

Estimating Neighborhood Choice Models: Lessons from the Moving To Opportunity Experiment

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Introduction

- ▶ Housing Policy Reform
- ▶ Neighborhood Effects
- ▶ Moving to Opportunity Experiments—> Specific Policy Intervention
- ▶ Other Policies May Require Understanding of Moving Decisions and Neighborhood Choices
- ▶ Trade-off between Paternalism and Outcomes.

Contributions

1. Formulate a Model of Neighborhood Choice for Public Housing Residents
2. Use Experimental Randomization to Estimate the Model
3. Use Additional Experimental Variation to Validate the Model
4. Disentangle Quantitative Role of Location Restrictions and Moving Counseling on Take Up rates
5. Policy Evaluation of More Restrictive Voucher Policies.
 - ▶ More Lower Cutoff for Allowed Poverty Rate
 - ▶ Add Race-Based Location Constraints

Related Literature

- ▶ Experimental Data and Structural Estimation.
 - ▶ Todd & Wolpin (2006) , Meghir, Attanasio & Santiago (2011)
 - ▶ Duflo, Hanna & Ryan (2007)
- ▶ MTO
 - ▶ Katz, Kling & Liebman (2001): ITT and TOT on outcomes (Boston)
 - ▶ Kling, Liebman & Katz (2007): Neighborhood Effects (All Sites)
 - ▶ Critique: Clampet-Lundquist & Massey (2008)
 - ▶ Response: Ludwig, Liebman, Kling, Duncan, Katz, Kessler & Sanbonmatsu (2008)
 - ▶ Aliprantis (2011): Re-Analysis of Kling, Liebman & Katz (2007)
- ▶ Neighborhood Choice : discrete choice approach.
 - ▶ Epple and Sieg (1999), Sieg, Smith, Banzhaf & Walsh (2004), Kuminoff (2008), Geyer (2011)
 - ▶ Bayer, Ferreira & McMillan (2007), Bayer, McMillan & Rueben (2011)
 - ▶ Ferreyra (2007)

The MTO Experiments

- ▶ Mid 1990s, 5 cities : Baltimore, Boston, Chicago, Los Angeles and New York.
- ▶ Eligible Public Housing Residents invited to enroll.
- ▶ Conditional on Enrollment $\longrightarrow$ Random Assignment to
 - ▶ Control Group
 - ▶ Section 8 Treatment Group: unrestricted voucher (σ, ρ)
 - ▶ Experimental Treatment Group : restricted voucher (σ, ρ, τ) + counseling (λ_1)

The MTO Data

- ▶ Focus on Data from Boston
- ▶ Baseline Covariates Z_i at time of Random Assignment
 - ▶ Race, Marital Status, Household Size, etc...
 - ▶ Treatment Status
 - ▶ Subsequent Neighborhood Choices (with or without voucher)

Table 1: MTO Data Descriptive Statistics

	Control	Experimental	Section 8	Total
White	0.10	0.12	0.11	0.11
Household Income (in 10,000s)	1.03	1.07	0.97	1.03
Ever Married	0.62	0.64	0.67	0.64
Household Size	3.25	3.14	3.16	3.18
Applied to Section 8 Before	0.56	0.55	0.59	0.56
Moved 3 Times Before	0.13	0.14	0.15	0.14
Dissatisfied with Neighborhood	0.33	0.35	0.30	0.33
Observations	200	221	192	613

Final analysis sample from Boston. Single headed households enrolled in the MTO demonstration. Variables in the table are measured at baseline. Annual Household Income in 10,000s of 1997 dollars includes welfare payments for those on welfare and estimated labor income for those working. See text for details.

Reduced Form Evidence I

► Notation

- Z_i is a vector of individual characteristics
- $G_i = [G_{1i} G_{2i}]$ is a vector of two random assignment indicators

$$G_{1i} = \begin{cases} 1 & \text{if } i \text{ assigned to Experimental Treatment} \\ 0 & \text{otherwise} \end{cases}$$

$$G_{2i} = \begin{cases} 1 & \text{if } i \text{ assigned to Standard S8 Treatment} \\ 0 & \text{otherwise} \end{cases}$$

- D_i is an indicator of voucher use

$$D_i = \alpha_0 + \alpha_1 \{G_i = \text{Experimental}\} + \alpha_2 \{G_i = \text{Section 8}\} + Z_i' \beta + u_i$$

