BOLD THINKERS DRIVING REAL-WORLD IMPACT

50 YEARS

Using ASPES (Analysis of Symmetrically-Predicted Endogenous Subgroups) to understand variation in program impacts

Presented by:

Laura R. Peck

OPRE Methods Meeting on What Works
Washington, DC | September 3-4, 2014

Today’s Agenda

- Motivating Challenge & Solutions
- Logic & Execution of ASPES
- Illustration: Supporting Healthy Marriage program
- Ideal Conditions for ASPES
- Conclusion

Motivating Challenge

- Policy guidance requires "more than just an estimate of the net effects of a program or policy; it is also necessary to understand…the circumstances under which a program or policy has effects, and how and why it works." (OPRE Meeting Summary)
- Relevant policy questions:
  – What are the effects of participating in the intervention (not just being offered access)? How does variation in dosage affect program impacts?
  – How does exposure to various levels of program quality influence program impacts?
  – What is the effect of participating in component A (or B or C) of a multi-faceted intervention?

Possible Solutions…

… that *use* the experimental design

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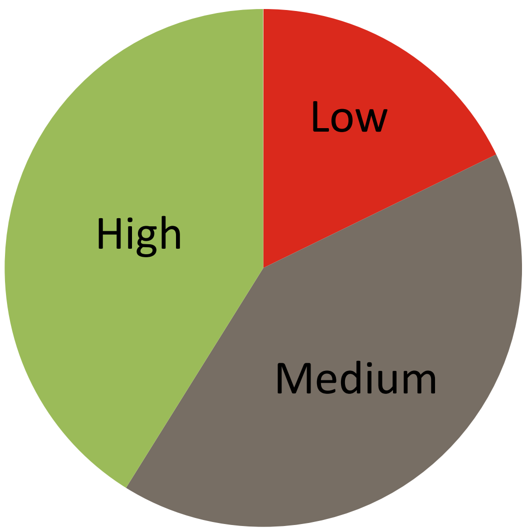
<u>Propensity Score Matching</u> predicts status in one arm to find matched counterparts in other arm	omitted variables in prediction create inconsistent impact estimates
<u>Principal Stratification</u> uses status in each arm to predict and compare potential outcomes in other arm	applicable when subgroup is observed in both experimental arms

Analysis of Symmetrically-Predicted Endogenous Subgroups (ASPES)

- Logic: any group in one experimental arm has a counterpart in the other arm

Treatment Group



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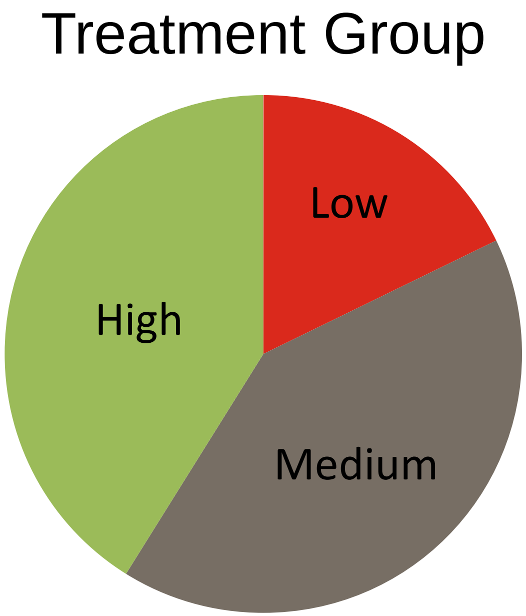

- Low, medium or high:
  - Dosage exposure
  - Quality experience
  - Likelihood of program component take-up
  - Risk of drop-out

