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Progress Together

Pre-post outcome analyses

Building a foundation for a future impact evaluation

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Agenda

- **The evidence from a pre-post outcome study: a foundation for an impact evaluation**
- **Estimating and reporting pre-post differences: the basics**
- **Additional analyses to enhance pre-post findings**

Evidence from a pre-post outcome study

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What is a pre-post outcome study?

- **A study that quantifies how participants' outcomes change over the course of a study**
  - Often, comparing how participants' outcomes change between program entry (baseline/pre) to program exit (follow-up/post)
- **Difference in outcomes from baseline/pre to follow-up/post represents individual change**
- **Aggregating this difference across all program participants quantifies how outcomes changed on average**
- ***Note: We will primarily focus on change analyses for two assessment points today***

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How to interpret average pre-post outcome change?

- **Average change = how individual outcomes among program participants changed over time on average**
- **Average change ≠ the impact or effect of the program**
  - Without a counterfactual, we cannot disentangle change in outcomes caused by the program from naturally occurring outcome changes (for example, maturation, testing, or regression; Campbell and Stanley 1975)
- **Be sure to describe the findings (and their limitations) appropriately!**
  - "Between program entry and program exit, participant knowledge scores improved by 30 percentage points."
  - "This analysis assesses individual change over time without a counterfactual – it is not appropriate to assert that the program was solely responsible for the observed improvement in outcomes."

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How can pre-post findings create the foundation for an impact study?

- **Are outcomes moving in the right direction?**
  - Logic model for an intervention presents a hypothesis about how participants' outcomes might change
  - Pre-post outcome findings provide data to test the hypothesis
  - At a minimum, proximal outcomes in the logic model should change over time!
- **Are the changes in outcomes *large*?**
  - In many cases, we might expect natural change in outcomes even in the absence of the program
  - Changes in outcomes might represent an upper-bound estimate of potential program impact for a subsequent impact evaluation
    - This information can inform statistical power analyses

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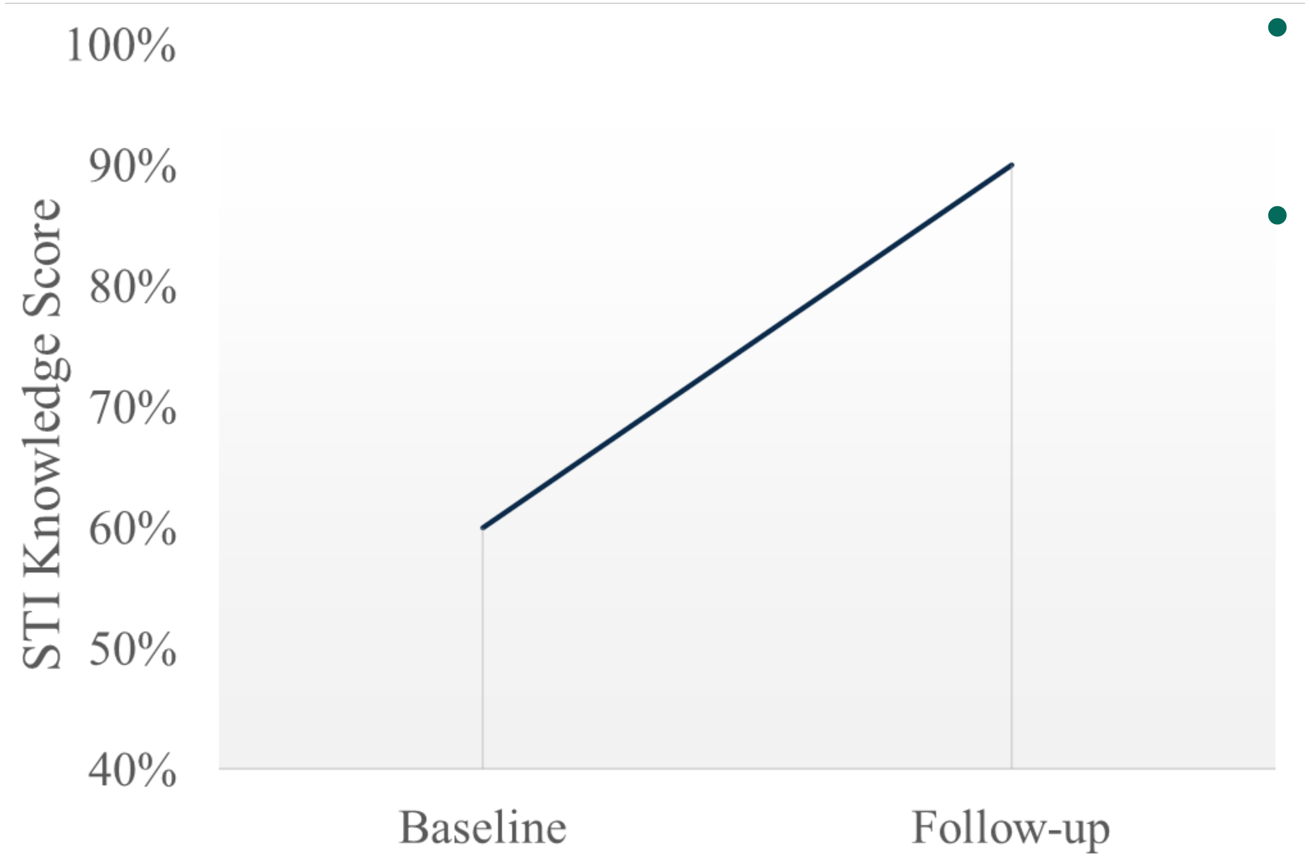
Example: Program participants improved sexually transmitted infection (STI) knowledge by 30 percentage points (30PP)!



