

The burden of HIV-1

- The HIV-1 epidemic the facts:
 - now in its fourth decade,
 - 2.5 million new infections occurring annually worldwide,
 - new infections outpace patients starting antiretroviral therapy.
- *Most efficacious* preventive vaccine: 31% reduction rate.
- Question: How can HIV-1 vaccines be improved by modulating immunogenic CD4+ or CD8+ response profiles?

HVTN 505 trial examined new antibody boost vaccines

- HIV Vaccine Trials Network (HVTN) 505 vaccine efficacy RCT with n = 2504 (Hammer et al. 2013).
- Immunogenic response profile only available for second-stage sample of n = 189 (Janes et al. 2017).
- Two-phased sampling mechanism: 100% inclusion rate if HIV-1 positive in week 28; variable otherwise.
- **Question:** How would HIV-1 infection risk in week 28 have differed had immunogenic response (due to vaccine) differed?

- Baseline covariates(*W*): sex, age, BMI, behavioral HIV risk.
- Intervention(s) (A): post-vaccination T-cell activity markers.
- Outcome (Y): HIV-1 infection status at week 28 of tiral.
- **Conclusion:** Understanding which immune responses impact vaccine efficacy helps develop more efficacious vaccines.
- A vaccine effective at preventing HIV-1 acquisition would be a cost-effective and durable approach to halting the worldwide epidemic.
- Identifying vaccine-induced immune-response biomarkers that predict a vaccine's ability to protect individuals from HIV-1 infection is a high priority.
- The study was halted on 22 April 2013 due to absence of vaccine efficacy. There was no significant effect of the vaccine on the primary infection endpoint of HIV-1 infection between week 28 and

Two-phase sampling censors the complete data structure

- Complete, unobserved data X = (W, A, Y) ~ P_0^X ∈ M_NP, as per the full HVTN 505 RCT (Hammer et al. 2013):
 - *W* baseline covariates: sex, age, BMI, behavioral HIV risk,
 - A intervention: immune response profile for CD4 and CD8,
 - Y outcome of interest: HIV-1 infection status by week 28.
- Observed data O = (Δ, ΔX) = (W, Δ, ΔA, Y), Δ ∈ {0,1}, as per the second-stage sample of Janes et al. (2017).

- P_0^X true (unknown) distribution of the full data X,
- *M*^X_{NP} nonparametric statistical model.

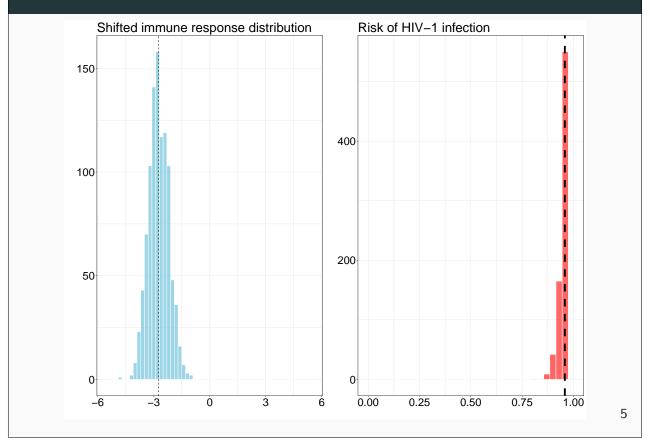
Stochastic interventions define the causal effects of shifts

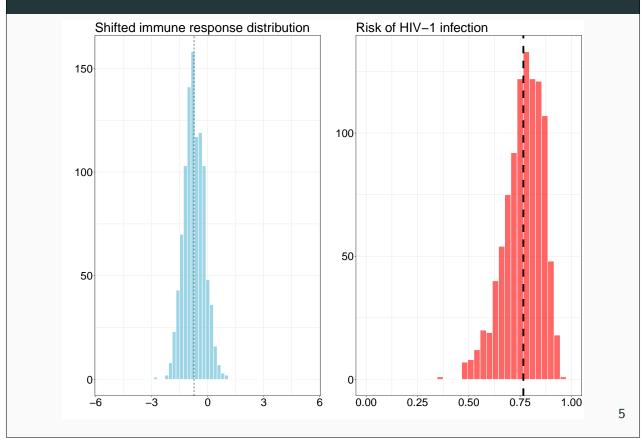
- Causal estimand: counterfactual mean of HIV-1 infection under a *shifted* immunogenic response distribution.
- Díaz and van der Laan (2012; 2018): Shift interventions?

