Using Mixed-Methods Evaluation to Support Better Non-Experimental Impact Analysis

Stephen H. Bell and Joseph M. Gasper, Westat

Westat-APPAM **Forum: Bringing Rigor and Intentionality to Mixed-Methods Evaluations of Social Programs**

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Mixing Methods to Obtain Better Non-Experimental Impact Findings

- Essence of any non-experimental impact analysis = opportunistic identification of a reliable counterfactual
- Our thesis = extensive, systematic use of <u>qualitative</u> information regarding
  - -- intervention's intake & service delivery process
  - -- intervention's context

  allows one to do this better—i.e., to make <u>quantitative</u> non-experimental impact analyses less subject to selection bias
- Selection bias = difference in participant & non-participant outcomes, interpreted as impact, that is not causal

Outline of Talk

- Framing the challenge . . . and opportunity
- Strengthening impact analyses by tapping
  - -- qualitative information on selection into intervention participation
  - -- qualitative information on service delivery and other influences on participant outcomes
- Defining an all-inclusive mixed-methods protocol
- Testing the performance of the protocol

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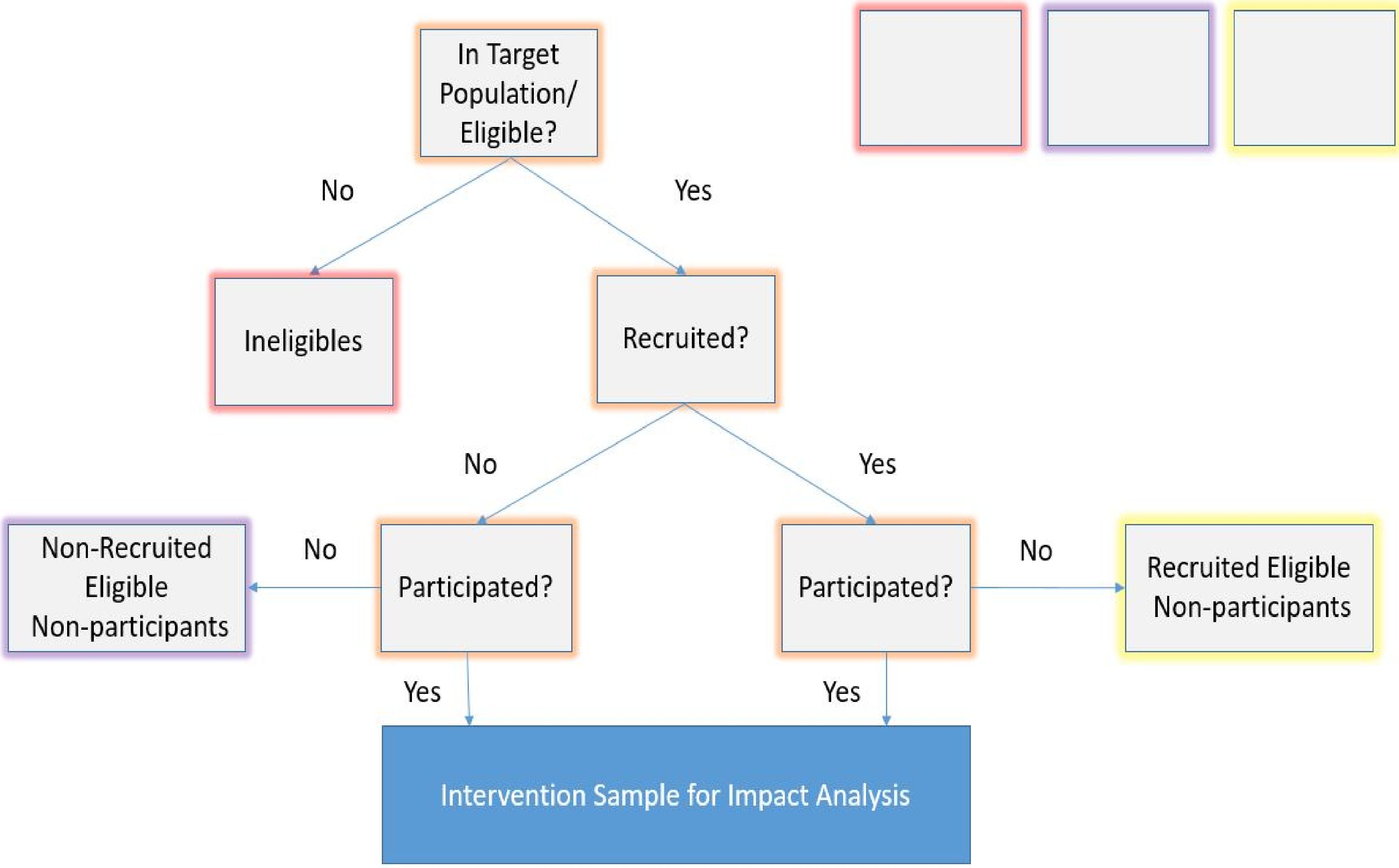
Framing the Challenge . . . and Opportunity