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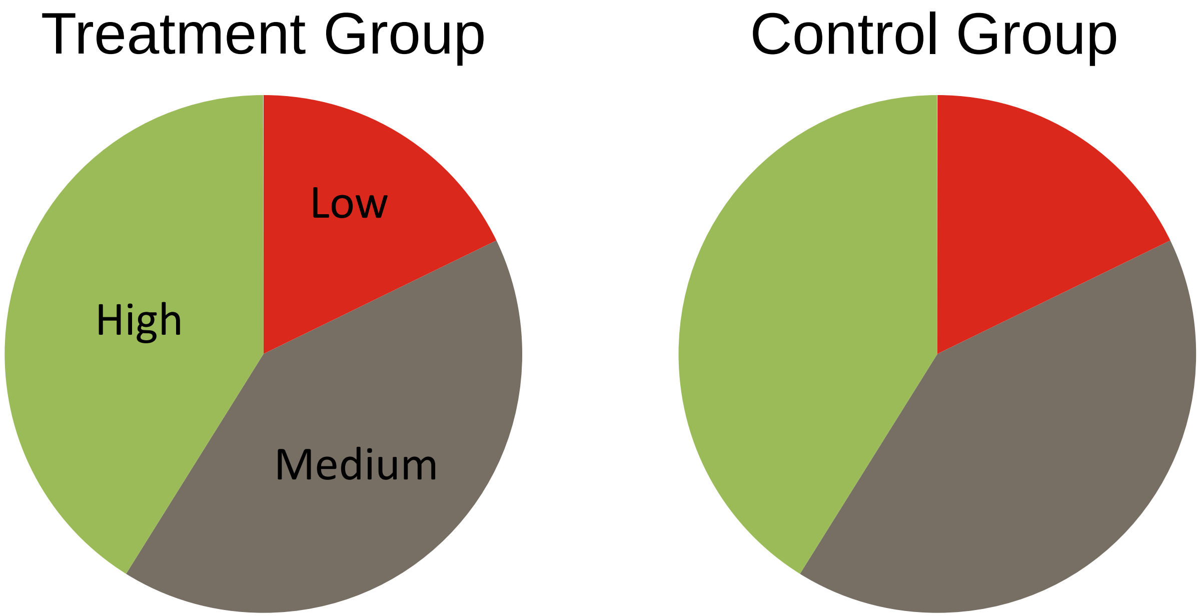

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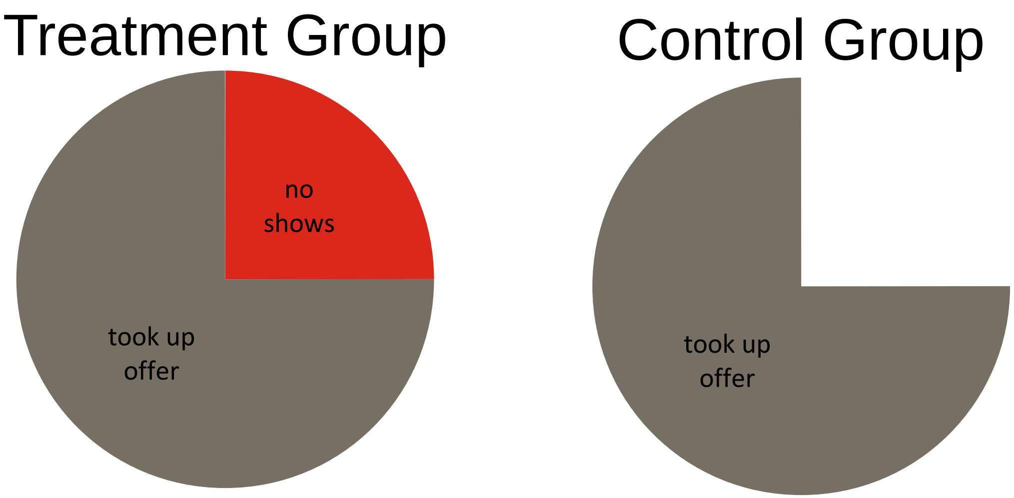

ASPES Defined & Compared

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- Symmetrically-predicted = leverages experimental design in identifying subgroups
- As opposed to (asymmetric) PSM strategy:

