Urban Economics

What's in a Neighborhood? Measuring Neighborhood Effects

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Next week

- New material on transportation

Housing Briefing Note on Nov. 12th & Nov 14th

- Form your groups
- This assignment is going to be different than prior briefing notes
- No assigned readings
- You can come to class and work on it in groups
- Or you can form groups outside of class
- I will not be in the classroom on both days

The last group briefing note will be different as well

- It will be a letter that you are sending your city council

Why Neighborhoods Matter?

Where we live matters for many life outcomes

- Victimization from crime
- Education (especially if there are school zone boundaries, whereby you need to go to a school in your zone)
- Health
- Employment

Why we need to know if neighborhoods matter?

- It is important to know what the effects of neighborhoods are, as this may indicate how public policy should be conducted
- For example, your peers in your neighborhood could affect you or your family, such as by affecting the educational outcomes for children
- Going to schools with children from low-income families may have a negative effect on your educational outcomes
- On the other hand, children from high-income families may have a positive effect
- Where you live may affect your access to jobs, quality of schools, exposure to crime, etc.
  - You neighbors could let you know about job opportunities
  - Which could affect your income
  - If there is a strong neighborhood effect, then maybe it is important to have mixed-income schools/neighborhoods/public housing

It is difficult to measure neighborhood effects

Neighborhood Effects

The effect of the characteristics of a neighborhood on the outcomes of its residents, above and beyond the individual characteristics of those residents.

What would a potential issue be with measuring neighborhood effects?

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Neighborhood Effects

The effect of the characteristics of a neighborhood on the outcomes of its residents, above and beyond the individual characteristics of those residents.

What would a potential issue be with measuring neighborhood effects?

- A fundamental issue is **selection bias**

Selection bias in neighborhood effects

- People are not randomly assigned to neighborhoods
- The choice of neighborhood is endogenous, and is influenced:
  - Income
  - Preferences for neighborhood characteristics (e.g., good schools, low crime, proximity to work)
  - Race
  - Employment (where to work)
  - Local schools
  - and more....

Crime is a common neighborhood effect studied

- The extent that your neighbors are involved in criminal activity may affect the likelihood that you engage in criminal activity
- Suppose we want to determine the effect that neighbors have on criminal behavior
- i.e., does moving to a high crime neighborhood increase the likelihood that you engage in criminal activity?
- We could measure if criminal activity changes when individuals move from a low crime to a high crime neighborhood (or vice-versa)
- The individual stays the same, but the neighborhood changes. So could this help us determine the effect of neighborhoods on crime?

But there is Selection Bias

- Individuals who choose to move into a higher crime neighborhood may be more likely to engage in criminal activity INDEPENDENTLY of the effect of their neighbors on them
- So we get an upward biased estimate of the effect of neighborhoods on crime
- Estimated effect = causal effect + selection bias
- So, if we see that moving to a high crime neighborhood increases the likelihood of criminal activity, is it because the neighbors changed (causal effect)?
- or is it because this individual already had a high propensity to engage in criminal activity (selection bias)?

We can add controls, but it is not enough

- To help make the comparison more apples to apples, we can control for individual or family characteristics that may affect criminal behavior and also effect neighborhood choice
- These control variables would be income, education, gender, race, ethnicity, family type, employment status, etc…
- But even with lots of data, we can't control for everything that affects neighborhood choice or criminal behavior
- Controls might be able to reduce selection bias, but it cannot eliminate it

Can we randomly assign people to neighborhoods?

- Suppose individuals were assigned to neighborhoods randomly
- Then we have no selection bias, since individuals don't choose neighborhoods based on factors that may also affect their criminal behavior
- The neighborhood is independent of all individual/family characteristics (e.g., income, education)
- In one neighborhood, individuals may randomly get high-crime neighbors, and other individuals may randomly get low-crime neighbors

Can we randomly assign people to neighborhoods?

