Propensity Score within complex survey

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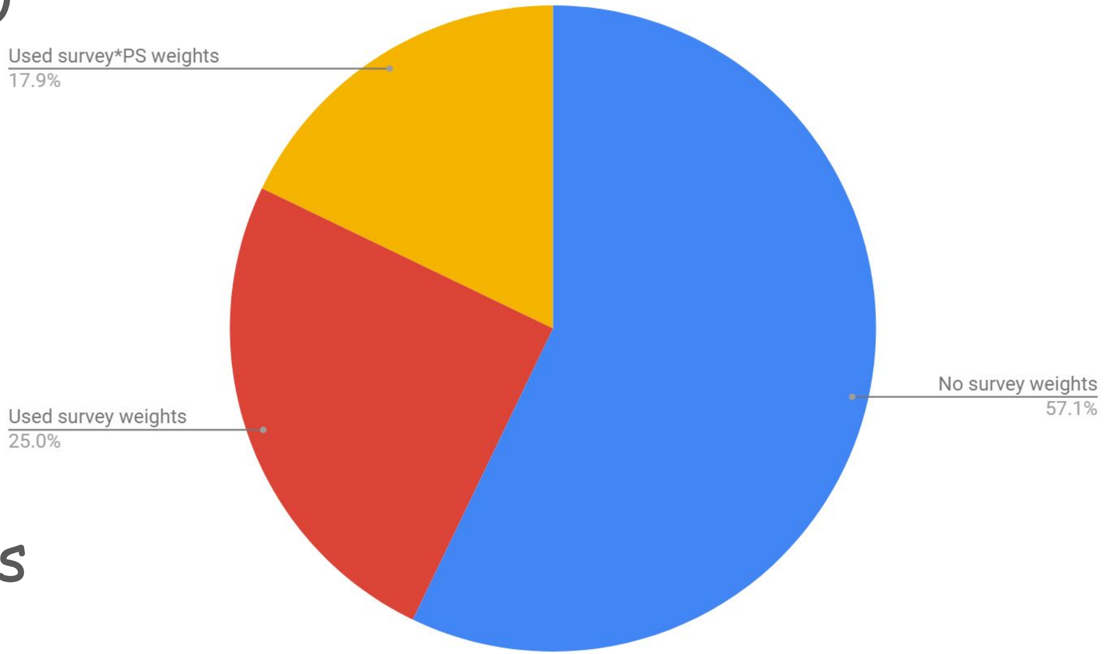
SPPH 504/007

Incorporating survey features in Propensity score matching

Propensity score matching in complex survey

DuGoff et al. (2014) reported

<u>57% of the PS related papers</u> did not even consider survey weights in the outcome analysis in their review.



Propensity score matching in complex survey

Step 1: Specify/fit PS model & predict to get PS

Step 2: Match subjects by PS

Step 3: Covariate balance in matched sample

Step 4: Estimate treatment effect

Exposure model (RA)

Should we use the survey features?

- Survey weight
- Cluster
- Strata

Outcome model (MI)

General suggestions (PATT / SATT):

A. Which survey features for PATT?
B. Which survey features for SATT?

Propensity score matching in complex survey

[PDF] A comparison of propensity score and linear regression analysis of complex survey data
EL Zanutto - Journal of data Science, 2006 - jds-online.com
We extend propensity score methodology to incorporate survey weights from complex survey data and compare the use of multiple linear regression and propensity score analysis to estimate treatment effects in observational data from a complex survey. For illustration, we use these two methods to estimate the effect of gender on information technology (IT) salaries. In our analysis, both methods agree on the size and statistical significance of the overall gender salary gaps in the United States in four different IT occupations after ...
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Exposure model (RA)

- "not necessary to use survey-weighted estimation for PS model" (step 1)

Outcome model (MI)

- "important to incorporate the survey design in both linear regression and propensity score analysis."
- "Ignoring the survey weights affects the estimates of population-level effects substantially" (step 4)

Propensity score matching in complex survey

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Exposure model (RA)

Fit PS model **without** design features (weights, cluster, strata),

and match using that PS

Outcome model (MI)

Fit outcome model in the matched data **with** design features (weights, cluster, strata) [adjust for imbalanced (high SMD)]

Propensity score matching in complex survey

Mostly agrees with Zanutto (2006), with one main difference in recommendation

Generalizing observational study results: applying propensity score methods to complex surveys
EH DuGoff, M Schuler, EA Stuart - Health services research, 2014 - Wiley Online Library
Objective To provide a tutorial for using propensity score methods with complex survey data. Data Sources Simulated data and the 2008 Medical Expenditure Panel Survey. Study Design Using simulation, we compared the following methods for estimating the treatment effect: a naïve estimate (ignoring both survey weights and propensity scores), survey weighting, propensity score methods (nearest neighbor matching, weighting, and subclassification), and propensity score methods in combination with survey weighting …
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Weights capture (proxy):
- Where lives
- Demographic characteristics
- Response probability

Exposure model (RA): Goal is to get predicted values, not variance

- "recommend including the survey weight as a predictor in the propensity score model. … (along with strata or cluster indicators)" (step 1)
- not crucial to include clustering, stratification & weights as design features

Outcome model (MI)

- Incorporate weight+cluster+strata as survey features for PATT (step 4)
- Incorporate cluster+strata as survey features for SATT (step 4)