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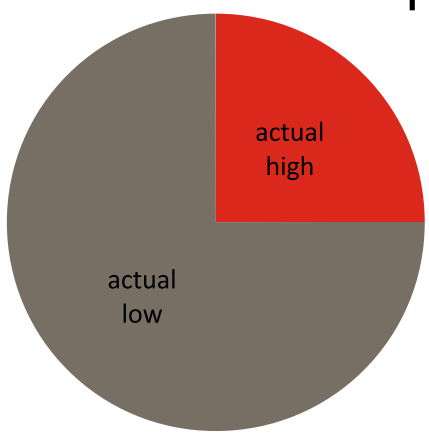
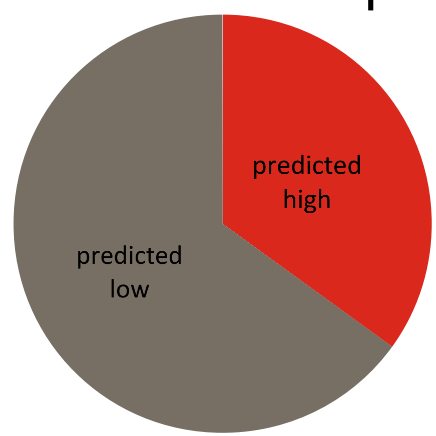


Control Group



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- Step 3: Convert estimated impacts for predicted subgroups into impacts for actual subgroups
- *Achieving external validity*: use assumptions to convert the experimental impact estimate

Execution of ASPES (cont.)

- Step 3: Convert estimated impacts for predicted subgroups into impacts for actual subgroups
  – Consider that the impact on predicteds is a weighted sum of the impacts on actuals, where the weights involve correct prediction rates:

$$\hat{I}_1 = p_1 I_1 + (1 - \mathrm{p}_1) I_2$$

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  - Use "homogeneity assumption" (and algebra) to solve for I

$$I_1 = \frac{p_2 \hat{I}_1 - (1 - p_1)\hat{I}_2}{p_1 + p_2 - 1}$$

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Illustrative Example: SHM

- What is the impact of the number of hours of SHM participation (which is endogenous) on couples' marital stability and relationship happiness?

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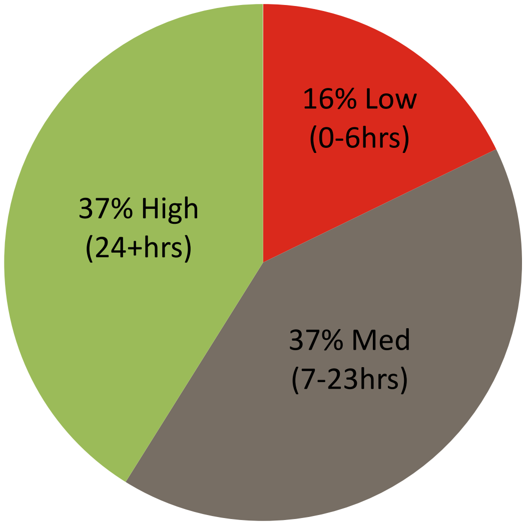
We know Ts' Dosage



Illustrative Example: SHM (cont.)

- Select random subsamples of the treatment group from which to predict SHM dosage levels: low (0-6 hrs), medium (7-23 hrs) and high (24+ hrs)
- Using baseline characteristics, predict dosage (used multinomial logit):
  - <u>Personal and Couple Characteristics</u> - earnings, education, age, race, ethnicity, children, psychological measures, marital tenure, communication, satisfaction measures
  - <u>Program Characteristics</u> - site dummies
- Use the resulting predicted dosage variable to symmetrically identify subgroups in the treatment and control groups, then compare groups' outcomes and convert

Illustrative Example: SHM (cont.)

Selected Outcomes → Impact Analyzed:	Relationship Status: % married		Average Happiness level	
Overall Study Sample	0.80		0.15	***
Predicted Low-Dosage Group	-0.40		0.12	
Predicted High-Dosage Group	2.20	***	0.15	***
between-group diffs	n.s.		n.s.	

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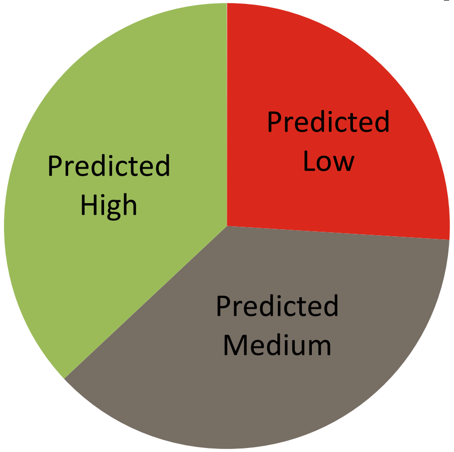

