Methodological Considerations in Assessing Causality in Studies of Residential Mobility

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Residential mobility may impact a range of developmental influences

- Disruption of moving
- Change in social networks (good or bad)
- Loss of local routines and coping strategies (good or bad)
- Change in community social, institutional and physical resources (good or bad)

What are the effects of moving?

- Answer likely depends on the specific counterfactual we have in mind to moving

What's the counterfactual?

- (Example 1) HH head loses job, family is evicted & moves in w/ relatives in medium-poverty area

- Counterfactual is … what?
  - Not losing job?
  - Losing job, but have savings (or bridge housing assistance) to avoid eviction until find a new job
  - Losing job and being evicted, but moving in with relatives who live in a high-poverty area?

What's the counterfactual?

- (Example 2) Head of household gets a promotion, moves from Hyde Park to Oak Park

- Counterfactual is … what?
  - Not getting a promotion?
  - Getting a promotion and moving from Hyde Park to Lincoln Park?
  - Getting a promotion and spending that money on sending child to Lab School rather than moving?

The John DiNardo rule

- "Discussions in social science about causes are more *intelligible* when they involve an intervention of some sort; moreover, a focus on such 'policy evaluation' questions often leads to more interesting questions, and importantly often leads to situations when we may be able to subject our views to some kind of test"
  - *Journal of Economic Literature*, review of *Freakonomics*

Assume a sharply framed policy evaluation question

- How should we best try to answer this question?
  - Observational approaches
    - Control for observables and/or difference out various "un-observables" and hope for the best
  - Randomized or "natural" experiments, specify the source of identifying variation

- How should we answer the question about what is the best way to answer the question?

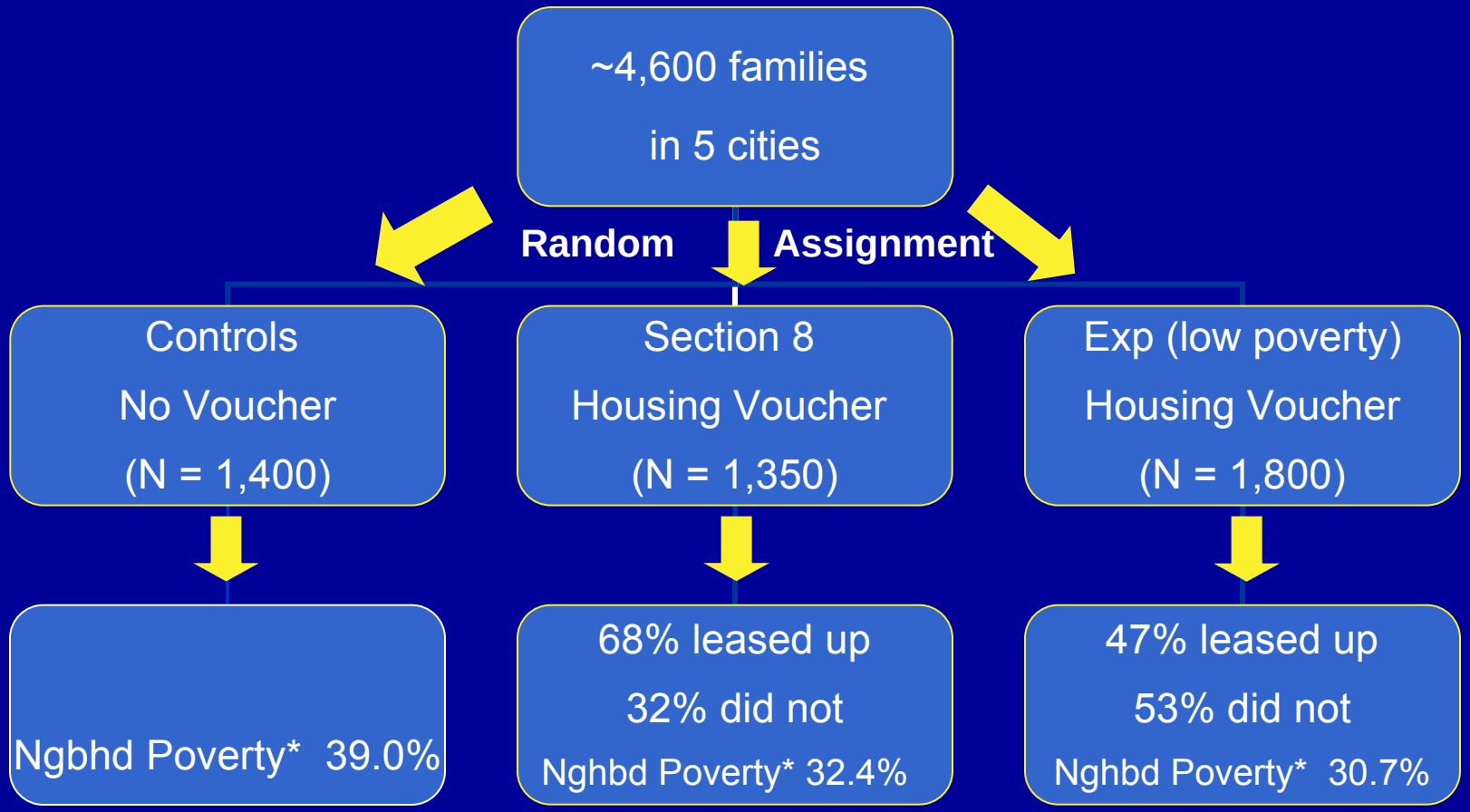
This is a scientific, not a religious, question