- Comparing individuals in one neighborhood to another captures only the casual effect of neighborhoods on crime
- Estimated effect = causal effect + selection bias = causal effect + 0 = causal effect
- It’s unethical to force people to move
- Is there a way we can still randomly assign neighborhoods so we can measure neighborhood effects?
- The Moving to Opportunity (MTO) program did this in an ethical and welfare-enhancing way

The moving to opportunity (MTO) experiment

- Moving to Opportunity (MTO) was a housing mobility experiment
- Conducted from 1994 to 1998
- Conducted in Baltimore, Boston, Chicago, Los Angeles, and New York
- Enrolled 4,604 low-income public housing families living in high poverty (poverty rate > 40%)

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Families were randomly assigned to one of three groups:

1. **Low-Poverty Voucher Group (LPV):** received housing vouchers to subsidize private-market rents but could only be used in census tracts with 1990 poverty rates below 10%
2. **Traditional Voucher (TRV) group:** received a housing voucher without the LPV constraint
3. **Control group:** Received no assistance

The outcome variables

The MTO research team was interested in the following outcomes:

- Economic self-sufficiency
- Physical health
- Mental health
- Subjective well-being

(more specific outcomes, e.g., impact of obesity, where looked at in other studies about MTO. The paper you had to read was a summary paper.)

This paper measures long term outcomes, measured 10 to 15 years later

Group comparisons

Comparing Traditional Voucher (TRV) to the Control Group allows us to estimate the causal effect of receiving a housing voucher on the outcome variables (economic self-sufficiency, physical health, mental health, subjective well-being)

Comparing Low-Poverty Voucher (LPV) to Traditional Voucher (TRV) allows us to estimate the causal effect of the low-poverty neighborhood constraint. Since this constraint forces families to move to better neighborhoods, this difference captures if better neighborhoods have different effects on the outcome variables

- In the assigned paper, they show the average differences between the control groups and the two treatment groups (TRV and LPV), and a pooled treatment group (TRV + LPV)

Summary of results

1) Did the randomization work? i.e., are the treatment and control groups on average identical?

- Evidence of this in Table 1 – Baseline characteristics

2) Assuming that 1) holds, did MTO affect the neighborhood you live in? i.e., did families actually move to better neighborhoods?

- Evidence of this in Table 2

3) Assuming that there is an effect in 2), then do we see an effect on long-term outcomes? (physical health, mental health, subjective well-being, economic self-sufficiency)

- Evidence in Figure 1

Summary of results

1) Did the randomization work? i.e., are the treatment and control groups on average identical?

- Evidence of this in Table 1 – Baseline characteristics
- **Yes, the groups look similar on average**

2) Assuming that 1) holds, did MTO affect the neighborhood you live in? i.e., did families actually move to better neighborhoods?

- Evidence of this in Table 2
- **Yes, strong evidence of this**

3) Assuming that there is an effect in 2), then do we see an effect on long-term outcomes? (physical health, mental health, subjective well-being, economic self-sufficiency)

- Evidence in Figure 1
- **No statistically significant effect on economic self-sufficiency, physical health, and mental health. Statistically significant effect on subjective well-being.**

Did the randomization work?

- The researchers gave out a survey of baseline characteristics
- Baseline means BEFORE they randomized everyone into treatment (voucher offered) and control (no voucher offered) groups
- Asked them questions about social-economic background (gender, race, ethnicity, education, household income, marital status, current neighborhood characteristics, reasons they want to move)
- If the randomization was successful, there should be few differences between the treatment and control groups

Did the randomization work?

- The means for each variable are similar for the control group and the treatment group
- Only twos estimates are weakly statistically significant

Table 1. Baseline characteristics (1994 to 1998) of adults interviewed as part of long-term survey (n = 3273 interviewees), by randomized MTO treatment status. Mean values represent shares, except for age and income; missing values have been imputed (except income). Values are weighted to account for changes over time in treatment assignment likelihood and for the follow-up survey sampling design (supplementary materials, section 1). ***$P < 0.01$, **$P < 0.05$, *$P < 0.10$ on two-tailed t test of difference between MTO treatment and control groups.

	Control group mean	MTO treatment (voucher) groups mean
	n = 1139	n = 2134
Gender and age		
Female	0.978	0.984
Age as of 31 December 2007 (years)	44.5	44.6
Race and ethnicity		
African-American (any ethnicity)	0.660	0.640
Hispanic ethnicity (any race)	0.304	0.325
Other demographic characteristics		
Never married	0.637	0.623
Working	0.245	0.270
High school diploma	0.361	0.367
General Educational Development (GED) certificate	0.199	0.169*
Receiving Aid to Families with Dependent Children (AFDC)	0.763	0.752
Household characteristics		
Household income (2009 dollars)	$12,438.64	$12,833.64
Site		
Baltimore	0.135	0.136
Boston	0.205	0.203
Chicago	0.205	0.206
Los Angeles	0.226	0.225
New York	0.229	0.229
Neighborhood characteristics		
Household member was crime victim in past 6 months	0.416	0.425
Very dissatisfied with neighborhood	0.467	0.478
Primary or secondary reason for wanting to move		
To get away from gangs and drugs	0.779	0.770
Better schools for children	0.481	0.516*
To get a bigger or better apartment	0.457	0.440
To get a job	0.069	0.058

How can randomization fail?