- **Shows improvement in key outcome**
- **Provides upper-bound estimate for future impact study**
  - ❑ Don't expect to see program impacts of 30PP in a future impact evaluation…

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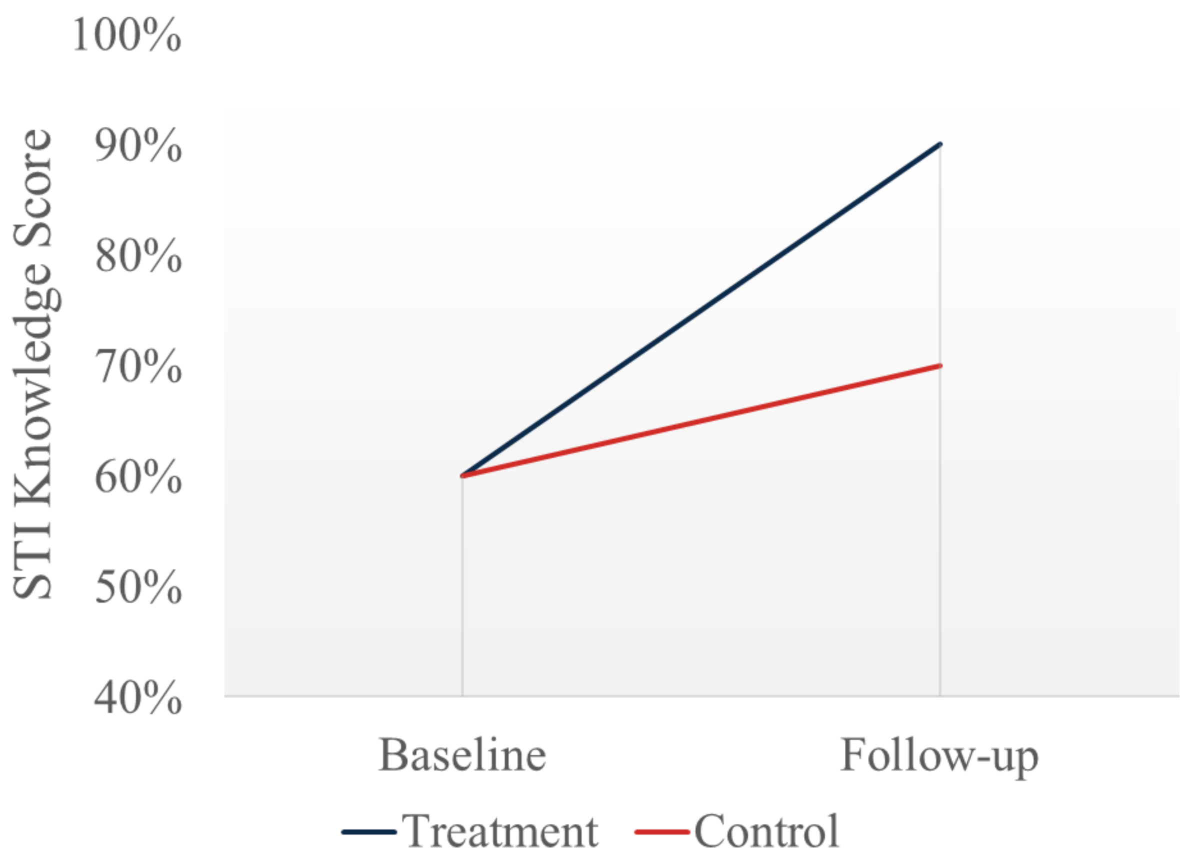
Use pre-post impact estimate as upper bound for statistical power calculations



