Characterizing Retrospective Constraints of Survey Designs for Estimating Population-level Causal Effects

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Evidence from General Use Population Surveys

- Large general use population surveys provide a unique data source for extracting causal evidence.
  - e.g., National Youth Tobacco Survey (NYTS)
- They are designed for *external validity*: population-level description and inference; unlike an internally valid RCT.
- Prior work on causal inference in complex survey design
  - Nattino et al. [2024] (henceforth NAL): exposure-sample selection from a finite population of potential outcomes.
  - NAL found the *available* sampling weight impacts analysis choice (e.g., use of survey weighted propensity score).

Retrospective Use for Causal Questions

- General use surveys release public-use files to secondary users.
- Survey managers construct design weights.
- Some undisclosed info may be crucial for constructing survey weights or mitigating bias during the original survey design.

Problem: Causal analyses can face constraints imposed by retrospective use of a survey design.

NYTS 2021: Prior E-cig Use and Future Intention to Smoke

What is the causal effect of **past e-cig use** on **intention to smoke** among never-smoking grade 6-12 students in the US?

Population ($\mathcal{P}$)	US students in grades 6–12 who have never tried cigarette smoking (cohort)
Exposure (Z)	Prior e-cigarette use
Outcome (Y)	Future intention to smoke
Confounders (X)	Age, sex, race, environmental, household, cognitive, exposure factors
Survey design ($S^* = S \cdot R = 1$)	design weights (nonresponse adjusted), sampling units, stratum, location

NYTS 2021: nationally representative, three-stage stratified cluster sample; 279 schools, $>$20,000 students.

NYTS 2021 Methodology Considerations

How might NYTS 2021 methodology impact causal effect estimation?

1. Location: "Where are you currently taking the survey?"
   - "On School Campus" reported higher e-cig prevalence than "At Home/Other Place." [Park-Lee et al., 2023]
2. Nonresponse adjustment in provided survey weights
   - Adjusts sex, grade, school level, census region, % of black students enrolled in school; *not* prior e-cig use.
   - The survey weights cannot be considered independent from prior e-cig use, due to correlation with NR-adjustment set.
3. Variance estimation*
   - Released design weights are fixed (e.g., no replicate weights provided).

Contributions

1. Formalize causal assumptions under retrospective use of complex survey designs.
2. Propose a post hoc weight class adjustment for certain practical scenarios.
3. Demonstration using NYTS 2021 data

Estimand and Causal Assumptions

Population Average Treatment Effect (PATE):

$$\text{PATE} := \frac{1}{N}\sum_{i=1}^{N}(Y_i^1 - Y_i^0) = E_{\mathcal{P}}\left(Y^1 - Y^0\right)$$

(A1) Ignorability.

$$(Z, S^*) \perp\!\!\!\perp (Y^1, Y^0) \mid H$$

(A2) Positivity.

$$0 < P(Z{=}z, S^*{=}1 \mid H) < 1$$

(A3) Consistency.

$$Y = Y^1 Z + Y^0(1 - Z)$$

Under (A1)–(A3), for $z = 0, 1$:

$$E(Y^z) = E\left\{\frac{Y\,S^*Z}{P(S^*{=}1, Z{=}z \mid H)}\right\}$$

Identification via inverse joint selection–exposure weighting.

A Few Structural Scenarios

The joint selection weight $w_i^{-1} = P(S^*{=}1, Z{=}z \mid H)$ factors two ways:

$$\underbrace{P(Z{=}z \mid S^*{=}1, H)\, P(S^*{=}1 \mid H)}_{\textbf{Path 1}} = \underbrace{P(S^*{=}1 \mid Z{=}z, H)\, P(Z{=}z \mid H)}_{\textbf{Path 2}}$$

- **Path 1** Propensity score in-sample $\times$ Sample selection probability.
- **Path 2** Sample selection adjusted for Z $\times$ Propensity score.

Partition the covariates into disclosed and undisclosed.

X	disclosed in the public-use file
W	undisclosed (used by managers to build weights)

Which path can we take to identify the PATE? We consider some structural scenarios about (Z, S^*, X, W).

Does the Released $P(S^*{=}1 \mid W)$ Identify the PATE?