In this case it looks like the randomization worked, and that is tested by comparing the means of the baseline characteristics. They are extremely similar

The randomization could fail if individuals who didn't randomly get assigned a voucher could get one anyways (e.g., pleading for one, bribing study officials)

Similarly, study officials who do the randomization may not do it correctly. They may decide to give out vouchers non-randomly. They may give a voucher to a family that seems to really need it, even if they weren't randomly supposed to get one

These non-random assignments could be reflected in differences in baseline characteristics

How can randomization fail? (cont'd)

Imagine an extreme scenario: Housing vouchers are supposed to be randomized. But the officials who give out the vouchers are corrupt, and will accept small bribes to exchange for vouchers

Families with higher incomes may be more likely to pay the bribe

So household income would be higher in baseline for the treatment group

Implication of this: selection bias!

The treatment and control groups are not on average identical

Choice of neighborhood (through getting a voucher or not) becomes a function of family characteristics because individuals can select into getting vouchers

Thus the experiment provides biased estimates of how neighborhoods affect outcomes

Did MTO affect the neighborhood you live in?

Table 2. MTO effects on post-randomization housing and neighborhood conditions of adult participants interviewed in long-term survey. Table shows average outcomes for control group adults and ITT contrast of outcomes for adults assigned to treatment (pooling the low-poverty and traditional voucher groups) rather than control. Housing and neighborhood conditions were measured from long-term survey data and census tract–level data interpolated from the 1990 and 2000 decennial censuses and the 2005–2009 American Community Survey. ITT was calculated by using ordinary least-squares regression controlling for baseline covariates, using weights (Table 1 and supplementary materials, sections 1 and 5). ***$P < 0.01$, **$P < 0.05$, *$P < 0.10$ on two-tailed t test.

	Control mean	MTO treatment (voucher) groups versus control			
		ITT		SE	n
Census tract characteristics					
Share poor at different points in time					
1 year after random assignment	0.499	−0.160	***	(0.007)	3224
5 years after random assignment	0.399	−0.089	***	(0.007)	3208
10 to 15 years after random assignment (May 2008)	0.311	−0.034	***	(0.007)	3206
Share poor for all addresses since random assignment (duration-weighted)					
Share poor	0.396	−0.082	***	(0.005)	3270
Share poor, z score using U.S. tract poverty distribution	2.082	−0.666	***	(0.041)	3270
Share poor, z score using MTO control group tract poverty distribution	0.000	−0.653	***	(0.040)	3270
Duration-weighted poverty rate is…					
Less than 20%	0.054	0.196	***	(0.013)	3270
Less than 30%	0.242	0.237	***	(0.018)	3270
Less than 40%	0.512	0.206	***	(0.018)	3270
Share minority					
10 to 15 years after random assignment (May 2008)	0.844	−0.024	**	(0.009)	3206
All addresses since random assignment (duration-weighted)	0.880	−0.046	***	(0.006)	3270
Residential mobility					
Number of moves after random assignment	2.165	0.584	***	(0.068)	3273
Self-reports on long-term (10- to 15-year) follow-up surveys about neighborhood and housing conditions					
Feel unsafe during day	0.196	−0.039	**	(0.015)	3262
Number of housing problems (0 to 7)	2.051	−0.380	***	(0.076)	3267
Likely or very likely to report kids spraying graffiti (collective efficacy)	0.589	0.064	***	(0.020)	3255
One or more friends with college degree	0.532	0.049	**	(0.020)	3203

Accepting or declining the "treatment"

Many families that were offered a voucher still chose not to move

Thus, they didn’t accept the “treatment”, where the treatment is moving and using the voucher. Those who moved and use the voucher “complied” with the treatment and are called “compliers”.

- Those who moved and use the voucher “complied” with the treatment and are called “compliers”

- Complier = You were randomly given a voucher and you used it

Compliance Rates

- 48% of families in the Low-Poverty Voucher (LPV) group managed to relocate using the MTO voucher

- 63% for the Traditional Voucher (TRV) group

The compliance rate is likely higher for the TRV group because the LPV had the restriction that they had to move to a low-poverty neighborhood

implications of compliance

So, families who got vouchers “selected” into if they wanted to take the voucher and move.

