Making Causal Critiques

Day 4 - How much are we Learning?

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    2. Reproducibility of the claim
    3. Scope (*generalizability*) of the claim

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- But these confidence intervals are usually for a *single* methodology and a fixed set of assumptions

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- If we can change all these things and still get the same answers, our result is **reliable** and **robust**

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- Robustness tests include:
  - Extra controls for disease, land, natural resources
  - Alternative model for spatial autocorrelation
  - Country fixed effects to focus only on within-country variation
  - Comparing only neighbouring societies
  - Alternative codings of centralized pre-colonial societies
  - Alternative measures of economic activity (nightlights etc.)
  - Different units of analysis - grid squares instead of ethnic territories

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  - But even if there was **no causal effect** in the data, *by chance* we would expect 10 models to produce significant effects

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2. If we take **another** sample of data and apply the same method, do we get the same result?
   - Very rarely done

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- If you’re reading a paper, think of the ten other papers you’re *not* reading that tried the same thing and found no effect

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- Compare the frquency of results in APSR and AJPS just above and below the 1.96 test statistic (for 5% significance)
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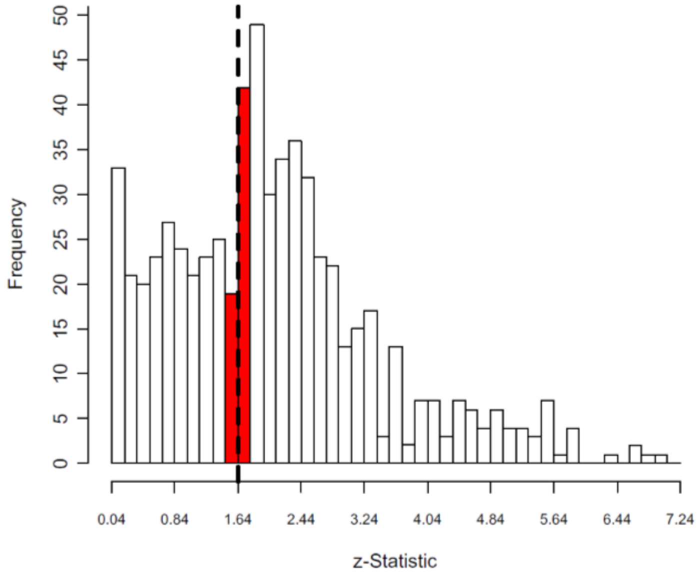
- Less than 1 in 32 billion chance this happened by chance!


Frequency
0
5
10
15
20
25
30
35
40
45
50
0.04
0.84
1.64
2.44
3.24
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z-Statistic

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  - Eg. EGAP Pre-Registration

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  - IgNobel Prize
  - "Suicide rates are linked to the amount of country music played on the radio"
  - "Is using voodoo dolls effective?"
  - "Why do old men have big ears?"
  - "How exposure to a crocodile encourages people to gamble"

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    2. How big, representative and interesting is that wider population?

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  - We have no evidence of how women leaders govern elsewhere in India or the world

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  - The new comparisons are often less representative or interesting
- Instead of an **Average Treatment Effect (ATE)** they represent a **Local Average Treatment Effect (LATE)**
  - A treatment effect applicable only to those units who were affected by the ’random’ part of treatment: **compliers**

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- Or maybe only to a sub-group of that sample

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  - How much do the results depend on researcher oversight?

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  - **Context effects**: The real-world always provides more information, more history
  - **Process effects**: People care *how* decisions are made
  - **Selection effects**: Actors in specific roles are rarely representative samples, 'WEIRD' or pro-social lab subjects

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- The lab differs from the field:
  - The stakes
  - The norms
  - The degree of scrutiny (Levitt and List 2006, “You tip more when you’re on a date”)
  - The sample of individuals
  - The degree of anonymity

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  - That's interesting in itself! We can manipulate the degree of scrutiny/anonymity etc.

Conjoint Survey Experiments

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- Profiles
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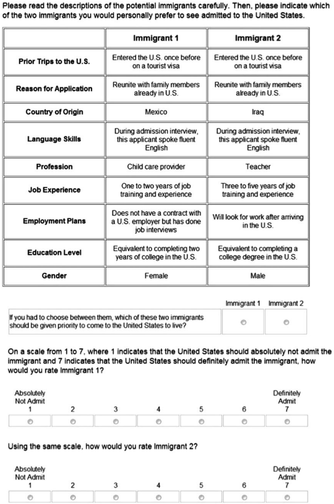
    - Values
- Randomize attribute order to prevent bias



Please read the descriptions of the potential immigrants carefully. Then, please indicate which of the two immigrants you would personally prefer to see admitted to the United States.