- **Natural improvement among comparison group suggests an impact evaluation will observe a smaller effect …**
  - ❑ Make sure you have sufficient power to detect impacts *smaller* than those observed in the pre-post analysis

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Estimating and reporting pre-post differences: The basics

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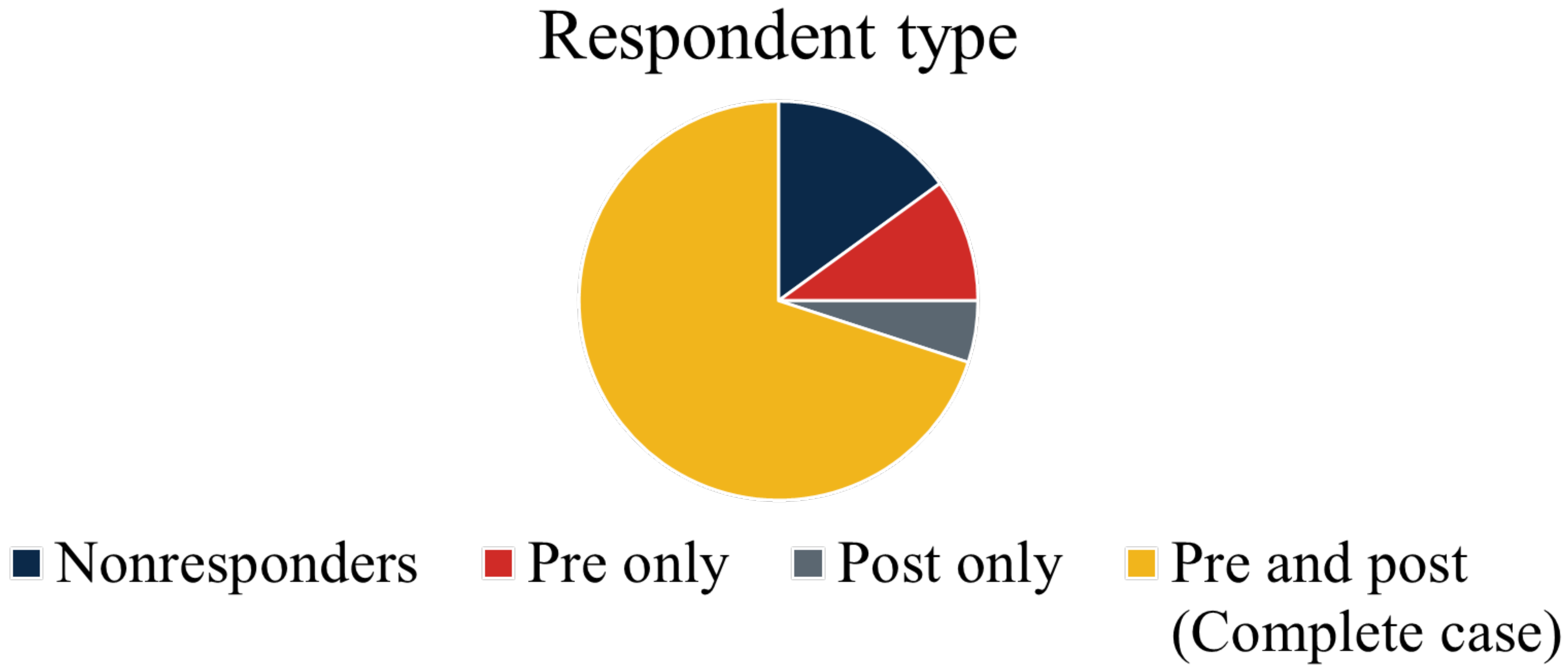
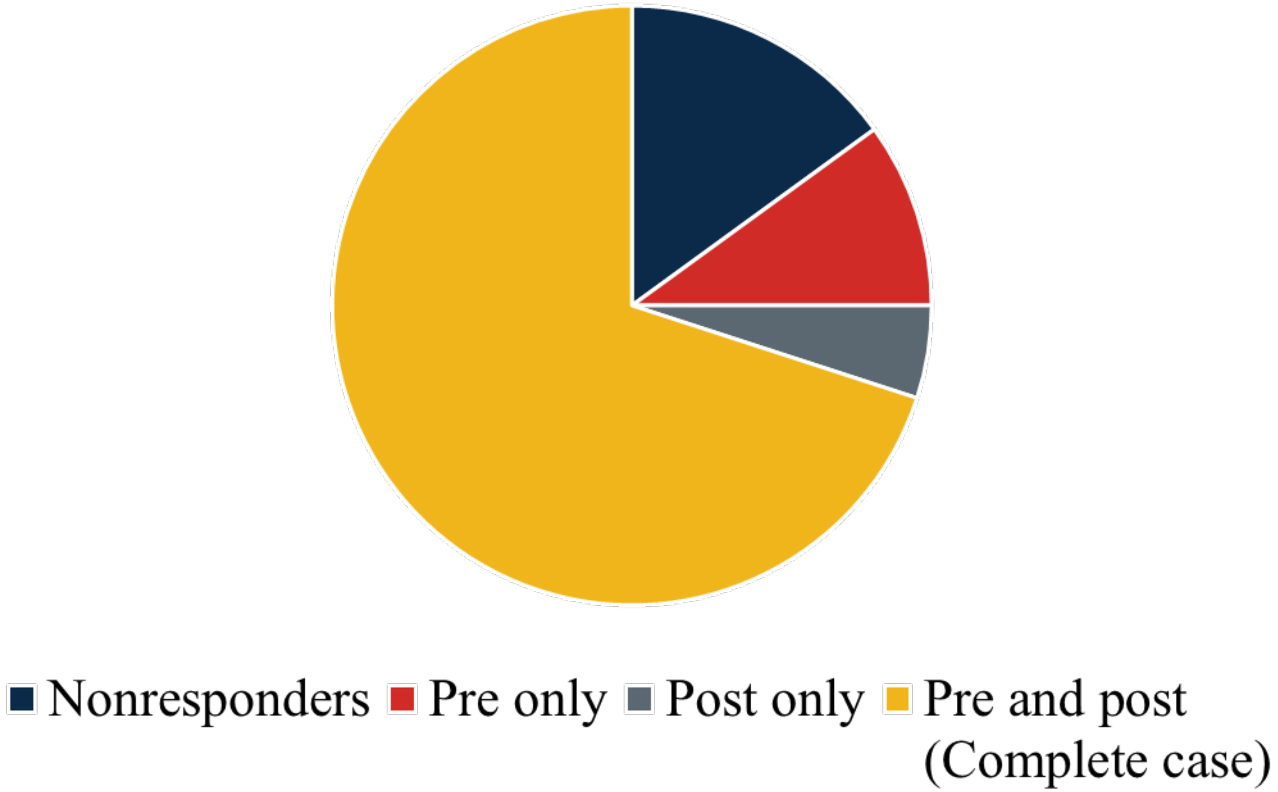
Goal: Describe how individual outcomes change over time

