Beyond Intention to Treat: Using the Incentives in *Moving to Opportunity* to Identify Neighborhood Effects

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Revised January 26, 2021

*Rodrigo Pinto is an Assistant Professor at the Economics Department of the University of California at Los Angeles. I am most grateful for extensive interaction with Professors James Heckman, Steven Durlauf, Paul Gertler, and Moshe Buchinsky. I also thank Aviv Nevo and three anonymous reviewers for insightful comments that helped shape the content and focus of this paper. I also benefited from useful suggestions from many Professors. Among those, I cite: Patrick Kline, David Card, Stephane Bonhomme, Magne Mogstad, Christopher Walters, Azeem Shaikh, Amanda Agan, Melissa Tartari, Thibaut Lamadon, Christopher Taber, Joshua Angrist, Jens Ludwig, Bernard Salanie, Yuichi Kitamura, Adriana Lleras-Muney, Dora Costa, Flavio Cunha, Maurizio Mazzocco, Orazio Attanasio, Richard Blundell, Andrew Chesher, Lawrence Katz, John Friedman, and Parag Pathak. I benefited from useful comments on presentations at Columbia University, Getulio Vargas Foundation (EPGE), NBER Meetings, Northwestern University, University of California at Los Angeles, University of California at Berkeley, University of Chicago, University College London, Princeton, University of Pennsylvania, University of Southern California (Schaeffer and CSSR Institutes), University of Wisconsin-Madison, Yale, and Washington University. All errors are my own.

Abstract

Moving to Opportunity (MTO) is a primary housing experiment designed to determine the benefits of relocating disadvantaged families from impoverished housing projects to better neighborhoods. The experiment randomly offered vouchers that subsidized rent in lower-poverty areas. Noncompliance was substantial. The raw experimental data identifies voucher effects but not the causal effect of changing neighborhoods. This paper uses revealed preference analysis to convert the economic incentives generated by the experiment's design into non-trivial monotonicity conditions. These conditions secure the nonparametric identification of neighborhood effects. While estimated voucher effects are not statistically significant, neighborhood effects are.
Keywords: Moving to Opportunity, Randomization, Social Experiment, Causal Effects, Identification, Revealed Preference Analysis.
JEL codes: H43, I18, I38, J38.

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1 Introduction

Moving to Opportunity (MTO) is the most influential housing experiment in the US. It used the method of randomized controlled trials to investigate the causal effect of relocating disadvantaged families living in high-poverty public housing to low-poverty neighborhoods (Orr et al., 2003). The experiment targeted over 4,000 households living in high-poverty housing projects across five US cities from 1994 to 1997.

Families were randomly assigned to one of three groups: experimental, Section 8 and control. Those assigned to the *experimental* group received a rent-subsidy voucher that paid them to relocate to low-poverty neighborhoods.[1] *Section 8* participants received a voucher that paid them to relocate to either low or medium poverty neighborhoods.[2] Participants assigned to the *control* group did not receive any voucher. Nearly half of the families who received vouchers *did not* use them to relocate, while 21% of control families living in high-poverty neighborhoods relocated to low-poverty areas throughout the study without receiving any payment.

Families who use the voucher differ from those who do not. The decision to use the voucher generates the problem of selection bias, which prevents the identification of neighborhood effects by comparing the outcome of families that reside in different neighborhoods. An influential literature evaluates MTO by reporting the intention-to-treat (ITT) and the treatment-on-the-treated (TOT) effects.[3,4] These estimates conflate the proportion of families using the voucher with the causal effect of residing in different neighborhoods. They evaluate the impact of the housing policy instead of the causal effects of neighborhood relocation.[5] This paper estimates the causal impact of neighborhood relocation by exploiting information on the incentives in MTO.

MTO is characterized by a model of multiple choices with categorical instrumental variables. Families decide among three types of neighborhoods: high (t_h), medium (t_m), or low poverty (t_l). Vouchers play the role of a three-valued instrumental variable. Experimental voucher (z_e) incentivizes the choice of low poverty neighborhood (t_l). Section 8 voucher (z_8) incentivizes choices of either low or medium poverty neighborhoods (t_l or t_m). The control group (z_c) is given no choice incentive.

My method builds on the well-known LATE framework of Imbens and Angrist (1994). However, I show that standard monotonicity conditions, such as invoked in LATE, cannot identify neighborhood effects in MTO. I use revealed preference analysis to convert MTO incentives into non-trivial monotonicity conditions that in turn secure the nonparametric identification of neighborhood effects. The method relates to Kline and Tartari (2016) and

[1] Low-poverty neighborhoods are defined as those whose share of poor residents is below 10% according to the 1990 Census (Orr et al., 2003). High poverty neighborhoods are the housing projects initially targeted by the intervention.

[2] Medium poverty neighborhoods are neither high poverty nor the ones classified as low poverty.

[3] ITT is the outcome difference-in-means between a voucher group and the control group, while treatment-on-the-treated is the intention-to-treat divided by the voucher take-up rate.

[4] See Hanratty et al. (2003); Katz et al. (2001, 2003); Kling et al. (2007, 2005); Ladd and Ludwig (2003); Leventhal and Brooks-Gunn (2003); Ludwig et al. (2012, 2005, 2001).

[5] One exception is Liebman et al. (2004), who show that TOT effects can be evaluated by a linear relation between neighborhood poverty and individual outcomes in MTO.

Kline and Walters (2016) who also invoke revealed preference analysis to study the choice of economic agents in IV settings. The identification strategy presented here is general, it applies to multiple choice models and categorical instrumental variables. I show that a version of Two-Stage Least Squares can estimate counterfactual outcomes.

MTO literature has found significant TOT effects on adult health, delinquency, risky behavior, psychological well-being, and various child outcomes.[6] In spite of these effects, TOT estimates of economic outcomes at adulthood are neither statistically nor economically significant.[7].

This paper investigates the adulthood labor market outcomes in Kling et al. (2007). My TOT estimates align with theirs. My methodology enables to go beyond the TOT evaluation. I show that the TOT is a mixture of three neighborhood causal effects that compare low versus high but also low versus medium poverty neighborhoods. Some of these effects are weak and imprecise, which contribute the overall lack of significance of the TOT estimates. Nevertheless, I find that the neighborhood effects of moving from a high poverty to a low poverty neighborhood for families who are most responsive to the voucher incentives are statistically and economically significant. Families who relocate experience a 14% increase in income, a 20% increase in employment, and a 38% reduction of being in poverty.

This paper describes a framework that extracts the information on incentives induced by the design of the MTO experiment to advance the causal analysis of the experiment. This approach enables to further investigate the MTO intervention shed new light on its effects. The analysis helps to reconciles the statistically insignificant effects reported in previous MTO literature with recent evidence that claims the importance of neighborhood quality in affecting residents' lives (Aliprantis and Richter, 2020; Chetty et al., 2017, 2016; Chyn, 2016; Galiani et al., 2015).

This paper proceeds as follows. Section 2 describes the MTO intervention. Section 3 describes my identification strategy. Section 4 shows how MTO incentives affect neighborhood choices. Section 5 presents identification results and estimation procedures. Section 6 reanalyses MTO data. Section 7 concludes.

2 The MTO Experiment: Data and Design

MTO was a housing experiment targeting low-income families living in public housing projects in five US cities: Baltimore, Boston, Chicago, Los Angeles, and New York. Eligible households are families with children under 18 years living in these cities' most impoverished housing projects. The sample totals 4,248 economically and socially disadvantaged families. Three-quarters of these families were on welfare, and only a third have a high school diploma. African Americans comprise 62% and Hispanics 30% of the sample. Females headed 92% of the households.

A baseline survey was conducted at the onset of the intervention, between June 1994 and July 1998. Families were re-contacted in 1997 and 2000. This paper focuses on data

[6] Primary works in this literature are Gennetian et al. (2012); Kling et al. (2007, 2005); Ludwig et al. (2012, 2001, 2011)

[7] Kling et al. (2007); Sanbonmatsu et al. (2011)

collected at the interim evaluation, conducted in 2002 (four to seven years after enrollment). The survey assessed six study domains: (1) mobility, housing, and neighborhood; (2) physical and mental health; (3) child educational achievement; (4) youth delinquency; (5) employment and earnings; and (6) household income and public assistance. Orr et al. (2003) documents the MTO experiment and the interim data. This paper focuses on the adult economic outcomes also investigated by Kling et al. (2007).

Housing Vouchers

MTO families were randomly allocated into three arms: 28% to "Section 8," 41% to "experimental," and 31% to "control" (this terminology is used by the original analysis and adopted by subsequent literature). Section 8 families were offered a rent-subsidy voucher that could be used if a family agreed to relocate from their high poverty neighborhood to eligible private-market dwellings. Vouchers were paid directly to the landlord. Families were required to pay 30% of the household's monthly adjusted gross income for rent and utilities. Subsidy amount and unit eligibility were based on criteria[8] set by the Department of Housing and Urban Development (HUD). Landlords could not discriminate against a voucher recipient, and leases were automatically renewed.

Experimental families were offered vouchers that could be used only in low-poverty neighborhoods with a fraction of low-income households below 10% according to the 1990 US Census. Families that decided to use the experimental voucher were required to live in the low-poverty neighborhood for a year but could move afterward. After this period, the families could use the experimental voucher as a regular Section 8 voucher without geographical constraints. Less than two percent of families that used the experimental voucher returned to their original neighborhood. Control families were offered no voucher.

Voucher Noncompliance

A sizeable share of families did not use the offered voucher. The take-up rate for the experimental voucher was 47%, while the take-up rate for Section 8 was 59 %. Table 1 describes family characteristics at the onset of the intervention. Columns 2–6 show that baseline variable means are balanced across voucher assignments. Column 2 presents control means, columns 3–4 test if baseline variables differ between experimental and control families. Columns 5–6 compare characteristics of control families with those assigned to the Section 8 voucher. Overall, mean differences between voucher assignments are not statistically significant in most cases.

In contrast, Table 1 shows that families who complied with the voucher differed substantially from those who did not comply. Columns 7–9 investigate families assigned to the experimental voucher. Column 8 compares the baseline characteristics of families that use and do not use the voucher. On average, families that used the voucher were smaller, had fewer teenagers and were less likely to have a household member with disabilities. Families that used the experimental voucher had fewer social connections and fewer friends. These families were less likely to chat with neighbors or watch out for their children. These families

[8] The Applicable Payment Standard (APS).

were also more likely to be victims of crimes and more inclined to feel unsafe in their original neighborhood. The head of these families was more likely to be single and to receive welfare benefits. Columns 10–12 compare families that decided to use the section 8 voucher with families that did not. We observe a similar but less pronounced pattern.

Neighborhood Choices

This paper exploits the variation of voucher assignments and the experiment's incentives to identify neighborhood effects. Families decided among three neighborhood options: (1) high-poverty t_h are the baseline housing projects targeted by the intervention; (2) low-poverty t_l are the neighborhoods targeted by the experimental voucher; (3) medium-poverty t_m are the remaining neighborhoods.

Families who used the experimental voucher (z_e) relocated to low-poverty neighborhoods (t_l). Families who used Section 8 voucher (z_8) decide between low (t_l) or medium (t_m) poverty neighborhoods. These families were supposed to move within six months after the voucher assignment. This relocation was extended to almost a year to enable families to find homes. Control families (z_c) and families that did not use the vouchers could choose freely among all three neighborhoods. Families that did not move during the relocation period chose high-poverty (t_h) neighborhoods, while those who did move decided between low (t_l) or medium (t_m) poverty neighborhoods. Appendix A gives a detailed description of neighborhood choices.

Outcomes

This paper focuses on labor market outcomes surveyed at the interim evaluation of MTO. Figure 1 displays the mean estimates for the household head's income in thousand dollars by neighborhood type and voucher assignment. Estimates are obtained by OLS using the standardized values of baseline variables in Table 1 and site-specific fixed effects as controls. The income for control families (z_c) that decide for high (t_h), median (t_m) and low (t_l) poverty neighborhoods are \$10.70, \$11.66 and \$15.13 respectively. The mean difference of income between low versus high poverty neighborhoods is \$15.13 − \$10.70 = \$4.43 thousand dollars per year. This difference is not causal as families that decide to move differ from those who do not.

The middle columns of Figure 1 display the mean incomes for families assigned Section 8 (z_8) vouchers. The difference in income between low versus high-poverty neighborhoods is \$11.72 − \$10.61 = \$1.11 thousand dollars/year. This difference is only a quarter of the estimate for z_c. This reduction is partially explained by self-selection as lower-income families that choose high-poverty neighborhoods under control (z_c), may decide for medium and low-poverty neighborhoods when assigned to section 8 (z_8).

