New Analytic Approaches:
Analyzing the Impact of Subsidy Receipt on Quality in Longitudinal Data

REBECCA M. RYAN, PH.D.
GEORGETOWN UNIVERSITY

ANNA D. JOHNSON, M.P.A.
TEACHERS COLLEGE, COLUMBIA UNIVERSITY

ANNUAL MEETING OF THE
CHILD CARE POLICY RESEARCH CONSORTIUM

OCTOBER 30, 2009

Research Questions

(1) Do child care subsidies allow parents to purchase higher-quality care than they could otherwise afford?
- Subsidy use when children are in preschool
- Quality when children are 2 and in preschool

(2) Does use of a subsidy lead to greater school readiness?
- Subsidy use when children are in preschool
- Child outcomes in preschool and kindergarten

Motivating the Issue: Why Do We Need New Approaches?

- Estimates from non-experimental studies may misstate the true causal impact of subsidy receipt on child care quality
- Selection bias: family characteristics related to subsidy receipt may also predict child care quality
- Omitted variable bias: excluding other independent variable(s), correlated with subsidy use, that may predict quality
- What to do?

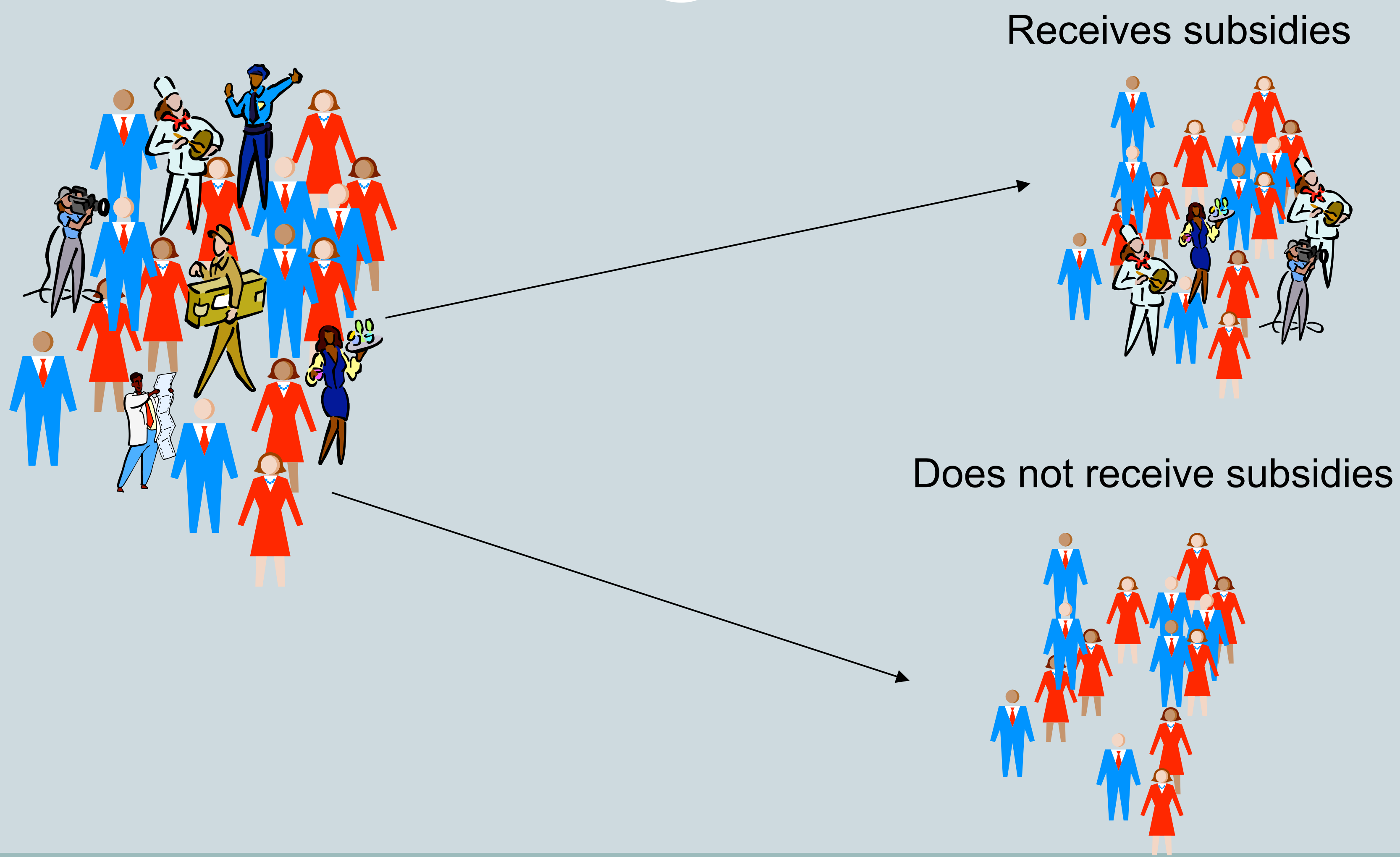
Newer Analytic Approaches

- Capitalize on rich longitudinal data of the ECLS-B
- Traditional method → OLS regression with extensive controls
- Better → Propensity score matching
- Best → Difference-in-Difference matching