Propensity score matching in complex survey

Generalizing observational study results: applying propensity score methods to complex surveys
EH DuGoff, M Schuler, EA Stuart - Health services research, 2014 - Wiley Online Library
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Exposure model (RA)

Fit PS model **without** design features (weights, cluster, strata), but use them as **covariates**

and match using that PS

Outcome model (MI)

Fit outcome model in the matched data **with** design features (weights, cluster, strata) [adjust for imbalanced (high SMD)]

Propensity score matching in complex survey

Propensity score matching and complex surveys
PC Austin, N Jembere, M Chiu - Statistical methods in ..., 2018 - journals.sagepub.com
Researchers are increasingly using complex population-based sample surveys to estimate the effects of treatments, exposures and interventions. In such analyses, statistical methods are essential to minimize the effect of confounding due to measured covariates, as treated subjects frequently differ from control subjects. Methods based on the propensity score are increasingly popular. Minimal research has been conducted on how to implement propensity score matching when using data from complex sample surveys. We used Monte ...
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Exposure model (RA)

- 3 PS models to compare: (1) unweighted, (2) weighted, (3) unweighted, but as covariate (step 1)
- (1), (2), (3) performed similarly in balance diagnostics, ATT comparison was inconsistent.

Outcome model (MI)

- Matched sample need to employ the survey weights to make inferences about a population parameter (step 4)
- Controls (a) having *original weights* (b) having *weights from matched treated*
  - Original control weights were better to keep.
- SE of ATT computed using bootstrap
  - Bootstrap worked better for binary outcome

Propensity score matching in complex survey

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Exposure model (RA)

Fit PS model **with** design features (weights, cluster, strata)

match using that PS

Outcome model (MI)

Fit outcome model in the matched data **with** design features (weights, cluster, strata) [adjust for imbalanced (high SMD)]

Propensity score matching in complex survey

It's all about balance: propensity score matching in the context of complex survey data

D Lenis, TQ Nguyen, N Dong, EA Stuart - Biostatistics, 2017 - academic.oup.com

Many research studies aim to draw causal inferences using data from large, nationally representative survey samples, and many of these studies use propensity score matching to make those causal inferences as rigorous as possible given the non-experimental nature of the data. However, very few applied studies are careful about incorporating the survey design with the propensity score analysis, which may mean that the results do not generate population inferences. This may be because few methodological studies examine how to …

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- Additionally focused on non-response mechanism.

Exposure model (RA)

- "How the survey weights are incorporated in the estimation of PS, does not affect the performance of the matching estimators" (step 1)
- "Balance is crucial to correctly estimate treatment effects using propensity score matching" (step 3)

Outcome model (MI)

- "survey weights should be incorporated in the outcome analysis" (step 4)
- "Adjusting for relevant covariates in the outcome model improves the performance of the estimators." (step 4)

Reasonable approach (my summary)

- PS model:
  - get the best model that provides best balance: using design variables or not.
  - Not using design features has the advantage of potentially using fancy predictive models (machine learning, etc.) [software availability is an issue: not all predictive models support design-based framework]
- Outcome model:
  - Must use all design features to get population level estimates
  - Must use strata+cluster in the design to get correct SE / CI

In the papers we considered, all (Austin, DuGoff, Lenis, Ridgeway, Zanutto) agreed that, for population level estimates,

survey weights must be incorporated as a design feature in the propensity score model (step 1)

survey weights should be incorporated as a covariate in the propensity score model (step 1)

survey weights should be a part of the design features in the outcome regression (step 4)

Causal inference in cross-sectional study?

Covariate → Exposure → Outcome

- NHANES is a cross-sectional survey
- Establishing cause vs. effect requires time element.
- Hard to do causal inference in cross sectional studies
- PS method is just an alternative to regression in reducing confounding

Causal inference in cross-sectional study?

Covariate → Exposure → Outcome

DID040 - Age when first told you had diabetes

Variable Name: DID040

SAS Label: Age when first told you had diabet

English Text: How old {was SP/were you} wher professional first told {you/him/he or sugar diabetes?

English Instructions: ENTER AGE IN YEARS.

Target: Both males and females 1 YEARS

Code or Value	Value Description	Count
1 to 79	Range of Values	754
80	80 years or older	12
666	Less than 1 year	4
777	Refused	0
999	Don't know	7
.	Missing	8889

MCQ180A - Age when told you had arthritis

Variable Name: MCQ180A

SAS Label: Age when told you had arthritis

English Text: How old {were you/was SP} wher {you/s/he} . . . had arthritis?

English Instructions: ENTER AGE IN YEARS.

Target: Both males and females 20 YEARS

Code or Value	Value Description	Count
1 to 79	Range of Values	1680
80	80 years or older	48
77777	Refused	0
99999	Don't know	27
.	Missing	7911

MCQ180E - Age when told you had heart attack

Variable Name: MCQ180E

SAS Label: Age when told you had heart atta

English Text: How old {were you/was SP} wher {you/s/he} . . .had a heart attack infarction)?

English Instructions: ENTER AGE IN YEARS.

Target: Both males and females 20 YEARS

Code or Value	Value Description	Count
4 to 79	Range of Values	263
80	80 years or older	11
77777	Refused	0
99999	Don't know	8
.	Missing	9384

Short Reference and Textbook List 📖

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Thanks!

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