effect

$$\hat{\bar{\pi}}_1(t_1, t_0, p(\mathbf{t})) = \sum_{(t,\mathbf{t})\in\tilde{\tau}} \{\mathbb{E}[Y_{ijk} | T_{ijkl} = t_1, T_{ijk[-l]} = t, \mathbf{T}_{i[-j]k} = \mathbf{t}]$$
$$- \mathbb{E}[Y_{ijk} | T_{ijkl} = t_0, T_{ijk[-l]} = t, \mathbf{T}_{i[-j]k} = \mathbf{t}]\}$$
$$\times\, p(T_{ijk[-l]} = t, \mathbf{T}_{i[-j]k} = \mathbf{t} | (T_{ijk[-l]}, \mathbf{T}_{i[-j]k}) \in \tilde{\tau})$$

- The marginal effect of attribute l averaged over the joint distribution of the remaining attributes
- ..the effect of a particular attribute (l) value (D) of interest against another value of the same attribute while holding equal the joint distribution of the other attributes in the design, averaged over this distribution as well as the sampling distribution from the population...

Estimating AMCE

- For any attribute of interest T_{ijkl} the subclassification estimate of the AMCE can be computed simply by dividing the sample into the strata defined by T_{ijk}
- Typically the attributes on which the assignment of the attribute of interest is restricted
- Calculate the difference in the average observed choice outcomes between the treatment ($T_{ijkl} = 1$) and control ($T_{ijkl} = 0$) groups within each stratum
- Take the weighted average of these differences in means, using the known distribution of the strata as the weights

Regression Estimation

- The linear regression estimator is fully nonparametric, even though the estimation is conducted by a routine typically used for a parametric linear regression model
- Regress the outcome variable on the L sets of dummy variables
- Interaction terms for the attributes that are involved in any of the randomization restrictions used in the study
- Take the weighted average of the appropriate coefficients

Variance Estimation

- Observed choice outcomes within choice tasks strongly negatively correlated
- Both potential choice and rating outcomes within respondents are likely to be positively correlated because of unobserved respondent characteristics influencing their preferences
- Point estimates of the AMCE can be coupled with standard errors corrected for within respondent clustering
- Obtain cluster-robust standard errors for the estimated regression coefficients by using the cluster option in Stata
- Block bootstrap where respondents are resampled with replacement and uncertainty estimates are calculated based on the empirical distribution of the AMCE over the resamples

Example: CANDOUR

- 248,576 rated profiles - 124,288 pairings
- 15,536 respondents
- Design yields 576 possible unique profiles
- Respondents indicated which of the candidates should get priority for the COVID-19 vaccine
- Respondents rated each selected vaccine candidate profile on a seven-point scale, where 1 indicates that the respondent considered the candidate a "Very Low Priority" and 7 indicates that the respondent considered the candidate a "Very High Priority"
- Rescaled to 0 and 1

AMCE for COVID-19 Vaccine Candidates

$$\begin{aligned}\text{rating}_{ijk} = &\beta_0 + \beta_1[\text{age}_{ijk} = 40] + \beta_2[\text{age}_{ijk} = 65] + \\ &\beta_3[\text{age}_{ijk} = 79] + \epsilon\end{aligned}$$

- The reference category is 25 years old
- βs are estimators for AMCE for ages 40, 65, 79 compared to 25

CANDOUR Linear Model Regression Estimation

	Model 1
(Intercept)	0.19***
	(0.02)
Vulnerability	
Moderate (risk of death)	0.05***
	(0.01)
High (risk of death)	0.18***
	(0.01)
Transmission	
Moderate risk (of transmission)	0.04***
	(0.00)
High risk (of transmission)	0.16***
	(0.01)
Income	
Average income level	−0.02***
	(0.00)
Highest 20% income level	−0.05***
	(0.01)
Occupation	
Non-Key worker: Can work at home	−0.01
	(0.01)
Non-Key worker: Cannot work at home	0.08***
	(0.01)
Key worker: Education and childcare	0.21***
	(0.01)
Key worker: Factory worker	0.14***
	(0.01)
Key worker: Water and electricity service	0.15***
	(0.01)
Key worker: Police and fire-fighting	0.21***
	(0.01)
Key worker: Health and social care	0.26***
	(0.02)
Age Category	
40 years old	0.05***
	(0.01)
65 years old	0.09***
	(0.01)
79 years old	0.09***
	(0.02)