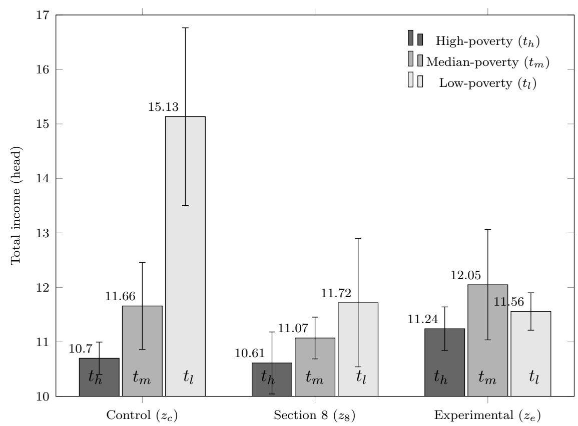
The right portion of Figure 1 displays the income means for families assigned to the experimental voucher (z_e). It shows the lowest income difference between low (t_l) and high-poverty (t_h) neighborhoods: \$11.56 − \$11.24 = \$0.32 thousand dollars per year. This difference suggests that families are negatively selected towards relocation. As the voucher changes from z_c to z_e, the incentive to choose low-poverty neighborhoods (t_l) increases. A larger fraction

Table 1: Baseline Variables of MTO by Voucher Assignment and Voucher Usage

Variable	Full Sample					Experimental Group			Section 8 Group		
	Control Group	Experimental vs. Control		Section 8 vs. Control		Used the Voucher	Comparison Used vs. Not		Used the Voucher	Comparison Used vs. Not	
	Mean	*Diff*	*p-val*	*Diff*	*p-val*	*Mean*	*Diff*	*p-val*	*Mean*	*Diff*	*p-val*
	2	3	4	5	6	7	8	9	10	11	12
Family											
Disabled Household Member	0.15	0.01	0.31	0.00	0.82	0.15	−0.04	**0.03**	0.13	−0.06	**0.01**
No teens (ages 13-17) at baseline	0.63	−0.03	0.12	−0.01	0.56	0.65	0.10	**0.00**	0.66	0.11	**0.00**
Household size is 2 or smaller	0.21	0.01	0.48	0.01	0.39	0.26	0.08	**0.00**	0.23	0.03	0.27
Never married (baseline)	0.62	−0.00	0.97	−0.02	0.36	0.66	0.06	**0.01**	0.63	0.05	0.06
Teen pregnancy	0.25	0.01	0.41	0.01	0.69	0.27	0.02	0.24	0.29	0.09	**0.00**
Neighborhood											
Victim last 6 months (baseline)	0.41	0.01	0.41	0.01	0.45	0.45	0.05	**0.04**	0.45	0.06	**0.04**
Living in neighborhood > 5 yrs.	0.60	0.00	0.97	0.02	0.28	0.59	−0.03	0.26	0.59	−0.08	**0.00**
Chat with neighbor	0.53	−0.01	0.60	−0.03	0.19	0.50	−0.05	**0.04**	0.51	0.01	0.77
Watch out for neighbor children	0.57	−0.02	0.31	−0.03	0.16	0.51	−0.07	**0.00**	0.55	0.03	0.39
Unsafe at night (baseline)	0.50	−0.02	0.27	−0.00	1.00	0.52	0.08	**0.00**	0.54	0.10	**0.00**
Moved due to gangs	0.78	−0.01	0.52	−0.02	0.24	0.79	0.04	**0.03**	0.78	0.04	0.07
Schooling											
Has a GED (baseline)	0.20	−0.03	**0.04**	0.00	0.80	0.18	0.03	0.10	0.20	0.00	0.97
Completed high school	0.35	0.04	**0.01**	0.01	0.47	0.41	0.02	0.49	0.39	0.06	**0.03**
Enrolled in school (baseline)	0.16	0.00	0.95	0.02	0.22	0.19	0.07	**0.00**	0.19	0.04	0.09
Missing GED and H.S. diploma	0.07	−0.01	0.12	−0.01	0.52	0.04	−0.03	**0.01**	0.06	−0.01	0.35
Sociability											
No family in the neigborhood	0.65	−0.02	0.35	0.00	1.00	0.65	0.03	0.15	0.65	0.01	0.67
Respondent reported no friends	0.41	−0.00	0.78	−0.01	0.56	0.44	0.06	**0.01**	0.41	0.02	0.38
Welfare/economics											
AFDC/TANF Recepient	0.74	0.02	0.34	0.00	0.85	0.78	0.04	**0.04**	0.78	0.08	**0.00**
Car Owner	0.17	−0.01	0.65	−0.01	0.43	0.19	0.04	**0.01**	0.17	0.04	0.10
Adult Employed (baseline)	0.25	0.02	0.28	0.01	0.76	0.26	−0.01	0.73	0.27	0.03	0.25

This table presents a statistical description of MTO baseline variables by group assignment and compliance decision. Baseline variables are pre-program variables surveyed at the onset of the intervention before neighborhood relocation. Columns 2–6 present the arithmetic means for selected baseline variables conditional on voucher assignments. Column 2 presents the control mean. Columns 3 displays the difference-in-means between the Experimental and Control groups. Columns 4 shows the double-sided single-hypothesis p-value associated with the equality in means test. Inference is based on the bootstrap method. Columns 5–6 compare the Section 8 group with the control group in the same fashion as columns 3–4. Columns 7–9 examine baseline variables for the experimental group conditional on the choice of voucher compliance. Column 7 presents the variable mean conditioned on voucher compliance. Column 8 gives the difference in means between the families assigned to the Experimental voucher that used the voucher and the ones that did not use the voucher for relocation. Columns 9 shows the double-sided p-value associated with the equality in means test. Columns 10–12 analyze the families assigned to the Section 8 group in the same fashion as columns 7–9.

Figure 1: Total Income of the Head of the Family by Neighborhood Choice and Voucher Assignment



This figure presents the estimates of Income of the Head of the Family (in $1000) conditioned on by voucher assignment and neighborhood choice. Estimates are obtained via OLS that uses site fixed effects and the baseline variables listed in Table 1 as control covariates. Estimates also account for the person-level weight for adult survey of the interim analyses as described in the MTO Interim Impacts Evaluation manual, 2003, Appendix B. Error bars denote estimated standard errors obtained by a stratified bootstrap procedure that resamples the full data set by site.

of lower-income families switches from high to low-poverty neighborhoods, which decreases the average income for low-poverty neighborhoods from $15.13 to $11.56.

The remailing income data consists of the sum of the income of the head and their spouse, and total household income, which is the sum of all sources of family income. Income is measured in thousand dollars per year and was surveyed in 2001. About 0.3% of income data is above five standard deviations of the sample mean. The five economic indicators of the household are as follows: (1)*Economic self-sufficiency* indicates whether the household income is above the poverty line and the family does not receive welfare benefits (AFDC/TANF, food stamps, SSI, or Medicaid); (2) *Employed without welfare* indicates if the sample adult is working and not receiving welfare; (3) *Food Stamps* indicates whether the family receives this benefit; (4) *Currently on welfare* indicates if family regularly receives welfare benefits (AFDC/TANF); (5) *Job tenure* indicates if the sample adult had been employed for more than one year.

Table 2 presents the means for a variety of labor market outcomes surveyed in 2001. The table suggests a selection pattern similar to the one observed in Figure 1. The larger the incentive to move from high-poverty to low or medium-poverty neighborhoods, the smaller the difference of mean outcomes between these neighborhood types. This paper presents a methodology that identifies the causal effects of neighborhood types on these outcomes.

Table 2: Outcome Means by Voucher Assignment and Neighborhood Choice

	Control (z_c)			**Section 8** (z_8)			**Experimental** (z_e)		
Neighborhood Choices	t_h	t_m	t_l	t_h	t_m	t_l	t_h	t_m	t_l
Income of Family Head	10.699	11.659	15.134	10.613	11.071	11.719	11.241	12.049	11.558
(s.e.)	0.297	0.799	1.631	0.569	0.383	1.177	0.401	1.012	0.344
Income of Head and Spouse	12.001	12.674	16.083	11.820	11.910	11.884	12.363	13.669	12.228
(s.e.)	0.333	0.890	1.960	0.626	0.421	1.128	0.473	1.279	0.362
Total household income	13.890	14.550	16.343	14.455	13.490	13.333	14.488	15.668	14.182
(s.e.)	0.370	1.032	1.893	0.626	0.439	1.262	0.481	1.307	0.381
Above Poverty Line	0.270	0.415	0.552	0.267	0.278	0.309	0.300	0.279	0.320
(s.e.)	0.015	0.057	0.089	0.026	0.021	0.064	0.022	0.064	0.020
Employed without welfare	0.446	0.457	0.430	0.475	0.449	0.535	0.472	0.474	0.482
(s.e.)	0.017	0.055	0.092	0.032	0.023	0.050	0.022	0.070	0.020
Currently on welfare	0.296	0.257	0.231	0.233	0.275	0.186	0.259	0.318	0.255
(s.e.)	0.016	0.045	0.071	0.023	0.020	0.042	0.018	0.061	0.017
Job tenure	0.366	0.339	0.291	0.375	0.388	0.413	0.398	0.471	0.390
(s.e.)	0.017	0.051	0.090	0.030	0.023	0.052	0.022	0.072	0.020
Economic self-sufficiency	0.174	0.186	0.249	0.183	0.210	0.195	0.180	0.164	0.199
(s.e.)	0.013	0.039	0.073	0.023	0.019	0.043	0.018	0.051	0.017
Neighborhood Poverty	40.630	31.938	8.010	40.026	30.054	7.898	41.065	38.148	7.901
(s.e.)	0.582	1.599	0.799	0.970	0.562	0.490	0.684	2.105	0.239

This table presents the estimated means of income variables by voucher assignment (z_c, z_m, z_l) and neighborhood choice (t_l, t_m, t_h). The outcome means are estimated via OLS using site fixed effects and baseline variables listed in Table 1 as covariates. Estimates employ the person-level weight for adult survey of the interim analyses as described in the MTO Interim Impacts Evaluation manual, 2003, Appendix B. Inference employs a stratified bootstrap procedure that resamples the full data set by site. The income data consists of: (1) income of the head of the family; (2) sum of the income of the head and their spouse, and (3) total household income, which is the sum of all sources of income of the family. Income is measured in thousand dollars per year and was surveyed in 2001. About 0.3% of income data is above five standard deviations of the sample mean. Outliers having the Cook's Distance above five standard deviations are deleted. The five economic indicators of the household are: (1)*Economic self-sufficiency* indicates whether the household income is above the poverty line and the family does not receive welfare benefits (AFDC/TANF, food stamps, SSI, or Medicaid); (2) *Employed without welfare* indicates if the sample adult is working and not receiving welfare; (3) *Food Stamps* indicates whether the family receives this benefit; (4) *Currently on welfare* indicates if family regularly receives welfare benefits (AFDC/TANF); (5) *Job tenure* indicates if the sample adult had been employed for more than one year.

3 Modeling Choices and Outcomes in MTO

The observed variables in MTO are: (1) voucher assignment $Z \in \{z_c, z_8, z_e\}$; (2) neighborhood choice $T \in \{t_h, t_m, t_l\}$; (3) outcome $Y \in \mathbb{R}$; and (4) baseline characteristics $\boldsymbol{X} \in \mathbb{R}^{|\boldsymbol{x}|}$. The MTO model is characterized by the following system of causal relations:

$$\begin{aligned} \text{Choice Equation}: &\quad T = f_T(Z, \boldsymbol{V}, \boldsymbol{X}), && (1) \\ \text{Outcome Equation}: &\quad Y = f_Y(T, \boldsymbol{V}, \boldsymbol{X}, \epsilon), && (2) \\ \text{Conditional Independence}: &\quad Z \perp\!\!\!\perp \boldsymbol{V} | \boldsymbol{X}, && (3) \end{aligned}$$

where $\boldsymbol{V}$ denotes the vector of family unobserved characteristics and ϵ is an unobserved variable satisfying $(Z, T, \boldsymbol{X}, \boldsymbol{V}) \perp\!\!\!\perp \epsilon$.[9] $\boldsymbol{V}$ is a confounding random vector that generates selection bias by causing both choice T and the outcome Y. Baseline variables $\boldsymbol{X}$ are family observed characteristics that cause T and Y. The experiment generates two required properties for Z to be an instrument: (2) implies that Z only affects Y through its impact on T (exclusion restriction); and (3) implies that Z is statistically independent of unobserved characteristics $\boldsymbol{V}$ given baseline variables $\boldsymbol{X}$.

The potential (counterfactual) outcome of family $i \in \mathcal{I}$ placed in neighborhood t is given by $Y_i(t) \equiv f_Y(t, \boldsymbol{V}_i, \boldsymbol{X}_i, \epsilon_i)$. It is the hypothetical outcome that would occur if the neighborhood choice of family i were exogenously set to $t \in \{t_h, t_m, t_l\}$. The potential choice of family i is given by $T_i(z) \equiv f_T(z, \boldsymbol{V}_i, \boldsymbol{X}_i)$. It is the choice that family i would take if it were exogenously assigned to voucher $z \in \{z_c, z_8, z_e\}$. Conditional independence (3) implies the IV exogeneity condition $\big(Y(t), T(z)\big) \perp\!\!\!\perp Z | \boldsymbol{X}$ for $(z, t) \in \{z_c, z_8, z_e\} \times \{t_h, t_m, t_l\}$. Outcome Y and choice T can be written in terms of potential variables as:

$$Y = \sum_{t \in \{t_l, t_m, t_h\}} D_t \cdot Y(t) = Y(T), \quad \text{and} \quad T = \sum_{z \in \{z_c, z_8, z_e\}} D_z \cdot T(z) = T(Z), \tag{4}$$

where $D_t = \mathbf{1}[T = t]; t \in \{t_h, t_m, t_l\}$ indicates neighborhood choices, $D_z = \mathbf{1}[Z = z]; z \in \{z_c, z_8, z_e\}$ indicates voucher assignment and $\mathbf{1}[A]$ is the indicator function that takes value 1 if event A is true and zero otherwise.

The causal effect of living in a low versus high-poverty neighborhood for family i is defined as $Y_i(t_l) - Y_i(t_h)$. It is the difference in the potential outcome of family i if it were to reside in each of these two neighborhood types. If responses are heterogeneous, this individual effect is not identified since we only observe the potential outcome corresponding to the neighborhood chosen by the family. A mean neighborhood treatment effect is the expectation of individual effects, such as $Y_i(t_l) - Y_i(t_h)$, for subsets of families $i \in \mathcal{I}$. To gain intuition, it is useful to write the observed outcome of families $i \in \mathcal{I}$ that choose t_l or t_h as:

$$Y_i = \beta_0 + \beta_i D_{t_l, i} + \epsilon_i, \tag{5}$$

where $\beta_i = Y_i(t_l) - Y_i(t_h)$, $\beta_0 = E(Y(t_h))$, $\epsilon_i = Y_i(t_h) - E(Y(t_h))$, and $D_{t,i} \equiv \mathbf{1}[T_i = t]$ is the choice indicator for a family i such that $T_i \in \{t_l, t_h\}$.