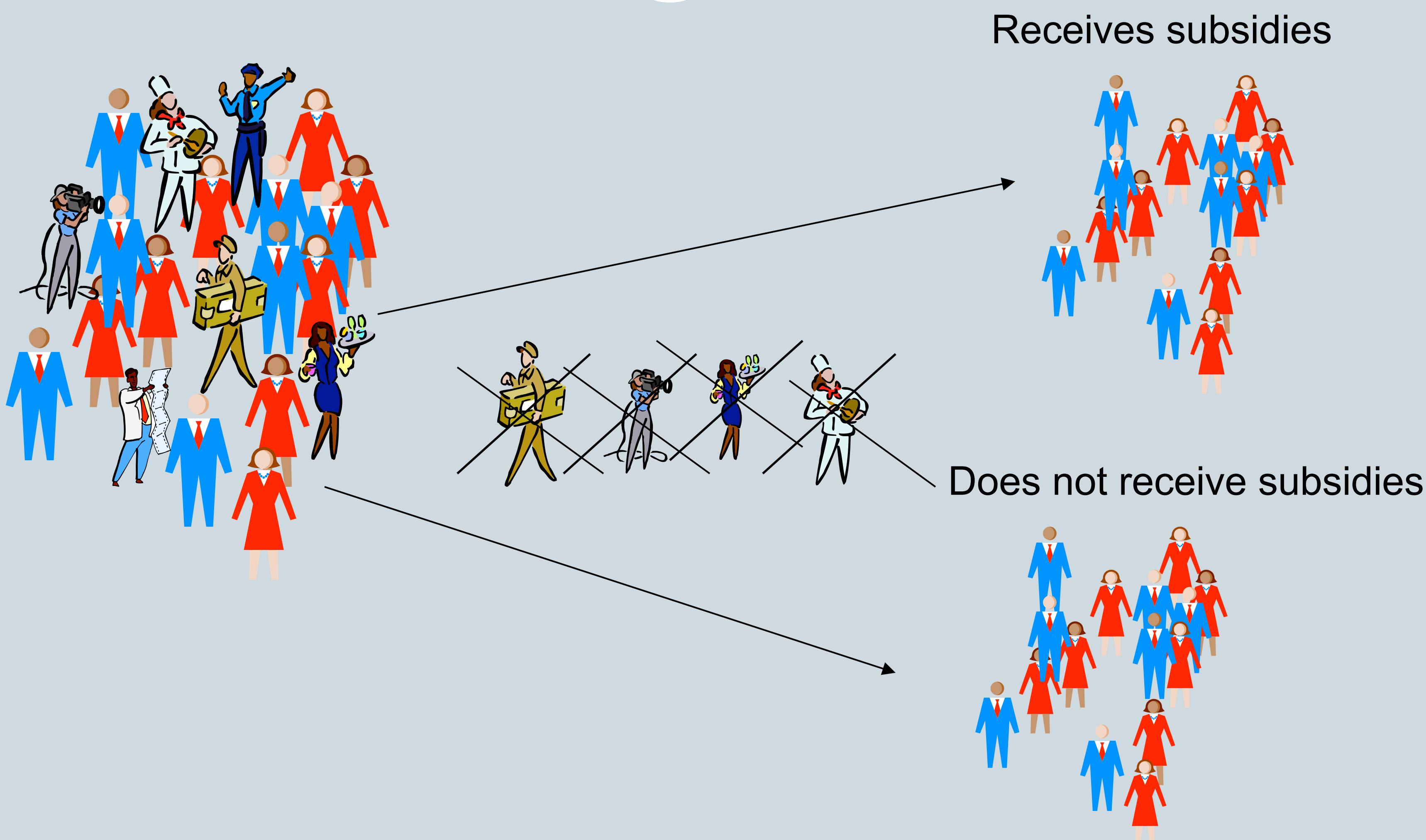
Propensity Score Matching

- Mimics randomization
- Matches cases on observable characteristics
- Excludes cases with no matches –subsidy recipients who are