Reduced Form Evidence II

Table 2: Voucher Take Up

	(1)	(2)
Experimental	0.457*** (0.0336)	0.445*** (0.0325)
Section 8	0.609*** (0.0353)	0.601*** (0.0358)
White		0.127** (0.0509)
Household Income		0.0101 (0.0220)
Ever Married		0.0178 (0.0333)
Household Size		-0.0348** (0.0160)
Applied to Section 8 Before		0.113*** (0.0322)
Moved 3 Times Before		0.151*** (0.0449)
Dissatisfied with Neighborhood		0.111*** (0.0335)
Constant	0 (0)	-0.0389 (0.0666)
Observations	613	613

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Boston MTO final analysis sample. The dependent variable is equal to one if the household uses the voucher, equals zero otherwise. Control group observations are the omitted category but they were not given vouchers so their dependent variable is always zero, and the regression without controls in column 1 goes through the origin.

Reduced Form Evidence III

- ▶ Differential Take Up: $\alpha_1 < \alpha_2$
 - ▶ but, what's the separate quantitative role of each experimental treatment feature?

The Model I

Households solve

$$\max_{\{d_i\}} U(C_i, X_j, \xi_j, I_i, Z_i, j_{i,t-1}, \epsilon_{ij}, \theta)$$

subject to

$$C_i + R_{ij} = I_i$$

$$R_{ij} = R(G_{i,j}, j_{t-1}, R_j^m, I_i, \sigma, \rho, \tau)$$

where

- ▶ X_j is a vector of K attributes of neighborhood j
- ▶ ξ_j summarizes the unobserved attributes of neighborhood j
- ▶ C_i is consumption of non-housing goods by household i
- ▶ I_i is total household income
- ▶ $R(\cdot)$ is the "out-of-pocket" rent function
- ▶ R_j^m is the median market rent for neighborhood j

The Model II

- ▶ j_{t-1} is baseline neighborhood of residence
- ▶ (σ, ρ, τ) are parameters of the housing voucher
 - ▶ σ is the percent of household income assigned to rent (also called "HUD Tax")
 - ▶ ρ is a voucher cap (given by the FMR)
 - ▶ τ is the maximum allowed poverty rate for voucher use in the experimental treatment group

The Model III

- ▶ Let $R_{ij} = R^{OOP} \left(G_i, j, j_{t-1}, R_j^m, l_i - A_i, \sigma, \rho, \tau \right)$
- ▶ Recast into a standard discrete choice framework with unobserved characteristics

$$u_{ij} = \alpha_i X_j + \beta_i R_{ij} + \lambda_{ij} + \xi_j + \epsilon_{ij}$$

where

$$\alpha_{i,k} = \alpha_{0,k} + \alpha_{1,k} Z_i$$

$$\beta_i = \beta_0 + \beta_l l_i + \beta_1 Z_i$$

$$\lambda_{ij} = \lambda_i 1 \{j \neq j_{i,t-1}\}$$

$$\lambda_i = \lambda_0 + \lambda_1 1 \{G_i = 1\}$$

$$\epsilon_{ij} \sim \text{i.i.d. Type 1 Extreme Value}$$

The Model IV

- Plug in (α_i, β_i)

$$u_{ij} = \alpha_0 X_j + \alpha_1 Z_i X_j + \beta_0 R_{ij} + \beta_l I_i R_{ij} + \beta_1 Z_i R_{ij} + \lambda_{ij} + \xi_j + \epsilon_{ij}$$

and add/subtract $\beta_0 R_j^m$ to get

$$u_{ij} = \delta_j + \alpha_1 Z_i X_j + \beta_0 (R_{ij} - R_j^m) + \beta_l I_i R_{ij} + \beta_1 Z_i R_{ij} + \lambda_{ij} + \epsilon_{ij}$$

$$\delta_j = \alpha_0 X_j + \beta_0 R_j^m + \xi_j$$

The Model: Rents and Voucher Structure

$$R_{ij} = \begin{cases} \sigma l_i & \text{if } j = j_{t-1}, \text{ all } G_i \\ R_j^m & \text{if } j \neq j_{t-1}, G_i = \text{Control} \\ \max \left\{ 0; R_j^m - [\rho - \sigma l_i] \right\} & \text{if } j \neq j_{t-1}, G_i = \text{Sec 8} \\ R_j^m & \text{if } j \neq j_{t-1}, G_i = \text{Exp, Poverty}_j > \tau \\ \max \left\{ 0; R_j^m - [\rho - \sigma l_i] \right\} & \text{if } j \neq j_{t-1}, G_i = \text{Exp, Poverty}_j < \tau \end{cases}$$