- **Choose the right types of outcomes**
- **Plan on conducting within-individual analyses**
  - Match pre and post outcomes for each individual
  - Eliminate individuals from analysis who are missing one or both assessments
  - Do this separately for *each outcome of interest*
- **Benefit of this approach**
  - Ease of interpretation: it eliminates compositional differences (biases) that can occur if analysis conducted with all available data
- **Limitation of this approach**

Different types of respondents observed in a pre-post study



Unpacking issue of composition as a source of bias in understanding individual change



Respondent type (prevalence rate)	Average score at baseline	Average score at follow-up
Nonresponders (15%)	-	-
Pre only (10%)	70	-
Post only (5%)	-	75
Pre and post (complete case = 70%)	60	80
Average of observed data	61.3	79.7

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What to report among the complete case sample?

- **Pre and post means and standard deviations**
- **Difference in means**
  - In raw units
  - In standard deviation units (relative to the post-test period)
- ***p*-value of the difference**
  - Based on a paired t-test (or nonparametric analogue)

Explore and report heterogeneity in outcome change

- **Conduct analyses for proximal and distal outcomes in logic model**
  - Larger improvements in proximal outcomes (relative to distal outcomes) validates features of program logic model
- **Conduct analyses by subgroups of interest**
- **Conduct analyses by whether participant received the program as intended or not**
  - Potentially supplement the within-group analysis with a between-group analyses

Additional analyses to enhance pre-post findings

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Skeptical readers will be unsatisfied with the basic presentation

- **Primary concern: The complete case sample does not adequately represent the full study sample**
- **We can address this limitation with additional analyses**
  - Response rate analyses
  - Nonresponse analyses
  - Use of nonresponse weights
  - Demonstrate value of nonresponse weights

Step 1: Response rate analysis

Response rate analysis

- **For each outcome of interest, categorize each individual as one of four types**
  - Nonresponder at both assessments
  - Pre only
  - Post only
  - Pre and post (complete case)
- **Report prevalence rates of types for each outcome**

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Respondent type prevalence rates will vary due to item non-response

Respondent type	Intentions to remain abstinent	Recent sexual behavior
Nonresponders	20%	23%
Pre only	8%	9%
Post only	3%	4%
Pre and post (complete case sample)	69%	64%

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Step 2: Nonresponse analysis

Nonresponse analysis approach

- **Identify factors that differentiate complete case respondents from the broader target population**
- **Likely limitation: Baseline survey is the key data source for describing characteristics of broader sample**
  - We won't have data on nonrespondents to baseline survey
  - Therefore, we won't be able to determine whether the complete case sample represents these baseline nonrespondents *on variables measured at baseline*
- **For today, we are going to focus on generalizing to individuals with key baseline measures**
  - We want baseline measures of outcome of interest (we want to know whether complete-case sample is a high-low risk group as defined by the baseline assessment)

Approach for assessing nonresponse bias (Step 1)

- **Assemble data for a list of variables to compare across complete case sample and target sample**
  - Demographics
  - Baseline assessment of outcome of interest
  - Site characteristics (if appropriate)
  - Other baseline variables in your data set that theory or literature suggests might predict survey response (for example, motivation, grit, persistence)
- **Create an indicator variable for whether an individual is in the complete case sample for that outcome**
  - For example, for an STI knowledge outcome, use an STI_CC indicator (= 1 if in the complete case sample, 0 otherwise)

Illustrative dataset

StudyID	Male	Hispanic	Age	GRIT	STI_Knowlege_Pre	STI_Knowlege_Post	STI_CC
101	1	0	15.5	8	78	79	1
102	1	0	15.7	7	77	82	1
103	1	1	16.1	8	45		0
104	0	1	15.8	9	56	54	1
105	0	1	15.9	10	65	67	1
106	1	1	16	8	91		0
107	0	0	16.1	8	25	52	1
108	1	1	16.5			95	0

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Approach for assessing nonresponse bias (Step 2)

- **Regress complete case indicator on predictors of interest using logit or probit regression**
  - Cluster standard errors, as appropriate, for predictors measured at cluster level
- **Report raw and standardized beta coefficients, *p*-values from analysis**
- **Summarize key takeaways**
  - “Students receiving free or reduced-price lunch (FRL) were 2.4 times less likely than non-FRL students to be included in the complete case sample.”
  - “The complete case sample tended to represent a lower-risk sample; the baseline assessment of the outcome was the single strongest predictor of whether an individual was in the complete case sample.”
  - “Complete case sample members tended to be non-Hispanic, have high levels of self-reported motivation, and attended services in schools, rather than community settings.”

Illustrative SAS Code and output

```
Proc logistic data=mydata;
Model STI_CC (event = '1') = male hispanic age
STI_knowledge_pre GRIT / link=logit stb;
Run;
```

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Standardized Estimate
Intercept	1	1.1096	2.8070	0.1562	0.6926	
male	1	0.1125	0.3780	0.0885	0.7660	0.0310
hispanic	1	0.7732	0.5226	2.1892	0.1390	0.1768
age	1	-0.0256	0.1812	0.0199	0.8877	-0.0143
STI_knowledge_pre	1	-0.00345	0.00771	0.2004	0.6544	-0.0473
grit	1	0.4623	0.0923	25.0890	<.0001	0.7487

Step 3: Calculate nonresponse weights

High-level summary of Step 3

- **The results from Step 2 might indicate that we are unsatisfied with our complete case pre-post results, knowing that the complete case respondents don't adequately represent the full study sample of interest**
- **We can calculate nonresponse *weights* using the same approach from Step 2, and incorporate these weights in our complete case analyses to make the complete case sample better represent the full study sample**