- LaLonde (1986)
  - Start with randomized job training experiment
  - Throw out randomized control group
  - Can you reconstruct the experimental answer using different non-experimental comparison groups & estimation methods?
  - LaLonde's paper has had a major influence on the field of empirical economics

This is a scientific, not a religious, question

- Bias of non-experimental estimates probably depends on the specific application, and quality of data available
- But evidence to date from a variety of studies is, on balance, pretty grim
  - Linear regression (even w/ rich set of covariates, including lagged dependent variables)
  - Difference-in-difference approaches
  - Propensity score matching
  - Heckman two-stage selection (Inverse Mill's ratio)
  - Note, no great tests to tell when these are working well or not
  - Exception seems to be well-done regression discontinuity estimates (but I would count those as "natural experiments")

MTO Residential Mobility Study



*Mean residential tract poverty rate (2000 Census) at follow-up 4-7 years after randomization.

LaLonding the MTO data

Neighborhood Poverty (W): serves as a proxy for correlated bundle of census tract characteristics changed by MTO

Outcomes (Y): survey or admin data, measured 5 years out

Instrument for Poverty with treatment group assignment (Z):

$$W = Z\pi 1 + X\beta 1 + \varepsilon 1$$

to estimate relationship ($\gamma 2$) of poverty and an outcome:

$$Y = W\gamma 2 + X\beta 2 + \varepsilon 2$$

MTO provides a reasonable chance of getting right non-experimental answer

Local-area comparison groups

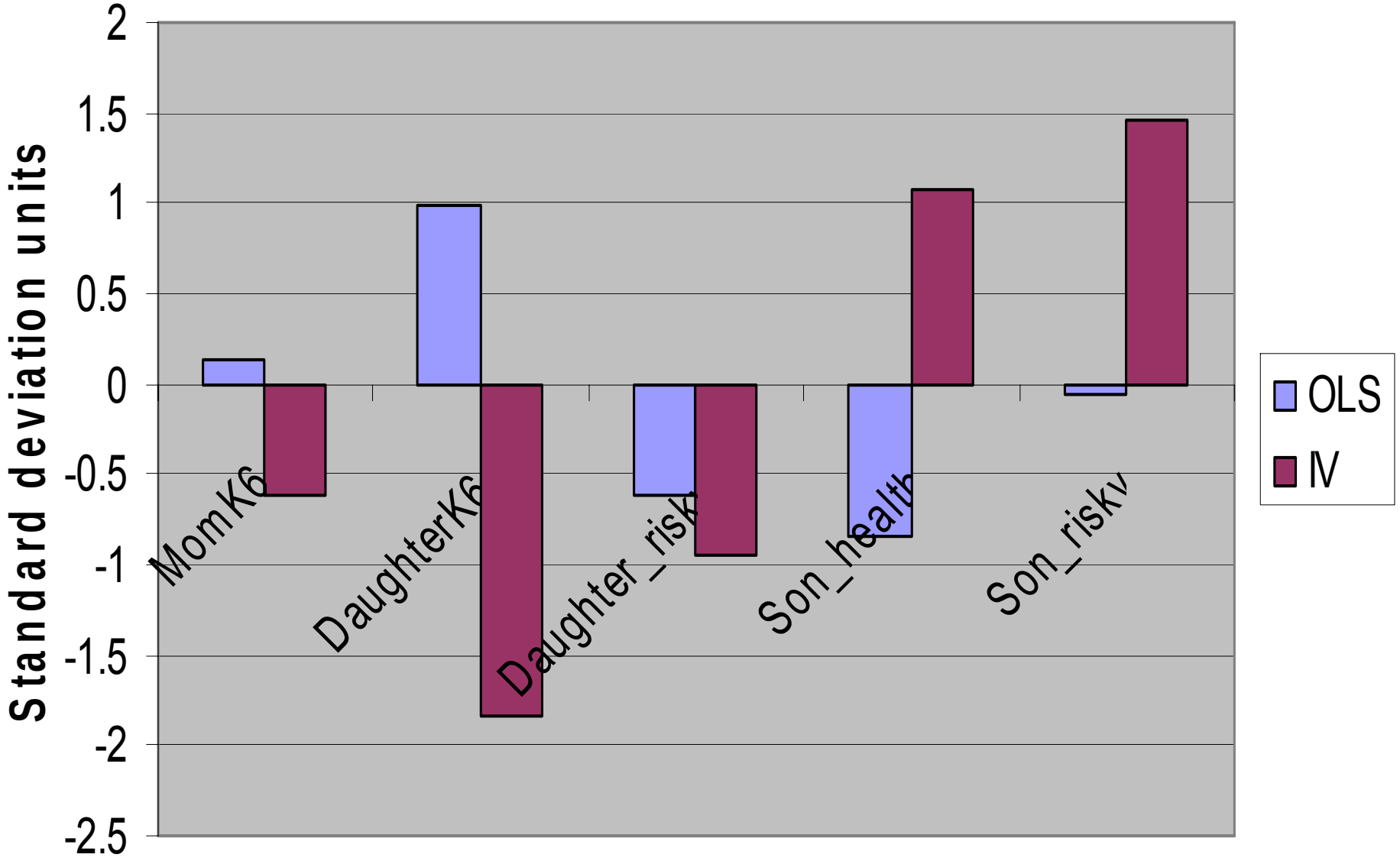
"Pre-propensity scored"
- Common support in socio-demographic attributes

Availability of rich covariates focused on treatment selection
- Why sign up for MTO
- Neighborhood experiences
- Neighborhood preferences

Can condition on lagged values of dependent variables

Covariates available for MTO

- Demographics: age, household size, race/ethnicity, and marital status of parent
- Socio-economic / behavioral: education, employment experience, public assistance/SSI receipt, earnings, total income, car ownership (plus baseline arrest records)
- Parenting: involvement in school, youth supervision
- Housing & mobility: number of moves, preferences about moving, experiences in different types of areas, current housing conditions
- Perceptions of neighborhood: family or friends in neighborhood, safety, victimization, nearest park or church, satisfaction, problems with trash, graffiti or public drinking


Standard deviation units
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
MomK6
DaughterK6
Daughter_risk
Son_health
Son_risk
OLS
IV

Does using theory to impose some structure on the data help?

- Note what the MTO OLS vs. IV differences imply about which families most likely to choose to move through MTO:
  - Adults and families with female teenagers likely to have more *adverse* outcomes more likely to move
  - Families with male teenagers who were more likely to have *beneficial* impacts were more likely to move

- What kind of theory would have predicted this sort of selection process (before seeing data)?

But there is no free lunch (even in studying mobility impacts)

- Non-experimental methods rely on assumptions that empirical evidence to date suggests are often wrong
  - It's possible that w/ longer panels & longitudinal methods, or super rich covariates, we might do better, but I'd like to see evidence of that before believing it
- Randomized or "natural" experiments can overcome selection, but limits range of questions we can address

Benefits to rebalancing our research portfolio in this area

- More randomized & natural experiments that push data harder on mechanisms
  - Let D = use of voucher to move to lower-poverty area
    - $P(D=1) = a_0 + a_1 X + v$
    - $Y = b_0 + b_1 T + b_2 P + b_3 T*P + b_4 X + e$
- Fewer (but definitely not no) observational regressions & propensity score estimates
- More rich, descriptive qualitative studies
  - Would help us do a better job both designing and understanding experiments in the future