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

- R Script for LM & Logit models
- Lab Module 2

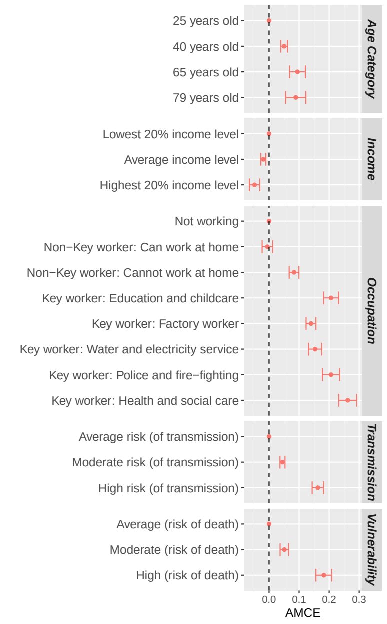
Caution with the AMCEs

- AMCE is an average of individual-level causal effects of an attribute
    - can hide important heterogeneity in the individual-level causal effects
    - a positive AMCE does not imply that a majority of respondents prefer the attribute value in question
- an average effect of an attribute level is always defined with respect to a particular baseline level (or "reference" value) of the same attribute, given a particular randomization distribution

Caution with the AMCEs

- the AMCE represents a causal effect of an attribute value against another averaged over possible interaction effects with the other included attributes, as well as over possible heterogenous effects across respondents
- the true value of the AMCE, as well as its substantive meaning, also changes when one changes the randomization distribution, unless the effect of the attribute has no interaction with other attributes
    - uniform versus non-uniform distributions

CANDOUR Conjoint AMCE Plots



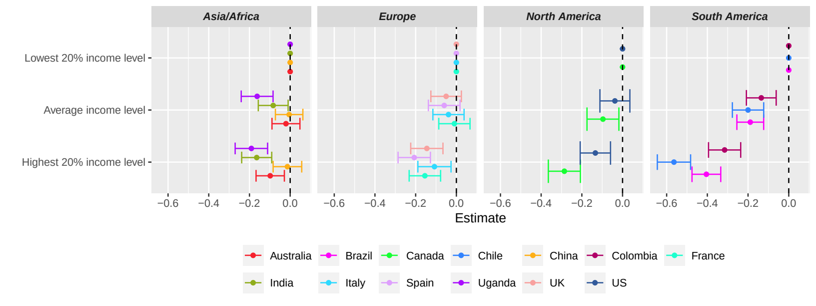
- R Script for ggplots
- Lab Module 2

Strongly consistent effects around the globe

Subjects want to vaccinate

- Older individuals and key-workers
- Higher risks of transmission and vulnerability

Evidence of preferring to vaccinate those on lower incomes:



CACE External Validity

- Hypothetical versus Behavioural choices
- Treatment versus Control
- Hainmueller et al 2015 PANS
- Behavioural data from Swiss referendum
- Results matched to conjoint experiment

Swiss Behavioural Data

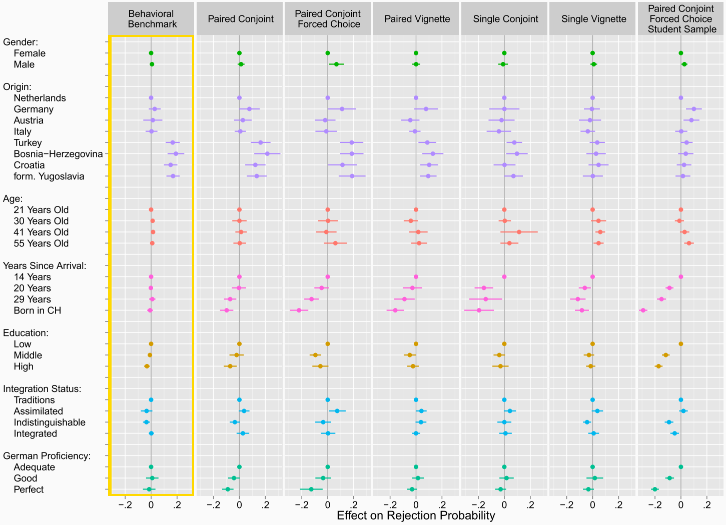
- Municipalities used referendums to vote on the naturalization applications of immigrants
- Voters received a voting leaflet with a short description of the applicant, including information about attributes, such as age, sex, education, origin, language skills, and integration status
- Voters then cast a secret ballot to accept or reject individual applicants
- These voting data yield an accurate measure of the revealed preferences of the voters what components of manipulation produce observed effect

