

Evaluating treatment efficacy in vaccine clinical trials with two-phase designs using stochastic-interventional effects


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Joint work with P.B. Gilbert (Fred Hutch & UW)

Immune Correlates of HIV-1 and COVID-19

The Fights Against HIV-1 and COVID-19

- The HIV-1 epidemic:
 - 1.5 million new infections occurring annually worldwide;
 - new infections outpace patients starting antiretroviral therapy;
 - HIV Vaccine Trials Network's (HVTN) 505 trial evaluated a novel antibody boost vaccine (?).
- The COVID-19 epi pan endemic (?):
 - ~~270 331 619~~ 643 million total cases detected globally;
 - new variants emerging, with vaccine uptake globally slowing;
 - COVID-19 Prevention Network's (CoVPN) COVE trial focused on Moderna's (mRNA-1273) vaccine (?).

Evaluating Vaccines for HIV-1 and COVID-19

- *505*: How would HIV-1 infection risk have differed had the boost vaccine modulated immunogenic responses differently?
- *COVE*: How would COVID-19 disease rate have differed for alternative vaccine-induced immunogenic response profiles?
- **Question**: How can [HIV-1, COVID-19] vaccines be improved through modulating immunogenic response profiles?

Why Measure and Analyze Immune Correlates?

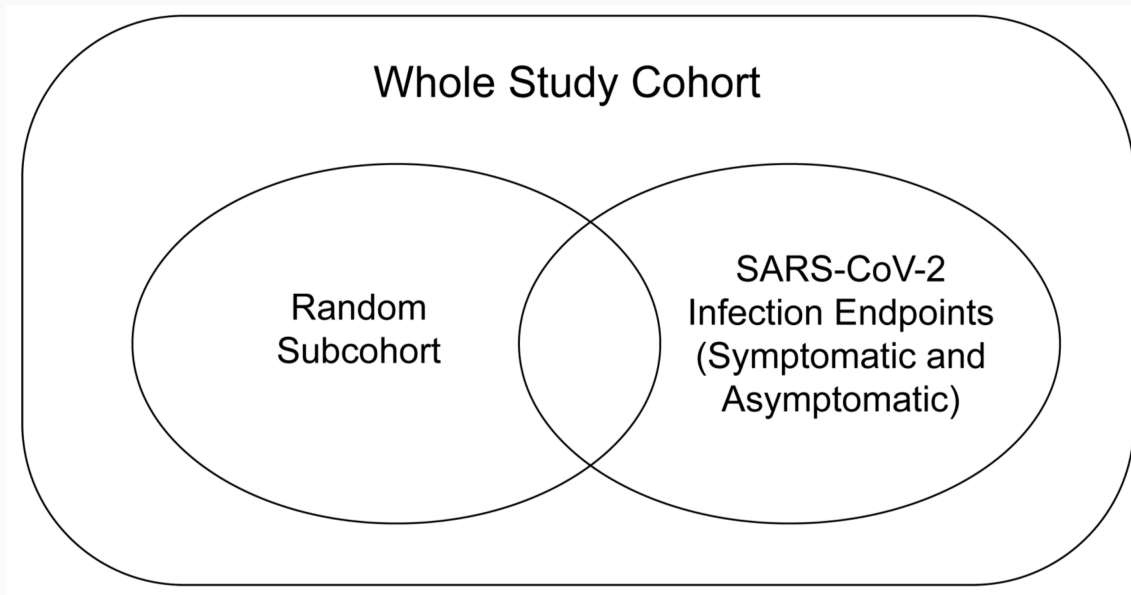
- Two, interrelated goals of vaccine correlates analyses are to
 - identify/validate possible *surrogate endpoints* (?);
 - understand *protective mechanisms* of vaccines.
- If an immune correlate is established to reliably predict VE, subsequent efficacy trials may use it as a primary endpoint.
- This may accelerate the approval of
 - existing vaccines in different populations (e.g., in children);
 - new vaccines within the same class.

Measuring Correlates: Two-Phase Designs

- Often, use case-cohort design (?), a special case of two-phase sampling (?).
- Phase 1: measure baseline, vaccination, endpoint on everyone.
- Phase 2: given baseline, vaccine, endpoint, select members of immune response subcohort with (possibly known) probability.
 - *505*: second-phase sample with 100% of HIV-1 cases and matching of non-cases ($n = 189$ per ?).
 - *COVE*: stratified random subcohort ($n \approx 1600$) and all SARS-CoV-2 infection and COVID-19 disease endpoints.

A Simple Two-Phase Design: Case-Cohort

Assaying >30k samples is expensive, statistically unnecessary.



Case-cohort design, per ?, as applied to COVE.

Two-phase Sampling Masks the Complete Data Structure

- Complete (unobserved) data $X = (L, A, S, Y) \sim P_0^X \in \mathcal{M}$:
 - L (baseline covariates): sex, age, BMI, behavioral HIV risk,
 - A (treatment): randomized assignment to vaccine/placebo,
 - S (exposure): immune response profile for relevant markers,
 - Y (outcome of interest): infection status at trial's end.
- Observed data $O = (B, BX) = (L, B, BS, Y) \sim P_0 \in \mathcal{M}$.
 - $B \in \{0, 1\}$ indicates inclusion in the second-phase sample.
 - $\pi_0 := \mathbb{P}(B = 1 \mid Y, L)$ must be *known by design* or estimated.
 - Implicitly conditioning on the vaccine arm: $O = \{X \mid A = 1\}$.

Causal Effects for Quantitative Exposures

Static Interventions Aren't Enough

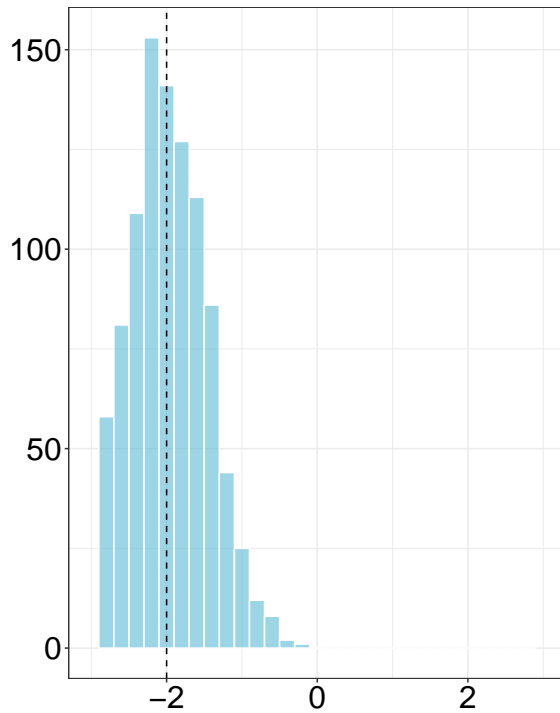
- Describe the manner in which X is hypothetically generated by a nonparametric structural equation model (?):

$$L = f_L(U_L); A \sim \text{Bern}(0.5); S = f_S(A, L, U_S); Y = f_Y(S, A, L, U_Y)$$

