# Bringing context into focus: Transportability framework on the effect of housing

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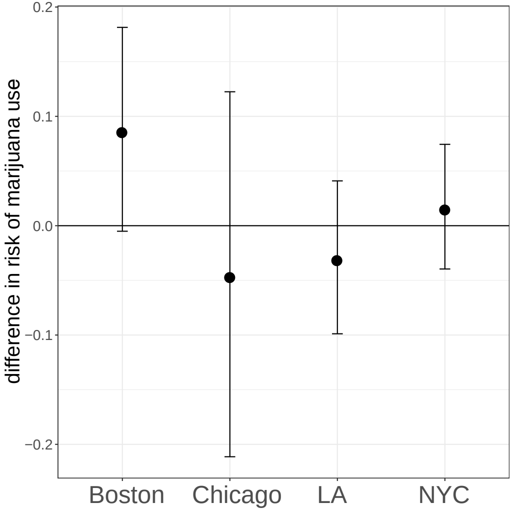
# Case Study: the Moving to Opportunity (MTO) experiment[1]


[1] Kling, J. R. *et al.* Experimental analysis of neighborhood effects. *Econometrica* **75,** 83–119 (2007).

# Case Study: MTO

Boys: Lack of replication across sites



# MTO Background: Site differences in effect estimates

In discussing differences in effects across sites, MTO researchers concluded:

> *With only five sites, which differ in innumerable potentially relevant ways, it was simply not possible to disentangle the underlying factors that cause impacts to vary across sites.*[2]

[2] Orr, L. *et al.* Moving to opportunity: Interim impacts evaluation. (2003), p.B11.

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Can transportability help us understand why impacts varied across sites?

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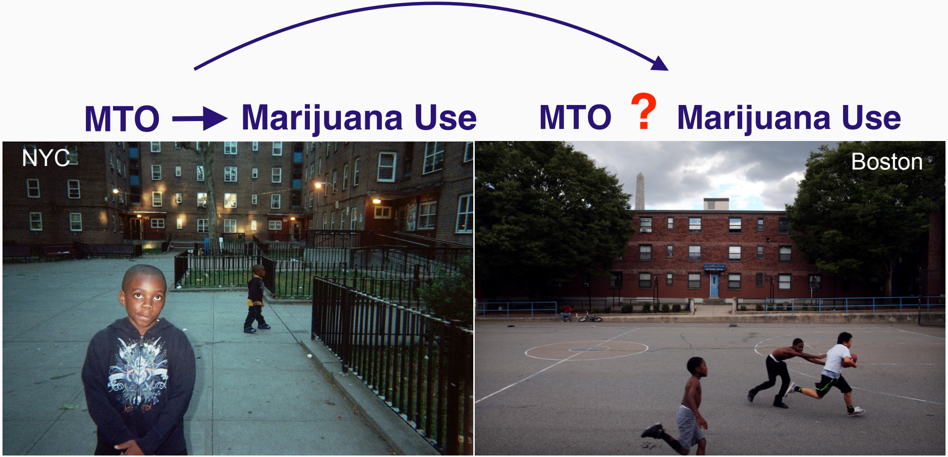

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  - Usually assumes that we expect the intervention effect in one site is the same as the other site
  - Why? Dummy variables for site changes the intercept but not the treatment effect coefficient. Assume that the conditional effect (regression coefficient) of the intervention in one site is the same as in another site

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So, in many cases, not reasonable to assume that effects will be the same in different populations!

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    - Assumes that the effects – even conditional effects – are different for each city.
    - We can't learn anything about how the intervention will work in one city from how it worked in another city.

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- Neither approach uses evidence to inform decision
- Transportability is a third option that looks to the data for evidence

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- Broad applications:
  - "Personalized" predictions for place
    - Predict long-term intervention effects in a new site based on results in an original site.
  - Surrogacy in clinical trials.

# Transportability: What's been done.

- Post-stratification/ direct standardization[3] E.g., age-adjusted rates of disease for comparisons between populations

[3] Miettinen, O. S. Standardization of risk ratios. *American Journal of Epidemiology* **96,** 383–388 (1972).
[4] Cole, S. R. & Stuart, E. A. Generalizing Evidence From Randomized Clinical Trials to Target Populations The ACTG 320 Trial. *American journal of epidemiology* **172,** 107–115 (2010).
[5] Stuart, E. A. *et al.* The use of propensity scores to assess the generalizability of results from randomized trials. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* **174,** 369–386 (2011).
[6] Frangakis, C. The calibration of treatment effects from clinical trials to target populations. *Clinical trials (London, England)* **6,** 136 (2009).
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- Selection model-based approaches: model-based standardization/ weighting,[4]propensity score matching,[5]and principal stratification[6]

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- Selection model-based approaches: model-based standardization/ weighting,[4]propensity score matching,[5]and principal stratification[6]
- Pearl and Bareinbom: formalized theory and assumptions for transportability[7]

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# Our contribution

Estimators for "transporting" effects from one population to another[8]

- Transport formula for multi-site encouragement-design interventions (extending Pearl and Bareinboim's work).