Conjoint Experiment Data

- Respondents are presented with profiles of immigrants and then asked to decide on their application for naturalization
- List of attributes matches attributes voters saw no the voting leaflets distributed for the referendums - presented in same order as on the original leaflets
- Each respondent is randomly assigned to one of five different designs and asked to complete 10 choice tasks

Experimental Designs

Designs	Profiles
single-profile vignette	accept/reject single profile
paired-profile vignette	accept/reject two profiles
single-profile conjoint	name/value of attributes
paired-profile conjoint	accept/reject 2 applicants
paired-profile conjoint	accept/reject 1 of 2 applicants

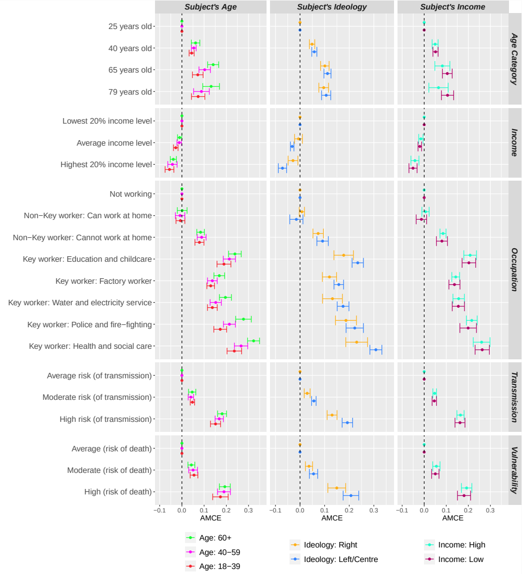

Behavioral Benchmark
Paired Conjoint
Paired Conjoint Forced Choice
Paired Vignette
Single Conjoint
Single Vignette
Paired Conjoint Forced Choice Student Sample
Gender:
Female
Male
Origin:
Netherlands
Germany
Austria
Italy
Turkey
Bosnia−Herzegovina
Croatia
form. Yugoslavia
Age:
21 Years Old
30 Years Old
41 Years Old
55 Years Old
Years Since Arrival:
14 Years
20 Years
29 Years
Born in CH
Education:
Low
Middle
High
Integration Status:
Traditions
Assimilated
Indistinguishable
Integrated
German Proficiency:
Adequate
Good
Perfect
-.2
0
.2
Effect on Rejection Probability

Conditional AMCE

Conditional AMCE

- AMCE for a particular subgroup of respondents defined based on a pretreatment respondent characteristic
  - can hide important heterogeneity in the individual-level causal effects
  - a positive AMCE does not imply that a majority of respondents prefer the attribute value in question
- the difference between two conditional AMCEs does not generally represent a causal effect of the conditioning respondent-level variable, unless the variable itself was also randomly assigned by the researcher
- the AMCE represents a causal effect of an attribute value against another averaged over possible interaction effects with the other included attributes, as well as over possible heterogenous effects across respondents

CANDOUR Conditional AMCE



- R Script for Conditional AMCE
- Lab Module 2

Causal Mechanisms in Conjoint Experiments

Acharya Political Analysis 2018

- Supreme Court Example
- Treatment of black and white nominees
- Mechanism?
  - racial animus
  - belief that black nominees are likely to be democrats
  - which candidates have more judicial experience
- Manipulate the information environment by including information about the nominee's partisanship

Total Effect (ATE)

- the total treatment is difference in support for a hypothetical black candidate versus hypothetical white candidate

$$ATE = [Y_i(t_a, M_i(t_a, d_*)) - Y_i(t_a, M_i(t_b, d_*))]$$

Average Controlled Direct Effect (ACDE)

- the total treatment is difference in support for a hypothetical black candidate versus hypothetical white candidate
- controlled direct effect is difference in support between two nominees when respondents are provided with the additional information that two nominees are of the same party
- total direct effect due to neither mediation nor interaction

$$ACDE = (t_a, t_b, m) = E[CDE_i(t_a, t_b, m)] = E[Y_i(t_a, m) - Y_i(t_b, m)]$$

Eliminated Effect

- difference between the overall treatment effect (ATE) and the controlled direct effect (ACDE)
- difference between the total effect of a black versus white nominee and the controlled direct effect for the same difference when both nominees are Democrats
- represents the amount of the total effect that is eliminated by setting party to a particular value

$$\Delta_i = [Y_i(t_a, M_i(t_a, d_*)) - Y_i(t_a, M_i(t_b, d_*))] - [Y_i(t_a, m) - Y_i(t_b, m)]$$