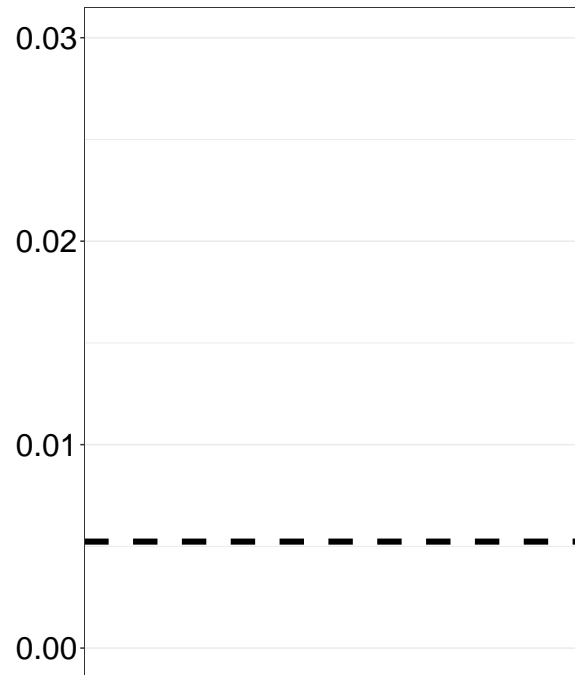
- Implies a model for the distribution of counterfactual random variables induced by interventions on the system.
- A *static* intervention replaces f_S with a specific value s in its conditional support $S \mid L$.
- This requires specifying *a priori* a particular value of exposure under which to evaluate the outcome — but what value?