The Data

1. MTO Data

- ▶ Baseline Covariates Z_i at time of RA
 - ▶ Race, Marital Status, Household Size, etc...
- ▶ Treatment Status
- ▶ Subsequent Neighborhood Choices (with or without voucher)

2. Census Data

- ▶ Joint Distribution of Race and Household Income $f_j(Z^1)$
 - ▶ for each 6d census tract in Boston Metropolitan Area.
 - ▶ among renters
 - ▶ have counts $\rightarrow$ construct quasi-microdata
- ▶ Median Market Rent for each Neighborhood R_j^m
- ▶ Neighborhood Characteristics $X_j = [\text{Poverty Rate, \% White}]$

The Estimation Strategy I

- ▶ We proceed in 2 steps
- ▶ First we estimate $\left(\alpha_1, \alpha_2, \beta_0, \beta_1, \beta_2, \lambda_0, \lambda_1, \{\delta_j\}_{j=1}^J\right)$ by combining
 - ▶ MTO microdata
 - ▶ Census quasi-microdata on $f(d, \text{Race}, \text{Income})$
 - ▶ Census data on neighborhood characteristics (X_j, R_j^m)
- ▶ The individual likelihood contribution is given by the choice probability

$$\pi_{ij} = \Pr \left(d_i = j \mid \{X_j, R_j^m, R_{ij}\}_{j=1}^J, Z_i, G_i, \theta \right)$$
$$\pi_{ij} = \frac{\exp \left(\begin{array}{l} \delta_j + \alpha_1 Z_i X_j + \beta_0 (R_{ij} - R_j^m) \\ + \beta_l l_i R_{ij} + \beta_1 Z_i R_{ij} + \lambda_{ij} \end{array} \right)}{\sum_{k=1}^J \exp \left(\begin{array}{l} \delta_k + \alpha_1 Z_i X_k + \beta_0 (R_{ik} - R_k^m) \\ + \beta_l l_i R_{ik} + \beta_1 Z_i R_{ik} + \lambda_{ik} \end{array} \right)}$$

The Estimation Strategy II

- ▶ For each trial of $(\alpha_1, \alpha_2, \beta_0, \beta_1, \beta_2, \lambda_0, \lambda_1)$ a contraction mapping solves out for $\{\delta_j\}_{j=1}^J$ by matching
 - ▶ neighborhood shares predicted by the model $\{\hat{\pi}_j\}_{j=1}^J$ and
 - ▶ neighborhood shares observed in the Census $\{\pi_j^{data}\}_{j=1}^J$.

$$\hat{\pi}_j(\delta) = \pi_j^{data} \text{ all } j$$

$$1 = \frac{\pi_j^{data}}{\hat{\pi}_j} \text{ all } j$$

$$0 = \log \left(\frac{\pi_j^{data}}{\hat{\pi}_j(\delta)} \right)$$

$$\delta_j = \delta_j + \log \left(\frac{\pi_j^{data}}{\hat{\pi}_j(\delta)} \right)$$

The Estimation Strategy III

- ▶ Starting with a guess $\left\{ \delta_j^{(0)} \right\}_{j=1}^J$ we iterate until the vector δ converges

$$\delta_j^{(n+1)} = \delta_j^{(n)} + \log \left(\frac{\pi_j^{data}}{\hat{\pi}_j(\delta^{(n)})} \right) \text{ all } j$$

- ▶ For each vector δ , the share for neighborhood j predicted by the model is

$$\hat{\pi}_j(\delta) = \int \hat{\pi}_{ij}(\delta) dF(Z_i)$$

The Estimation Strategy IV

- ▶ KEY IDEA : unlike in standard BLP-type approach, we are able to consistently estimate β_0 in a first step because
 - ▶ we control for $\tilde{\xi}_j$ in δ ,
 - ▶ we have individual variation in rental prices, R_{ij}
 - ▶ the variation in $R_{ij} - R_j^m$ is literally random and therefore, uncorrelated with ε_{ij}