Eliminated Effect: Supreme Court Example

Mediator arm (D_i)	Treatment (T_i) Black profile (t_a)	White profile (t_b)	Difference
Inferred-party arm (d_*)	$\mathbb{E}[Y_i(\texttt{black})]$	$\mathbb{E}[Y_i(\texttt{white})]$	$TE(\texttt{black}, \texttt{white})$
Manipulated-party arm (d_0)	$\mathbb{E}[Y_i(\texttt{black}, \texttt{dem})]$	$\mathbb{E}[Y_i(\texttt{white}, \texttt{dem})]$	$ACDE(\texttt{black}, \texttt{white}, \texttt{dem})$
Difference	$ANME(\texttt{black}, \texttt{dem})$	$ANME(\texttt{white}, \texttt{dem})$	$\Delta(\texttt{black}, \texttt{white}, \texttt{dem})$

Supreme Court Conjoint: Demographics

- Demographic
    - Age: 30–40, 40–50, 50–60, 60–70, or over 70 years old
    - Gender: male or female
    - Race/ethnicity: white, black, Hispanic or Latino/a, Asian American
    - Religion: Catholic, Evangelical Protestant, Jewish, Mormon, or Mainline Protestant

Supreme Court Conjoint: Qualifications

- Qualifications
  - Education: Law school ranked in the Top 14,[7] law school ranked 15–25, law school ranked 25–50, law school ranked 50–100, or law school not ranked in Top 100
  - Previous work experience: elected politician, law professor, lawyer in private practice, lower federal judge, non-profit lawyer, prosecutor, public defender, state judge
  - Clerkship experience: Did not serve as law clerk or served as law clerk

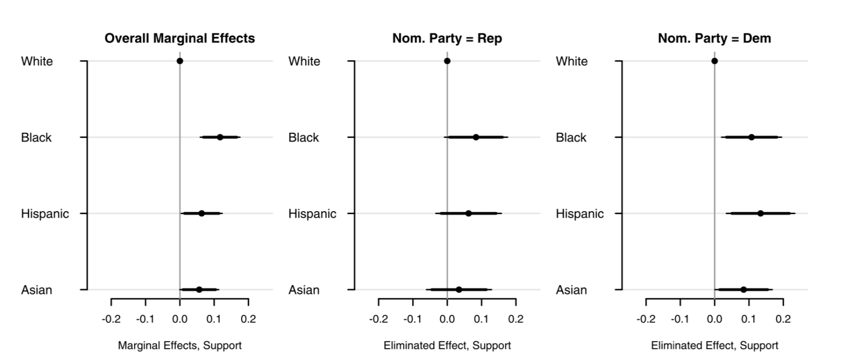
Supreme Court Conjoint: Excluded Partisanship

- Political (withheld randomly from half of respondents):
  - Political leaning: strong Democrat, leans Democrat, Independent, leans Republican, or strong Republican

Supreme Court Example

- Focus on 583 respondents who identify as Democrats
- copartisanship between respondent and profile can be viewed as randomly assigned in mediator-manipulator arm of experiment
- estimate AMCE for each race category from the natural-mediator arm
- then estimate the ACDEs from one of the manipulated-mediator arms
- use these two quantities to estimate the eliminated effect
    - eliminated effect is the difference between the effect of a black profile (compared to a white profile) under no party information and the same effect when party is set to Republican or Democrat.

Supreme Court Conjoint: Results



Causal Inference with Text (Fong and Grimmer 2021

Lottery versus Triage Vignette

Lottery Vignette

Q14.1.

Consider the following situation: a major clinic has developed plans for allocating limited supplies of the COVID-19 vaccine. It would like to vaccinate all 1000 nurses who work in the clinic. There will only be 500 vaccines available for the 1000 nurses who work in the clinic. Because of the limited supply, the vaccine will be allocated by a **lottery**. The names of the 1000 nurses will be put into a large container and shuffled. 500 names will be randomly selected from the container. These 500 randomly selected names will receive the vaccine.

Do you agree or disagree that this **lottery** method is an appropriate way to allocate the scarce vaccines to the nurses? Use the slider to indicate whether you disagree or agree: 0 means strongly disagree and 100 means strongly agree.