Disease Risk Under Shifted Immunogenic Responses

nAb response at $\delta = -2$

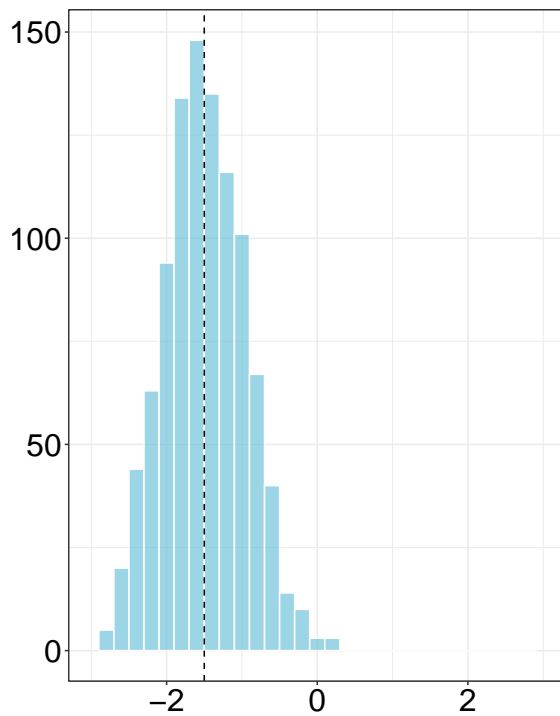


Mean risk of COVID-19

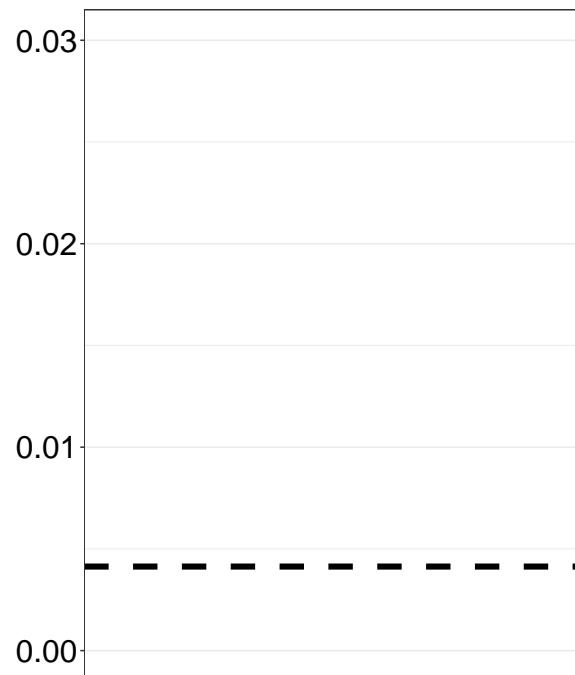


Disease Risk Under Shifted Immunogenic Responses

nAb response at $\delta = -1.5$

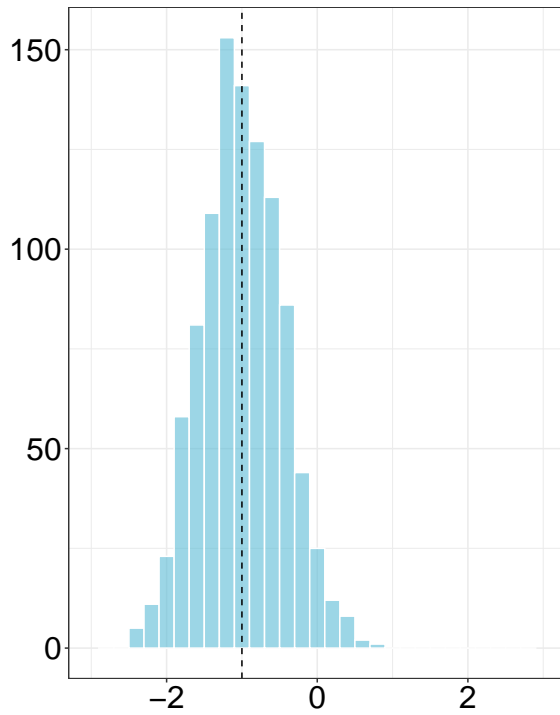


Mean risk of COVID-19

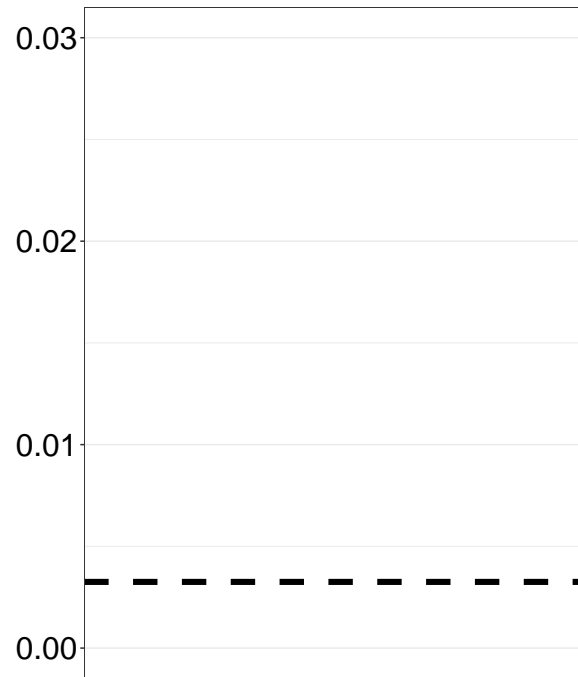


Disease Risk Under Shifted Immunogenic Responses

nAb response at $\delta = -1$

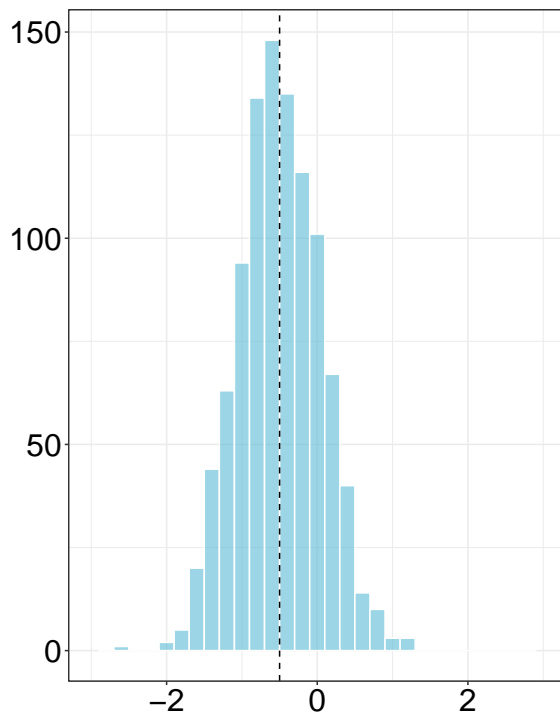


Mean risk of COVID-19

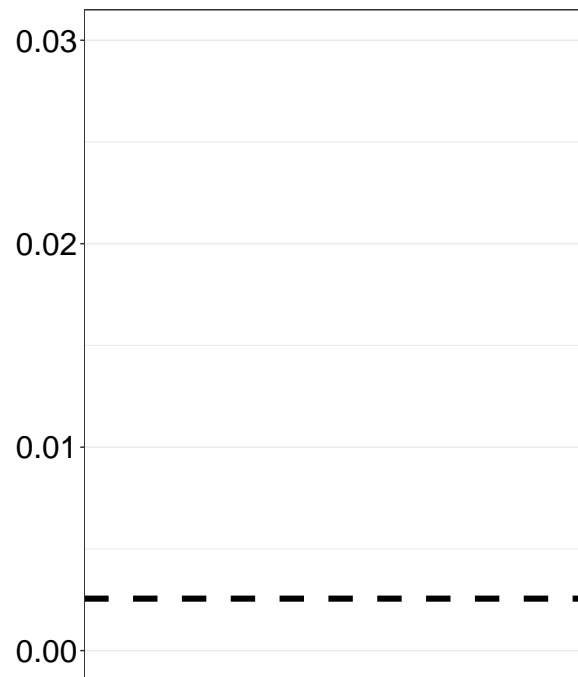


Disease Risk Under Shifted Immunogenic Responses

nAb response at $\delta = -0.5$



Mean risk of COVID-19



Stochastic Interventions Define the Causal Effects of Shifts

- Stochastic interventions modify the value S would naturally assume by *shifting* the natural exposure distribution.

- ??'s shift interventions¹

$$d(s, l) = \begin{cases} s + \delta, & s + \delta < u(l) \quad (\text{if plausible}) \\ s, & s + \delta \geq u(l) \quad (\text{otherwise}) \end{cases}$$

- Our estimand is $\psi_{0,\delta} := \mathbb{E}_{P_0^\delta} \{ Y_{d(S,L)} \}$, which is identified by

$$\psi_{0,\delta} = \int_{\mathcal{L}} \int_{\mathcal{S}} \mathbb{E}_{P_0} \{ Y \mid S = d(s, l), L = l \} g_{0,S}(s \mid L = l) q_{0,L}(l) d\mu(s) d\nu(l)$$

¹? introduced modified treatment policies.

Interpreting the Causal Effects of Shift Interventions

- Consider a data structure: $(Y_s, s \in \mathcal{S})$.
- Let $Y_s = \beta_0 + \beta_1 s + \epsilon_s$, with error $\epsilon_s \sim N(0, \sigma_s^2) \forall s \in \mathcal{S}$.
- For the counterfactual outcomes $(Y_{s'+\delta}, Y_{s'})$, their difference $Y_{s'+\delta} - Y_{s'}$ may be expressed (for some $s' \in \mathcal{S}$)

$$\begin{aligned} \mathbb{E}Y_{s'+\delta} - \mathbb{E}Y_{s'} &= [\beta_0 + \beta_1(s' + \delta) + \mathbb{E}\epsilon_{s'+\delta}] - [\beta_0 + \beta_1 s' + \mathbb{E}\epsilon_{s'}] \\ &= \beta_1 \delta \end{aligned}$$

- A *unit shift* for $s' \in \mathcal{S}$ (i.e., $\delta = 1$) causes a counterfactual difference in Y of magnitude β_1 .

Stochastic–Interventional Vaccine Efficacy

- Causal parameter based on vaccine efficacy (VE) estimands:

$$\begin{aligned} \text{SVE}(\delta) &= 1 - \frac{\mathbb{E}[\mathbb{P}(Y = 1 \mid S = d(s, l), A = 1, L = l)]}{\mathbb{P}(Y(0) = 1)} \\ &= 1 - \frac{\psi_{0,\delta}}{\mathbb{P}(Y(0) = 1)} \end{aligned}$$

- $\mathbb{P}(Y(0) = 1)$: counterfactual infection risk in the placebo arm
— under randomization, $\mathbb{P}(Y(0) = 1) \equiv \mathbb{P}(Y = 1 \mid A = 0)$.
- Summarizes VE via stochastic interventions across δ , per the CoVPN immune correlates SAP² (??).

²SAP published at <https://doi.org/10.6084/m9.figshare.13198595>.

Efficient Estimation in Two-Phase Designs

Estimation of the Counterfactual Mean $\psi_{0,\delta}$

An estimator $\psi_{n,\delta}$ of $\psi_{0,\delta} := \Psi(P_0)$ is *efficient* if and only if

$$\psi_{n,\delta} - \psi_{0,\delta} = n^{-1} \sum_{i=1}^n D^*(P_0)(O_i) + o_P(n^{-1/2}),$$

where $D^*(P)$ is the *efficient influence function* (EIF) of $\psi_{0,\delta}$ with respect to the nonparametric model \mathcal{M} at a distribution P .

