

# Methods for Comparing Mark-specific Hazards and Cumulative Incidence Functions Between Two Groups, with Application to HIV Vaccine Trials

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- Motivating Example: HIV vaccine efficacy trial
- Statistical Methods
  - Hypothesis testing
  - Estimation
- Illustration

# Example: HIV Vaccine Efficacy Trial

- **Primary objective:** Assess vaccine efficacy ( $VE$ ) to prevent HIV infection
- **Secondary objective:** Assess if and how  $VE$  varies with genotypic/phenotypic characteristics of HIV
- For each infected subject, measure the **distance  $V$**  between the infecting virus and the virus(es) represented in the vaccine
- **Available data:**
  - Vaccine group:  $(T_{1i}, \delta_{1i}, \delta_{1i}V_{1i}), \quad i = 1, \dots, n_1$
  - Placebo group:  $(T_{2i}, \delta_{2i}, \delta_{2i}V_{2i}), \quad i = 1, \dots, n_2$

# Example: HIV Vaccine Efficacy Trial

- **Case 1:**  $V$  a small number of ordered categories
  - E.g.:  $V \in \{0, 1, 2, 3+\}$  substitutions/deletions in the HIV V3 loop tip sequence GPGRAF
  - For each strain category  $j$ , can study  $VE(t, j)$  using cause-specific hazard functions or cumulative incidence functions:

$$VE(t, j) = 1 - \frac{\lambda_{1j}(t)}{\lambda_{2j}(t)} \quad \text{or} \quad VE(t, j) = 1 - \frac{F_{1j}(t)}{F_{2j}(t)}$$

Prentice et al. (1978, Biometrics);  
Gilbert (2000, Statistics in Medicine)

# Example: HIV Vaccine Efficacy Trial

- **Case 2:**  $V$  a large number of ordered categories
  - E.g.: percent amino acid mismatch computed over hundreds or thousands of positions
    - ⇒ Treat  $V$  as continuous,  $V \in [0, 1]$
  - Gilbert et al. (1999, Biometrika; 2000, Annals of Statistics) developed semiparametric methods for studying  $OR(v)$ 
    - $OR(v) =$  odds that the infecting strain has distance  $v$  for vaccine versus placebo recipients

# Example: HIV Vaccine Efficacy Trial

- **Semiparametric biased sampling model:**

$$F_1(v, \theta) = \frac{\int_0^v w(z, \theta) dF_2(z)}{\int_0^\infty w(z, \theta) dF_2(z)}$$

- **Limitations:**
  - Interpretation conditional on infection
  - $OR(v)$  assumed to satisfy a parametric form
  - Does not account for time to HIV infection

- **Objective:** Develop methods for testing and estimation of  $VE(t, v)$  defined based on continuous mark-specific hazard and cumulative incidence functions

- Mark-specific hazard functions:

$$\lambda_k(t, v) = \lim_{h_1, h_2 \rightarrow 0} P\{T_k \in [t, t + h_1), V_k \in [v, v + h_2)\} / h_1 h_2$$

- Mark-specific cumulative incidence functions:

$$F_k(t, v) = \lim_{h_2 \rightarrow 0} P\{T_k \leq t, V_k \in [v, v + h_2)\} / h_2$$

- The functions have a *crude* (not *net*) interpretation

- Define  $VE(t, v) = 1 - \frac{\lambda_1(t, v)}{\lambda_2(t, v)}$ ;  $VE(t) = 1 - \frac{\lambda_1(t)}{\lambda_2(t)}$

- Test

$$H_0 : VE(t, v) = VE(t) \text{ for all } t \in [0, \tau]$$

versus

$$H_1 : VE(t, v_1) \leq VE(t, v_2) \text{ for all } v_1 \leq v_2, t \in [0, \tau]$$

$$H_2 : VE(t, v_1) \neq VE(t, v_2) \text{ for some } v_1 \leq v_2, t \in [0, \tau]$$

- $H_0 \Leftrightarrow \lambda_1(t, v)/\lambda_2(t, v)$  does not depend on  $v$



- Define doubly cumulative mark-specific hazard functions

$$\Lambda_k(t, v) = \int_0^v \int_0^t \lambda_k(s, u) ds du, \quad k = 1, 2$$

- **Idea of testing procedures:** Compare a nonparametric estimate of  $\Lambda_1(t, v) - \Lambda_2(t, v)$  with an estimate under  $H_0$

- Nelson–Aalen-type estimator (Huang and Louis, 1998, Biometrika):

$$\hat{\Lambda}_k(t, v) = \int_0^t \frac{N_k(ds, v)}{Y_k(s)}, \quad t \geq 0, \quad v \in [0, 1]$$

$$Y_k(t) = \sum_{i=1}^{n_k} I(X_{ki} \geq t)$$

$$N_k(t, v) = \sum_{i=1}^{n_k} I(X_{ki} \leq t, \delta_{ki} = 1, V_{ki} \leq v)$$

- $H_0$  holds  $\Leftrightarrow$

$$\Lambda_1(t, v) = \int_0^t \frac{\lambda_1(s)}{\lambda_2(s)} \Lambda_2(ds, v)$$