[9] Measurement error and misspecification are possible sources of the unobserved error term ϵ.

Equation (5) is a random coefficient model where β_i varies across $i \in \mathcal{I}$.[10] If $Y(t)$ and T were statistically independent, $Y(t) \perp\!\!\!\perp T$, then we could evaluate the average neighborhood effect $E(Y(t_h) - Y(t_h))$ by least squares taking mean differences. Selection bias induces a correlation between $Y(t)$ and T via $\boldsymbol{V}$. As a consequence, the regressor $D_{t_l,i}$ in (5) correlates with both the error term $\epsilon_i = Y_i(t_h) - E(Y(t_h))$ and the random coefficient $\beta_i = Y_i(t_l) - Y_i(t_h)$. Without further assumptions, neither least squares nor two-stage least squares identifies $E(Y(t_h) - Y(t_h))$.[11]

A popular identification strategy invokes a *matching* condition which assumes that T and $Y(t)$ are independent conditioned on $\boldsymbol{X}$, $Y(t) \perp\!\!\!\perp T|\boldsymbol{X}$. This assumption enables the analyst to identify counterfactual outcomes by controlling for $\boldsymbol{X}$: $E(Y|T = t, \boldsymbol{X}) = E(Y(t)|T = t, \boldsymbol{X}) = E(Y(t)|\boldsymbol{X})$, where the first equality is due to (4) and the second is due to $Y(t) \perp\!\!\!\perp T|\boldsymbol{X}$. The average neighborhood effect across all families in $i \in \mathcal{I}$ is obtained by integrating out $\boldsymbol{X}$:

$$E(Y(t_l) - Y(t_h)) = \int (E(Y|T = t_l, \boldsymbol{X} = \boldsymbol{x}) - E(Y|T = t_h, \boldsymbol{X} = \boldsymbol{x}))\, dF_{\boldsymbol{X}}(\boldsymbol{x}), \qquad (6)$$

where $F_{\boldsymbol{X}}(\cdot)$ is the cumulative distribution function (CDF) of $\boldsymbol{X}$.

A matching assumption is not valid if there is selection bias on unobservables that are not in $\boldsymbol{X}$. However, it is always true that $Y(t) \perp\!\!\!\perp T|(\boldsymbol{X}, \boldsymbol{V})$ holds. The identification of causal effects hinges on controlling for $\boldsymbol{X}$ as well as for the unobservables $\boldsymbol{V}$. This paper presents a nonparametric method to control for $\boldsymbol{V}$. I suppress $\boldsymbol{X}$ henceforward to simplify notation. The analysis should be understood as conditioned on $\boldsymbol{X}$.

One identification strategy invokes a parametric model that uses Z to control for $\boldsymbol{V}$. Examples of such approach in the MTO literature are Aliprantis and Richter (2020); Chesher et al. (2020); Galiani et al. (2015). This paper takes a different approach. I exploit the instrument Z and the incentives in MTO to *nonparametrically* control for $\boldsymbol{V}$. The approach does not rely on any functional form assumptions, nor does it require intensive computational effort.

It is possible to control for $\boldsymbol{V}$ by partitioning families based on choice behavior described by *response-types* or *principal strata*, namely, the counterfactual choices that the family would take across the instrumental values.[12] Let the *Response vector* $\boldsymbol{S}_i = [T_i(z_c), T_i(z_8), T_i(z_e)]'$ be the neighborhood choices made by family i when assigned to each of the instrumental values z_c, z_8, z_e. A response-type consists of a vector of choice values that $\boldsymbol{S}$ may take. For instance, family i that has *response-type* $\boldsymbol{S}_i = [t_h, t_m, t_l]'$ chooses a high-poverty neighborhood when offered z_c $(T_i(z_c) = t_h)$, a medium-poverty neighborhood when offered z_8 $(T_i(z_8) = t_h)$, and a low-poverty neighborhood when offered z_e $(T_i(z_c) = t_h)$.

Choice T is determined by Z and $\boldsymbol{S}$. Given a response-type, choice T depends only on assignment Z, which is independent of its potential outcome $Y(t)$. Therefore $Y(t) \perp\!\!\!\perp T|\boldsymbol{S}$ holds. Intuitively, the neighborhood choice within a group of families that share the same response-type can be understood as if it were generated by randomized controlled trial RCT

[10] Also called Switching Regression Model (Quandt, 1958, 1972).

[11] Later in this paper I present assumptions that enable the analyst to use a modified version of the two-stage least square regression to identify counterfactual outcomes.

[12] The use of response-types dates back to Balke and Pearl (1994) and Frangakis and Rubin (2002). See Pinto (2016) or Heckman and Pinto (2018) for a discussion.

where Z determines the neighborhood assignment. If we knew all the families $i \in \mathcal{I}$ that have type $\boldsymbol{S}_i = [t_h, t_m, t_l]$, we would be able to identify the causal effect of low t_l versus high t_h from:

$$\begin{aligned}
&E(Y|Z=z_e, \boldsymbol{S}=[t_h,t_m,t_l]') - E(Y|Z=z_c, \boldsymbol{S}=[t_h,t_m,t_l]') && (7)\\
&\quad = E(Y|T=t_l, \boldsymbol{S}=[t_h,t_m,t_l]') - E(Y|T=t_h, \boldsymbol{S}=[t_h,t_m,t_l]'), \text{ due to response-type} && (8)\\
&\quad = E(Y(t_l)|T=t_l, \boldsymbol{S}=[t_h,t_m,t_l]') - E(Y(t_h)|T=t_h, \boldsymbol{S}=[t_h,t_m,t_l]'), \quad \text{due to (4)} && (9)\\
&\quad = E(Y(t_l)-Y(t_h)|\boldsymbol{S}=[t_h,t_m,t_l]), \qquad \text{due to } Y(t) \perp\!\!\!\perp T|\boldsymbol{S} && (10)
\end{aligned}$$

Response-types control for unobserved characteristics $\boldsymbol{V}$ by generating a useful partition of its support. Holding $\boldsymbol{X}$ fixed, the potential choice $\boldsymbol{T}(z) = f_T(z, \boldsymbol{V})$ depends only on $\boldsymbol{V}$. The set of unobserved characteristics corresponding to response-type $\boldsymbol{s} = [t_h, t_m, t_l]$ is given by:

$$\mathcal{V}_{\boldsymbol{s}} = \{\boldsymbol{v} \in supp(\boldsymbol{V}) \text{ such that } f_T(z_c, \boldsymbol{v}) = t_h, f_T(z_8, \boldsymbol{v}) = t_m, f_T(z_e, \boldsymbol{v}) = t_l\}.$$

Events $\boldsymbol{S} = \boldsymbol{s}$ and $\boldsymbol{V} \in \mathcal{V}_{\boldsymbol{s}}$ are equivalent. $Y(t) \perp\!\!\!\perp T|(\boldsymbol{S} = \boldsymbol{s})$ implies that $Y(t) \perp\!\!\!\perp T|(\boldsymbol{V} \in \mathcal{V}_{\boldsymbol{s}})$ holds. Conditioning on $\boldsymbol{S} = \boldsymbol{s}$ is equivalent to conditioning on the set of unobserved variables $\boldsymbol{V} \in \mathcal{V}_{\boldsymbol{s}}$ that renders the choice T statistically independent of the counterfactual outcomes $Y(t)$.[13] As $\boldsymbol{s}$ ranges in $supp(\boldsymbol{S})$, it spans the support of $\boldsymbol{V}$ as $supp(\boldsymbol{V}) = \bigcup_{\boldsymbol{s} \in supp(S)} \mathcal{V}_{\boldsymbol{s}}$.

Response-types are not observed, but we can express observed outcomes as a mixture[14] of potential outcomes conditioned on response-types:[15]

$$\underbrace{E(YD_t|Z=z)}_{\text{Observed}} = \sum_{\boldsymbol{s} \in supp(\boldsymbol{S})} \underbrace{\mathbf{1}[T=t|\boldsymbol{S}=\boldsymbol{s}, Z=z]}_{\text{Deterministic}} \underbrace{E(Y(t)|\boldsymbol{S}=\boldsymbol{s})\, P(\boldsymbol{S}=\boldsymbol{s})}_{\text{Unobserved}}. \tag{11}$$

Equation (11) is central to my identification analysis. It shows that the indicator $\mathbf{1}[T = t|\boldsymbol{S} = \boldsymbol{s}, Z = z]$ connects observed data, i.e., the expectation of the outcome multiplied by the choice indicator, with the unobserved parameters we seek to identify, i.e. potential outcomes $E(Y(t)|\boldsymbol{S} = \boldsymbol{s})$ and response-type probabilities $P(\boldsymbol{S} = \boldsymbol{s})$. Setting $Y = 1$ in (11) generates an equation that relates propensity scores $E(D_t|Z = z) = P(T = t|Z = z)$ (right-hand side) with response-type probabilities $P(\boldsymbol{S} = \boldsymbol{s})$ (left-hand side).[16] The identification problem addressed in this paper consists of expressing the unobserved variables in the right-hand side of (11) in terms of the observed variables of the left-hand side. This problem is best stated in matrix form.

Let $supp(\boldsymbol{S}) \equiv \{\boldsymbol{s}_1, ..., \boldsymbol{s}_N\}$ be the set of response-types which are stacked as the $3 \times N$ *response matrix* $\boldsymbol{R} = [\boldsymbol{s}_1, ..., \boldsymbol{s}_N]$. The $(z, \boldsymbol{s})$-input of matrix $\boldsymbol{R}$ is $\boldsymbol{R}[z, \boldsymbol{s}] \equiv (T|Z = z, \boldsymbol{S} = \boldsymbol{s})$.

[13] $\boldsymbol{S}$ plays the role of a control function in Heckman and Robb (1985) and Powell (1994) as well as an unobserved balancing score in Rosenbaum and Rubin (1983).

[14] This is an instance of the latent class model studied by Prakasa Rao (1992).

[15] See Pinto (2016) for a proof.

[16] Heckman and Pinto (2018); Pinto (2016) show that replacing Y by $\mathbf{1}[Y \leq y]$ for some $y \in \mathbb{R}$, relates the outcome cumulative distribution function (CDF) and a mixture of counterfactual CDFs: $P(Y(t) \leq y|\boldsymbol{S})$. Replacing Y by pre-program variables $\boldsymbol{X}$ enables us to evaluate the distribution of baseline characteristics conditioned on response-types.

Let $\boldsymbol{B}_t = \mathbf{1}[\boldsymbol{R} = t]$ be the $3 \times N$ binary matrix that indicates which elements in $\boldsymbol{R}$ are equal to $t \in \{t_h, t_m, t_l\}$. The $(z, \boldsymbol{s})$-input of $\boldsymbol{B}_t$ is $\boldsymbol{B}_t[z, \boldsymbol{s}] \equiv \mathbf{1}[T = t | Z = z, \boldsymbol{S} = \boldsymbol{s}]$. In this notation, equation (11) can be expressed as:

$$\begin{aligned} \boldsymbol{Q}_Z(t) &= \boldsymbol{B}_t \cdot \Big(\boldsymbol{Q}_S(t) \odot \boldsymbol{P}_S \Big); \quad t \in \{t_h, t_m, t_l\}, \qquad (12) \\ \text{where} \quad \boldsymbol{Q}_Z(t) &= [E(YD_t | Z = z_c), E(YD_t | Z = z_8), E(YD_t | Z = z_e)]', \\ \boldsymbol{Q}_S(t) &= [E(Y(t) | \boldsymbol{S} = \boldsymbol{s}_1), ..., E(Y(t) | \boldsymbol{S} = \boldsymbol{s}_N)]', \\ \boldsymbol{P}_S &= [P(\boldsymbol{S} = \boldsymbol{s}_1), ..., P(\boldsymbol{S} = \boldsymbol{s}_N)]', \end{aligned}$$

where $\odot$ denotes element-wise multiplication, $\boldsymbol{Q}_Z(t)$ is the observed vector of expectation of outcomes and $\boldsymbol{Q}_S(t), \boldsymbol{P}_S$ are the unobserved vectors of potential outcomes and response-type probabilities. If Y is set to one, equation (12) becomes $\boldsymbol{P}_Z(t) = \boldsymbol{B}_t \boldsymbol{P}_S$, where $\boldsymbol{P}_Z(t) = [E(D_t | Z = z_c), E(D_t | Z = z_8), E(D_t | Z = z_e)]'$ is the vector of propensity scores for $t \in \{t_h, t_m, t_l\}$.

Equation (12) clarifies that the identification of $\boldsymbol{Q}_S(t)$ and $\boldsymbol{P}_S$ hinges on the (rank) properties of the binary indicator $\boldsymbol{B}_t$ of the response matrix $\boldsymbol{R}$. If $\boldsymbol{B}_t$ were invertible (full rank), then $\boldsymbol{P}_S$ would be point identified by by $\boldsymbol{P}_S = \boldsymbol{B}_t^{-1} \boldsymbol{P}_Z(t)$, and $\boldsymbol{Q}_S(t)$ could be obtained by $\boldsymbol{Q}_S(t) \odot \boldsymbol{P}_S = \boldsymbol{B}_t^{-1} \boldsymbol{Q}_Z(t)$. But for matrix $\boldsymbol{B}_t$ to be invertible, it must be square, which means that the number of instrumental values (row-dimension) must be equal to the number of response-types (column-dimension). In reality, while Z takes three values, the number of possible response-types is 27 since each of counterfactual choices in $\boldsymbol{S} = [T_i(z_c), T_i(z_8), T_i(z_e)]'$ may take three possible values t_l, t_m, t_h.