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- Transport formula for multi-site encouragement-design interventions (extending Pearl and Bareinboim’s work).
- Estimator features:
  - + Inference based on theory (even when using machine learning)
  - + Doubly or multiply robust: can misspecify multiple models and still get unbiased estimates

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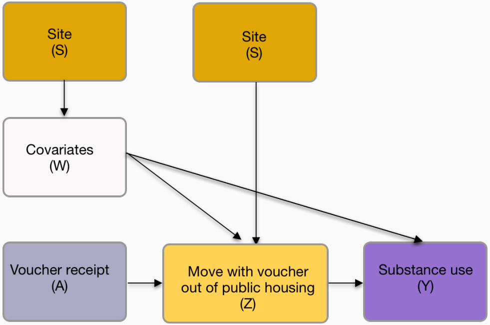
# Transport estimators

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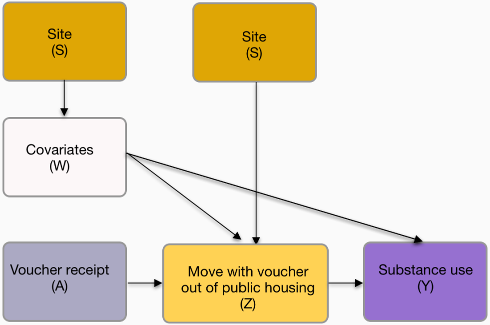


- Targeted minimum loss-based estimators (TMLE) for several types of effects predicted in a new site:
  - presenting results for transport ITTATE – effect of randomization to voucher receipt on outcome in a new population

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- We take two of the sites: LA and Boston.
- Outcome: adolescent school drop out at follow-up.
- We use full data from Boston. We ignore the outcome data from LA. Using the outcome model from Boston, we predict the intervention effect in LA, accounting for differences in population composition between the two cities.

# Methodological Approach

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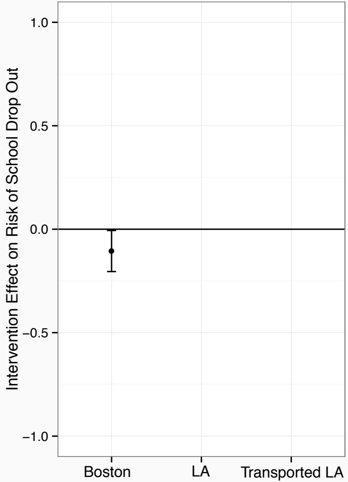
- If predicted effect estimate $=$ observed effect estimate, then differences were largely due to composition.
- If predicted effect estimate $\neq$ observed effect estimate, then differences were largely due to context.

# Results

## Real results: Boston[9]

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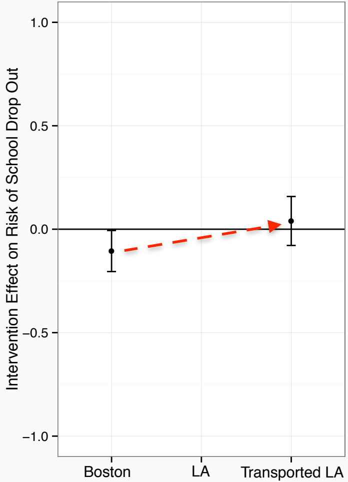


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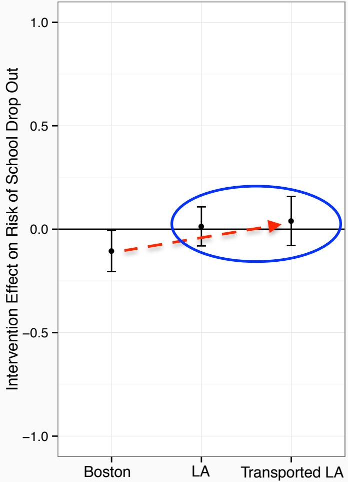
## Predicted vs. real results: LA[11]

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- The transported predictions for LA are similar to true LA estimates.

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# Results[12]

- The transported predictions for LA are similar to true LA estimates.
- Using population composition, we can predict the effect for LA $\rightarrow$ intervention effect on school dropout is transportable.

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# Results[12]

- The transported predictions for LA are similar to true LA estimates.
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- This means that the difference in effects between Boston and LA can be largely explained by population composition.

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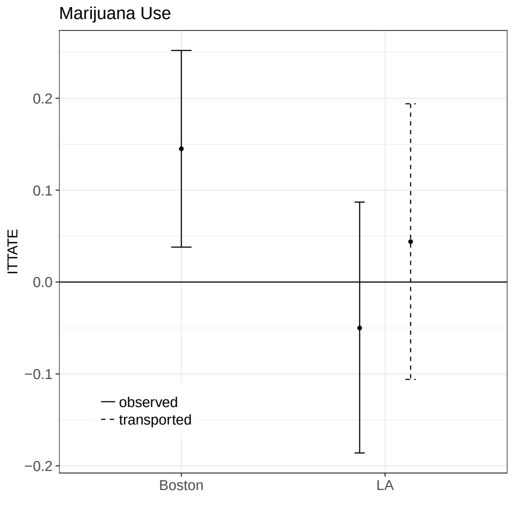
# Results: other risk behavior outcomes[13]

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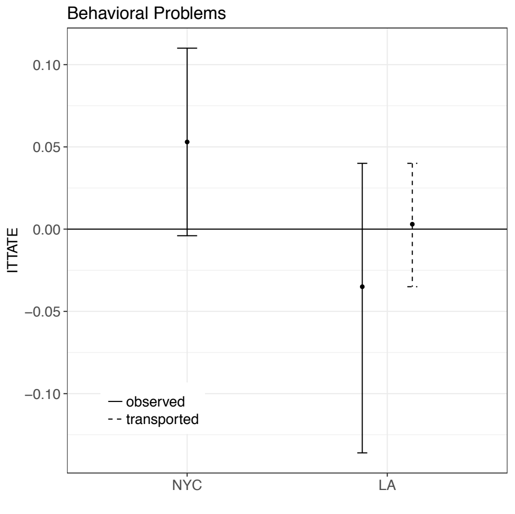


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# Thanks!

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- Elizabeth Stuart, Johns Hopkins
- Mark van der Laan, UC Berkeley