The EIF of $\psi_{0,\delta}$ is indexed by two key *nuisance parameters*

$$\begin{aligned} \bar{Q}_Y(S, L) &:= \mathbb{E}_P(Y | S, L) && \text{outcome mechanism} \\ g_S(S | L) &:= p(S | L) && \text{generalized propensity score} \end{aligned}$$

Flexible, Efficient, Doubly Robust Estimation

- The efficient influence function of $\psi_{0,\delta}$ with respect to \mathcal{M} is

$$D_F^*(P_0)(o) = \frac{g_{0,S}(d^{-1}(s, l) | l)}{g_{0,S}(s | l)} (y - \bar{Q}_{0,Y}(s, l)) + \bar{Q}_{0,Y}(d(s, l), l) - \psi_{0,\delta}.$$

- The one-step bias-corrected estimator:

$$\psi_n^+ = \frac{1}{n} \sum_{i=1}^n \bar{Q}_{n,Y}(d(S_i, L_i), L_i) + D_n^*(O_i).$$

- The TML estimator updates initial estimates of \bar{Q}_n by tilting:

$$\psi_n^* = \frac{1}{n} \sum_{i=1}^n \bar{Q}_{n,Y}^*(d(S_i, L_i), L_i).$$

- Both doubly robust: flexible modeling for nuisance estimation.

Augmented Estimators for Two-Phase Sampling Designs

- ? suggested inverse probability of censoring weighted (IPCW) loss functions:

$$\mathcal{L}(P_0^X)(O) = \frac{B}{\pi_0(Y, L)} \mathcal{L}(P_0^X)(X)$$

- When the sampling mechanism $\pi_0(Y, L)$ is known by design, this procedure yields a reasonably reliable estimator.
- When data-adaptive regression must be used — that is, when $\pi_0(Y, L)$ is not known by design³— this is insufficient.

³Sampling of non-cases in HVTN 505 used matching (?).

Efficiency and Multiple Robustness (?)

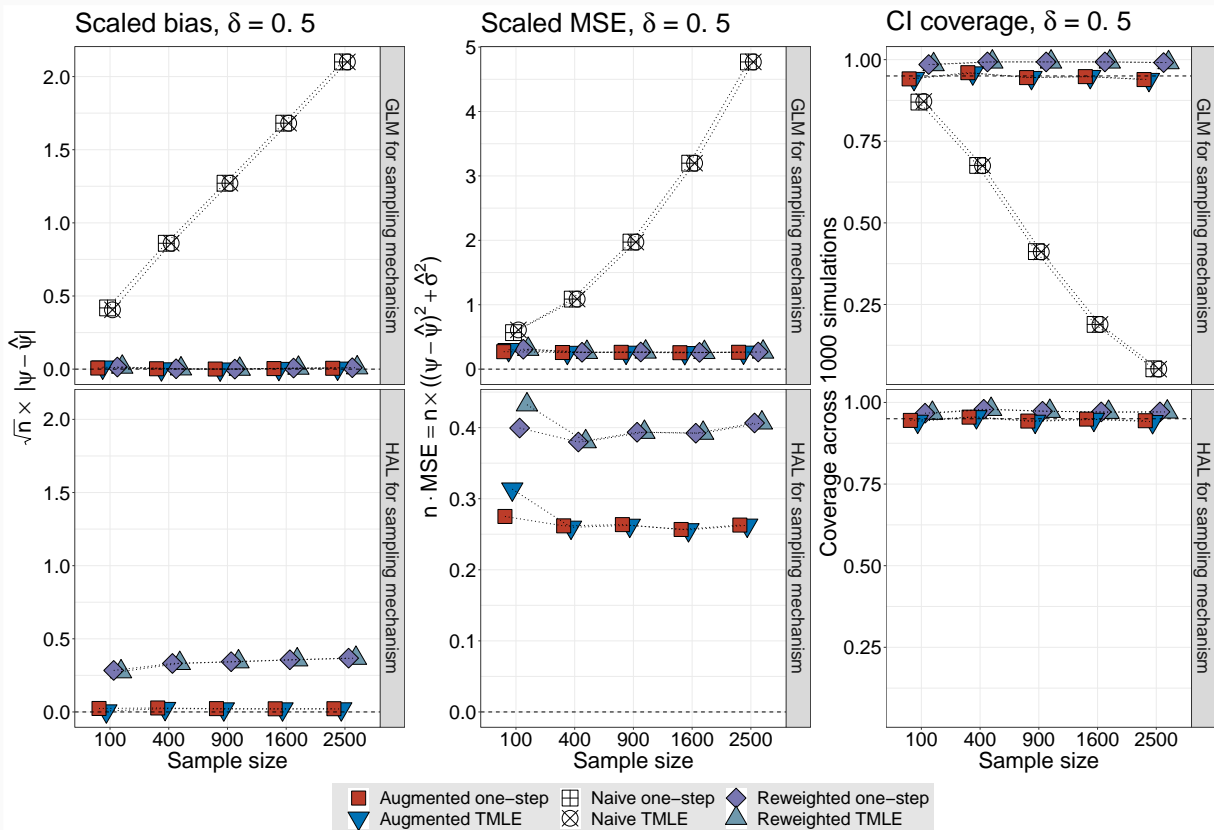
- Then, the IPCW augmentation must be applied to the EIF⁴:

$$D^*(P_0^X)(o) = \frac{b}{\pi_0(y, l)} D_F^*(P_0^X)(x) - \left(1 - \frac{b}{\pi_0(y, l)}\right) \mathbb{E}(D_F^*(P_0^X)(x) \mid B = 1, Y = y, L = l).$$

- Expresses observed data EIF $D^*(P_0^X)(o)$ via complete data EIF $D_F^*(P_0^X)(x)$; inclusion of second term improves efficiency.
- An emergent multiple robustness property — combinations of $\{g_0(S \mid L), \bar{Q}_0(S, L)\} \times \{\pi_0(Y, L), \mathbb{E}(D_F^*(P_0^X)(x) \mid B = 1, Y, L)\}$.
- Our `txshift` R package implements our estimators of $\psi_{0,\delta}$.