Identification requires that the number of admissible response-types be sufficiently small relative to the number of choices and instrumental values. For instance, MTO has nine propensity scores, but only six of them are linearly independent.[17] Thus, we can identity up to six linearly independent response-types probabilities, which enables us to characterize the distribution of at most *seven* response-types. The next section shows that extending the two-choice monotonicity condition used in LATE is not sufficient to secure identification in MTO's three-choice case. My solution is to exploit MTO incentives via revealed preferences.[18] I show that this approach justifies seven response-types of the following response matrix:

$$\text{MTO Response Matrix:} \quad \boldsymbol{R} = \begin{array}{c} \begin{array}{ccccccc} \boldsymbol{s}_{ah} & \boldsymbol{s}_{am} & \boldsymbol{s}_{al} & \boldsymbol{s}_{fc} & \boldsymbol{s}_{pl} & \boldsymbol{s}_{pm} & \boldsymbol{s}_{ph} \end{array} \\ \begin{bmatrix} t_h & t_m & t_l & t_h & t_h & t_m & t_h \\ t_h & t_m & t_l & t_m & t_l & t_m & t_m \\ t_h & t_m & t_l & t_l & t_l & t_l & t_h \end{bmatrix} \end{array} \begin{array}{c} T_i(z_c) \\ T_i(z_8) \\ T_i(z_e) \end{array} \qquad (13)$$

Each column of the response matrix $\boldsymbol{R}$ displays a response-type. Response-types $\boldsymbol{s}_{ah}, \boldsymbol{s}_{al}, \boldsymbol{s}_{al}$ are *always-takers*. They correspond to families that always choose high, medium, and low-poverty neighborhoods respectively. Response-type $\boldsymbol{s}_{fc} = [t_h, t_m, t_l]'$ is called *full-complier*. It corresponds to families that choose high-poverty if assigned to control, medium-poverty under Section 8, and low-poverty under the experimental voucher.

[17]For each $z \in \{z_c, z_8, z_e\}$, there are three propensity scores $P(T = t | Z = z); t \in \{t_h, t_m, t_l\}$ that sum to one. This yields two linearly independent propensity scores for each of the three instrumental values.

[18]I show in the next section that monotonicity conditions used in LATE for a two-choice model do not secure identification in MTO's three-choice case.

Response-types $\boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{ph}$ are called *partial-compliers* and refer to families that choose between two neighborhood types across voucher assignments. Families of type $\boldsymbol{s}_{pl} = [t_h, t_l, t_l]'$ choose low-poverty (t_l) when subsidised (z_8 or z_e) and high-poverty (t_h) under no subsidy (z_c). Families of type $\boldsymbol{s}_{pm} = [t_m, t_m, t_l]'$ choose low-poverty (t_l) if this is the only available subsidy (z_e), and choose medium-poverty otherwise (z_c or z_8). Families of type $\boldsymbol{s}_{ph} = [t_h, t_m, t_h]'$ chose medium-poverty when subsidized (z_8) and high-poverty (t_h) otherwise (z_c or z_e). The next section shows how MTO incentives generate response matrix (59).

4 Exploiting MTO Incentives to Characterise Response-types

The LATE model of Angrist, Imbens, and Rubin (1996) is a familiar starting point for motivating the identification strategy in MTO. Consider a hypothetical program where families choose between two neighborhood choices – low-poverty (t_l) or high-poverty (t_h) – and are randomly offered an experimental voucher (z_e) that subsidizes low-poverty neighborhoods or a control voucher (z_c) that offers no subsidy. The response vector $\boldsymbol{S}_i = [T_i(z_c)\ ,\ T_i(z_e)]'$ lists the potential choices of family i across voucher assignments. Possible response-types are never-takers $\boldsymbol{s}_{nt} = [t_h, t_h]'$; compliers $\boldsymbol{s}_c = [t_h, t_l]'$; always-takers $\boldsymbol{s}_{at} = [t_l, t_l]'$; and defiers $\boldsymbol{s}_d = [t_l, t_h]'$. Experimental voucher z_e justifies a monotonicity condition stating that a change from z_c to z_e induces families to lean towards choosing low-poverty neighborhoods t_l. This condition can be equivalently expressed as a choice inequality or choice restriction:

$$\underbrace{\mathbf{1}[T_i(z_c) = t_l] \leq \mathbf{1}[T_i(z_e) = t_l]}_{\text{Choice Inequality}} \quad \equiv \quad \underbrace{T_i(z_c) = t_l \Rightarrow T_i(z_e) = t_l}_{\text{Choice Restriction}} \text{ for all families } i, \tag{14}$$

Choice restriction in (14) states that if family i chooses t_l under voucher z_c then it must also choose t_l under z_e. This restriction *eliminates* the defiers $\boldsymbol{s}_d$ and permits the identification of the Local Average Treatment Effect (LATE), the causal effect of low versus high-poverty for compliers $\boldsymbol{s}_c$, $E(Y(t_h) - Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_c)$.

The intuition justifying LATE breaks down in the case of the three-valued instrument and three-valued choice of MTO. Recall that number of possible response-types in MTO is 27 while LATE has four. The identification of causal parameters in MTO requires eliminating some of these response-types similar to the way that eliminating defiers identifies LATE.

MTO incentives justify three monotonicity conditions. Experimental voucher z_e subsidizes low-poverty t_l neighborhoods while Section 8 z_8 subsidizes both low t_l and medium-poverty t_m neighborhoods. Thus it is safe to assume that: (1) changes from z_c to z_e induce families toward low-poverty t_l neighborhoods; (2) changes from z_c to z_8 induce families toward t_l or t_m; and (3) changes from z_e to z_8 induce families toward medium-poverty t_m. Table 3 displays these monotonicity conditions.

Table 3: Monotonicity Argument : Choice Inequalities and Equivalent Choice Restrictions

	Monotonicity Conditions	Equivalent Choice Restrictions
1	$\mathbf{1}[T_i(z_c) = t_l] \leq \mathbf{1}[T_i(z_e) = t_l]$	$T_i(z_c) = t_l \Rightarrow T_i(z_e) = t_l$
2	$\mathbf{1}[T_i(z_c) \in \{t_m, t_l\}] \leq \mathbf{1}[T_i(z_8) \in \{t_m, t_l\}]$	$T_i(z_c) \neq t_h \Rightarrow T_i(z_8) \neq t_h$
3	$\mathbf{1}[T_i(z_e) = t_m] \leq \mathbf{1}[T_i(z_8) = t_m]$	$T_i(z_e) = t_m \Rightarrow T_i(z_8) = t_m$

The first monotonicity condition $\mathbf{1}[T_i(z_c) = t_l] \leq \mathbf{1}[T_i(z_e) = t_l]$ of Table 3 means that the changes from z_c to z_e induce choice t_l. This implies choice restriction $T_i(z_c) = t_l \Rightarrow T_i(z_e) = t_l$, namely, if family i chooses t_l under z_c, then it also choose t_l under z_e. Table 4 lists the response-types that are eliminated by each monotonicity condition in Table 3. Panel A of Table 4 lists the 27 possible response-types of MTO: Panel B indicates the response-types eliminated by each of the three monotonicity conditions in Table 3. The conditions jointly eliminate 13 out of the 27 response-types. The number of remaining response-types is, nonetheless, too large to secure the identification of causal parameters. Panel C in this table is discussed below.

We can try to eliminate additional response-types by investigating each of the remaining 14 response-types on a case-by-case basis.[19] That is a daunting task that becomes prohibitive the larger the support of T or Z. Ny strategy uses a general argument of revealed preference analysis to eliminate response-types systematically. This approach offers several benefits: (1) it invokes choice axioms instead of investigating response-types on a case-by-case basis; (2) it applies to arbitrary schemes of incentives; and (3) it subsumes the monotonicity conditions of Table 3. The approach builds on Kline and Tartari (2016) and Kline and Walters (2016), who use revealed preference arguments to evaluate social programs. I add to this literature by providing a more general method for translating incentives into identification conditions.

Translating Incentives into Choice Restrictions

MTO incentives can be described by *incentive matrix* $\boldsymbol{L}$ that displays the incentives of voucher assignments (rows) toward neighborhood choices (columns): z_c is a neutral baseline; z_8 incentivizes t_m, t_l; and z_e incentivizes t_l.[20]

$$\textbf{Incentive Matrix } \boldsymbol{L} = \begin{array}{c} \begin{array}{ccc} t_h & t_m & t_l \end{array} \\ \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \end{array} \begin{array}{c} \\ z_c \\ z_8 \\ z_e \end{array} \tag{15}$$

[19]For example, one can argue that the response-type $\boldsymbol{S}_i = [t_m, t_m, t_h]'$ is unlikely to occur. It means that family i chooses a medium-poverty neighborhood under no voucher ($T_i(z_c) = t_m$), but switches to high-poverty under the experimental voucher ($T_i(z_e) = t_h$). The switch lacks justification as neither of these vouchers subsidizes high or medium-poverty neighborhoods.

[20]The incentive matrix is ordinal. $\boldsymbol{L}[z, t] < \boldsymbol{L}[z', t]$ means that the incentive for choosing t increases when instrument changes from z to z'. Any monotonic transformation of the values in $\boldsymbol{L}$ characterizes equivalent incentives and delivers identical analysis.

Table 4: Elimination of MTO Response-types

Panel A	**All 27 Possible Response-types**																										
Counterfactual Choices	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
$T_i(z_c)$	t_h	t_h	t_h	t_h	t_h	t_h	t_h	t_h	t_h	t_m	t_m	t_m	t_m	t_m	t_m	t_m	t_m	t_m	t_l	t_l	t_l	t_l	t_l	t_l	t_l	t_l	t_l
$T_i(z_8)$	t_h	t_h	t_h	t_m	t_m	t_m	t_l	t_l	t_l	t_h	t_h	t_h	t_m	t_m	t_m	t_l	t_l	t_l	t_h	t_h	t_h	t_m	t_m	t_m	t_l	t_l	t_l
$T_i(z_e)$	t_h	t_m	t_l	t_h	t_m	t_l	t_h	t_m	t_l	t_h	t_m	t_l	t_h	t_m	t_l	t_h	t_m	t_l	t_h	t_m	t_l	t_h	t_m	t_l	t_h	t_m	t_l
Panel B	**Response-type Eliminated by Monotonicity Conditions of Table 3**																										
Condition 1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓	✗	✗	✓	✗	✗	✓
Condition 2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓	✓
Condition 3	✓	✗	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓
Not Eliminated	1		3	4	5	6	7		9				13	14	15	16		18						24			27
Panel C	**Response-type Eliminated by Revealed Preference Analysis of Table 5**																										
Restriction 1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✓	✗	✗	✓
Restriction 2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Restriction 3	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓
Restriction 4	✓	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓
Restriction 5	✓	✗	✗	✓	✓	✓	✓	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓	✓
Restriction 6	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
Restriction 7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✓	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓
Not Eliminated	1			4		6			9					14	15												27

Panel A lists the 27 possible response-types that the response variable $S_i = [T_i(z_c)\,,\, T_i(z_8)\,,\, T_i(z_e)]$ can take. Rows present the counterfactual neighborhood choices that a family i could choose if it were assigned to control group (z_c), Section 8 (z_8), and experimental group (z_e) respectively. Columns present all the values of response-type as choices range over $supp(T) = \{t_h, t_m, t_l\}$. Panel B describes an elimination process based on the three monotonicity criteria of Table 3 in Section 3. These criteria are also stated in Panel B′ below. Panel C describes an elimination process based on the seven choice restrictions generated by the revealed preference analysis. These choice restrictions are also displayed in Panel C′ below.

Panel B′ – Monotonicity Relations

Monotonicity Condition 1	$\mathbf{1}[T_i(z_c) = t_l]$	$\leq$	$\mathbf{1}[T_i(z_e) = t_l]$
Monotonicity Condition 2	$\mathbf{1}[T_i(z_c) \in \{t_m, t_l\}]$	$\leq$	$\mathbf{1}[T_i(z_8) \in \{t_m, t_l\}]$
Monotonicity Condition 3	$\mathbf{1}[T_i(z_e) = t_m]$	$\leq$	$\mathbf{1}[T_i(z_8) = t_m]$

Panel C′ – Choice Restrictions

Choice Restriction 1	$T_i(z_c) = t_l$	$\Rightarrow$	$T_i(z_8) \in \{t_m, t_l\}$ and $T_i(z_e) = t_l$
Choice Restriction 2	$T_i(z_c) = t_m$	$\Rightarrow$	$T_i(z_8) \in \{t_m, t_l\}$ and $T_i(z_e) \in \{t_m, t_l\}$
Choice Restriction 3	$T_i(z_e) = t_m$	$\Rightarrow$	$T_i(z_c) = t_m$ and $T_i(z_8) = t_m$
Choice Restriction 4	$T_i(z_e) = t_h$	$\Rightarrow$	$T_i(z_c) = t_h$ and $T_i(z_8) \in \{t_h, t_m\}$
Choice Restriction 5	$T_i(z_8) = t_h$	$\Rightarrow$	$T_i(z_c) = t_h$ and $T_i(z_e) = t_h$
Choice Restriction 6	$T_i(z_8) = t_l$	$\Rightarrow$	$T_i(z_e) = t_l$
Choice Restriction 7	$T_i(z_c) \neq t_h$	$\Rightarrow$	$T_i(z_8) = T_i(z_c)$

Check mark ✓ indicates that the response-type displayed by the top column of the table does not violate the choice restriction denoted by the panel row. Cross sign ✗indicates that the response-type violates the choice restriction and should be eliminated. The last row in each panel presents the response-types that survive the elimination process.