- Under  $H_0$ , estimate  $\Lambda_1(t, v) - \Lambda_2(t, v)$  by

$$\int_0^t \left[ \frac{\hat{\lambda}_1(s)}{\hat{\lambda}_2(s)} - 1 \right] \hat{\Lambda}_2(ds, v)$$

with

$$\hat{\lambda}_k(t) = \frac{1}{b_k} \int_{u_1}^{u_2} K \left( \frac{t-s}{b_k} \right) d\hat{\Lambda}_k(s)$$

# Test Process and Test Statistics

- **Test process:**

$$L_n(t, v) = \sqrt{\frac{n_1 n_2}{n}} \int_0^t H_n(s) \left[ \hat{\Lambda}_1(ds, v) - \frac{\hat{\lambda}_1(s)}{\hat{\lambda}_2(s)} \hat{\Lambda}_2(ds, v) \right]$$

- **Test statistics:**

$$\hat{U}_1 = \sup_{v_1 < v_2} \sup_{0 < t_1 < t_2 < \tau} \{ L_n(t_2, v_2) - L_n(t_2, v_1) - L_n(t_1, v_2) + L_n(t_1, v_1) \}$$

$$\hat{U}_2 = \sup_{0 \leq v \leq 1} \sup_{0 < t_1 < t_2 < \tau} |L_n(t_2, v) - L_n(t_1, v)|$$

- **Theorem 1:** Under regularity conditions

$$L_n(t, v) \rightarrow^d L(t, v)$$

in  $D([0, \tau] \times [0, 1])$  as  $n \rightarrow \infty$

- $\Rightarrow$  Under  $H_0$ ,  $\hat{U}_1 \rightarrow^d U_1$  and  $\hat{U}_2 \rightarrow^d U_2$
- Let  $c_{1\alpha}$  and  $c_{2\alpha}$  be the  $(1 - \alpha)$  quantile of  $U_1$  and  $U_2$ 
  - $P(\hat{U}_j > c_{j\alpha}) \rightarrow \alpha$  under  $H_0$

- **Theorem 2:** Under regularity conditions

$$P(\hat{U}_1 > c_{1\alpha}) \rightarrow 1 \text{ under } H_1$$

$$P(\hat{U}_2 > c_{2\alpha}) \rightarrow 1 \text{ under } H_2$$

- Critical values  $c_{j\alpha}$  unknown and difficult to obtain
- $\Rightarrow$  Use a resampling procedure to approximate  $c_{j\alpha}$

- Let  $W_{1i} \sim N(0, 1), i = 1, \dots, n_1; W_{2i} \sim N(0, 1), i = 1, \dots, n_2$
- Define a simulated test process  $\tilde{L}_n(t, \nu)$ , a function of:
  - $W_{1i}, W_{2i}$
  - $\hat{\lambda}_1(t), \hat{\lambda}_2(t)$
  - A smooth estimate of  $\Lambda'_2(t, \nu) = \frac{d}{ds} \Lambda_2(s, \nu)|_{s=t}$
- **Theorem 3:** Under regularity conditions, conditional on the observed data sequence

$$\tilde{L}_n(t, \nu) \rightarrow^d L(t, \nu)$$

in  $D([0, \tau] \times [0, 1])$  under  $H_0$  as  $n \rightarrow \infty$

- Acceptance/Rejection procedure:
  - Compute  $\hat{U}_1$  and  $\hat{U}_2$  based on  $\tilde{L}_n(t, \nu)$
  - Based on  $B$  replicates  $\hat{U}_j$ , compute  $\hat{c}_{j\alpha} = (1 - \alpha)^{th}$  percentile of  $\hat{U}_{j1}, \dots, \hat{U}_{jB}$
  - Reject  $H_0$  if  $\hat{U}_j > \hat{c}_{j\alpha}$



- Sample size too small to reliably estimate

$$VE(t, v) = 1 - \frac{\lambda_1(t, v)}{\lambda_2(t, v)}$$

- Alternatively, consider

$$\begin{aligned} VE(t, v) &= 1 - \frac{F_1(t, v)}{F_2(t, v)} \\ &= 1 - \lim_{h \rightarrow 0} \frac{P(T \leq t, V \in [v, v+h] | 1)}{P(T \leq t, V \in [v, v+h] | 2)} \end{aligned}$$

- Estimate  $VE(t, v)$  by  $1 - \frac{\hat{F}_1(t, v)}{\hat{F}_2(t, v)}$ , where

$$\hat{F}_k(t, v) = \frac{1}{2b} \int_0^t \frac{\hat{S}_k(s-)}{Y_k(s)} N_{vk}(ds)$$

$$N_{vk}(t) = \sum_{i=1}^{n_k} I(X_i \leq t, \delta_i = 1, v - b < V_i \leq v + b)$$

$$\hat{S}_k(t) = \text{Kaplan-Meier estimate of } S_k(t)$$

- $\hat{F}_k(t, v) =$  continuous analog of  $\hat{F}_{kj}(t)$  for a discrete mark  $j$

- $Var\{\widehat{F}_k(t, v)\}$  can be estimated by

$$\frac{1}{(2b)^2} \int_0^t \left[ \frac{\widehat{S}_k(s-)}{Y_k(s)} \right]^2 N_{vk}(ds)$$