	Immigrant 1	Immigrant 2
Prior Trips to the U.S.	Entered the U.S. once before on a tourist visa	Entered the U.S. once before on a tourist visa
Reason for Application	Reunite with family members already in U.S.	Reunite with family members already in U.S.
Country of Origin	Mexico	Iraq
Language Skills	During admission interview, this applicant spoke fluent English	During admission interview, this applicant spoke fluent English
Profession	Child care provider	Teacher
Job Experience	One to two years of job training and experience	Three to five years of job training and experience
Employment Plans	Does not have a contract with a U.S. employer but has done job interviews	Will look for work after arriving in the U.S.
Education Level	Equivalent to completing two years of college in the U.S.	Equivalent to completing a college degree in the U.S.
Gender	Female	Male

	Immigrant 1	Immigrant 2
If you had to choose between them, which of these two immigrants should be given priority to come to the United States to live?	◎	◎

On a scale from 1 to 7, where 1 indicates that the United States should absolutely not admit the immigrant and 7 indicates that the United States should definitely admit the immigrant, how would you rate Immigrant 1?

Absolutely Not Admit 1	2	3	4	5	6	Definitely Admit 7
◎	◎	◎	◎	◎	◎	◎

Using the same scale, how would you rate Immigrant 2?

Absolutely Not Admit 1	2	3	4	5	6	Definitely Admit 7
◎	◎	◎	◎	◎	◎	◎

Fig. 1 Experimental design: Immigration conjoint. This figure illustrates the experimental design for the conjoint analysis that examines immigrant admission to the United States.

choice outcomes hereafter. Second, in "rating-based conjoint analysis," respondents give a numerical rating to each profile which represents their degree of preference for the profile. This format is preferred by some analysts who contend that such ratings provide more direct, finely grained information about respondents' preferences. We call this latter type of outcome a *rating outcome*.

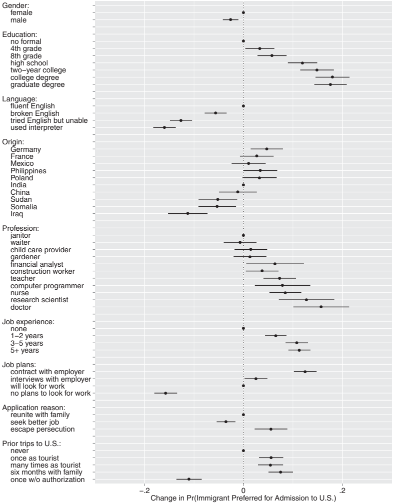


Fig. 3 Effects of immigrant attributes on preference for admission. This plot shows estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the United States. Estimates are based on the regression estimators with clustered standard errors; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

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- Citizens voted on specific naturalization applicants (Really!)

Figure S11: Effects of Applicant Attributes on Opposition to Naturalization Request (Unweighted Survey Sample)

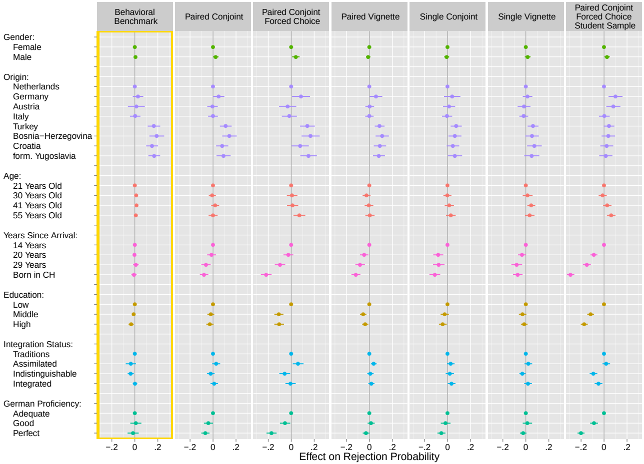

Figure shows point estimates (dots) and corresponding, cluster-robust 95 % confidence intervals (horizontal lines) from ordinary least squares regressions. The dots on the zero line without confidence intervals denote the reference category for each applicant attribute.

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- But note the conjoint method still hugely under-estimated the overall rejection rate
- 21% versus 37% in reality

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    - It depends on our research/policy question
    - A trade-off between representativeness and accuracy of our estimates

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  - Those municipalities were more urban, southern and wealthy than the rest
  - We do not learn anything about places where the result was a landslide (70-80%)
    - But these are the places where incumbents probably benefitted a lot!

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- Similarly, geographic regression discontinuities only tells us the effect of living on one side of the border *for people who live by the border*

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  - Self-selection bias has come back!

Instrumental Variables

- Instrumental Variables also estimate LATE
  - A causal effect estimate for **compliers**, units that received treatment *because of variation in the instrument*
  - "Better LATE than never"
- Compliers
- Always-takers
- Never-takers
- Defiers

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