The Estimation Strategy: Decomposition

- Recall that

$$\delta_j = \alpha_0 X_j + \beta_0 R_j^m + \xi_j$$

so we can estimate α_0 by OLS in

$$\hat{\delta}_j - \hat{\beta}_0 R_j^m = \alpha_0 X_j + \xi_j$$

Estimation Results: Parameter Estimates I

$$Z_i = \begin{bmatrix} \text{White} \\ \text{EverMarried}_i \\ \text{HouseholdSize}_i \\ \text{Applied to S8 before}_i \\ \text{Moved 3 times before}_i \\ \text{Very Dissatisfied with Neighborhood}_i \end{bmatrix}$$

$$X_j = \begin{bmatrix} \text{Percent White}_j \\ \text{Poverty Rate}_j \end{bmatrix}$$

Estimation Results: Parameter Estimates II

Table 3: Estimated Parameters

		Marginal Utility from Percent White			Marginal Utility from Poverty Rate	
		Coef.	SE		Coef.	SE
White		4.318	(0.1259)		-0.072	(0.1275)
Ever Married		-0.190	(0.0607)		-0.425	(0.1094)
Household Size		-0.553	(0.0266)		0.110	(0.0518)
Applied S8 before	α_1	-0.609	(0.0509)	α_1	-2.514	(0.1165)
Moved 3 times before		0.233	(0.0691)		-3.054	(0.1529)
Very Dissatisfied		1.009	(0.0550)		-1.676	(0.1154)

Standard errors in parentheses computed using bootstrap. The table shows the first stage structural parameters for price sensitivity, moving costs and parameters of marginal utility from neighborhood characteristics (poverty rate and % white). The parameters associated with the six observable household characteristics represent utility interaction effects between such characteristics and the corresponding neighborhood characteristic (rental price, poverty rate, % white). Estimation Sample includes only Control group (G=0) and Experimental Group (G=1) observations. Section 8 held out for out-sample validation.

Estimation Results: Parameter Estimates III

Table 3: Estimated Parameters

		Price			
		Coef.	SE		
Constant	β_0	-0.657	(0.0148)	Mobility Costs	
Annual Income (in 10,000s)	β_1	0.145	(0.006)	Coef.	SE
White	β_1	-0.025	(0.0094)	λ_0	-5.255 (0.0260)
Ever Married		0.091	(0.0084)	λ_1	1.290 (0.0259)
Household Size		0.064	(0.0041)		
Applied S8 before		-0.110	(0.0085)		
Moved 3 times before		0.011	(0.0100)		
Very Dissatisfied		0.122	(0.0084)		

Standard errors in parentheses computed using bootstrap. The table shows the first stage structural parameters for price sensitivity, moving costs and parameters of marginal utility from neighborhood characteristics (poverty rate and % white). The parameters associated with the six observable household characteristics represent utility interaction effects between such characteristics and the corresponding neighborhood characteristic (rental price, poverty rate, % white). Estimation Sample includes only Control group (G=0) and Experimental Group (G=1) observations. Section 8 held out for out-sample validation.

Estimation Results: Parameter Estimates IV

- ▶ Price hurts $\beta_0 < 0$, but less so for richer households $\beta_I > 0$
- ▶ It is very costly to move $\lambda_0 < 0$, but less so for the Experimental Treatment Group $\lambda_0 > 0$: counseling works.

Estimation Results: Parameter Estimates V

- ▶ Non-White Household Annual Willingness to Pay (in dollars) for 1 percentage point increase in the incidence of Whites in neighborhood of residence

$$-\frac{\frac{\bar{\alpha}}{100}}{\frac{\bar{\beta}}{12*100}} = -\frac{\left(\frac{\alpha_0 + \alpha_1 \bar{Z}}{100}\right)}{\frac{(\beta_0 + \beta_1 \bar{Z} + \beta_I \bar{I})}{12*100}} = \$ - 174.3$$

- ▶ We divide α by 100 because Percent White is measured between 0 and 1.
- ▶ We divide β by 12 and by 100 because Rent is measured monthly and in hundreds of dollars.