I now link the incentive matrix to the response matrix (59). Let $u_i(t,g)$ represent the rational preferences of a family i over the neighborhood types $t \in \{t_h, t_m, t_l\}$ and consumption goods $g \in \mathcal{G}$. $\mathcal{B}_i(z,t) \subset \mathcal{G}$ is the budget set of consumption goods for family i when the neighborhood choice is *fixed* at $t \in \{t_h, t_m, t_l\}$ and the voucher assignment is *fixed* at $z \in \{z_c, z_8, z_e\}$. The budget set $\mathcal{B}_i(z,t)$ must be understood broadly. It includes typical items such as food, clothing, and leisure, but also housing characteristics. The neighborhood choice of family i when the voucher is fixed at z is:

$$T_i(z) = \underbrace{\operatorname*{arg\,max}_{t \in \{t_l, t_m, t_h\}} \left(\max_{g \in \mathcal{B}_i(z,t)} u_i(t,g) \right)}_{\text{Economic Model}} = \underbrace{f_T(z, \boldsymbol{V}_i)}_{\text{Causal Model}} \tag{16}$$

Family preferences are subsumed by unobserved characteristics $\boldsymbol{V}_i$ in the causal model (1)–(3).

Incentive matrix (15) determines inclusion relations among budget sets as characterized by (17)–(19).[21] Equation (17) compares budget sets across voucher assignments when the neighborhood choice is fixed at high poverty (t_h). Vouchers offer no subsidy for t_h; therefore, budget sets remain the same. Equation (18) examines budget sets for t_m. Voucher z_8 is the only voucher that subsidizes t_m; therefore, budget set $\mathcal{B}_i(z_8, t_m)$ is larger than $\mathcal{B}_i(z_c, t_m)$ and $\mathcal{B}_i(z_e, t_m)$, as in (18). Equation (19) compares budget sets for t_l. Vouchers z_8 and z_e subsidize t_l while z_c does not. As a consequence, budget sets $\mathcal{B}_i(z_e, t_l), \mathcal{B}_i(z_8, t_l)$ are larger than $\mathcal{B}_i(z_c, t_l)$.

$$\boldsymbol{L}[z_c, t_h] = \boldsymbol{L}[z_e, t_h] = \boldsymbol{L}[z_8, t_h] \quad \Rightarrow \quad \mathcal{B}_i(z_c, t_h) = \mathcal{B}_i(z_e, t_h) = \mathcal{B}_i(z_8, t_h). \tag{17}$$

$$\boldsymbol{L}[z_c, t_m] = \boldsymbol{L}[z_e, t_m] < \boldsymbol{L}[z_8, t_m] \quad \Rightarrow \quad \mathcal{B}_i(z_c, t_m) = \mathcal{B}_i(z_e, t_m) \subset \mathcal{B}_i(z_8, t_m). \tag{18}$$

$$\boldsymbol{L}[z_c, t_l] < \boldsymbol{L}[z_e, t_l] = \boldsymbol{L}[z_8, t_l] \quad \Rightarrow \quad \mathcal{B}_i(z_c, t_l) \subset \mathcal{B}_i(z_e, t_l) = \mathcal{B}_i(z_8, t_l). \tag{19}$$

Budget set relations permit the use of Weak Axiom of Revealed Preferences (WARP) to generate choice restrictions. If family i chooses high-poverty under experimental voucher, $T_i(z_e) = t_h$, then high-poverty neighborhood (t_h) is revealed preferred to low-poverty (t_l) under z_e.[22] Consider a voucher change from z_e to z_8. Budget sets for t_l remain the same $\mathcal{B}_i(z_e, t_l) = \mathcal{B}_i(z_8, t_l)$, as z_e and z_8 subsidize t_l. Budget sets for t_h also remain the same $\mathcal{B}_i(z_e, t_h) = \mathcal{B}_i(z_8, t_h)$, as t_h is not subsidized. Under WARP,[23] t_l cannot be revealed preferred to t_h and thus the choice restriction $T_i(z_e) = t_h \Rightarrow T_i(z_8) \neq t_l$ holds.[24] This choice restriction eliminates three response-types: $[t_l, t_l, t_h]$, $[t_m, t_l, t_h]$, and $[t_h, t_l, t_h]$. Two of them are not eliminated by the monotonicity condition of Table 3.

[21] In summary, we have that $\boldsymbol{L}[z,t] \leq \boldsymbol{L}[z',t] \Rightarrow \mathcal{B}_i(z,t) \subset \mathcal{B}_i(z',t) \; \forall \, i$.

[22] Notationally, $T_i(z_e) = t_h$ implies $(t_h \succ_i^d t_l)|z_e$, which means that there exists a bundle $(t_h, g^*) \in \mathcal{B}_i(z_e, t_h)$ that is directed and strictly revealed preferred to all available bundles $(t_l, g) \in \mathcal{B}_i(z_e, t_l)$.

[23] The WARP criteria of Richter (1971) states that if bundle (t,g) is directly and strictly revealed preferred to (t',g'), that is, $(t,g) \succ_i^d (t',g')$. then it cannot be the case that (t',g') is revealed preferred to (t,g), namely, $(t,g) \succ_i^d (t',g') \Rightarrow (t',g') \not\succ_i^d (t,g)$.

[24] Formally, $(t_h \succ_i^d t_l)|z_e$ means that a bundle $(t_h, g^*) \in \mathcal{B}_i(z_e, t_h)$ is directed revealed preferred to all bundles $(t_l, g) \in \mathcal{B}_i(z_e, t_l)$. But $\mathcal{B}_i(z_e, t_h) = \mathcal{B}_i(z_8, t_h)$ implies that bundle (t_l, g^*) is still available under z_8. Moreover the equality between budget sets for low-poverty, $\mathcal{B}_i(z_e, t_l) = \mathcal{B}_i(z_8, t_l)$ implies that the bundle $(t_l, g^*) \in \mathcal{B}_i(z_8, t_h)$ is directed revealed preferred to all bundles $(t_l, g) \in \mathcal{B}_i(z_8, t_l)$. Therefore family i does not choose low-poverty under the Section 8 voucher.

We can exploit the concept of normal goods to generate additional choice restrictions. Consider a family i that debates between low-poverty t_l and medium-poverty t_m under no subsidy z_c. Suppose the voucher changes to z_8, which subsidizes both neighborhood choices being considered. This change can be understood as an increase in income. If we interpret neighborhood choice as a normal good, then an increase in income cannot decrease its consumption. Thus the family maintains its neighborhood decision, that is, $T_i(z_c) \neq t_h \Rightarrow T_i(z_8) = T_i(z_c)$. Normal Choice can be formally expressed as a no-crossing condition across the rankings of family preferences.[25] WARP and Normal Choice generate an intuitive rule that translates incentives into choice restrictions:[26]

$$\text{If} \quad T_i(z) = t \quad \text{and} \quad \boldsymbol{L}[z', t'] - \boldsymbol{L}[z, t'] \leq \boldsymbol{L}[z', t] - \boldsymbol{L}[z, t] \quad \text{then} \quad T_i(z') \neq t'. \qquad (20)$$

Choice rule (20) states that if family i chooses choice t under z and the change from z to z' induces greater incentives towards t instead of t', then family i does not choose t' under z'. Choice rule (20) can be applied to all combinations $(t, t') \in \{t_h, t_m, t_l\}^2$ and $(z, z') \in \{z_c, z_8, z_e\}^2$. Table 5 lists the choice restrictions generated by the MTO incentive matrix (15).[27]

Table 5: Choice Restrictions generated by applying WARP and Normal Choice to the MTO Incentive Matrix

1	$T_i(z_c) = t_l$	$\Rightarrow$	$T_i(z_e) = t_l$ and $T_i(z_8) \neq t_h$
2	$T_i(z_c) = t_m$	$\Rightarrow$	$T_i(z_e) \neq t_h$ and $T_i(z_8) \neq t_h$
3	$T_i(z_e) = t_m$	$\Rightarrow$	$T_i(z_c) = t_m$ and $T_i(z_8) = t_m$
4	$T_i(z_e) = t_h$	$\Rightarrow$	$T_i(z_c) = t_h$ and $T_i(z_8) \neq t_l$
5	$T_i(z_8) = t_h$	$\Rightarrow$	$T_i(z_c) = t_h$ and $T_i(z_e) = t_h$
6	$T_i(z_8) = t_l$	$\Rightarrow$	$T_i(z_e) = t_l$
7	$T_i(z_c) \neq t_h$	$\Rightarrow$	$T_i(z_8) = T_i(z_c)$

The choice restrictions of Table 5 are economically justifiable. The first restriction states that if a family chooses low-poverty t_l under control group z_c (no subsidy) then this family should also choose t_l under z_e, which subsidizes t_l. Moreover, this family does not choose high-poverty t_h under z_8, but may choose t_l or t_m, which are indeed subsidized by z_8. Choice restrictions 1–6 are generated by WARP, while choice last restriction is generated by Normal Choice. Choice restrictions 1–3 subsume the monotonicity conditions of Table 3. These restrictions hold for each family i regardless if budget sets are observed or if the family uses the voucher to relocate.

Panel C of Table 4 shows that choice restrictions of Table 5 jointly eliminate 20 of the 27 possible response-types. The remaining seven response-types are the ones arranged into the response matrix $\boldsymbol{R}$ (59) displayed in Section 3.

[25] Formally, Normal Choice can be defined as: $(t \succ_i t')|z$ and $\mathcal{B}_i(z, t') = \mathcal{B}_i(z, t) \subset \mathcal{B}_i(z', t') = \mathcal{B}_i(z', t)$ then $(t' \not\succ_i t)|z'$.

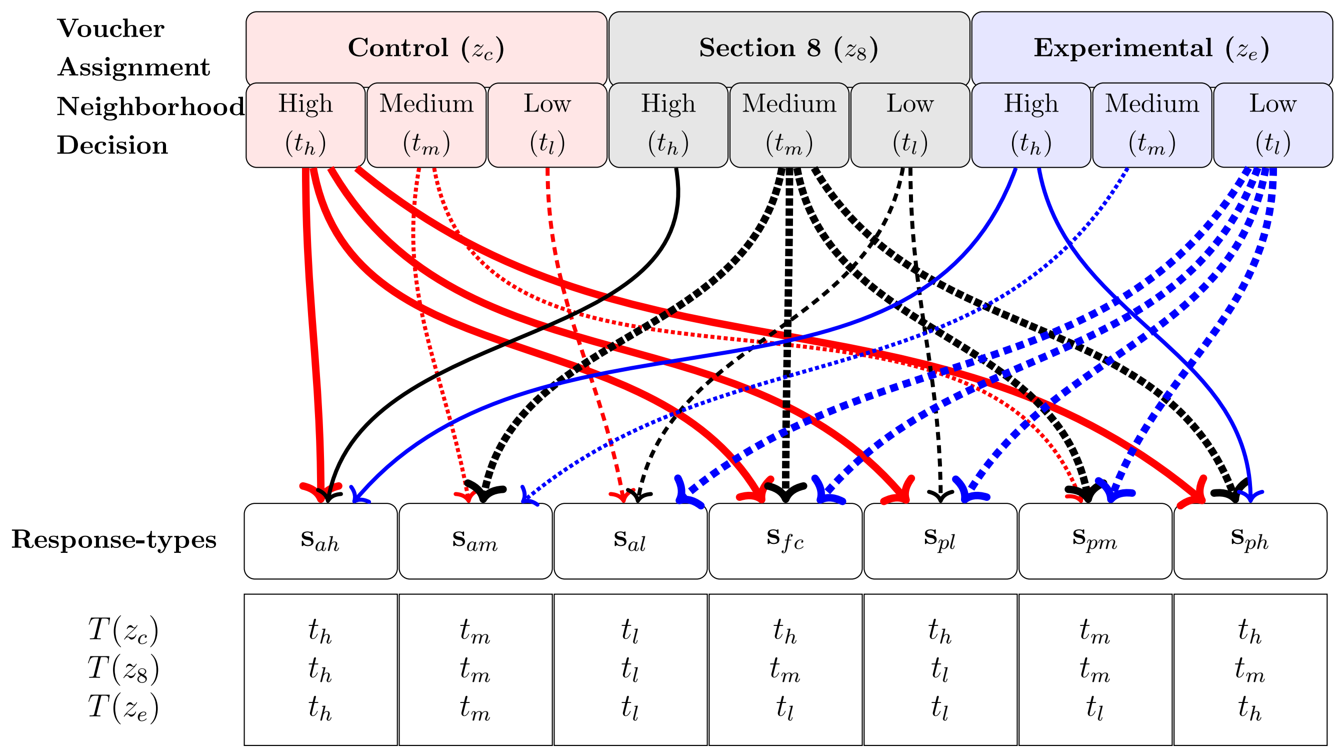
[26] See (Pinto, 2016).

[27] See Appendix B for full derivation.

Response matrix (59) determines a mapping between observed choices and latent response-types displayed in Figure 2. The first row of the response matrix lists the choices for control z_c. Families that choose t_l under z_c can only be low-poverty always-takers $\boldsymbol{s}_{al}$. Families that choose t_m under z_c are a mixture of $\boldsymbol{s}_{al}$ and $\boldsymbol{s}_{al}$, while those who choose t_l under z_c can be of four types: $\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}$ or , $\boldsymbol{s}_{ph}$. Identification of causal parameters disentangles this mapping.

It seems natural to model the neighborhood choices in MTO as ordered. This approach justifies the well-known monotonicity condition of Angrist and Imbens (1995), which is equivalent to an ordered choice model with random thresholds (Vytlacil, 2006). Unfortunately, the ordered choice model is incompatible with MTO incentives. Appendix C shows that monotonicity condition of Angrist and Imbens (1995) does not hold regardless of the ordering of neighborhood choices and instrumental values. The appendix also presents alternative incentive schemes that justify ordered choice models.

Figure 2: **From Observed Vouchers Assignments and Neighborhood Choices to Unobserved Response-types**



This figure describes how voucher assignments and neighborhood choices map into the MTO response-types. There are three possible voucher assignments: Control (z_c), Section 8 (z_8), or Experimental (z_e). There are three neighborhood choices: high-poverty neighborhood (t_h), medium-poverty neighborhood (t_m) or low-poverty neighborhood (t_l). The combination of voucher assignment and neighborhood choice generate nine possibilities. There are seven response-types according to the response matrix $\boldsymbol{R}$ in (59). These response-types are denoted by $\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}, \boldsymbol{s}_{al}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{ph}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{pl}$. The mapping between the voucher assignments and neighborhood choices into response-types is represented by connecting lines. Solid lines denote the choice of high-poverty neighborhood. Dotted lines denote the choice of medium-poverty neighborhood. Dashed lines denote the choice of low-poverty neighborhood. Bold lines refer to the most frequent neighborhood choice for each voucher assignment.