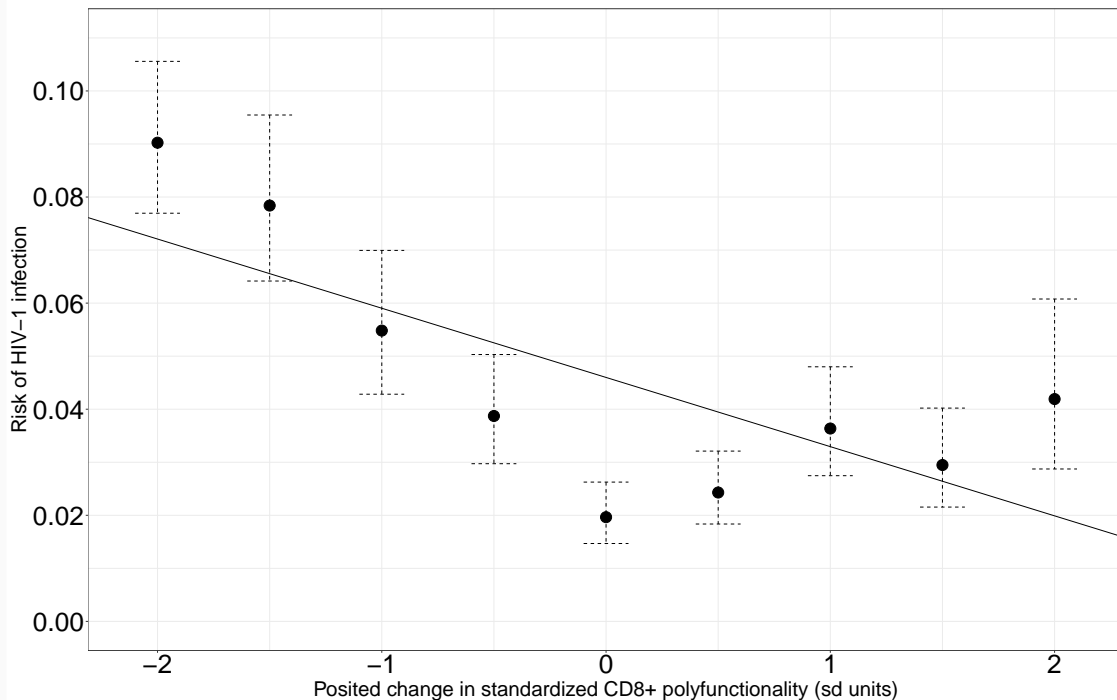
⁴A very general version appears to have been presented in ?.

Comparing Reweighted and Augmented Estimators



SVE Prediction of HIV-1 Risk thru CD8+ Immune Response

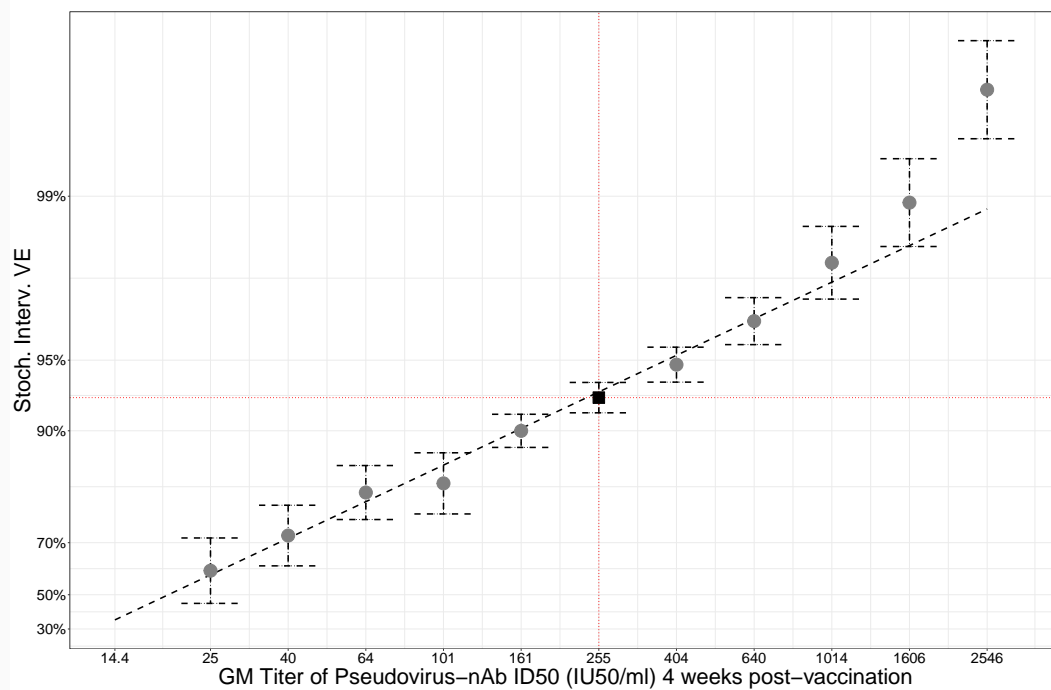
TML estimates of mean counterfactual HIV-1 infection risk under shifted CD8+ polyfunctionality with pointwise confidence intervals and summarization via working marginal structural model ($\hat{\beta}_{\text{TMLE}} = -0.013$)



HIV-1 risk change across CD8+ response (txshift R package).