Factor $P(Z{=}1, S^*{=}1 \mid X, W)$ two ways:

$$\textbf{Path 1:} \quad P(Z{=}1 \mid X, W, S^*{=}1)\, P(S^*{=}1 \mid X, W)$$

$$\textbf{Path 2:} \quad P(S^*{=}1 \mid X, W, Z{=}1)\, P(Z{=}1 \mid X, W)$$

X → **exposure,** W → **selection**: $Z \perp\!\!\!\perp (S^*, W) \mid X$ and $S^* \perp\!\!\!\perp (Z, X) \mid W$

$$\text{Path 1} = \text{Path 2} = P(Z{=}1 \mid X)\, P(S^*{=}1 \mid W)$$

Exposure-dependent selection: $Z \perp\!\!\!\perp W | X$ and $S^* \not\perp\!\!\!\perp Z | X, W$

Path 1: $P(Z{=}1 \mid X, W, S^*{=}1)$ does not reduce

Path 2: $P(S^*{=}1 \mid X, W, Z{=}1)\, P(Z{=}1 \mid X)$

The released $P(S^*{=}1 \mid W)$ does not recover $P(S^*{=}1 \mid X, W, Z{=}1)$

Weight Class Adjustment (WCA)

The released weight corrects for nonresponse, but was built without exposure Z, which may affect who responds.

Assumption: undisclosed design variables W affect *selection*, not exposure. Then, we can adjust the released weight as follows.

WCA on Quantiles of Design Weight

1. Group observations into K classes by their released weight.
2. Within each class, take the proportion reporting exposure:

$$\hat{P}(Z{=}z \mid \text{class}_i) = \frac{1}{|\text{class}_i|} \sum_{j \in \text{class}_i} \mathbb{I}(Z_j = z)$$

3. Scale each weight by this proportion.

The adjusted weight now reflects the exposure the original weight ignored.

WCA Estimator

The released weight is $\hat{\pi}(X_i, W_i) = 1/a_i$. The WCA weight combines confounding and selection corrections:

$$\hat{w}_i^{\text{WCA}} = \hat{w}_{ps_i} \cdot \frac{1}{\hat{\pi}(X_i, W_i)\, \hat{P}(Z_i{=}z \mid \text{class}_i)}, \qquad \hat{w}_{ps_i} = \frac{Z_i}{\hat{e}(X_i)} + \frac{1 - Z_i}{1 - \hat{e}(X_i)}$$

PATE estimator:

$$\hat{\tau}_{\text{WCA}} = \frac{\sum_i \hat{w}_i^{\text{WCA}} Y_i Z_i}{\sum_i \hat{w}_i^{\text{WCA}} Z_i} - \frac{\sum_i \hat{w}_i^{\text{WCA}} Y_i (1 - Z_i)}{\sum_i \hat{w}_i^{\text{WCA}} (1 - Z_i)}$$

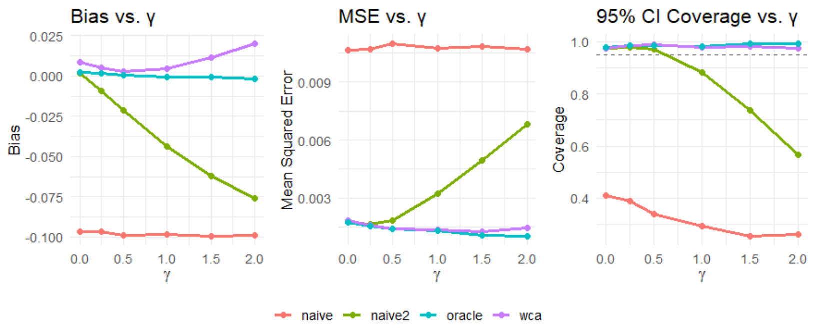
Consistency (fixed K)

$$\hat{\tau}_{\text{WCA}} \xrightarrow{p} \tau + (\text{bias from coarse } K)$$

$\sqrt{n}$-consistent to τ plus coarsening bias {which vanishes as K grows (or as within class distribution of (X,W) becomes more homogeneous}.

Simulation Study

Design. Selection depends on X and, through γ, on exposure ($\gamma > 0$: Z-dependent). Compare four estimators as γ grows: two naïve, WCA, and Oracle.