- 95% pointwise confidence intervals:

$$\widehat{VE}(t, v) \pm 1.96 \times \widehat{Var}\{\widehat{VE}(t, v)\}^{1/2}$$

- First preventive HIV vaccine efficacy trial completed in February 2003
- AIDSVAX, a bivalent recombinant gp120 vaccine, developed and tested by VaxGen, Inc.
- Trial conducted in the U.S./Netherlands/Canada/Caribbean,  $n = 5403$ , 2:1 randomization to vaccine:placebo
- Volunteers tested for HIV infection every 6 months for 3 years
- For HIV infected subjects, the gp120 region of HIV was sequenced

- **Primary analysis:**

	Number Randomized	Number Infected	Percent Infected
Vaccine	3598	241	6.7%
Placebo	1805	127	7.0%

$$\widehat{VE} = 5.9\%, \quad 95\% \text{ CI } (-16.7\%, 24.2\%), \quad p = 0.58$$

# *Sieve Analysis Illustration*

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- Define  $V$  as the percent mismatch in V1-V2-V3 of the infecting strain relative to the MN vaccine strain
- Two pseudo examples:
  1. (**null case**) Use the real failure times, indicators, and marks, and randomly permute the vaccination statuses to achieve  $\approx 2:1$  vaccine:placebo ratio

2. (alternative case) Use the real failure times, indicators, and marks, and select the vaccination statuses such that

$$P(Z = 1|V = v) = \frac{\exp\{\alpha + \beta v\}}{1 + \exp\{\alpha + \beta v\}}$$

with  $\alpha$  and  $\beta$  chosen such that  $P(Z = 1|V = \bar{V}) = 2/3$  and  $P(Z = 1|V = \max(V)) = 0.99$

## ***Example 1 (null case)***

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	<i>n</i>	mean	range
Vaccine	217	0.348	0.12-0.43
Placebo	120	0.335	0.14-0.44

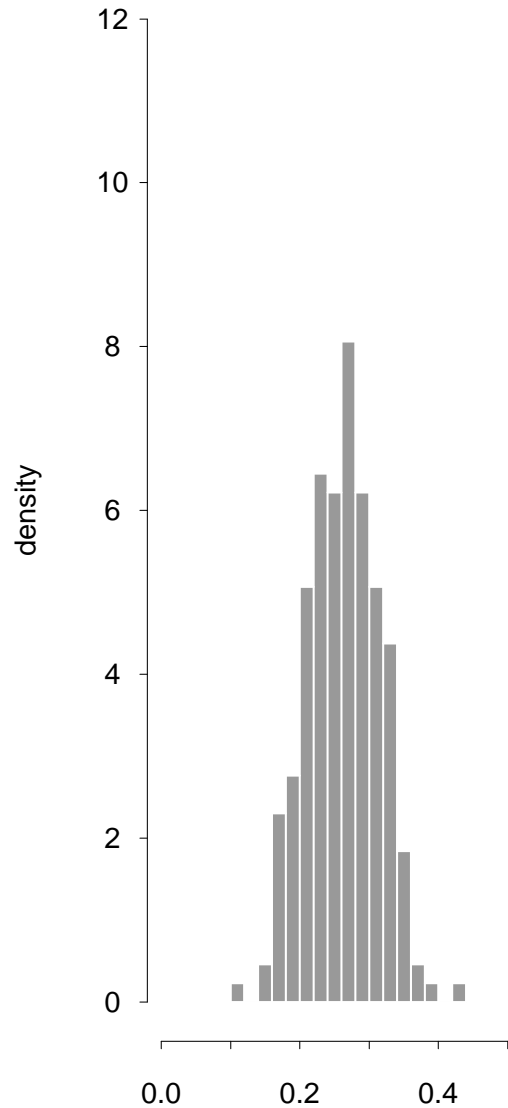
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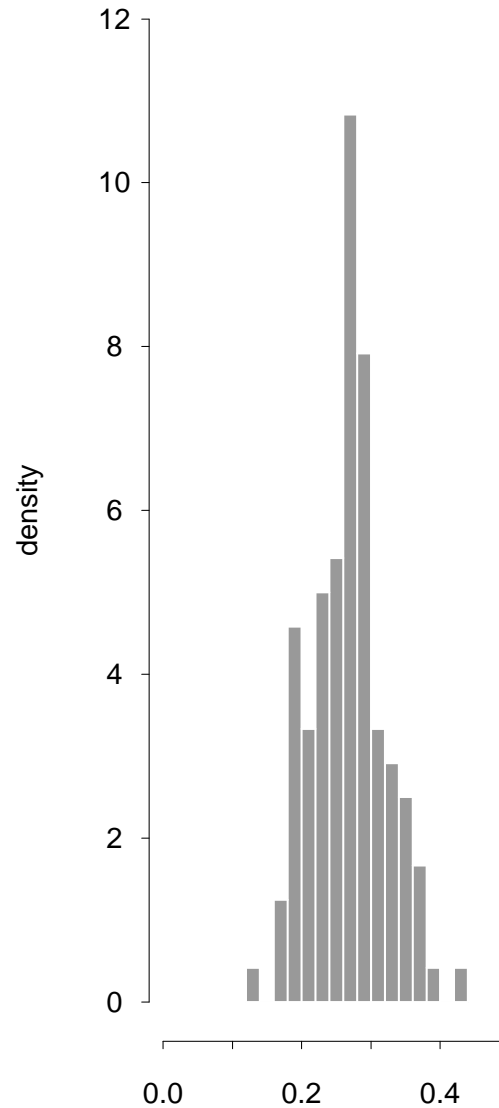
# Example 1 (null case)