- Stylized situation
  - -- know outcomes for participants & non-participants
  - -- have data to balance on background characteristics
  - -- no other knowledge
- Add qualitative information on . . .
  - -- <u>selection into intervention participation</u>—what real-world process makes some individuals participants and others not
  - -- <u>outcome-generating process among participants</u>—places all-other-things-equal conditions are violated
- Choose the most promising non-experimental impact analysis strategy based on this qualitative information

Strengthening Impact Analyses by Tapping Qualitative Information on <u>Selection Into Intervention Participation</u>

How Eligibility → Recruitment → Participation Defines Comparison Group Possibilities



Qualitative Data's Source & Role: Eligibility- and Recruitment-Based Comparison Groups

	Qualitative	Data	Uses of Qualitative Data		
Candidate Comparison Group	Topic	Source	Assess candidate comparison group	Identify confounding variables to equalize	Look for single continuous selection variable (RDD)
Ineligibles	Eligibility criteria	Program staff	√	√	√
Non-recruited eligible non-participants	Recruiting practices	Program staff	√	√	
Recruited eligible non-participants	Recruiting practices	Program staff	√	√	

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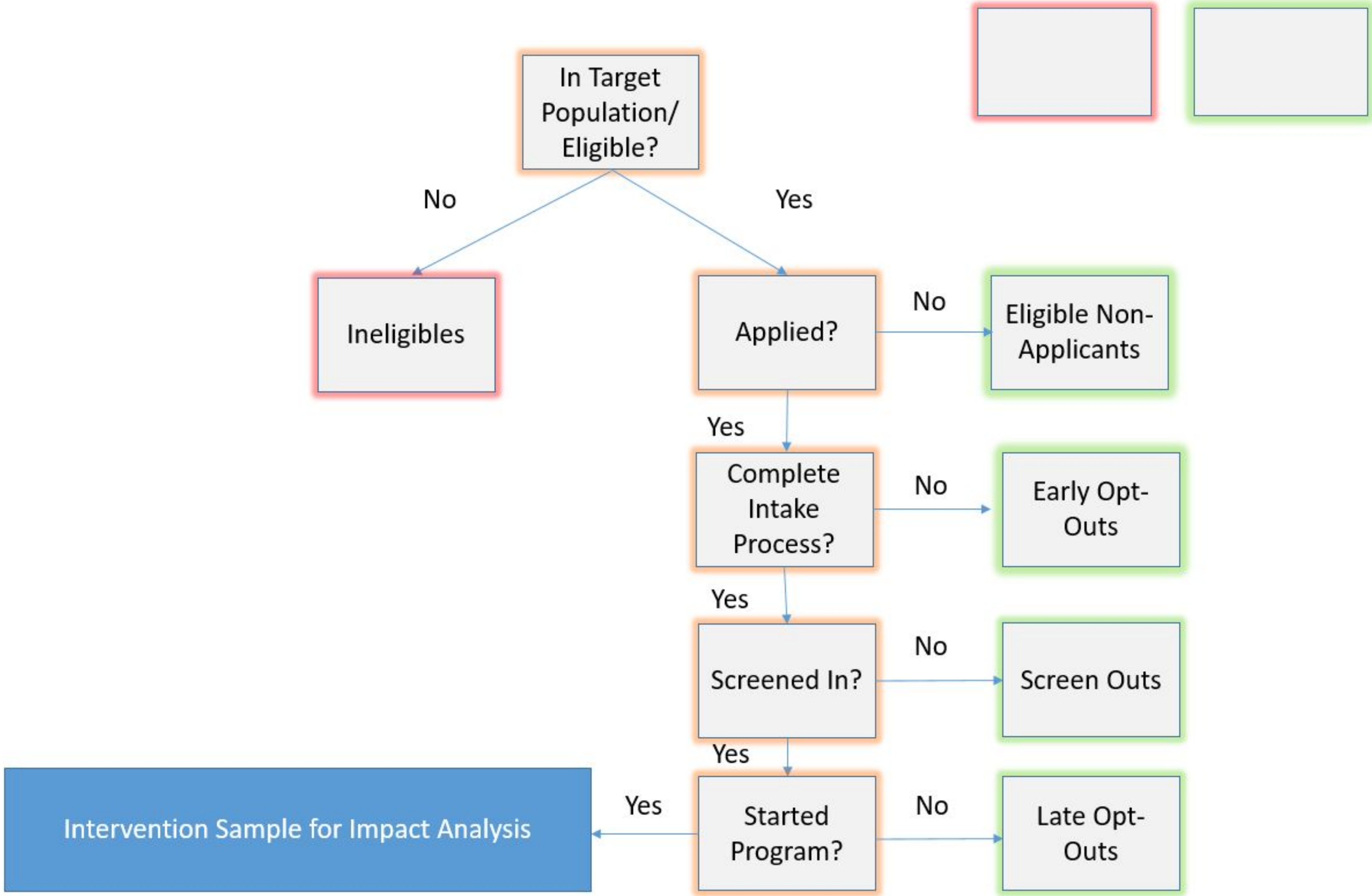
How Application → Acceptance → Participation Defines Comparison Group Possibilities