Several factors may affect the decision to take the voucher or not. For example:

- Family structure
- Income
- Employment (especially work location)
- Race/Ethnicity
- Schools

implications of compliance

So, families who got vouchers “selected” into if they wanted to take the voucher and move.

Several factors may affect the decision to take the voucher or not. For example:

- Family structure
- Income
- Employment (especially work location)
- Race/Ethnicity
- Schools

Is there still selection bias?

Ignoring the fact that families “select” into using the voucher leads to selection bias. How do the authors deal with this? The authors calculate and present two types of estimates: intent to treat (ITT) and the treatment-on-the-treated (TOT) (to be explained in the next several slides)

Intent to Treat (ITT)

- The "Intent to Treat" (ITT) estimate answers: **What is the effect of being offered a voucher?**
- ITT is calculated as:

$$\text{ITT estimate} = \text{Average outcome of those offered voucher} - \text{Average outcome for control group}$$

- The treatment group includes:
  - **Compliers:** used the voucher (moved)
  - **Non-compliers:** did not use the voucher (did not move)
- Not all individuals in the treatment group are "treated."

What does ITT mean?

- ITT answers: **What is the effect of being offered a voucher?**
- Some people move (compliers), some do not (non-compliers).
- The ITT estimate is **not** the same as the effect of actually moving.

Treatment-on-the-Treated (TOT)

- TOT answers: **What is the effect for those who actually moved?**
- TOT is always larger in magnitude than ITT when compliance is less than 100%.
- TOT does **not** include non-movers (non-compliers).

ITT vs. TOT (Summary)

- **ITT:** Effect of being offered a voucher (includes both movers and non-movers)
- **TOT:** Effect for those who actually moved (compliers only)
- **TOT > ITT** (in magnitude) when not everyone moves

A Silly but Helpful Example

- (Based on Kevin Lang, Boston University)
- Suppose I want to know the effect of giving you a chocolate bar on how many you have.
- I randomly give out chocolate bars:
  - Flip a coin for each person
  - HEADS = gets a chocolate bar
  - TAILS = does not get a chocolate bar

Chocolate bar survey (100% compliance)

- After random assignment, I survey the class: “How many chocolate bars do you have?”
- Everyone in the treatment group has one more chocolate bar than everyone in the control group.
- **ITT = 1 bar**
- Since everyone who was assigned a chocolate bar got one (**100% compliance**),
    - **ITT = TOT**

Chocolate, with restrictions (Imperfect compliance)

- Now, instead of handing out chocolate bars, I email the treatment group to pick up a bar during office hours.
- Not everyone will come. Decision depends on:
    - Preference for chocolate
    - Like/dislike for professor
    - Time constraints
    - Dietary restrictions

Chocolate, with restrictions (Imperfect compliance)

- Suppose 40% of the treatment group shows up (compliers), 60% do not (non-compliers).
- Control group: 0 bars.
- **ITT = 0.4 bars** (average difference between groups)
- **TOT = 1 bar** (for those who actually got a bar)

Inflating ITT to get TOT

- If you know the ITT effect and the compliance rate, you can get the TOT:
    - **ITT = 0.4 bars**
    - **Compliance rate = 40%**
    - **TOT = ITT / compliance rate = 0.4 / 0.4 = 1**
- This tells us what the effect would be if everyone in the treatment group had picked up a chocolate bar.

ITT Example from MTO

- In the control group, 19.6% of families indicated they “felt unsafe during day.”
- The ITT point estimate is **-0.039** (3.9 percentage point decrease).
- This means the treatment group had a 15.7% probability of saying they “felt unsafe during the day.”
- This decrease comes from both movers (compliers) and non-movers (non-compliers).
- If everyone had moved, the effect would have been larger than 3.9 percentage points!

From ITT to TOT in MTO

- ITT for “feel unsafe during day” = **-0.039**
- Compliance rates:
  - 48% in LPV group
  - 63% in TRV group
  - Average compliance rate = **55.5%**
- If everyone had moved, the effect would be larger.
- To get TOT:
  - **TOT = ITT / compliance rate = -0.039 / 0.555 ≈ -0.070**
- The ITT estimate gets inflated by 1.8 times (1/0.555 = 1.8) to get the TOT estimate.