## Distributions of V1-V2-V3 Strain Distance

Vaccine



Placebo

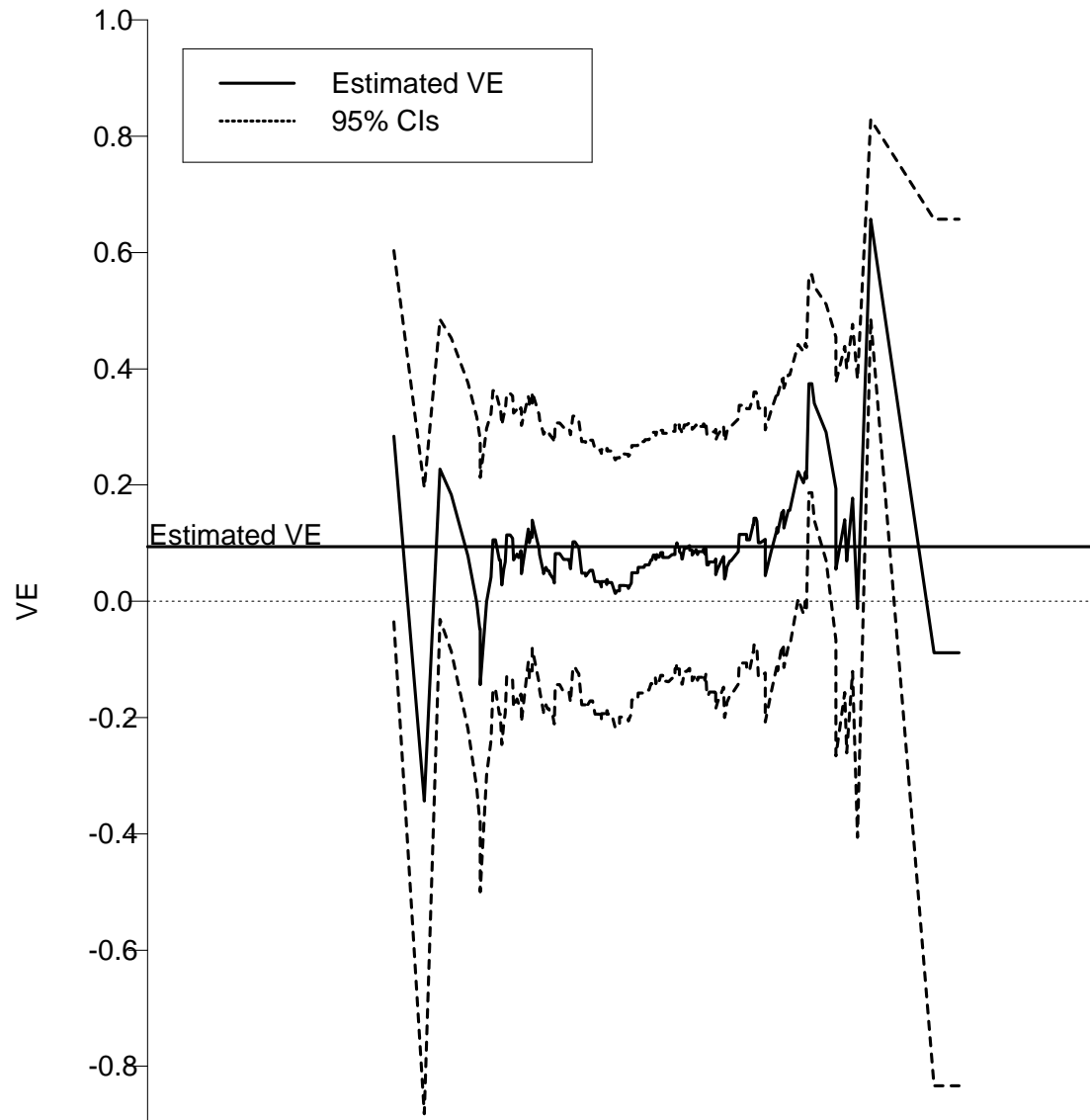


## ***Example 1 (null case)***

- Implementation of testing and estimation procedures:
  - Time range 2-36 months
  - bandwidth = 8.5 months
  - Distance range 0.12-0.44
  - bandwidth = 0.10, 0.15, 0.20
- $\tilde{U}_1 = 0.348, \tilde{U}_2 = 0.335$ 
  - Based on 1000 simulations,  $p_1 = 0.677, p_2 = 0.523$