5 Identification Results and Estimation Methods

It is helpful to reorder the columns of the response matrix (59) so that all choices t_l lie in the *lower triangular* portion of the matrix. This triangularity property is shown in (21) and it is central to my identification analysis.

$$\text{Reordered Response Matrix: } \begin{array}{c} \begin{matrix} \boldsymbol{s}_{al} & \boldsymbol{s}_{pl} & \boldsymbol{s}_{fc} & \boldsymbol{s}_{pm} & \boldsymbol{s}_{ah} & \boldsymbol{s}_{am} & \boldsymbol{s}_{pl} \end{matrix} \\ \begin{bmatrix} \boxed{t_l} & t_h & t_h & t_m & t_h & t_m & t_h \\ \boxed{t_l} & \boxed{t_l} & t_m & t_m & t_h & t_m & t_m \\ \boxed{t_l} & \boxed{t_l} & \boxed{t_l} & \boxed{t_l} & t_h & t_m & t_h \end{bmatrix} \end{array} \begin{matrix} z_c \\ z_8 \\ z_e \end{matrix} \tag{21}$$

The first row in (21) shows that $\boldsymbol{s}_{al}$ is the only response-type that takes value t_l given z_c. Applying equation (11) to the first row gives:

$$E(YD_{t_l}|Z = z_c) = E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{al})P(\boldsymbol{S} = \boldsymbol{s}_{al}). \tag{22}$$

Setting $Y = 1$ identifies the response-type probability $P(\boldsymbol{S} = \boldsymbol{s}_{al}) = E(D_{t_l}|Z = z_c) = P(T = t_l|Z = z_c)$, which enables us to identify the counterfactual outcome for $\boldsymbol{s}_{al}$ by:

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{al}) = \frac{E(YD_{t_l}|Z = z_c)}{E(D_{t_l}|Z = z_c)}. \tag{23}$$

The second row in (21) shows that $\boldsymbol{s}_{al}$ and $\boldsymbol{s}_{pl}$ take value t_l given z_8. Applying (11) to the second row gives:

$$E(YD_{t_l}|Z = z_8) = \Big(E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{al})P(\boldsymbol{S} = \boldsymbol{s}_{al}) + E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl})P(\boldsymbol{S} = \boldsymbol{s}_{pl})\Big). \tag{24}$$

The difference between the second row (24) and the first row (22) equations is given by (25). It identifies the response-type probability (26) and the counterfactual outcome (27) for $\boldsymbol{s}_{pl}$:

$$E(YD_{t_l}|Z = z_8) - E(YD_{t_l}|Z = z_c) = E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl})P(\boldsymbol{S} = \boldsymbol{s}_{pl}) \tag{25}$$

$$\text{Setting } Y = 1 \quad \Rightarrow P(\boldsymbol{S} = \boldsymbol{s}_{pl}) = E(D_{t_l}|Z = z_8) - E(D_{t_l}|Z = z_c) \tag{26}$$

$$\text{Substituting (26) in (25)} \Rightarrow E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl}) = \frac{E(YD_{t_l}|Z = z_8) - E(YD_{t_l}|Z = z_c)}{E(D_{t_l}|Z = z_8) - E(D_{t_l}|Z = z_c)} \tag{27}$$

A similar argument applies to the third row. Response-types $\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}$ take value t_l under z_8. The third row version of (11) is given by (28) and the difference between the third row (28) and the second row (24) equations is given by (29):

$$E(YD_{t_l}|Z = z_e) = \sum_{\boldsymbol{s} \in \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}} E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s})P(\boldsymbol{S} = \boldsymbol{s})E(YD_{t_l}|Z = z_e) - E(YD_{t_l}|Z = z_8) \tag{28}$$

$$\begin{aligned} &= E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})P(\boldsymbol{S} = \boldsymbol{s}_{fc}) + E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm})P(\boldsymbol{S} = \boldsymbol{s}_{pm}), \\ &= E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}). \end{aligned} \tag{29}$$

Equation (29) identifies the response-type probability (30) and counterfactual outcome (31) for the joint set of response-types $\{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}$:

$$\text{Setting } Y = 1 \quad \Rightarrow P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}) = E(D_{t_l}|Z = z_e) - E(D_{t_l}|Z = z_8), \tag{30}$$

$$\text{Substituting (30) in (29)} \Rightarrow E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}) = \frac{E(YD_{t_l}|Z = z_e) - E(YD_{t_l}|Z = z_8)}{E(D_{t_l}|Z = z_e) - E(D_{t_l}|Z = z_8)}. \tag{31}$$

An heuristic argument summarises the identification results for t_l. Matrix (21) shows that the sequence of instrumental variables z_c, z_8, z_e corresponds to the sequence of *nested sets* $\{\boldsymbol{s}_{al}\} \subset \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}\} \subset \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}$. Instrumental value z_c identifies counterfactuals for $\boldsymbol{s}_{al}$. The difference between the nested sets associated with z_8 and z_c is $\boldsymbol{s}_{pl}$. Counterfactuals for $\boldsymbol{s}_{pl}$ employ the difference between z_8 and z_c. By the same token, counterfactuals for $\{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}$ employ the difference z_e and z_8.

The triangularity property of t_l in (21) also characterises t_h and t_m. It is possible to reorder rows and columns of the response matrix such that choices t_h and t_m lie in the *lower triangular* portion of the matrix:

$$\begin{array}{cc} \begin{array}{ccccccc} \boldsymbol{s}_{ah} & \boldsymbol{s}_{ph} & \boldsymbol{s}_{fc} & \boldsymbol{s}_{pl} & \boldsymbol{s}_{pm} & \boldsymbol{s}_{am} & \boldsymbol{s}_{al} \end{array} & \\ \begin{bmatrix} \boxed{t_h} & t_m & t_m & t_l & t_m & t_m & t_l \\ \boxed{t_h} & \boxed{t_h} & t_l & t_l & t_l & t_m & t_l \\ \boxed{t_h} & \boxed{t_h} & \boxed{t_h} & \boxed{t_h} & t_m & t_m & t_l \end{bmatrix} & \begin{matrix} z_8 \\ z_e \\ z_c \end{matrix} \end{array}, \quad \begin{array}{cc} \begin{array}{ccccccc} \boldsymbol{s}_{am} & \boldsymbol{s}_{pm} & \boldsymbol{s}_{ph} & \boldsymbol{s}_{fc} & \boldsymbol{s}_{pl} & \boldsymbol{s}_{ah} & \boldsymbol{s}_{al} \end{array} & \\ \begin{bmatrix} \boxed{t_m} & t_l & t_h & t_l & t_l & t_h & t_l \\ \boxed{t_m} & \boxed{t_m} & t_h & t_h & t_h & t_h & t_l \\ \boxed{t_m} & \boxed{t_m} & \boxed{t_m} & \boxed{t_m} & t_l & t_h & t_l \end{bmatrix} & \begin{matrix} z_e \\ z_c \\ z_8 \end{matrix} \end{array} \tag{32}$$

The first matrix in (32) shows that for z_8 (first row) response-type $\boldsymbol{s}_{ah}$ takes value t_h. For z_c (second row) response-types $\boldsymbol{s}_{ah}, \boldsymbol{s}_{ph}$ take value t_l, and for z_8 (third row) response-types $\boldsymbol{s}_{ah}, \boldsymbol{s}_{ph}, \boldsymbol{s}_{ph}, \boldsymbol{s}_{pl}$ take value t_h. Thus, for t_h, the IV sequence z_8, z_e, z_c corresponds to the nested sets $\{\boldsymbol{s}_{ah}\} \subset \{\boldsymbol{s}_{ah}, \boldsymbol{s}_{ph}\} \subset \{\boldsymbol{s}_{ah}, \boldsymbol{s}_{ph}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\}$. Following the same argument of t_l, we can identify $E(Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{ah})$, $P(\boldsymbol{S} = \boldsymbol{s}_{ah})$ using z_8; $E(Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{pl})$, $P(\boldsymbol{S} = \boldsymbol{s}_{pl})$ using the difference between z_e and z_8; and $E(Y(t_h)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\})$, $P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\})$. using the difference between z_c and z_e.

The second matrix in (32) investigates medium-poverty t_m. It shows that the IV sequence z_e, z_c, z_8, corresponds to nested sets $\{\boldsymbol{s}_{am}\} \subset \{\boldsymbol{s}_{am}, \boldsymbol{s}_{pm}\} \subset \{\boldsymbol{s}_{am}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{ph}\}$. It follows that we can identify $E(Y(t_m)|\boldsymbol{S} = \boldsymbol{s}_{am})$, $P(\boldsymbol{S} = \boldsymbol{s}_{am})$ using z_e; $E(Y(t_m)|\boldsymbol{S} = \boldsymbol{s}_{pm})$, $P(\boldsymbol{S} = \boldsymbol{s}_{pm})$ using the difference between z_c and z_8; and $E(Y(t_m)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{ph}\})$, $P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{ph}\})$ using the difference between z_8 and z_c.

We have identified six out of the seven response-type probabilities. Since they sum to one, all response-type probabilities are identified. Replacing Y by $\boldsymbol{X}$ in equation (11) enables us to identify the baseline outcome means conditioned on response-types $E(\boldsymbol{X}|\boldsymbol{S} = \boldsymbol{s})$. Appendix D derives these identification results using linear algebra.

Triangular Property and Estimators of Binary Choice Models

We can connect the triangular property of the response matrices in (21) and (32) to results in the literature of binary choice models. Similar to Imbens and Angrist (1994), counterfactual outcomes can be estimated by Two-Stage Least Squares (TSLS). The identification of $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl})$ in (27) depends on z_8 and z_c. It can be estimated by the TSLS (33)–(34) that regresses the choice indicator D_{t_l} on two IV indicators, $\mathbf{1}[Z = z_8]$ and $\mathbf{1}[Z = z_c]$ without a constant term (first stage) and then regresses the interaction YD_{t_l} on a constant and the fitted values $\hat{D}_{t_l}$ (second stage):

$$\text{First Stage:} \qquad D_{t_l} = \gamma_1 \mathbf{1}[Z = z_8] + \gamma_2 \mathbf{1}[Z = z_c] + \epsilon_D \tag{33}$$

$$\text{Second Stage:} \qquad YD_{t_l} = \beta_0 + \beta_{IV} \hat{D}_{t_l} + \epsilon_Y, \tag{34}$$

γ_1, γ_2 are linear coefficients of the first stage, β_0 is the intercept of the second stage, and β_{IV} is the linear coefficient that estimates $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl})$. We can estimate different counterfactual outcomes by varying the IV-indicators and neighborhood choices as listed in Table 6.

Table 6: Two-Stage Least Square Estimation for Identified Parameters

Data Transformations				Identified Parameters
Endogenous Variables Choice Indicator	Dependent Variable Outcome Interaction	Instrumental Variable IV Indicators		
$D_{t_h} \equiv \mathbf{1}[T = t_h]$	$D_{t_h} \cdot Y$	$\mathbf{1}[Z = z_c]$ $\mathbf{1}[Z = z_8]$	$\mathbf{1}[Z = z_e]$ $\mathbf{1}[Z = z_e]$	$E(Y(t_h)|S \in \{s_4, s_5\})$ $E(Y(t_h)|S = s_7)$
$D_{t_m} \equiv \mathbf{1}[T = t_m]$	$D_{t_m} \cdot Y$	$\mathbf{1}[Z = z_c]$ $\mathbf{1}[Z = z_c]$	$\mathbf{1}[Z = z_8]$ $\mathbf{1}[Z = z_e]$	$E(Y(t_m)|S \in \{s_4, s_7\})$ $E(Y(t_m)|S = s_6)$
$D_{t_l} \equiv \mathbf{1}[T = t_l]$	$D_{t_l} \cdot Y$	$\mathbf{1}[Z = z_c]$ $\mathbf{1}[Z = z_8]$	$\mathbf{1}[Z = z_8]$ $\mathbf{1}[Z = z_e]$	$E(Y(t_l)|S = s_5)$ $E(Y(t_l)|S \in \{s_4, s_6\})$

This table lists the counterfactual outcome means estimated by 2SLS procedures. The first stage estimates use two IV indicators (columns 3 and 4) that are multiplied by γ_1, γ_2 in (33). The choice indicator (column 1) is the endogenous variable estimated in the first stage (33). The second stage uses the interaction of the outcome and the choice indicator (column 2) as dependent variable and uses the estimate of the first stage, which is multiplied by the linear coefficient β_{IV} in . The last column lists the identified counterfactual outcome mean.

We can control for pre-program variables $\boldsymbol{X}$ parametrically by including them as covariates in the TSLS regressions.[28] Abadie (2003) proposes a κ-weighting scheme that nonparametrically controls for baseline variables in the LATE model.[29] The triangular property in (21) and (32) enables us to extend Abadie's κ to the case of multiple choices.