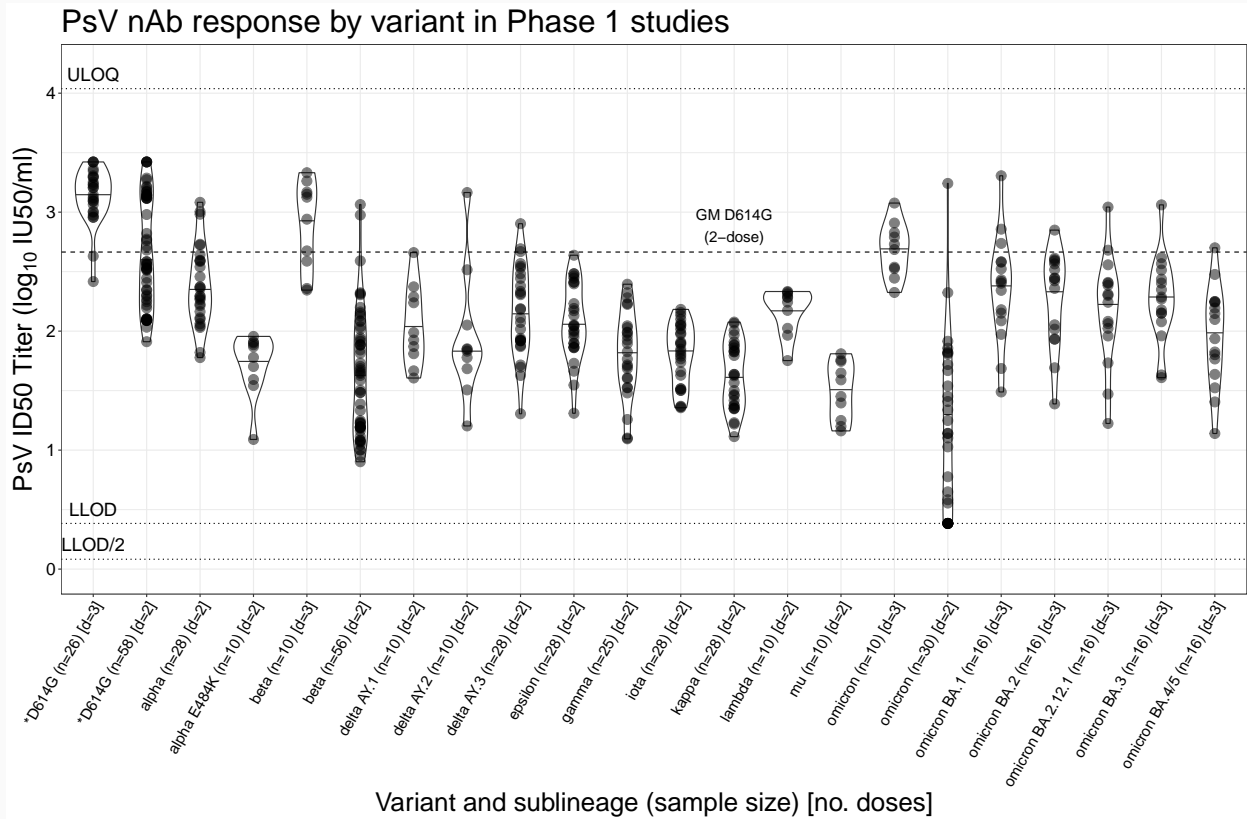
SVE Prediction of mRNA-1273 VE thru PsV nAb Correlate

Stoch. Interv. VE vs. COVID-19 (4 weeks post-vaccination with 100 days follow-up)



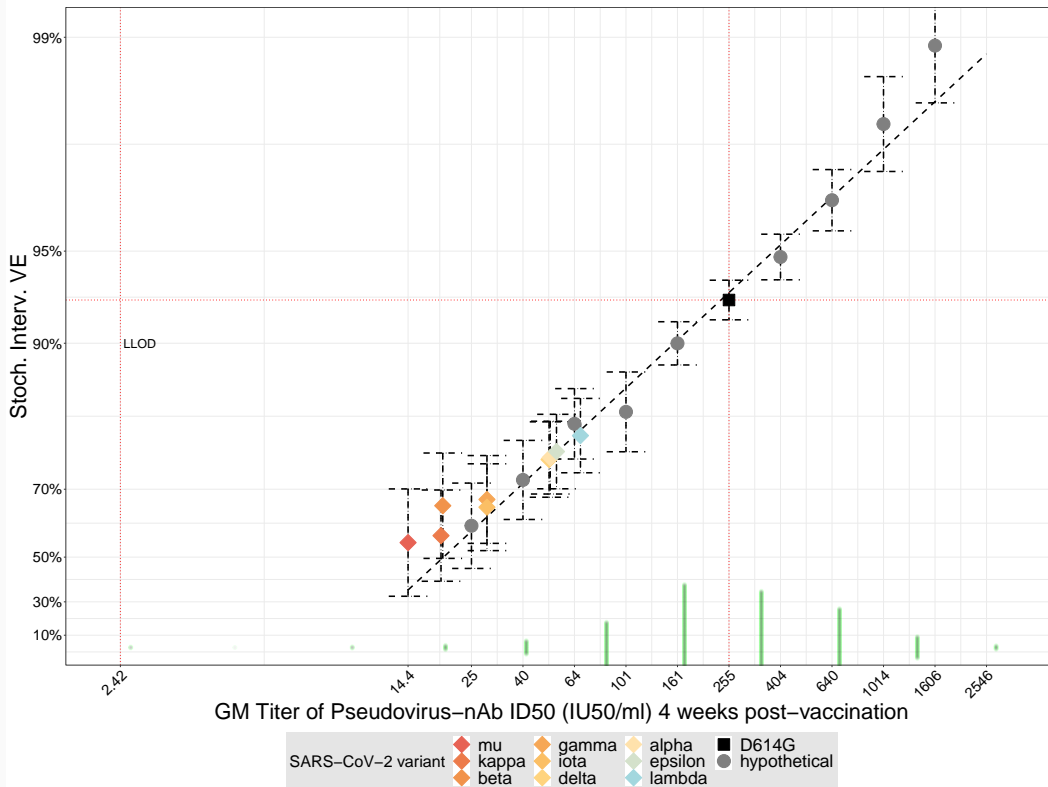
Bridging VE Using Immune Correlates

Pooled Phase 1 Studies: PsV nAb Responses Across Variants



SVE Bridging of mRNA-1273 VE thru PsV nAb Correlate

Stoch. Interv. VE vs. COVID-19 (4 weeks post-vaccination with 100 days follow-up)
After 2 doses of mRNA-1273



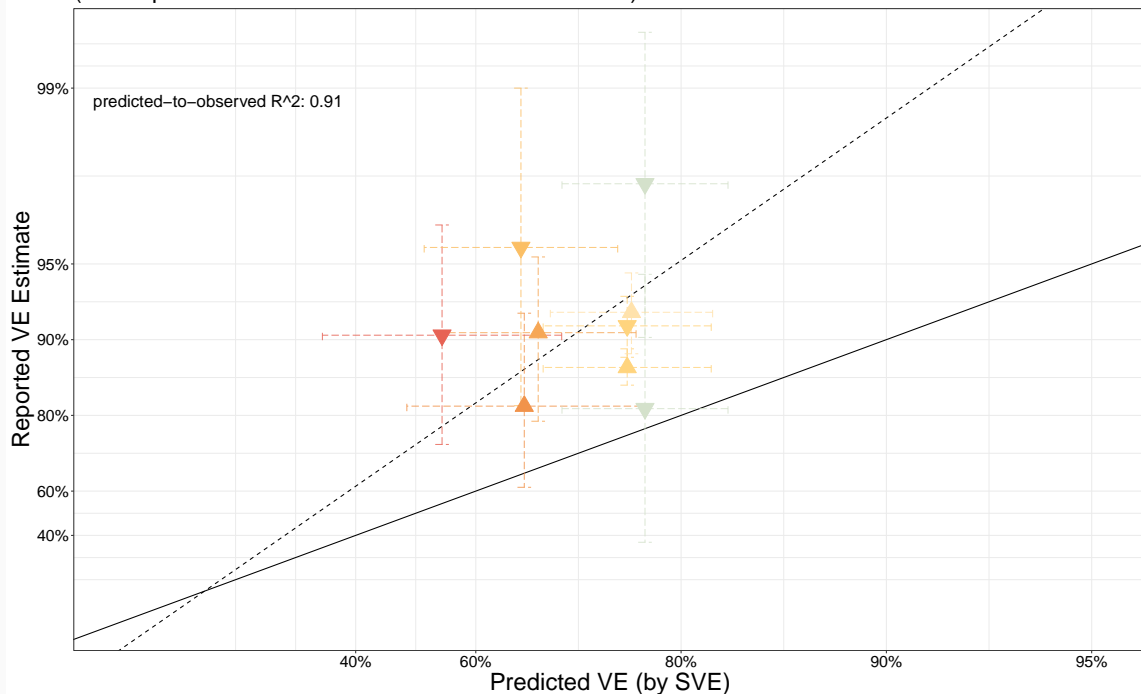
SVE Predictions vs. Real-World Reported Estimates