unlike all non-recipients on observable characteristics

Self-selection into treatment groups



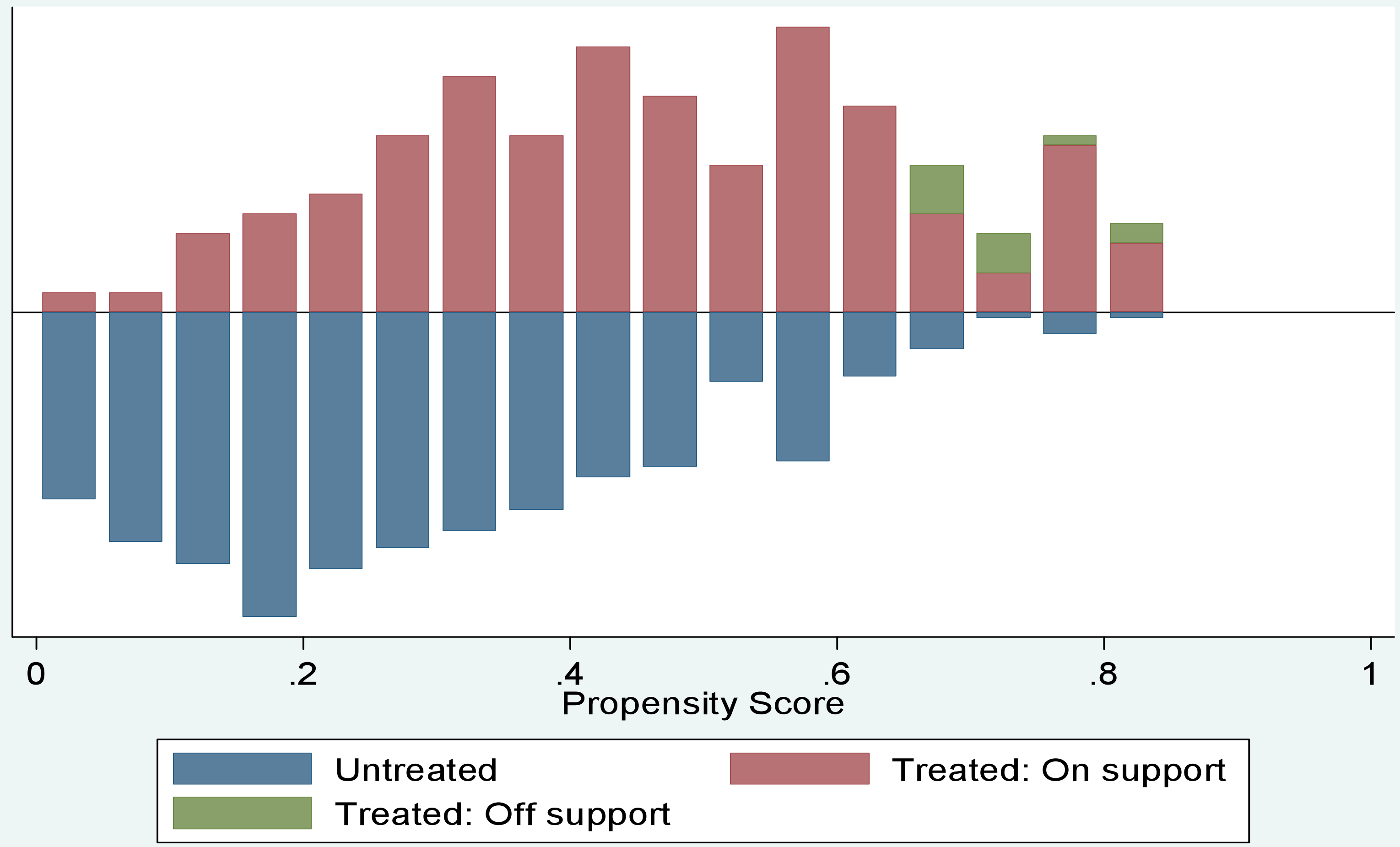
Propensity Score Matching: Identifies Most Similar Groups