A more formal way to get the TOT

- "Inflating" the ITT is a simple way to get the TOT.
- The more formal way is through a regression analysis strategy called **instrumental variables (IV)**.
- We saw IV previously in the Bhuller et al. (2016) paper (incarceration and criminality).
- IV allows researchers to:
  - Ignore variation due to selection bias
  - Use only the random variation induced by the experiment (e.g., random assignment of judges or vouchers)

IV in this MTO Paper

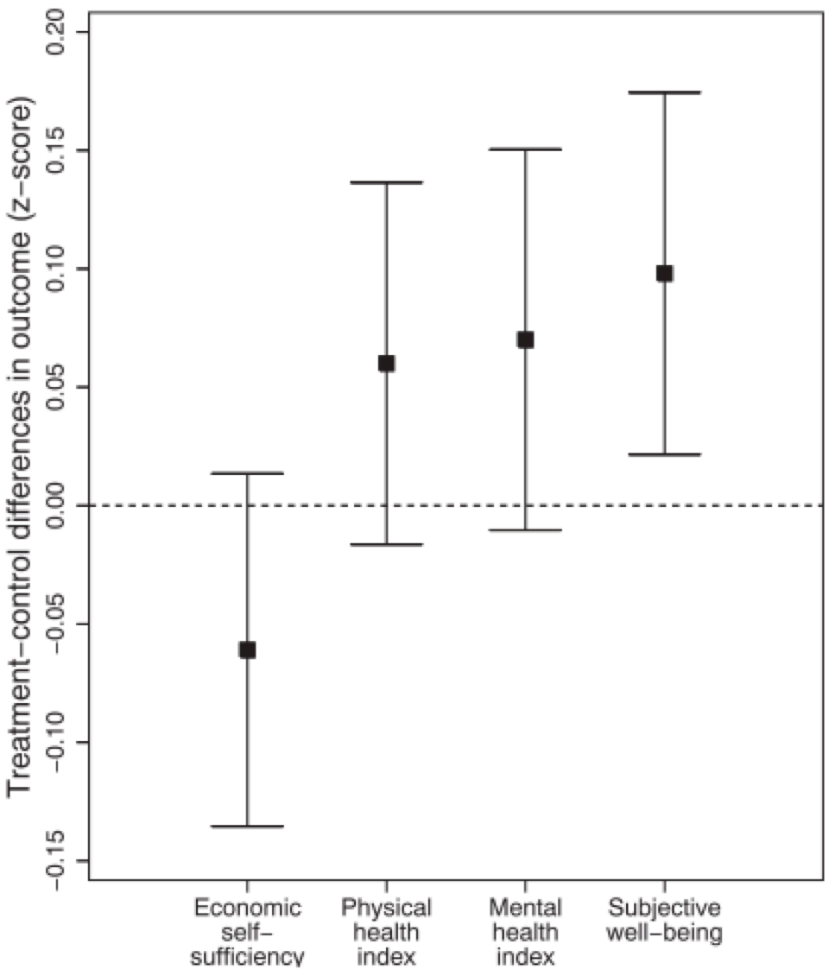
- The IV approach here is similar to the previous example.
- Researchers do **not** compare:
  - Those that moved to those that did not, **or**
  - Those that used the voucher to those that did not.
- In both cases, there would be selection bias.

IV in this MTO Paper (cont.)

- Instead, they use IV to only use the variation in where you live that is induced by the **random voucher offer**.
- This allows them to estimate the effect of neighborhoods on outcomes, using just this random variation, and not other variation in neighborhoods that would have selection bias.
- This is as much detail as you need to know about IV for this class.
- You don’t need to know the equations or technical aspects.

Effects of MTO on Long-Term Outcomes

Fig. 1. Impact on each outcome of assignment to the MTO treatment (voucher) groups for adults interviewed in a long-term survey. The squares represent the ITT estimate for the effect of being assigned to MTO treatment (pooling low-poverty and traditional voucher groups), rather than control, for the outcomes listed on the *x* axis: economic self-sufficiency, physical health, mental health, and SWB (Table 2 and supplementary materials, sections 1, 4, and 5). The box whiskers represent the 95th percent confidence interval around the estimates.



Policy Implications of the Results

Moving to Opportunity had a positive and statistically significant effect on subjective well-being, but no statistically significant effects on physical or mental health, or economic self-sufficiency. Suggests the housing vouchers can't be used to affect certain policy outcomes in the long run (e.g., improve health, increase income) but it does increase well-being.