Result: WCA tracks the Oracle across all γ; the naïve estimators degrade as exposure-dependent selection grows.

Weight Class Adjustment in the NYTS 2021

- Conditioning on $S^*\!=\!1$ links survey setting and prior e-cig use (School Campus **16.0%** vs. Home/Other **12.3%**).
- We adjust `finwgt` on Location cells, as in the NYTS nonresponse adjustment [CDC's Office on Smoking and Health, 2021].

Location	Z	n	$\hat{c}$
School Campus	0	6,845	1.118
School Campus	1	1,074	0.924
Home/Other	0	5,609	0.906
Home/Other	1	814	0.940

$\hat{c}$ = sample share $\div$ weighted share.

Small adjustment, reflecting a well-designed survey.

WCA $\rightarrow$ adjusted weight $\rightarrow$ $\hat{e}(X)$ $\rightarrow$ balance $\rightarrow$ $\widehat{\text{PATE}}$

Population-level Covariate Balance

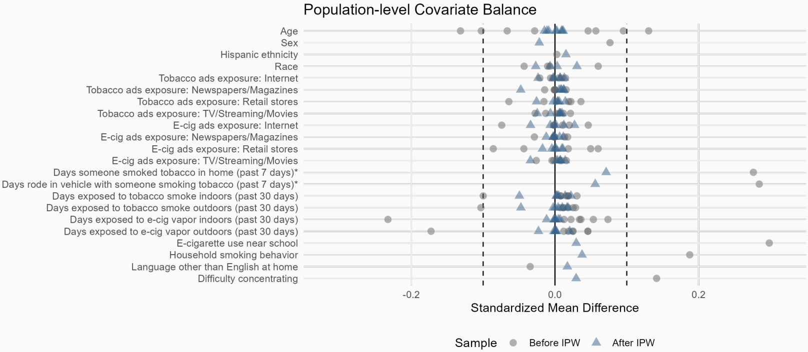


Figure 1: Population-level covariate balance before-after propensity score adjustment with WCA design weights.

Estimated PATE with Post Hoc WCA on Design Weights

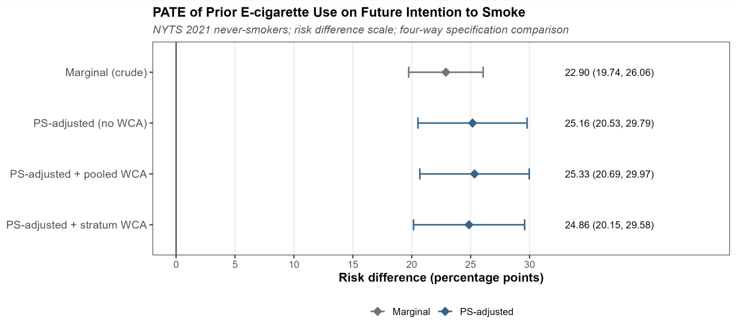


Figure 2: Estimated PATEs (risk difference in %) of prior e-cig use on future intention to smoke among never-smokers, NYTS 2021.

Result: $\widehat{\text{PATE}} = 25.33\%$ [95% CI: 20.69, 29.97]. Prior e-cig use increases the the risk of future intention to smoke among never-smoking US grade 6-12 students.

Variance Estimation as a Retrospective Constraint

Released weights are treated as fixed, but were estimated by survey managers. Analysts could propagate that uncertainty using survey bootstrap methods [Preston, 2009].

	SE (pp)	**95% CI (pp)**
Linearization (`svyglm`)	2.33	(20.7, 30.0)
Survey bootstrap	2.74	(20.0, 30.7)

$$\mathrm{Var}(\hat{\tau} \mid \text{weights fixed}) \;\leq\; \mathrm{Var}(\hat{\tau})$$

Survey bootstrapped SE ≈18% larger than treating survey weights as fixed.

Discussion

- We formalized some constraints to identification when estimating causal effects from complex survey design.
- Post-hoc WCA may be used in some scenarios
- Demonstration using NYTS 2021
- Ongoing: Sensitivity analysis with complex survey design, survey bootstrap methods, other constraints

References

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