



IDM Annual Symposium 2023 Session 3E

Estimating the population-level impact of vaccines using counterfactual prediction with LASSO regression

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The pneumococcal conjugate vaccines (PCVs)

• Streptococcus pneumoniae causes pneumonia and invasive diseases



The pneumococcal conjugate vaccines (PCVs)

- Streptococcus pneumoniae causes pneumonia and invasive diseases
- PCVs cover up to **20** out of 100 serotypes¹
- Serotype replacement may erode vaccine impact



• Population impact: direct effect + indirect effect¹







Fully unvaccinated

1. Halloran et al. Design and Analysis of Vaccine Studies. New York: Springer US; 2010.

- Population impact: direct effect + indirect effect¹
- Indirect effect cannot be easily estimated in RCTs



Direct effect

1. Halloran et al. Design and Analysis of Vaccine Studies. New York: Springer US; 2010.

Mixed vaccinated

and unvaccinated

- Population impact: direct effect + indirect effect¹
- Indirect effect cannot be easily estimated in RCTs
- Vaccine impact can be estimated from observational studies

- Population impact: direct effect + indirect effect¹
- Indirect effect cannot be easily estimated in RCTs
- Vaccine impact can be estimated from observational studies
- But confounding bias may occur
 - overestimation: improved living condition and infection prevention
 - underestimation: increased surveillance and diagnosis

1. Halloran et al. *Design and Analysis of Vaccine Studies*. New York: Springer US; 2010.

How to estimate vaccine impact?



Defined evaluation period

How to estimate vaccine impact?



Defined evaluation period

How to predict counterfactual outcome?

Rely on outcome of interest		Synthetic control		
Interrupted Time Series (ITS)	ITS + offset	Hand-picked: Select unaffected controls ¹	Data-driven: Bayesian variable selection ²	
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Image: Bernal et al. (2017) Int I Epidemiol	Image: Bernal et al. (2018) Int I Epidemiol			

- 1. Thorrington et al. (2018) *BMC Medicine*
- 2. Bruhn et al. (2017) PNAS

How to predict counterfactual outcome?

Rely on outcome of interest		Synthetic control			
			Data driven		
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Interrupted Time Series (ITS)	ITS + offset ITS	Hand-picked controls	Bayesian variable selection SC	LASSO regression ¹ LASSO	
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Study design



00 01 02 03 04 05 06 07 08 09 10 11 12 13 Year

We simulated outcome based on real data



We estimated IRR in each simulated data set



We estimated IRR in each simulated data set



We estimated IRR in each simulated data set



ITS estimates were sometimes biased



SC estimates were accurate across simulation scenarios



LASSO estimates were accurate across simulation scenarios



Incidence Rate Ratio

LASSO selected the controls used to simulate data



Simulation ID

LASSO selected the controls used to simulate data



Take-home messages

- Nice features of LASSO method
 - Accurate estimation
 - Interpretable models
 - Easy to implement (pkg "glmnet"¹)
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- Some remaining challenges
 - Methods to obtain confidence intervals not readily available
 - Suboptimal performance in sparse data

1. Friedman J, Hastie T, Tibshirani R, et al. glmnet: Lasso and Elastic-Net Regularized Generalized Linear Models. https://cran.r-project.org/web/packages/glmnet/index.html.

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Using LASSO regression to estimate the populationlevel impact of pneumococcal conjugate vaccines 3

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Q & A

We simulated outcome based on real data



log(annual)

14

12

10

(a) $Y_t \sim \text{Poisson}(\mu_t)$ $\ln(\mu_t) = \alpha + \ln(NRH_t) + \sum_{i=1}^n \beta_i X_{it} + S_t + \gamma \,\mathbb{1}(t \ge t_{vac})$ $where \, \alpha = \ln\left(\frac{\overline{Y}}{\overline{NRH}}\right)$ $and \, S_t = \sum_{s=1}^6 \delta_s \cos\left(\frac{2\pi st}{12}\right) + \sum_{s=1}^5 \zeta_s \sin\left(\frac{2\pi st}{12}\right)$



- Draw 5 controls & assign beta (x5)
- Draw 10 controls & assign beta (x5)
- 10% binomial subsample from 1st set (x1)

*Eliminate if annual max:min ratio > 10 (unrealistic)

Sensitivity test

• Instead of a null-impact vaccine, we tested a vaccine with VE=10%



Incidence Rate Ratio