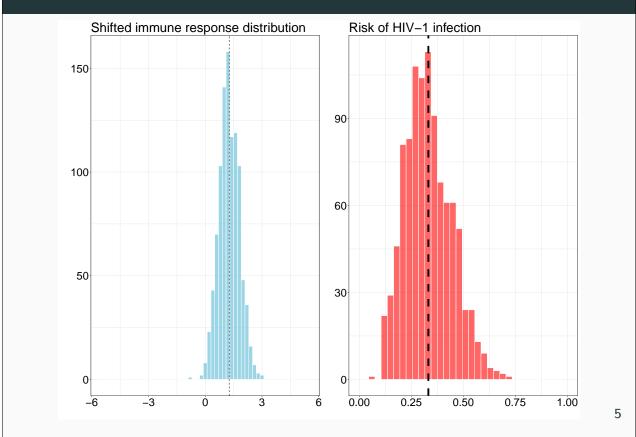
$$\mathit{d}(\mathit{a},\mathit{w}) = egin{cases} \mathit{a} + \delta, & ext{if plausible} \ \mathit{a}, & ext{otherwise} \end{cases}$$

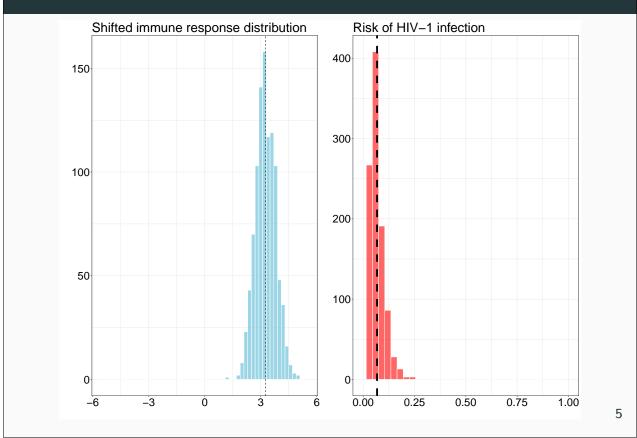
- Díaz and van der Laan (2012; 2018) give a statistical target parameter and influence function for the complete data case.
- **Challenge:** parameter estimation requires conditional density estimation. Nonparametric options?

- For HVTN 505, $\psi_{0,d}$ is the counterfactual risk of HIV-1 infection, had the observed value of the immune response been modifed to originate from the distribution of the rule d(A, W).
- Several different ways to consider stochastic interventions.
- Starts with Mark and Ivan's simple stochastic shift.
- Extensions to modified treatment policies.
- The new value of A may be denoted A* ~ G*(· | W), where
 A* = d(W, U*) for a rule d and random error U*.









Efficient estimators in spite of two-phase sampling

- What if sampling mechanism π₀(Y, W) = P(Δ = 1 | Y, W) is not known by design? Nonparametric estimation of π₀(Y, W)?
- Building on Rose and van der Laan (2011), we provide
 - asymptotically linear and nonparametric-efficient estimators;
 - multiply robust, with 2 forms of double robustness;
 - Gaussian limiting distributions and Wald-type CIs.
- New open source software for deploying such estimators:
 - https://github.com/nhejazi/haldensify (densities)
 - https://github.com/nhejazi/txshift (AIPW, TMLE)
 - https://github.com/tlverse/tmle3shift (TMLE)

Asymptotic linearity:

$$\Psi(P_n^\star)-\Psi(P_0^X)=rac{1}{n}\sum_{i=1}^n D(P_0^X)(X_i)+o_P\left(rac{1}{\sqrt{n}}
ight)$$

• Gaussian limiting distribution:

$$\sqrt{n}(\Psi(P_n^{\star}) - \Psi(P_0^{X})) \rightarrow N(0, \operatorname{Var}(D(P_0^{X})(X)))$$

• Statistical inference:

Wald-type confidence interval : $\Psi(P_n^*) \pm z_\alpha \cdot \frac{\sigma_n}{\sqrt{n}}$,

where σ_n^2 is computed directly via $\sigma_n^2 = \frac{1}{n} \sum_{i=1}^n D^2(\cdot)(X_i)$.

How does this help in fighting the HIV-1 epidemic?

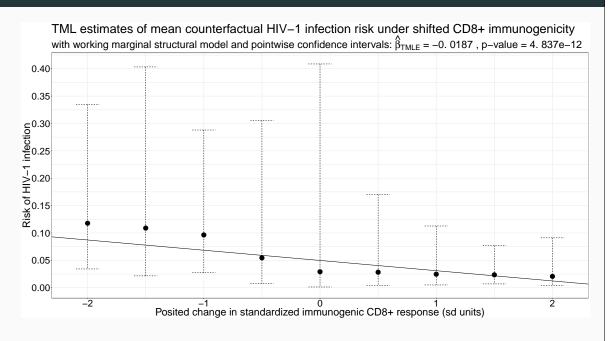


Figure 1: Analysis of HIV-1 risk as a function of CD8+ immunogenicity, using R package txshift (https://github.com/nhejazi/txshift.)

References

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