

Statistical Methods for Addressing Missing Data in HIV/AIDS Surveillance Systems Secondary Analysis of the HPTN 065 Trial

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May 17, 2018















1 HPTN 065 Study and National HIV Surveillance

2 Missing Data in HIV Surveillance





HPTN 065 Study



Assess feasibility of a community-focused enhanced test and link-to-care strategy



- Improve performance of the HIV care cascade
- Community randomized trial with randomization at care facilities
- Used surveillance data for the design and analysis

HPTN 065 Study - ctd



Intervention cities: Bronx NY and Washington DC (38 care facilities total)

- Control Groups: Enhanced community outreach programs (ECOP)
- Treatment Groups: ECOP plus financial incentives

Non-intervention cities: Chicago, Philadelphia, Miami & Houston (ECOP underway)



National HIV Surveillance System (NHSS)



Collect and analyze data on all persons living with HIV/AIDS (PLWHA) in the U.S.

- Monitor resources nationally and locally
- Improve program implementation in PLWHA

Features

- Data available in aggregate form for HPTN 065
- Unified reporting systems
- Dynamic data extraction: quarterly data uploads



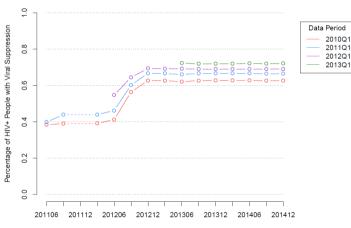
Monitor performance of the HIV care cascade

Use surveillance data to estimate

- Proportion of individuals linked to HIV care (LC)
- Proportion of individuals virally suppressed (VLS)

Monitoring measured VLS in Philadelphia, PA.



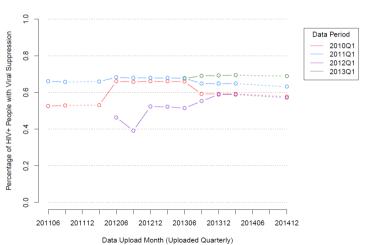


Percentage of HIV+ People with Viral Suppression, by Data Upload Quarter: PA

Data Upload Month (Uploaded Quarterly)

Monitoring measured VLS in Washington, DC.





Percentage of HIV+ People with Viral Suppression, by Data Upload Quarter: DC





HPTN 065 Study and National HIV Surveillance







Missingness in surveillance data



Adherence

• Inferred VL suppression status

Data quality and surveillance coverage

- Reporting lag
- Administrative missingness (common issue in EMR data)
- Lost specimens and/or records
- Identify presence of bias
- Correct biases in estimates when present

Change point estimation (Tapsoba et al, 2018)



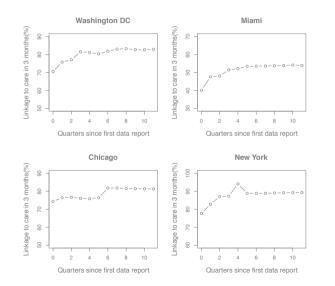
Identify data stabilization using observed aggregated data

- Dependence between observation at different time points
- Develop methods for inference

Predict value of estimand after the change-point, e.g. the "stabilized" value

Bias-corrected value using change points





City	CP(q)	LC ₂₀₁₁ (%)
DC	3.00	82.13
Miami	3.20	53.54
Chicago	7.93	81.44
NY	3.74	89.68

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Missingness due to lack of full coverage



Address 'other' sources of missingness

For each person, observe a sequence of lab measurements collected over time

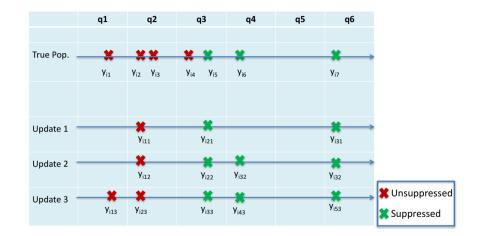
 $\hat{p}_{VLS,q} = \frac{\text{\# of people virally suppressed during quarter } q}{\text{\# of people in care during quarter } q}$

Person i is **in care** during quarter q

• Lab results in at least two of the past five quarters

Individual-level data





Missing data in measurements



For individuals in care, HPTN 065 defined

$$\mathsf{VL} \text{ status}_{iq} = \begin{cases} 1, & \text{if } VL_{iq} \text{ observed and } VL_{iq} < 400 \\ 1, & \text{if } VL_{iq} \text{ unobserved but } VL_{i(q-1)} < 400 \\ 0, & \text{if } VL_{iq} \text{ observed and } VL_{iq} > 400 \\ 0, & \text{if } VL_{iq} \text{ unobserved and } VL_{i(q-1)} > 400 \\ 0, & \text{otherwise} \end{cases}$$

Assume all missingness to be driven by non-adherence

Missing data in measurements



For individuals in care, we propose

$$VL \text{ status}_{iq} = \begin{cases} 1, & \text{if } VL_{iq} \text{ observed and } VL_{iq} < 400 \\ 1, & \text{if } VL_{iq} \text{ unobserved but } VL_{i(q-1)} < 400 \\ 0, & \text{if } VL_{iq} \text{ observed and } VL_{iq} > 400 \\ 0, & \text{if } VL_{iq} \text{ unobserved and } VL_{i(q-1)} > 400 \\ 0, & \text{otherwise} \end{cases}$$
(2)

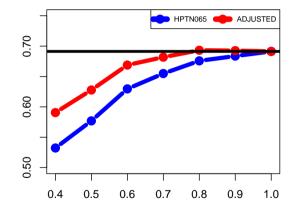
Could be 0 or 1 with probability depending on coverage of lab measurements

Missingness driven by non-adherence or non-coverage

Simulation study



If we knew the true coverage of lab measurements in surveillance



Use auxiliary data to estimate coverage of lab measurements in surveillance 🛓 🚕

Estimating surveillance coverage



Use sample survey data from the Medical Monitoring Project (MMP)

- Better coverage of lab measurements
- Restricted to 400 individuals in each jurisdiction

Need individual level data

- Two-dimensional matching
- Oual-system estimation to estimate coverage of labs

Use computer-simulated data, and request analysis using real data





HPTN 065 Study and National HIV Surveillance

Missing Data in HIV Surveillance









Data quality raises challenges, beyond what was anticipated during design stage

Many issues leading to missingness

Addressed two ways of mitigating bias from missing measurements

Second project is ongoing

- Developing software for estimating surveillance coverage
- Developing method to quantify the uncertainty

Acknowledgements

Fred Hutch

- Deborah Donnell
- Ying Chen
- Jean de Dieu Tapsoba
- CY Wang

This work was partially supported by the National Institutes of Health grant MH105857. The HIV Prevention Trials Network is funded by the National Institute of Allergy and Infectious Diseases (UM1AI068619, UM1AI068613, UM1AI1068617), with co-funding from the National Institute of Mental Health, and the National Institute on Drug Abuse, all components of the U.S. National Institutes of Health.

DOH Philadelphia

- Kathleen Brady
- Tanner Nassau
- Antonios Mashas

DOH New York

- Qiang Xia
- Lucia Torian