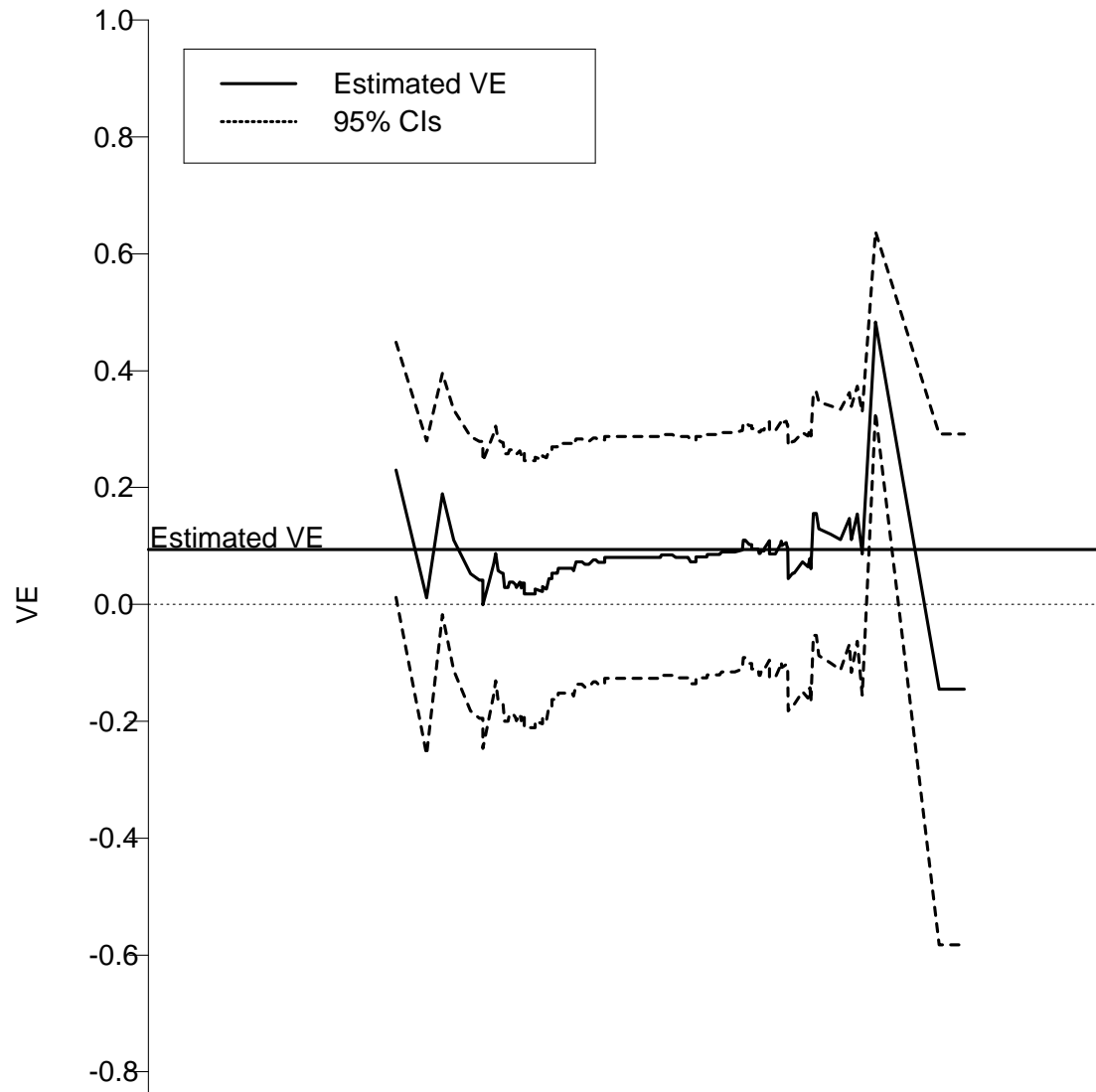
# Example 1 (null case)