Nonresponse weights

- **Nonresponse weights are the inverse of the probability of being in the complete case sample**
  - Individuals who were very likely to be in the complete case sample and were a complete case sample member have a small nonresponse weight
  - And vice versa
- **Probability of being in the complete case sample for each individual can be output from logit or probit model in Step 2**

Illustrative SAS Code and output

```
Proc logistic data=mydata;
model STI_CC (event = '1') = male hispanic age STI_knowledge_pre GRIT / link=logit stb;
Output out=psdata predicted=P_STI_CC;
Run;
```

StudyID	STI_CC	P_STI_CC
101	1	0.67
102	1	0.87
103	0	0.42
104	1	0.89
105	1	0.91
106	0	0.51
107	1	0.49

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Calculate nonresponse weights, and rescale

- **Nonresponse weight for complete case sample members**

  = 1 / Probability of being in the complete case sample

- **Rescale weights so that sum of weights = number of complete case respondents**

StudyID	STI_CC	P_STI_CC	STI_weight_raw *(= 1 / P_STI_CC)*	STI_weight_rescaled *(= **5** * STI_weight_raw / **6.91**)*
101	1	0.67	1.49	1.08
102	1	0.87	1.15	0.83
103	0	0.42	.	.
104	1	0.89	1.12	0.81
105	1	0.91	1.10	0.80
106	0	0.51		
107	1	0.49	2.04	1.48
TOTAL	**5**		**6.91**	**5**

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Incorporate the nonresponse weight in a revised version of the pre-post analysis

- **Calculate the same statistics reported previously:**
  - Pre and post means and standard deviations
  - Difference in means
    - In raw units
    - In standard deviation units (relative to the post-test period)
  - *p*-value of the difference
    - Based on a paired t-test
- **However, incorporate the nonresponse weights when estimating the descriptive and inferential statistics**
- **Revised pre-post results make the complete case sample better represent the target sample**

Illustrative SAS Code and output

```
proc ttest data=psdata;
Where STI_CC = 1;
paired STI_knowledge_pre * STI_knowledge_post;
run;
```

The TTEST Procedure

Difference: STI_knowledge_pre - STI_knowledge_post

N	Mean	Std Dev	Std Err	Minimum	Maximum
365	10.0247	6.9974	0.3663	-9.0000	30.0000

```
proc ttest data=psdata;
Where STI_CC = 1;
paired STI_knowledge_pre * STI_knowledge_post;
weight STI_weight_rescaled;
run;
```

The TTEST Procedure

Difference: STI_knowledge_pre - STI_knowledge_post

Weight: STI_weight_rescaled

N	Mean	Std Dev	Std Err	Minimum	Maximum
365	9.9515	7.3428	0.3665	-9.0000	30.0000

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Step 4 (Bonus!): Show that your nonresponse weights improved representability

Goal: Convince your audience that your nonresponse weights helped address the problem

- **Present how the nonresponse weights, when applied to the complete case sample, improve point estimates**
- **Calculate pre and post means for a given variable**
  1. Using all observed data (the “true” means)
  2. The complete case sample, without weights
  3. The complete case sample, after applying nonresponse weights
- **The findings from approach 3 should be closer to findings from 1 than findings from 2**
  - This conveys that the nonresponse weights helped recover the true population averages among the complete case sample

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Illustrative example: STI knowledge scores with and without weights

	Average at pre-test	Average at post-test
1) Based on all observed data	61.3	79.7
2) Complete case sample average, without weights	60.0	80.0
3) Complete case sample average, after weighting	60.5	79.9

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Conclusion

Summary of key takeaways

- **Pre-post findings do provide value**
  - Information on how program participants’ outcomes change over time
- **But they do *not* demonstrate the impact of a program**
- **They can establish a foundation of an argument for an impact evaluation**
  - Outcomes trending in the right direction (validating logic model)
  - Magnitude of outcome change as an upper-bound estimate for power calculations

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Best practices for pre-post analyses

- **Don't be satisfied by solely doing a basic complete case pre-post analysis**
- **Supplement with**
  - Response rate calculations
  - Nonresponse analysis
  - Estimation of nonresponse weights and use of weights in pre-post analyses
  - (Bonus): Justify that the nonresponse weights improved the representativeness of the findings

Questions?

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