Counterfactual outcome $E\left(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl}\right)$ in (27) is identified as a ratio of two *matching estimators* that depend on z_8 and z_c. This counterfactual outcome can also be expressed in (35) as the expectation of the observed outcome Y multiplied by a weighting function $\kappa(t_l, \boldsymbol{s}_{pl})$ in (36) which depends on z_8 and z_c.[30]

$$E\left(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl}\right) = E\left(Y \cdot \frac{\kappa(t_l, \boldsymbol{s}_{pl})}{E(\kappa(t_l, \boldsymbol{s}_{pl}))}\right), \tag{35}$$

$$\text{such that } \kappa(t_l, \boldsymbol{s}_{pl}) = D_{t_l}\left(\frac{\mathbf{1}[Z = z_8]}{P(Z = z_8|\boldsymbol{X})} - \frac{\mathbf{1}[Z = z_c]}{P(Z = z_c|\boldsymbol{X})}\right). \tag{36}$$

The κ-weighting in (36) can be evaluated from data; it consists of the choice indicator D_{t_l} multiplied by the difference between IV indicators of z_8 and z_c divided by their respective

[28] Angrist and Imbens (1995) show that the TSLS estimate is a weighted average of the counterfactual outcomes conditioned on the covariates. Weights consist of the variance of the choice indicators conditioned on the covariates.

[29] Abadie (2003) shows that the counterfactual outcomes of the LATE model can be evaluated by a weighted average of the outcome across the whole population. He names the weighting functions κ.

[30] Equation (35) also holds if Y were to be replaced by any measurable function $g(Y, D_{t_l}, \boldsymbol{X})$. See Navjeevan, Pinto, and Santos (2020) for an extension of Abadie's (2003) kappa-weighting scheme for multiple choice models and for arbitrary monotonicity conditions.

probabilities conditional on baseline variables $\boldsymbol{X}$. $E\left(Y(t_l)|\boldsymbol{S}=\boldsymbol{s}_{pl}\right)$ can be estimated by the sample counterpart of (35), that is, $\sum_i Y_i \cdot \omega_i$, where $\omega_i = \kappa_i(t_l, \boldsymbol{s}_{pl})/(\sum_i \kappa_i(t_l, \boldsymbol{s}_{pl}))$ are weights that sum to one and $\kappa_i(t_l, \boldsymbol{s}_{pl})$ is the κ-weight of family i.[31] Weights κ for counterfactual outcomes in Table 6 can be obtained by replacing D_{t_l}, z_8, z_c in (36) by their corresponding neighborhood choice and IV indicators.

Interpreting the TOT Parameter

The treatment-on-the-treated (TOT) is defined as the ratio of the causal effect of being offered a voucher divided by the voucher compliance rate. $\mathbf{TOT}(z_e, z_c)$ in (37) compares experimental and control vouchers.[32]

$$\mathbf{TOT}(z_e, z_c) = \frac{E(Y|Z=z_e) - E(Y|Z=z_c)}{P(T=t_l|Z=z_e)}. \tag{37}$$

$\mathbf{TOT}(z_e, z_c)$ compares the z_c-row (first) and z_e-row (last) of the response matrix $\boldsymbol{R}$ in (59). Equation (11) enables us to rewrite $\mathbf{TOT}(z_e, z_c)$ as a weighted average of two neighborhood effects – low versus high-poverty neighborhoods for response-types $\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}$ and low versus medium-poverty neighborhoods for the response-type $\boldsymbol{s}_{pm}$ – multiplied by the conditional probability:

$$\begin{aligned}&\mathbf{TOT}(z_e, z_c) = \\ &\left(\frac{E(Y(t_l)-Y(t_h)|\boldsymbol{S}\in\{\boldsymbol{s}_{fc},\boldsymbol{s}_{pl}\})\,P(\boldsymbol{S}\in\{\boldsymbol{s}_{fc},\boldsymbol{s}_{pl}\}) + E(Y(t_l)-Y(t_m)|\boldsymbol{S}=\boldsymbol{s}_{pm})\,P(\boldsymbol{S}=\boldsymbol{s}_{pm})}{P(\boldsymbol{S}\in\{\boldsymbol{s}_{fc},\boldsymbol{s}_{pl},\boldsymbol{s}_{pm}\})}\right) \\ &\cdot \left(1 - P(\boldsymbol{S}=\boldsymbol{s}_{al}|\boldsymbol{S}\in\{\boldsymbol{s}_{al},\boldsymbol{s}_{fc},\boldsymbol{s}_{pl},\boldsymbol{s}_{pm}\})\right)\end{aligned} \tag{38}$$

This decomposition relates to Kline and Walters (2016), who study a preschool experiment that randomly offered Head Start day-care services to children. They decompose LATE into two sub-effects associated with children that choose either no preschool or a preschool other than Head Start when assigned to the control group.

Unordered Monotonicity

The triangular property of the response matrix in (21) and (32) is a necessary and sufficient criteria for the unordered monotonicity condition of Heckman and Pinto (2018) to hold. Unordered monotonicity (39) means that a change in the instrument variable Z cannot induce some agents towards a choice t while inducing others against the same choice t.[33]

$$\mathbf{1}[T_i(z)=t] \geq \mathbf{1}[T_i(z')=t] \text{ for all } i\in\mathcal{I} \text{ or } \mathbf{1}[T_i(z)=t] \leq \mathbf{1}[T_i(z')=t] \text{ for all } i\in\mathcal{I}. \tag{39}$$

[31] The practical use of the κ-weights is to evaluate causal parameters via conventional estimation procedures that reweighed data according to the estimated values of κ. An example of an estimation procedure for $E\left(Y(t_l)|\boldsymbol{S}=\boldsymbol{s}_{pl}\right)$ is: (1) estimate $P(Z=z_8|\boldsymbol{X}), P(Z=z_c|\boldsymbol{X})$; (2) construct weights $\hat{\kappa}(t_l, \boldsymbol{s}_{pl})$ as in (36); (3) estimate β_1 in regression $Y\cdot D_{t_l} = \beta_0 + \beta_1 \hat{D}_{t_l} + \beta_2 \boldsymbol{X} + \epsilon_Y$ via weighted least squares (WLS) that employ weights $\hat{\kappa}(t_l, \boldsymbol{s}_{pl})$. The WLS solves the sample analog of $(\beta_0, \beta_1, \beta_2) = \arg\min_{b_0,b_1,b_2} E(\kappa \cdot g(Y, D, \boldsymbol{X}))$, where $g(Y, D, \boldsymbol{X}) = (YD_{t_l} - (b_0 + b_1\hat{D}_{t_l} + b_2\boldsymbol{X}))^2$.

[32] Compliance rates are given by $P(T=t_l|Z=z_e)$.

[33] Unordered monotonicity does not imply or is implied by the monotonicity criteria of Angrist and Imbens (1995), which, according to Vytlacil (2006), is equivalent to an ordered choice model.

In the case of MTO, unordered monotonicity consists of nine inequalities – one for each combination of $t \in \{t_h, t_m, t_l\}$ and $(z, z') \in \{z_c, z_8, z_e\} \times \{z_c, z_8, z_e\}$ – listed in Table 7. These monotonicity inequalities are equivalent to the seven choice restrictions of Table 5 as both generate the same response matrix.[34]

Each set of monotonicity inequalities yields a unique response matrix. Each monotonicity inequality implies a propensity score inequality that can be checked on data. The third column of Table 7 shows that the propensity score inequalities estimated from data are consistent with the unordered monotonicity condition that generates the MTO response matrix.[35]

Table 7: MTO Unordered Monotonicity and Respective Propensity Scores Inequalities

	Values of Z-pairs	T	Unordered Monotonicity Condition	Propensity Score Inequalities
Relation 1	(z_c, z_8)	t_h	$\mathbf{1}[T_i(z_c) = t_h] \ \geq \ \mathbf{1}[T_i(z_8) = t_h]$	$P(T = t_h \vert Z = z_c) = 0.82 \ > \ 0.34 = P(T = t_h \vert Z = z_8)$
Relation 2	(z_8, z_e)	t_h	$\mathbf{1}[T_i(z_8) = t_h] \ \leq \ \mathbf{1}[T_i(z_e) = t_h]$	$P(T = t_h \vert Z = z_8) = 0.34 \ < \ 0.44 = P(T = t_h \vert Z = z_e)$
Relation 3	(z_e, z_c)	t_h	$\mathbf{1}[T_i(z_e) = t_h] \ \leq \ \mathbf{1}[T_i(z_c) = t_h]$	$P(T = t_h \vert Z = z_e) = 0.44 \ < \ 0.82 = P(T = t_h \vert Z = z_c)$
Relation 4	(z_c, z_8)	t_m	$\mathbf{1}[T_i(z_c) = t_m] \ \leq \ \mathbf{1}[T_i(z_8) = t_m]$	$P(T = t_m \vert Z = z_c) = 0.15 \ < \ 0.57 = P(T = t_m \vert Z = z_8)$
Relation 5	(z_8, z_e)	t_m	$\mathbf{1}[T_i(z_8) = t_m] \ \geq \ \mathbf{1}[T_i(z_e) = t_m]$	$P(T = t_m \vert Z = z_8) = 0.57 \ > \ 0.07 = P(T = t_m \vert Z = z_e)$
Relation 6	(z_e, z_c)	t_m	$\mathbf{1}[T_i(z_e) = t_m] \ \leq \ \mathbf{1}[T_i(z_c) = t_m]$	$P(T = t_m \vert Z = z_e) = 0.07 \ < \ 0.15 = P(T = t_m \vert Z = z_c)$
Relation 7	(z_c, z_8)	t_l	$\mathbf{1}[T_i(z_c) = t_l] \ \leq \ \mathbf{1}[T_i(z_8) = t_l]$	$P(T = t_l \vert Z = z_c) = 0.03 \ < \ 0.09 = P(T = t_l \vert Z = z_8)$
Relation 8	(z_8, z_e)	t_l	$\mathbf{1}[T_i(z_8) = t_l] \ \leq \ \mathbf{1}[T_i(z_e) = t_l]$	$P(T = t_l \vert Z = z_8) = 0.09 \ < \ 0.49 = P(T = t_l \vert Z = z_e)$
Relation 9	(z_e, z_c)	t_l	$\mathbf{1}[T_i(z_e) = t_l] \ \geq \ \mathbf{1}[T_i(z_c) = t_l]$	$P(T = t_l \vert Z = z_e) = 0.49 \ > \ 0.03 = P(T = t_l \vert Z = z_c)$

The third column displays the nine monotonicity inequalities of unordered monotonicity. These inequalities are equivalent to the choice restrictions generated by revealed preference analysis. Each monotonicity inequality corresponds to a propensity score inequality that can be evaluated by observed data. The last column presents the estimates for the unconditional propensity scores. The direction monotonicity inequalities and propensity score inequalities match.

Using Choice Data to Identify Additional Causal Partitions

Table 6 lists six identified counterfactual outcomes. Three are defined conditional on two response-types: $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$, $E(Y(t_m)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{ph}\})$, and $E(Y(t_h)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\})$. Information on choice t_l does not allow us to decompose $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$ into $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ and $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm})$. However, it is possible to decompose this counterfactual outcome by using the choice information on t_h and t_m.

Heckman and Pinto (2018) show that under unordered monotonicity, the indicator of each choice t can be expressed as a separable function that depends only on its own propensity score $P_t(Z)$ (and not on the propensity scores of the remaining choices), that is, $D_t =$

[34] See Table A.7 of the Appendix for the elimination of response-types induced by unordered monotonicity.

[35] Table 7 relates to Kline and Tartari (2016), who study labor market participation and generate a set of economically justified inequalities of observed response probabilities.

$\mathbf{1}[P_t(Z) \geq U_t]$, where $P_t(Z) = P(T = t|Z)$ and $U_t \sim Unif[0,1]$ stands for the unobserved confounder we seek to control.[36] Counterfactual outcomes are given by the integral of the marginal response $E(Y(t)|U_t = u)$ over propensity score intervals determined by IV values. In the case of t_l, the counterfactual outcomes in (23), (27), (31) can be expressed as:[37]

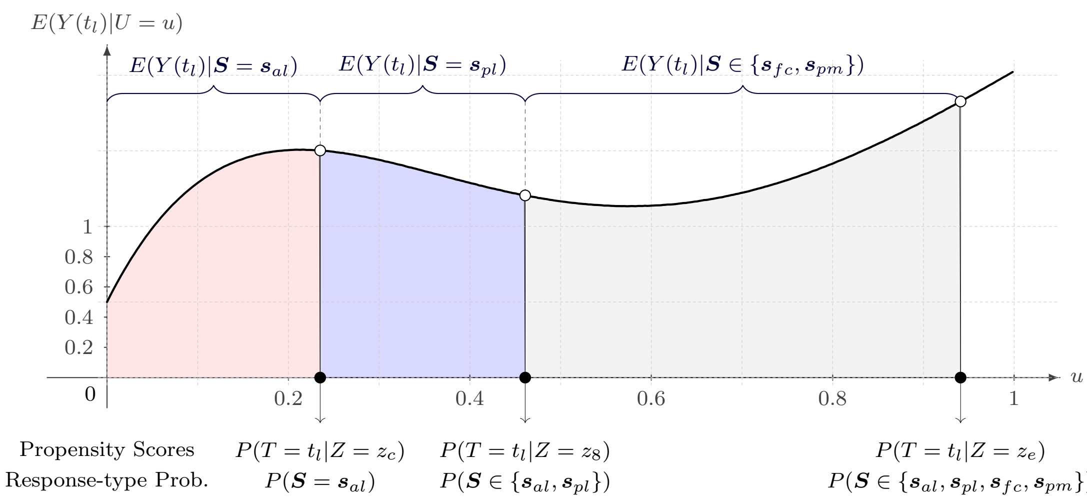
$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{al}) = \frac{\int_0^{P_{t_l}(z_c)} E(Y(t_l)|U_{t_l} = u)du}{P_{t_l}(z_c)}, \tag{40}$$

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl}) = \frac{\int_{P_{t_l}(z_c)}^{P_{t_l}(z_8)} E(Y(t_l)|U_{t_l} = u)du}{P_{t_l}(z_8) - P_{t_l}(z_c)}, \tag{41}$$

$$E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}) = \frac{\int_{P_{t_l}(z_8)}^{P_{t_l}(z_e)} E(Y(t_l)|U_{t_l} = u)du}{P_{t_l}(z_e) - P_{t_l}(z_8)}. \tag{42}$$

Figure 3 displays these results graphically.