Vaccine efficacy as a function of strain distance,  
bandwidth = 0.10



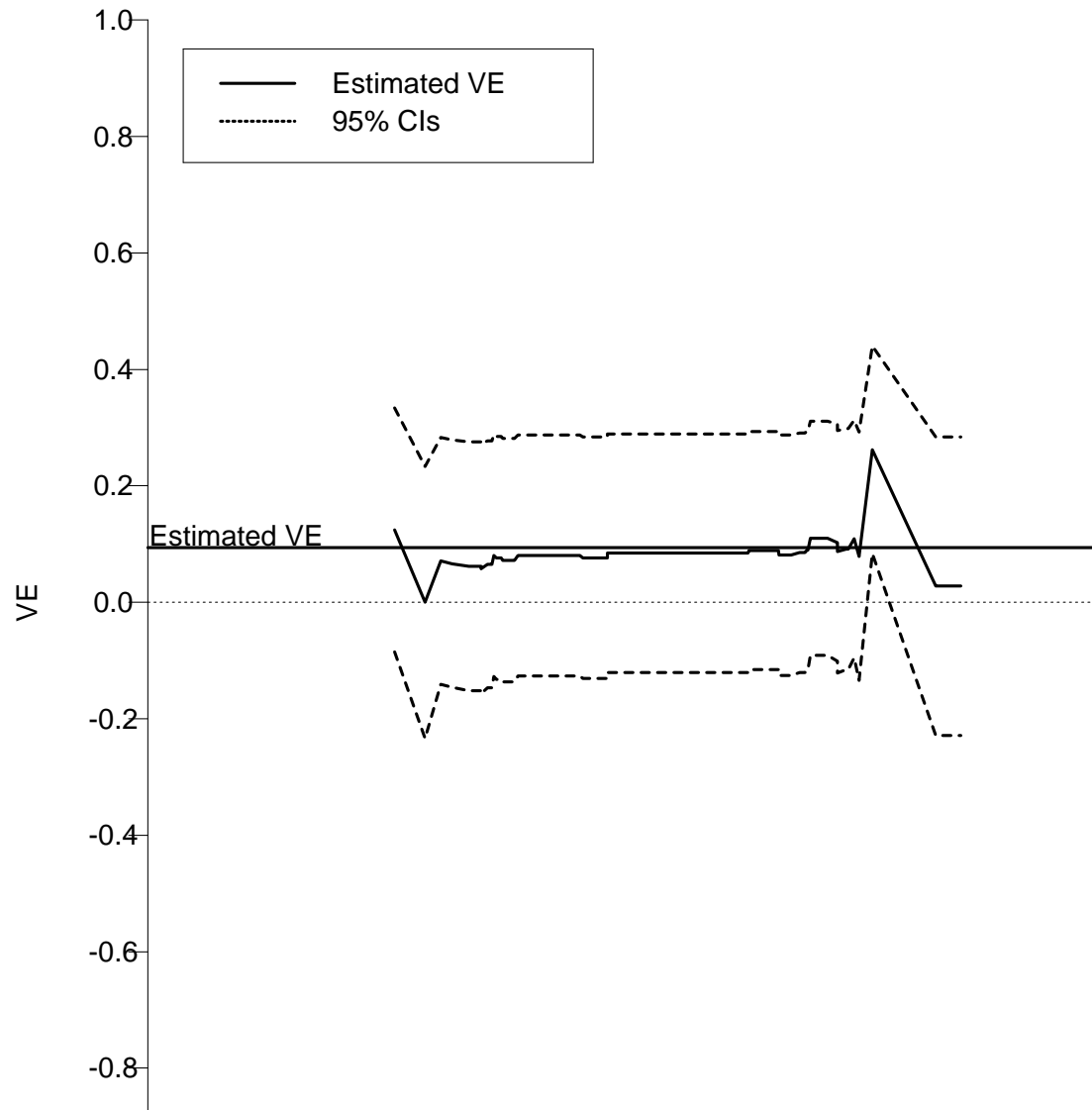
# Example 1 (null case)

Vaccine efficacy as a function of strain distance,  
bandwidth = 0.15



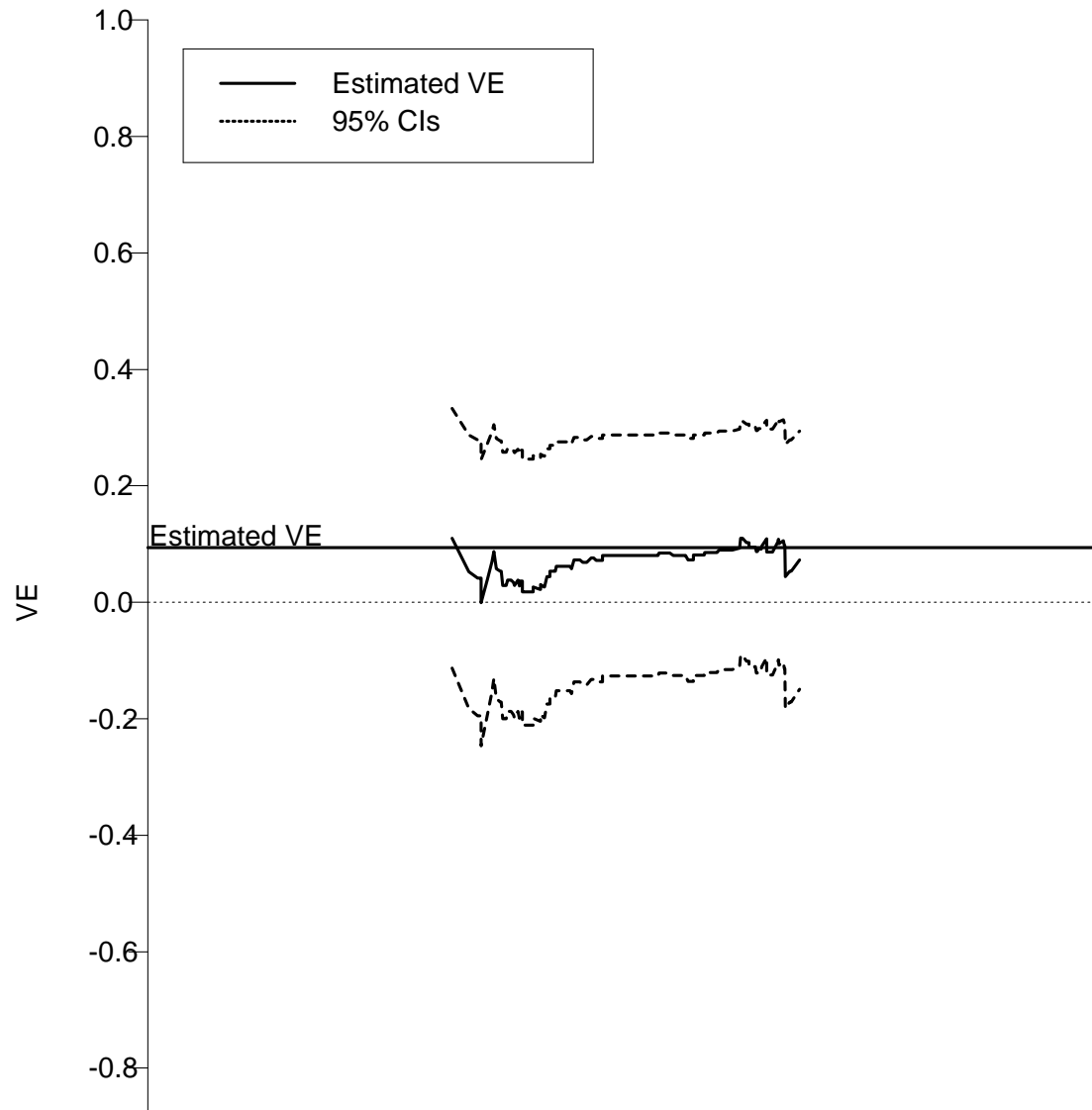
# Example 1 (null case)