Strongly Disagree   Strongly Agree

0 10 20 30 40 50 60 70 80 90 100

Lottery Allocation?

Lottery versus Triage Vignette

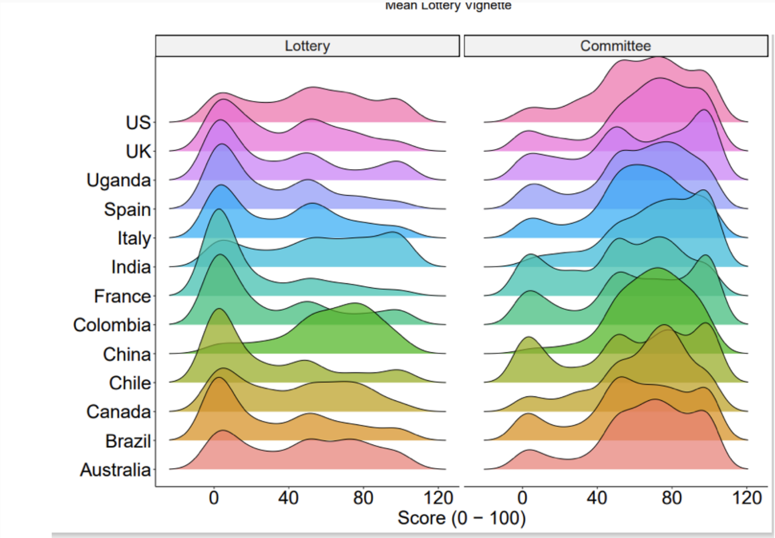
Q481.

Consider the following situation: a major clinic has developed plans for allocating limited supplies of the COVID-19 vaccine. It would like to vaccinate all 1000 nurses who work in the clinic. There will only be 500 vaccines available for the 1000 nurses who work in the clinic. Because of the limited supply, the vaccine will be allocated by an **independent committee of expert physicians**, who have no personal connection with the clinic and do not know any of the nurses involved. The medical histories of the 1000 nurses will be provided to the committee of experts. The committee of expert physicians will select the 500 nurses who they believe will most benefit from the vaccine.

Do you agree or disagree that this **expert committee** method is an appropriate way to allocate the scarce vaccines to the nurses? Use the slider to indicate whether you disagree or agree: 0 means strongly disagree and 100 means strongly agree.

	Strongly Disagree		Strongly Agree
	0 10 20 30 40 50 60 70 80 90 100		
Expert Committee Allocation?			

Lottery versus Triage Vignette



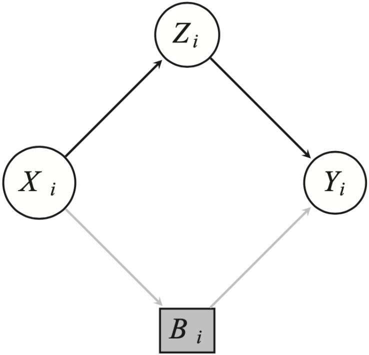
A Common Problem

TABLE 1 Extensive Use of Latent Treatments

Experiment type	Count	Latent	Aliased	Single vignette	Both
Survey experiment	29	100%	66%	97%	62%
Field experiment	13	92	54	77	46
Conjoint experiment	5	100	0	100	0
Lab experiment	4	100	75	100	75

Acyclit

FIGURE 1 Directed Acyclic Graph for Causal Text Diagram



Note: The text, $\boldsymbol{X}_i$, causes both the latent treatment of interest, Z_i, and the unmeasured latent treatments, $\boldsymbol{B}_i$. These latent treatments, in turn, cause the outcome, Y_i.

Hong Kong

TABLE 4 Hong Kong Experiment Treatments

	December 2019	October 2020
Intercept	64.23	69.03
	(3.14)	(1.07)
Commitment	5.23	2.68
	(1.74)	(1.23)
Bravery	−0.72	1.85
	(1.82)	(1.38)
Mistreatment	0.97	0.14
	(1.77)	(1.39)
Flags	0.04	−2.12
	(1.81)	(1.41)
Threat	−2.50	−2.07
	(1.86)	(1.36)
Economy	−0.44	−0.94
	(1.84)	(1.35)
Violation	−0.98	0.75
	(1.81)	(1.38)
N	1,983	2,072

Note: Results come from a linear model, in which the outcome is the degree to which the respondent agrees the U.S. government should help Hong Kong. The left column refers to the original experiment and the right column refers to a replication experiment.