Propensity Score Matching

- The propensity score represents likelihood of receiving a subsidy
- It is a one-dimensional summary score of all covariates
- Treated cases are then matched with untreated cases based on the propensity score

Overlap Histogram



Limitations of Propensity Score Matching

- Selection on observables – differences may remain after matching!
- Need to account for unmeasured covariates that may predict the treatment, the outcome, or both
- Solution: exploit longitudinal data to control for *unobserved* characteristics of individuals that are time invariant

Difference-in-Difference Matching

- Estimate propensity scores
- Calculate change in quality from age 2 to preschool for children who did not have subsidies at age 2 but did in preschool and…
- Compare to the change in quality from age 2 to preschool for those who never received subsidies:

Recipients **Non-recipients**

$$(\text{Quality}_{\text{Preschool}} - \text{Quality}_{\text{Age2}}) - (\text{Quality}_{\text{Preschool}} - \text{Quality}_{\text{Age2}})$$

Limitations of Difference-in-Difference Matching

- Only uses cases that did not have subsidy at Age 2
  - Reduces sample size
  - Who are the "changers"?

- Unobservable variables may not be time-invariant

Further Reading

Propensity score matching

- Dehejia, Rajeev H. and Wahba, Sadek (1999) "Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs", Journal of the American Statistical Association, 94: 1053—1062.
- Hill, Jennifer, Waldfogel Jane, Brooks-Gunn Jeanne (2002) "Differential effects of high-quality child care," Journal of Policy Analysis and Management, 21 (4): 601-627
- O'Keefe, Suzanne (2004) "Job creation in California's enterprise zones: a comparison using a propensity score matching model" Journal of Urban Economics, 55: 131-150.

Further Reading

<u>Propensity score matching, continued</u>

- Rosenbaum, P.R. and Rubin, D.B. (1983), "The Central Role of the Propensity Score in Observational Studies for Causal Effects", Biometrika 70, 1, 41-55.

- Rubin, D.B. (1974), "Estimating Causal Effects of Treatments in Randomised and Non-Randomised Studies", Journal of Educational Psychology 66, 688-701.

- Smith, J. A. & Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators?" Journal of Econometrics, 125, 305-353.

Further Reading

Caliper matching

- Cochran, W. and Rubin, D.B. (1973), "Controlling Bias in Observational Studies", Sankyha 35, 417-446.

Kernel-based matching

- Heckman, J.J., Ichimura, H. and Todd, P.E. (1997), "Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme", *Review of Economic Studies, 64, 605*-654.

Mahalanobis distance matching

- Rubin, D.B. (1980), "Bias Reduction Using Mahalanobis-Metric Matching", *Biometrics, 36, 293-298*.