Vaccine efficacy as a function of strain distance,  
bandwidth = 0.20



# Example 1 (null case)

Vaccine efficacy as a function of strain distance,  
bandwidth = 0.10



## ***Example 2 (alternative case)***

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	<i>n</i>	mean	range
Vaccine	208	0.285	0.17-0.44
Placebo	129	0.232	0.12-0.34

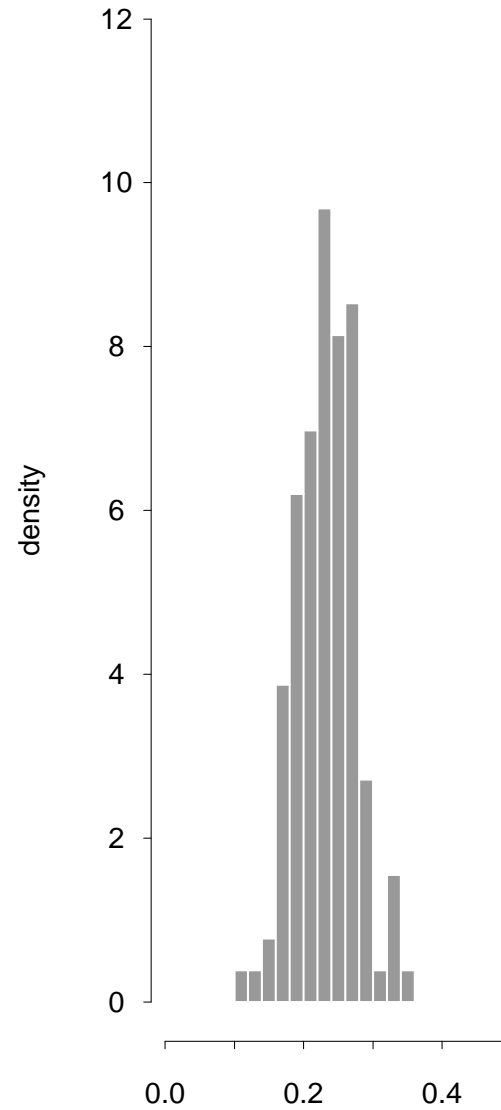
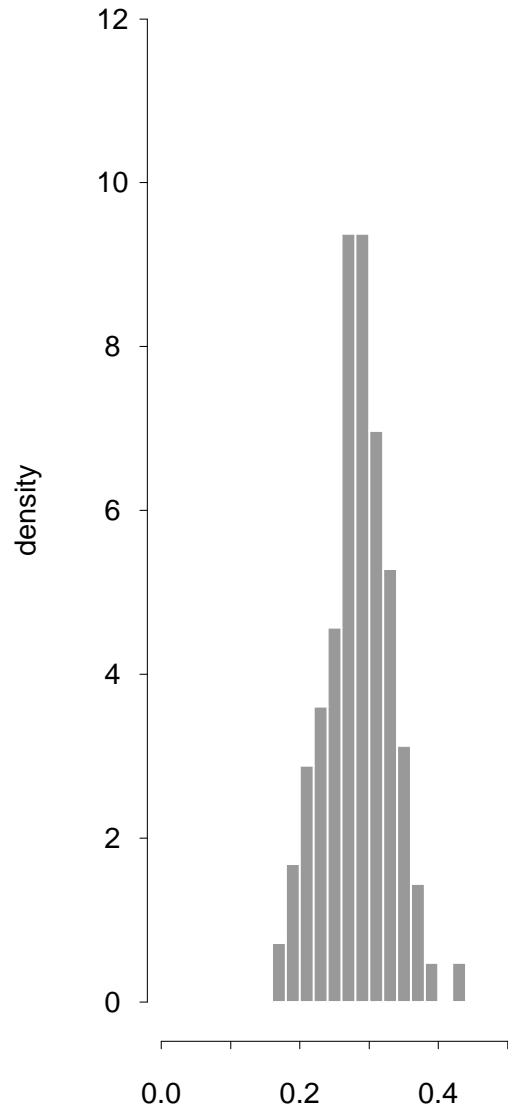
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# Example 2 (alternative case)