- Compared δ -calibrated SVE predictions to reported VE estimates, from TND studies or RCTs.
- Inclusion/exclusion criteria for TND-based VE estimates⁵:
 - VE estimated by direct measurement of SARS-CoV-2 variants.
 - Reported VE estimates for mRNA vaccines (BNT162b2 or mRNA-1273), studying VE 2–6 months post-2nd dose.
 - Allowed flexibility in choice of dosing interval, with some studies extending to 12 weeks between doses.
- Studied concordance of SVE predictions and reported (TND or RCT) estimates of VE following most recent vaccine dose.

⁵Comparison of TND studies performed in collaboration with Dr. Lindsay Carpp.

Concordance of SVE Predictions and Reported VE Estimates

Comparison of VE vs. COVID-19 for SARS-CoV-2 variants of concern post dose 2 (with reported or estimated 95% confidence intervals)



TND or RCT VE as reported for infection or symptomatic disease

Summary of SVE Prediction for Immunobridging

- SVE prediction shows sharp changes in VE with shifts to the GM titer of the PsV nAb correlate in vaccinees.
- Bridging VE across variants indicates VE drops but stabilizes at 50%, if the model based on ancestral D614G strain holds.
- Post-2nd dose: For most variants (excepting omicron), the VE estimate ranges from 50% (μ) to 80% (ϵ).
- SVE predictions and real-world VE estimates well-correlated, but SVE predictions may be underestimates, as PsV nAb correlate is an *imperfect* causal *mediator* of total VE.

The Big Picture

- Stochastic interventions provide a framework for formulating novel policies based on natural treatment conditions.
- These modified treatment policies address causal questions about *realistic* interventions on quantitative treatments.
- Large-scale vaccine trials rely upon two-phase designs — but need to (very carefully!) adjust for the resultant sampling bias.
- Efficient estimators with double/multiple robustness can safely answer such questions *while* incorporating machine learning.
- Open source software for such statistical analyses is critical for the methods to have any impact on real-world studies.

Thank you

Thanks for listening. Any questions?

📄 <https://nimahejazi.org>

🐙 <https://github.com/nhejazi>

🐦 <https://twitter.com/nshejazi>

Appendix

Immune Correlates of Protection (?)

- Correlate of Protection (CoP): immune marker statistically predictive of vaccine efficacy, not necessarily mechanistic.
- Mechanistic CoP (mCoP): immune marker that is causally and mechanistically responsible for protection.
- Nonmechanistic CoP (nCoP): immune marker that is predictive but not a causal agent of protection.
- A CoP is a *candidate surrogate* endpoint (?) — primary endpoint in future trials if reliably predictive.

From the Causal to the Statistical Target Parameter

Assumption 1: *Stable Unit Treatment Value (SUTVA)*

- $Y_i^{d(s_i, l_i)}$ does not depend on $d(s_j, l_j)$ for $i = 1, \dots, n$ and $j \neq i$, or lack of interference (?)
- $Y^{d(s, l)} = Y$ in the event $S = d(s, l)$, for $i = 1, \dots, n$

Assumption 2: *No Unmeasured Confounding*

$$S \perp\!\!\!\perp Y^{d(s, l)} \mid L = l, \text{ for } i = 1, \dots, n$$

Assumption 3: *Positivity*

$s \in \mathcal{S} \implies d(s, l) \in \mathcal{S}$ for all $l \in \mathcal{L}$, where \mathcal{S} denotes the support of S conditional on $L = l$ for all $i = 1, \dots, n$

Literature: ??

- *Proposal*: Evaluate outcome under an altered *intervention distribution* — e.g., $P_\delta(g_{0,S})(S = s | L) = g_{0,S}(s - \delta(L) | L)$.
- Identification conditions for a statistical parameter of the counterfactual outcome $\psi_{0,\delta}$ under such an intervention.
- Show that the causal quantity of interest $\mathbb{E}_{P_0^\delta}\{Y_{d(S,L)}\}$ is identified by a functional of the distribution of O , i.e.,

$$\psi_{0,\delta} = \int_{\mathcal{L}} \int_{\mathcal{S}} \mathbb{E}_{P_0}\{Y | S = d(s, l), L = l\} \\ g_{0,S}(s | L = l) \cdot q_{0,L}(l) d\mu(s) d\nu(l)$$

Literature: ?

- *Proposal*: Characterization of stochastic interventions as *modified treatment policies* (MTPs).
- Assumption of *piecewise smooth invertibility* allows for the post-intervention distribution of any MTP to be recovered:

$$g_{0,S}(s | l; \delta) = \sum_{j=1}^{J(l)} \mathbb{I}_{\delta,j}\{h_j(s, l), l\} g_0\{h_j(s, l) | l\} h_j'(s, l)$$

- MTPs account for the natural value of exposure S yet may be interpreted as imposing an altered intervention mechanism.

A Linear Modeling Perspective

- Briefly consider a simple data structure: $X = (Y, S)$; we seek to model the outcome Y as a function of S .
- Linear model: consider $Y_i = \beta_0 + \beta_1 S_i + \epsilon_i$, with error $\epsilon_i \sim N(0, 1)$.
- Letting δ be a change in S , $Y_{S+\delta} - Y_S$ may be expressed

$$\begin{aligned}\mathbb{E}Y_{S+\delta} - \mathbb{E}Y_S &= [\beta_0 + \beta_1(\mathbb{E}S + \delta)] - [\beta_0 + \beta_1(\mathbb{E}S)] \\ &= \beta_0 - \beta_0 + \beta_1\mathbb{E}S - \beta_1\mathbb{E}S + \beta_1\delta \\ &= \beta_1\delta\end{aligned}$$

- So, a *unit shift* in S (i.e., $\delta = 1$) induces a change in the difference in outcomes of magnitude β_1 .