The Validation Strategy: Within Sample Fit I

- ▶ Many choices so no attempt to match neighborhood choice distribution
- ▶ We focus on how the model fits some key moments.
- ▶ Mean Exposure to Neighborhood Attribute X by Assignment Group g

Mean Exposure to Neighborhood Attribute X by Assignment Group

$$E[X|G = g] = \sum_j X_j [\Pr(d = j|G = g)]$$

$$E[X|G = g] = \sum_j X_j \left[\frac{1}{N_g} \sum_{i=1}^{N_g} \Pr(d = j|G_i = g, Z_i) \right]$$

$$E[X|G = g] = \sum_j X_j \left[\frac{1}{N_g} \sum_{i=1}^{N_g} \pi_{ij} \right]$$

The Validation Strategy: Within Sample Fit II

Take Up Rate by Assignment Group $g =$

$$\begin{aligned} &= E[I\{D = 1\} | G] \\ &= \begin{cases} 0 & \text{if } G=0 \\ \Pr(d \neq d_{t-1} \text{ and } \text{PovRate}_j < 10\% | G = 1) & \text{if } G=1 \\ \Pr(d \neq d_{t-1} | G = 2) & \text{if } G=2 \end{cases} \end{aligned}$$

The Validation Strategy: Within Sample Fit III

Mean Exposure to Neighborhood Attribute X by Assignment Group g
Conditional on Voucher Take Up

$$E[X|G, D = 1] = \sum_j X_j [\Pr(d = j|G, D = 1)]$$

$$E[X|G, D = 1] = \sum_j X_j \left[\sum_{i: G=g, D_i=1} \Pr(d = j|G, D = 1, Z_i) \left(\frac{1}{N_{g,1}} \right) \right]$$

$$E[X|G, D = 1] = \sum_j X_j \left[\frac{1}{N_{g,1}} \sum_{i: G=g, D_i=1} \Pr(d = j|G_i = g, D_i = 1, Z_i) \right]$$

The Validation Strategy: Within Sample Fit IV

Table 4: Within Sample Fit

	All	0	1	All	0	1
	C+E	Control	Exp	C+E	Control	Exp
	Data			Model		
<u>Unconditional on Move Using the Voucher</u>						
% Who Move	0.54	0.35	0.71	0.54	0.35	0.71
Mean Poverty Rate	0.27	0.33	0.21	0.28	0.34	0.22
Mean % White	0.41	0.36	0.47	0.43	0.37	0.48
<u>% Who Move Using the Voucher</u>						
		0	0.47		0	0.41
<u>Conditional on Move Using the Voucher</u>						
Mean Poverty Rate		n/a	0.06		n/a	0.07
Mean % White		n/a	0.76		n/a	0.78
Observations	422	200	222			

Empirical moments computed directly from final analysis sample of MTO households. Within sample fit evaluated only on observations used in estimation (control and experimental groups only). See appendix for details about construction of moments predicted by the model. Control group observation are not assigned vouchers so none of them move using the voucher. Note that moments computed conditional on voucher take up are not defined for the control group.

The Validation Strategy: Out of Sample Fit I

- ▶ Use subsample of MTO participants assigned to the standard treatment groups (Unrestricted Section 8)
 - ▶ not used in estimation.
 - ▶ subsample is random.
 - ▶ but faced different moving incentives
- ▶ More challenging to match.

The Validation Strategy: Out of Sample Fit II

Table 5: Out of Sample Fit

	Section 8	
	Data	Model
<u>Unconditional on Move Using the Voucher</u>		
% Who Move	0.61	0.60
Mean Poverty Rate	0.27	0.28
Mean % White	0.38	0.40
<u>% Who Move Using the Voucher</u>	0.61	0.60
<u>Conditional on Move Using the Voucher</u>		
Mean Poverty Rate	0.21	0.20
Mean % White	0.41	0.49
Observations	192	

Subsample of Section 8 households held out for external model validation. Empirical moments computed directly from final analysis sample of MTO households. Out-of-sample fit evaluated on observations not used in estimation (Section 8 group only). See appendix for details about construction of moments predicted by the model.

Understanding Take Up I

- ▶ Take up rates for the 2 treatment groups are very different.
- ▶ Two effects going in opposite directions
 - ▶ Counseling promotes moving
 - ▶ Location Restrictions discourage moving
- ▶ Using Experiment Only we
 - ▶ can conclude that Location Restrictions dominate Counseling...
 - ▶ but cannot identify separate magnitudes.
- ▶ Experimental way: run a larger experiment including a 3rd treatment group that receives counseling and unrestricted voucher.
- ▶ Our way: Simulate Moving Behavior for the Experimental Treatment Group without Moving counseling by setting $\lambda_1 = 0$

Understanding Take Up II

	Take Up Rate
Unrestricted Voucher	60%
Restricted Voucher	27%
Restricted Voucher + Counseling	41%

- Location Restrictions and Counseling are both quantitatively large.