## Distributions of V1-V2-V3 Strain Distance

Vaccine

Placebo





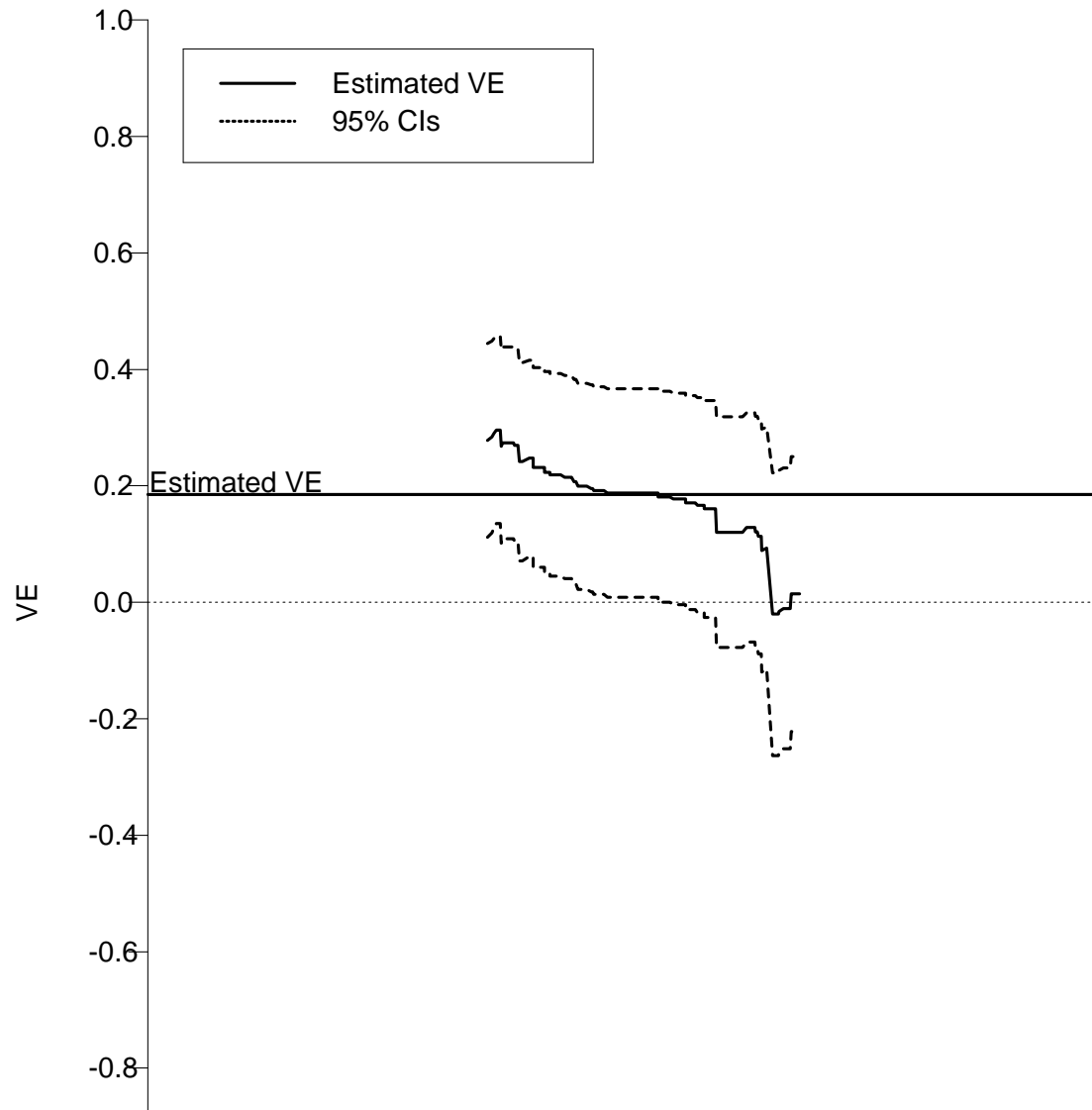
## ***Example 2 (alternative case)***

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- Implementation of testing and estimation procedures:
  - Time range 2-36 months
  - bandwidth = 8.5 months
  - Distance range 0.15-0.35
  - bandwidth = 0.15
- $\tilde{U}_1 = 1.169, \tilde{U}_2 = 1.272$ 
  - Based on 1000 simulations,  $p_1 < 0.001, p_2 < 0.001$

## Example 2 (alternative case)

Vaccine efficacy as a function of strain distance,  
bandwidth = 0.10



- Simultaneous confidence bands for  $VE(t, v)$  in  $v$  for  $t$  fixed and in  $t$  for  $v$  fixed
- Study  $VE(t, v)$  with covariate adjustment
  - Continuous mark-specific Cox regression model
- Causal inference/Sensitivity analysis to address the fundamental nonidentifiability problem for competing risks data
  - Principal stratification approach (Frangakis and Rubin, 2002, Biometrics)