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Qualitative Data's Source & Role: Application- and Acceptance-Based Comparison Groups

			Uses of Qualitative Data		
Candidate Comparison Group	**Qualitative Topic**	**Data Source**	**Assess candidate comparison group**	**Identify confounding variables to equalize**	**Look for single continuous selection variable (RDD)**
Eligible non-applicants	Application motivations	Client focus groups	√	√	
Intake opt-outs	Opt-out patterns	Intake staff	√	√	
Intake screen-outs	Reasons for excluding eligibles	Intake staff	√	√	√

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Strengthening Impact Analyses by Tapping Qualitative Information on the Outcome-Generation Process

Model the Outcome-Generation Process to Create Counterfactual Free from Intake Selection Bias

- Calculate no-intervention counterfactual outcomes from data on individuals who <u>select into</u> the intervention
- Doesn't matter if those who select <u>out</u> of the intervention (previous source of counterfactual outcomes) are different
- Model how participant outcome Y_i varies with level of intervention services received (e.g., $ spent)
  - -- for categories of spending, S_i, intervention staff believe most likely to push outcomes upward

$$\hat{Y}_i = \hat{e} + \hat{g} S_i + \underline{\hat{h}}' \underline{X}_i$$

- Create no-intervention counterfactual outcome by reducing spending to $0 (i.e., by S_i): $Y_i^{Counter} = Y_i - \hat{g} S_i$

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Does This Model Suffer from Omitted-Variable Bias that Distorts $\hat{g}$?

- Yes, if correlates of S_i also correlate with Y_i without being part of the causal path from S_i to Y_i – and are not in $\underline{X}_i$
- Factors that correlate with S_i depend on sources of variation in spending from participant to participant
  - -- availability of funds when enrolled
  - -- staff decisions on extent of needed services
  - -- participant decisions on duration of participation
- Participant decisions can create omitted variable bias in

$$\hat{Y}_i = \hat{e} + \hat{g} S_i + \underline{\hat{h}}' \underline{X}_i$$

  - -- exit early from low motivation ➔ low S_i non-causally accompanies low Y_i ➔ $\hat{g}$ too large
  - -- exit early due to high ability ➔ low S_i non-causally accompanies high Y_i ➔ $\hat{g}$ too small

Using Additional Qualitative Information Can Turn Selection Risk into a "Specification Test"

- Gauge—and report—direction of skewing from qualitative information on program staff beliefs about predominant reasons for early exit
  - -- low motivation ➔ impact estimate too large
  - -- high ability ➔ impact estimate too small
- Use as "specification test" for initial analysis model
  - -- initial estimate **>** biased upward cost-based estimate➔ switch to comparison group yielding smaller estimate
  - -- initial estimate **<** biased downward cost-based estimate➔ switch to comparison group yielding larger estimate

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Outcome-Generation Process Matters If Comparison Group Data Come from Different Times/Places

- Multiple reasons data on “untreated” cases can come from different times & places than participant data
  - -- different cost & legal permission issues when accessing data for people not connected to focal intervention
  - -- intervention begins at same time for <u>all</u> reasonably similar individuals in a locality ➔ “untreated” cases must come from different times/places
  - -- for statistical power, insufficient number of comparison group cases available from times and places that supply participant sample

Equalizing Service Environment and External Conditions When Lack Time/Place Alignment

- Need qualitative information to decide which services in community resemble focal intervention enough to matter
- Descriptive information on local environmental conditions (labor market, housing market, crime rate, etc.) also important
- Formal quantitative modeling = complex, over-taxing of degrees of freedom (need to take account of alternative services in community at <u>all</u> points in follow-up period)
- Qualitative strategy:
  - -- pick comparison samples with longitudinal paths for these factors most similar to participant samples
  - -- through manual inspection & judgmental selection

Defining and Testing a Comprehensive Mixed-Methods Protocol

Mixed-Methods Protocol for Non-Experimental Impact Analysis: Comprehensive Approach

- Gather all the above qualitative data types to support selection & execution of best non-experimental impact analysis design based on external comparison groups
- All qualitative data types have modest costs
  - -- program staff interviews
  - -- applicant focus groups
  - -- field studies/document review
- Implement spending-at-$0 counterfactual analysis
  - -- "specification test" of success of comparison group approach at avoiding intake selection bias
  - -- modest marginal cost if already doing cost-benefit analysis

Testing Performance of the Mixed-Methods Protocol

- Embed the all-inclusive protocol in a future random assignment experiment
- Check accuracy of resulting impact estimates, compared to experimental “Gold Standard” results
- Track & compare costs as well

“If non-experimental designs supported by a mixed methods approach are ever to be trusted in place of experiments, a test of this sort—or, better yet, a series of such tests—seems indispensable.”

- Bell & Gasper, forthcoming

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stephenbell@westat.com

josephgasper@westat.com

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