How Binding are Poverty-Based Location Constraints on Voucher Use? I

- ▶ Simulate neighborhood choice and voucher take up under alternative cutoffs for the poverty-based location constraint

$$\tau \in \{2.5, 5, 7.5, 15, 20\}$$

- ▶ How much take up is reduced with tighter constraints?
- ▶ Does unconditional exposure to poverty decline?
- ▶ If they have an MTO experimental voucher, how much are recipients willing to pay
 - ▶ to get a less stringent (high τ) voucher
 - ▶ to avoid a more stringent (low τ) voucher.

$$\frac{1}{N_1} \sum_{i=1}^{N_1} \frac{E [\max_j u_{ij} (\tau)] - E [\max_j u_{ij} (\tau^{MTO})]}{\beta_i}$$

How Binding are Poverty-Based Location Constraints on Voucher Use? II

Table 7: Alternative Neighborhood Poverty Rate Cutoffs

(1)	(2)	(3)	(4)	(5)	(6)	(7)
τ	Take-up	Mean Poverty Rate (given take-up)	Mean Poverty Rate (unconditional)	Mean % White (given take-up)	Mean % White (unconditional)	WTP relative to MTO
2.5%	3%	2%	28.1%	93%	38%	-\$1,636
5%	14%	3%	26.1%	90%	42%	-\$1,250
7.5%	28%	5%	23.8%	78%	45%	-\$641
10%	41%	7%	22.1%	78%	48%	\$0
15%	51%	9%	21.3%	73%	49%	\$577
20%	59%	11%	21.0%	66%	48%	\$1,075

Column (1) indexes counterfactual voucher policies that would introduce more stringent ($\tau < 10\%$) or lenient ($\tau > 10\%$) location constraint relative to that implemented in MTO ($\tau = 10\%$). Column (2) shows what the take up rate for the experimental group under each of the policies would be. Columns (3) and (5) display the resulting exposure to neighborhood characteristics (poverty rate and %white) for those experimental households who decide to use the voucher under each policy. Columns (4) and (6) show the unconditional exposures for the experimental group, by taking also into account the residential outcomes of those households that do not take up the voucher. Column (7) measures annual willingness to pay in 1997 dollars for each of the alternative policies (relative to the specific MTO policy). See text for details on the computation of WTP. All counterfactual policies in this table include counseling services. MTO policy allowed some households to move to places with poverty rate slightly over 10% but still below 11%.

Supplementing MTO with Race-Based Location Constraints? I

- ▶ It has been argued that MTO should have included a more aggressive desegregation incentive.
- ▶ Simulate neighborhood choice and voucher take up under MTO + Race-Based Location Constraint ($\% \text{ White} > 70$)
- ▶ Focus on non-white households (additional constraint more binding)

Supplementing MTO with Race-Based Location Constraints? II

Table 8 : Adding Race-Based Location Constraints to MTO

Take-up	Mean Poverty Rate (unconditional)	Mean Poverty Rate (given take-up)	Mean % White (unconditional)	Mean % White (given take-up)
<u>MTO (Experimental Voucher)</u>				
36.3%	23.3%	7.11%	43.3%	75.5%
<u>MTO + Race-Based Location Constraint</u>				
29.0%	24.4%	6.81%	43.7%	87.3%

Simulations in this table are for non-white households. First row shows take up and exposure to neighborhood characteristics (conditional on take-up and unconditionally) for the experimental voucher as implemented in MTO. This is similar to the 4th row in Table 7 but for non-white households only. The second row shows the impact of adding a race constraint to the poverty-constrained, counseling-assisted MTO voucher given to the experimental group. The race constraint resembles that used in Gautreaux by conditioning voucher use to neighborhoods with less than 30% minority households.

Conclusions

- ▶ Use experimentally generated data from the MTO experiments to estimate model of neighborhood choice.
- ▶ Experimental variation also used for out-of-sample validation.
- ▶ Show implications for consistent estimation of WTP for neighborhood attributes.
- ▶ Use the model to
 - ▶ understand the separate quantitative role of bundled features of treatment: role of counseling and constraints both large, but constraints dominate
 - ▶ learn whether tighter constraints would have severely reduced take-up: yes, they would have.
 - ▶ explore implications of adding race-based constraints to MTO vouchers: no change in average unconditional exposure to neighborhood characteristics.