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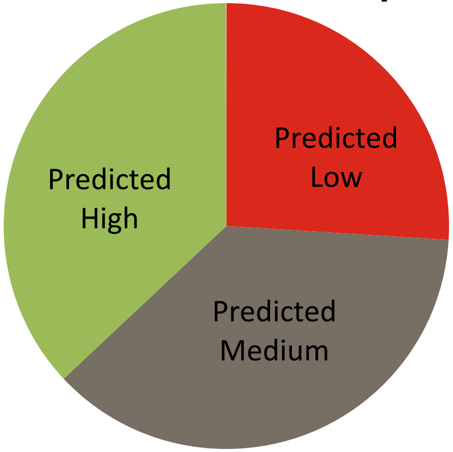

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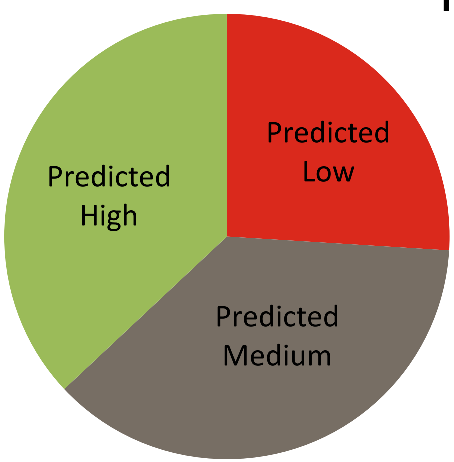

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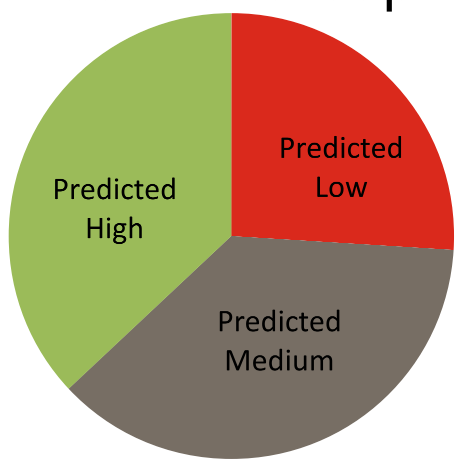
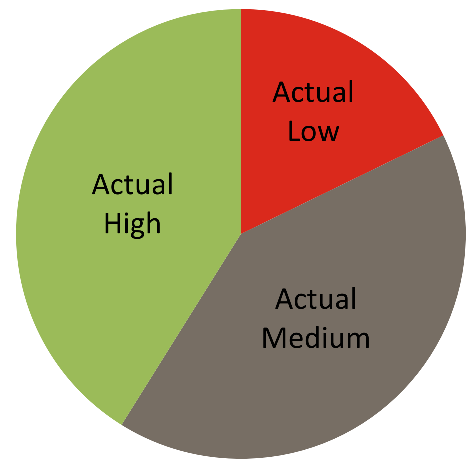


→ Convert to Actuals



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Predicted High-Dosage Group	2.20	***	0.15	***
between-group diffs	n.s.		n.s.	
Actual Low-Dosage Group	-5.10		-0.07	
Actual High-Dosage Group	6.10		0.16	
between-group diffs	n.s.		n.s.	

Ideal Conditions for ASPES

- Baseline data
  - Standard: demographics, education, works/earnings history
  - “Unobservables”: motivation, behaviors, preferences
- First stage prediction “success”
  - Better than chance?
- Predicted → actual conversion assumption credibility
- Sample size
  - OLS → IV requires greater sample
  - 1,000 for 0.30ES within predicted subgroup → 12,500 for 0.30ES within actual (sample, prediction, noise dependent)

Conclusion

- Assumptions Tradeoffs
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- Research Questions
  - Participation, including potential effects on "no-shows"
    - MTO: what is the effect of using a voucher when offered?
  - Treatment dosage or quality
    - HSIS: what generates greater impacts… two years, rather than one? being in a better quality center?
  - Multi-faceted treatment components/pathways
    - HPOG: *what is it* about the intervention that drives impacts? (experience of boot camp style orientation; participation in facilitated peer support groups; use of emergency assistance…)

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For more information, please contact:

Laura R. Peck

Principal Scientist

Social & Economic Policy Division

T: 301.347.5537

E: Laura_Peck@abtassoc.com