Slope in a Semiparametric Model

- Consider the stochastic intervention $g_\delta(\cdot | L)$:

$$\begin{aligned}\mathbb{E}Y_{g_\delta} &= \int_L \int_s \mathbb{E}(Y | S = s, L) g(s - \delta | L) ds dP_0(L) \\ &= \int_L \int_z \mathbb{E}(Y | S = z + \delta, L) g(z | L) dz dP_0(L),\end{aligned}$$

defining the change of variable $z = s - \delta$.

- For a semiparametric model, $\mathbb{E}(Y | S = z, L) = \beta z + \theta(L)$:

$$\begin{aligned}\mathbb{E}Y_{g_\delta} - \mathbb{E}Y &= \int_L \int_z [\mathbb{E}(Y | S = z + \delta, L) - \mathbb{E}(Y | S = z, L)] \\ &\quad g(z | L) dz dP_0(L) \\ &= [\beta(z + \delta) + \theta(L)] - [\beta z + \theta(L)] \\ &= \beta\delta\end{aligned}$$

Flexible Conditional Density Estimation of $g_{0,S}$

- ?'s conditional density estimator:

$$g_{n,\alpha}(s | L) = \frac{\mathbb{P}(s \in [\alpha_{t-1}, \alpha_t] | L)}{\alpha_t - \alpha_{t-1}}.$$

- Re-expressed as hazard regressions in repeated measures data.
- Tuning parameter $t \approx$ bandwidth in kernel density estimation.
- When càdlàg (RCLL) with finite sectional variation, we have

$$\text{logit}\{\mathbb{P}(s \in [\alpha_{t-1}, \alpha_t] | L)\} = \beta_0 + \sum_{w \in \{1, \dots, d\}} \sum_{i=1}^n \beta_{w,i} \phi_{w,i},$$

for appropriate basis functions $\{\phi_{w,i}\}_{i=1}^n$ (?).

Flexible Conditional Density Estimation of $g_{0,S}$

- Utilizing a particular basis construction for ϕ_w , ?'s HAL estimator achieves $n^{-1/4}$ convergence rate⁶.
- Loss-based cross-validation allows selection of a suitable HAL estimator, which has only the ℓ_1 regularization term λ :

$$\beta_{n,\lambda} = \arg \min_{\beta: |\beta_0| + \sum_{w \in \{1, \dots, d\}} \sum_{i=1}^n |\beta_{w,i}| < \lambda} P_n \mathcal{L}(g_{\beta,\lambda}, S),$$

where $\mathcal{L}(\cdot)$ is an appropriate loss function, giving $\{\lambda_n, \beta_n\}$.

- We denote by $g_{n,\lambda,S} := g_{\beta_n,\lambda,S}$, the HAL estimate of $g_{0,S}$.
- Our `haldensify` R package implements our estimator of $g_{0,S}$.

⁶Similar rates can be achieved via *local* (vs. global) smoothness assumptions on $g_{n,S}$ (see, e.g., ???).

A Useful Class of Functions

Consider space of *cadlag* functions with *finite variation norm*.

Def. *cadlag* = *left-hand continuous* with *right-hand limits*

Variation norm Let $\theta_s(u) = \theta(u_s, 0_{s^c})$ be the *section* of θ that sets the coordinates in s equal to zero.

The *variation norm* of θ can be written:

$$|\theta|_v = \sum_{s \subset \{1, \dots, d\}} \int |d\theta_s(u_s)|,$$

where $x_s = (x(j) : j \in s)$ and the sum is over all subsets.

Variation Norm

We can represent the function θ as

$$\theta(x) = \theta(0) + \sum_{s \subset \{1, \dots, d\}} \int \mathbb{I}(x_s \geq u_s) d\theta_s(u_s),$$

For discrete measures $d\theta_s$ with *support points* $\{u_{s,j} : j\}$ we get a *linear combination* of indicator *basis functions*:

$$\theta(x) = \theta(0) + \sum_{s \subset \{1, \dots, d\}} \sum_j \beta_{s,j} \theta_{u_{s,j}}(x),$$

where $\beta_{s,j} = d\theta_s(u_{s,j})$, $\theta_{u_{s,j}}(x) = \mathbb{I}(x_s \geq u_{s,j})$, and

$$|\theta|_v = \theta(0) + \sum_{s \subset \{1, \dots, d\}} \sum_j |\beta_{s,j}|.$$

Convergence Rate of HAL

We have, for $\alpha(d) = 1/(d + 1)$,

$$|\theta_{n,M} - \theta_{0,M}|_{P_0} = o_P(n^{-(1/4+\alpha(d)/8)}).$$

Thus, if we select $M > |\theta_0|_v$, then

$$|\theta_{n,M} - \theta_0|_{P_0} = o_P(n^{-(1/4+\alpha(d)/8)}).$$

Due to oracle inequality for the cross-validation selector M_n ,

$$|\theta_{n,M_n} - \theta_0|_{P_0} = o_P(n^{-(1/4+\alpha(d)/8)}).$$

Improved convergence rate (?):

$$|\theta_{n,M_n} - \theta_0|_{P_0} = o_P(n^{-1/3} \log(n)^{d/2}).$$

Algorithm for TML Estimation

1. Construct initial estimators g_n of $g_0(S, L)$ and Q_n of $\bar{Q}_0(S, L)$, perhaps using data-adaptive regression techniques.
2. For each observation i , compute an estimate $H_n(s_i, l_i)$ of the auxiliary covariate $H(s_i, l_i)$.

3. Estimate the parameter ϵ in the logistic regression model

$$\text{logit} \bar{Q}_{\epsilon,n}(s, l) = \text{logit} \bar{Q}_n(s, l) + \epsilon H_n(s, l),$$

or an alternative regression model incorporating weights.

4. Compute TML estimator Ψ_n of the target parameter, defining update \bar{Q}_n^* of the initial estimate \bar{Q}_{n,ϵ_n} :

$$\Psi_n = \Psi(P_n^*) = \frac{1}{n} \sum_{i=1}^n \bar{Q}_n^*(d(S_i, L_i), L_i).$$

Algorithm for IPCW-TML Estimation

1. Using all observed units (X), estimate sampling mechanism $\pi(Y, L)$, perhaps using data-adaptive regression methods.
2. Using only observed units in the second-stage sample $C = 1$, construct initial estimators $g_n(S, L)$ and $\bar{Q}_n(S, L)$, weighting by the sampling mechanism estimate $\pi_n(Y, L)$.
3. With the approach described for the full data case, compute $H_n(s_i, l_i)$, and fluctuate submodel via logistic regression.
4. Compute IPCW-TML estimator Ψ_n of the target parameter, by solving the IPCW-augmented EIF estimating equation.
5. Iteratively update estimated sampling weights $\pi_n(Y, L)$ and IPCW-augmented EIF, updating TMLE in each iteration.

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