Figure 3: Response-types Under Monotonicity Assumptions



Each of the identified parameters $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{al})$, $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl})$, $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$, can be expressed as integrals $\int E(Y(t_l)|U_{t_l} = u)du$ over intervals bounded by the propensity scores $0 < P_{t_l}(z_c) < P_{t_l}(z_8) < P_{t_l}(z_e)$.

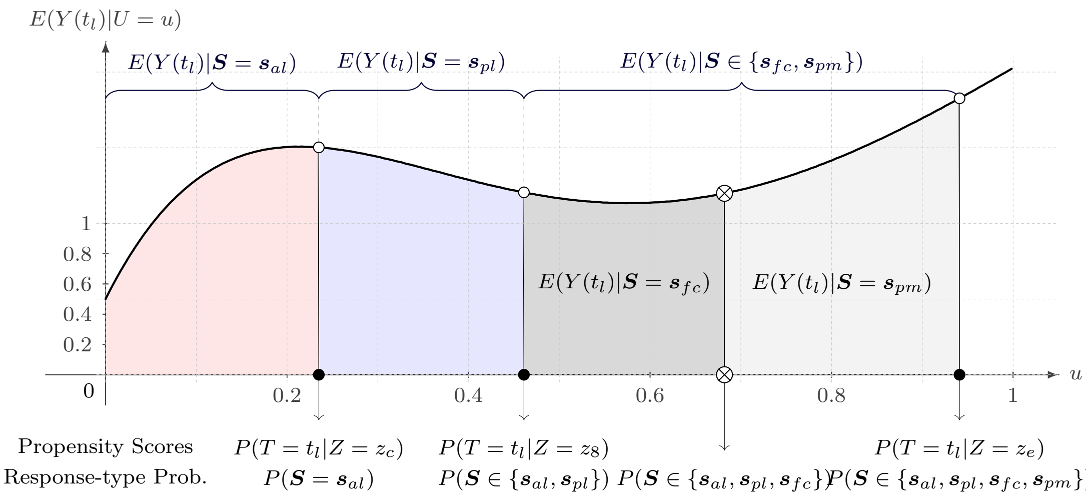
Figure 3 clarifies that the area under the marginal response function $E(Y(t_l)|U_{t_l} = u)$ for the interval $u \in [P_{t_l}(z_8), P_{t_l}(z_e)]$ corresponds to the counterfactual outcome $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$. Decomposing $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$ requires us to split the interval $[P_{t_l}(z_8), P_{t_l}(z_e)]$ into two segments corresponding to $\boldsymbol{s}_{fc}$ and $\boldsymbol{s}_{pm}$. The ordering of these two response-types

[36] Heckman and Pinto (2018) show that we can represent the choice indicator as $D_t = \mathbf{1}[\varphi_t(Z) \geq \phi_t(\boldsymbol{V})]$. Let the distribution of $\phi_t(\boldsymbol{V})$ be absolutely continuous and let $F_{\psi_t(\boldsymbol{V})}(\cdot)$ denotes its CDF. Then we can rewrite the choice indicator as $D_t = \mathbf{1}[F_{\phi_t(\boldsymbol{V})}(\varphi_t(Z)) \geq U_t]$, where $U_t \equiv F_{\phi_t(\boldsymbol{V})}(\phi_t(\boldsymbol{V})) \sim Unif[0,1]$. $P_t(z) \equiv P(T = t|Z = z) = p$ implies that $P(F_{\phi_t(\boldsymbol{V})}(\varphi_t(z)) \geq U_t) = p$, but U_t has uniform distribution, thus $F_{\phi_t(\boldsymbol{V})}(\varphi_t(z)) = p$, thereby $F_{\phi_t(\boldsymbol{V})}(\varphi_t(Z)) = P_t(Z)$.

[37] The integral $\int_p^{p'} E(Y(t)|U_t = u)du$ is identified by $E(YD_t|P_t = p') - E(YD_t|P_t = p)$. See Appendix D for a discussion on the topic.

within this segment in unclear. The sequence of response-types in the horizontal axis of Figure 3 could be $\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}$ or $\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{fc}$. While both sequences are compatible with the unordered monotonicity condition of choice t_l, only sequence $\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}$ is compatible with the unordered montotonicity of the remaining choices.[38] Thus the probability in the u-axis that sets the boundary between $\boldsymbol{s}_{fc}$ and $\boldsymbol{s}_{pm}$ is $p^* = P(\boldsymbol{S} \in \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{fc}\})$. Figure 4 summarises these results graphically.

Figure 4: Disentangling $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$ into $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ and $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm})$



$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ is given by integration of $E(Y(t_l)|U_{t_l} = u)$ over $[P_{t_l}(z_8), p^*]$, and $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm})$ by integration over $[p^*, P_{t_l}(z_e)]$, where $P_{t_l}(z_8), P_{t_l}(z_e)$ identify $P(\boldsymbol{S} = \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}\}), P(\boldsymbol{S} = \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{fc}, \boldsymbol{s}_8\})$ and p^* is given by $P(\boldsymbol{S} = \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{fc}\})$.

Setting $Y = 1$ in (24) yields $P_{t_l}(z_8) = P(\boldsymbol{S} \in \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}\})$, thus the probability p^* can be expressed as $p^* = P_{t_l}(z_8) + P(\boldsymbol{S} = \boldsymbol{s}_{fc})$, and we can decompose $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$ in (42) as:

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc}) = \frac{\int_{P_{t_l}(z_8)}^{P_{t_l}(z_8)+P(\boldsymbol{S}=\boldsymbol{s}_{fc})} E(Y(t_l)|U_{t_l} = u)du}{P(\boldsymbol{S} = \boldsymbol{s}_{fc})} \tag{43}$$

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm}) = \frac{\int_{P_{t_l}(z_8)+P(\boldsymbol{S}=\boldsymbol{s}_{fc})}^{P_{t_l}(z_e)} E(Y(t_l)|U_{t_l} = u)du}{P_{t_l}(z_e) - P_{t_l}(z_8) - P(\boldsymbol{S} = \boldsymbol{s}_{fc})}. \tag{44}$$

Probability $P(\boldsymbol{S} = \boldsymbol{s}_{fc})$ is identified by using the propensity scores of t_h and t_m : $P(\boldsymbol{S} = \boldsymbol{s}_{fc}) = (P_{t_h}(z_8) - P_{t_h}(z_e)) - (P_{t_m}(z_c) - P_{t_m}(z_8))$. Appendix E shows that similar solutions apply to the problems of decomposing $E(Y(t_m)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\})$ and $E(Y(t_h)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\})$.

Estimation

Counterfactual outcomes can be estimated by nonparametric propensity score estimators[39] that exploit the variation of baseline variables $\boldsymbol{X}$. Let $P_t(z, \boldsymbol{x}) = P(T = t|Z =$

[38] Appendix E shows that the sequence $\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{fc}$ violates unordered monotonicity for choice t_m.
[39] See, for instance, Frölich (2007).

$z, \boldsymbol{X} = \boldsymbol{x})$ be the conditional propensity score given baseline variables $\boldsymbol{X} = \boldsymbol{x}$ for $(t, z) \in \{t_h, t_m, t_l\} \times \{z_c, z_8, z_e\}$ and the conditional expectation of interaction YD_t be $M_t(p, \boldsymbol{x}) = E(Y \cdot D_t | P_t = p, \boldsymbol{X} = \boldsymbol{x})$. The counterfactual outcome $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ in (43) can be identified as:

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc}) = \frac{\int \big(M_{t_l}(P_{t_l}(z_8, \boldsymbol{x}) + P_{fc}(\boldsymbol{x}), \boldsymbol{X} = \boldsymbol{x}) - M_{t_l}(P_{t_l}(z_8, \boldsymbol{x}), \boldsymbol{X} = \boldsymbol{x})\big) dF_{\boldsymbol{X}}(\boldsymbol{x})}{\int P_{fc}(\boldsymbol{x}) dF_{\boldsymbol{X}}(\boldsymbol{x})}, \quad (45)$$

$$\text{where } P_{fc}(\boldsymbol{x}) = \big(P_{t_h}(z_8, \boldsymbol{x}) - P_{t_h}(z_e, \boldsymbol{x})\big) - \big(P_{t_m}(z_c, \boldsymbol{x}) - P_{t_m}(z_8, \boldsymbol{x})\big). \quad (46)$$

$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ can be evaluated by the empirical counterpart of (45) as described in Section 6. Appendix F describes the propensity score estimator in greater detail. Appendix G explains how the propensity score estimator relates to the TSLS of Table 6.

The Role of Incentives

Identification depends crucially on the pattern of incentives in the MTO intervention. Section 4 develops a general algorithm that uses revealed preferences to convert incentives into response matrices. It enables us to examine small departures from the MTO incentive matrix $\boldsymbol{L}$ in 15. Incentives described by the identity matrix $\boldsymbol{L}_1$ in (64) generate a response matrix that contains *ten* response-types while the response matrix associated to $\boldsymbol{L}_2$ contains *six* response-types. Response-type probabilities are *not* point identified in either case. On the other hand, $\boldsymbol{L}_3$ in (64) generates *five* response-types that point-identify response-type probabilities.

$$\boldsymbol{L}_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \boldsymbol{L}_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}, \boldsymbol{L}_3 = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}. \quad (47)$$

My identification in MTO is more general than it might appear. It applies to all interventions that have *monotonic incentives* (Pinto, 2016), the case in which changes of the instrumental variable weakly increase incentives for *all choices*. In MTO, we have that $\boldsymbol{L}[z_c, t] \leq \boldsymbol{L}[z_e, t] \leq \boldsymbol{L}[z_8, t]$ for all $t \in \{t_h, t_m, t_l\}$. Identification results also hold if a constant is added to any column or row of the incentive matrix. For example, the first column of the incentive matrix (15) denotes the baseline incentive to remain in a high-poverty neighborhood t_h. Changing this incentive level to either -1, 0.5 or 2 generates the same identification results.

6 Causal Analysis of MTO Data

This section applies the response-type machinery developed in this paper to estimate neighborhood effects. I first estimate the response-type probabilities and the baseline variable means conditional on response-types. I then estimate counterfactual outcome means and neighborhood effects. Finally, I unravel TOT estimates into neighborhood effects.

All estimates use the adult weights in Orr et al. (2003). Let $\boldsymbol{X}$ denote the baseline variables of Table 1 and $\boldsymbol{K}$ denote site fixed effects. $\boldsymbol{X}, \boldsymbol{K}$ are normalized so that they have weighted averages of zero and standard deviations of one. The inference is based on a stratified bootstrap method that ressamples the full data set by using the MTO weights.[40] $\boldsymbol{X}_i, \boldsymbol{K}_i, Y_i, Z_i$ denote the values of variables for family i; $D_{t,i} = \mathbf{1}[T_i = t]$ indicates if family i chooses neighborhood $t \in \{t_h, t_m, t_l\}$.

Estimating Response-types

The relationship between response-type probabilities and propensity scores is given by equation (12) when Y is set to 1. Namely, $\boldsymbol{P}_Z(t) = \boldsymbol{B}_t \boldsymbol{P}_S$, where $\boldsymbol{B}_t = \mathbf{1}[\boldsymbol{R} = t]$ is the 3×7 binary matrix that indicates the elements in $\boldsymbol{R}$ that are equal to $t \in \{t_h, t_m, t_l\}$. These matrices are used to estimate response-type probabilities. Let $\boldsymbol{B}_{t,i} \equiv \boldsymbol{B}_t[Z_i, \cdot]$ denote the row of matrix $\boldsymbol{B}_t$ associated with instrumental value Z_i assigned to family i. Response-type probabilities are estimated by the parameter $\boldsymbol{\beta}_P$ in the following linear probability model:[41]

$$D_{t,i} = \boldsymbol{B}_{t,i}\boldsymbol{\beta}_P + \boldsymbol{X}_i\boldsymbol{\theta}_t + \boldsymbol{K}_i\boldsymbol{\gamma}_t + \epsilon_{t,i} \text{ across all } t \in \{t_l, t_m, t_h\}. \tag{48}$$

Figure 5 presents the estimates of the response-type probabilities. More than 40% of the sample consists of always-takers, $P(\boldsymbol{S} \in \{\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}, \boldsymbol{s}_{al}\}) = 0.43$. These families do not change their neighborhood choice regardless of the voucher assignment. In particular, a third of the families always remain in a high-poverty neighborhood, $P(\boldsymbol{S} = \boldsymbol{s}_{ah}) = 0.35$. Another third of the sample consists of full-compliers, $P(\boldsymbol{S} = \boldsymbol{s}_{fc}) = 0.31$. These families choose high, medium and low-poverty neighborhoods if assigned to z_c, z_8, and z_e respectively. Partial compliers $\boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{ph}$ account for almost a quarter (24.1%) of the total sample.

Replacing Y by X in equation (12) identifies the mean of baseline variables X conditioned on response-types. These are estimated by replacing the dependent variable $D_{t,i}$ in (48) by the interaction $X_i D_{t,i}$, which leads to equation (49). Parameter $\boldsymbol{\beta}_X$ estimates the vector $E(X|\boldsymbol{S} = \boldsymbol{s})P(\boldsymbol{S} = \boldsymbol{s})$ across $\boldsymbol{s}$. Estimates for $E(X|\boldsymbol{S} = \boldsymbol{s})$ are obtained by dividing $\boldsymbol{\beta}_X$ by the estimates of response-type probabilities $P(\boldsymbol{S} = \boldsymbol{s})$.[42] See Appendix D for further discussion on the identified parameters.

$$X_i \cdot D_{t,i} = \boldsymbol{B}_{t,i}\boldsymbol{\beta}_X + \boldsymbol{K}_i\boldsymbol{\theta}_t + \epsilon_{t,i} \text{ across all } t \in \{t_l, t_m, t_h\}. \tag{49}$$

Table 8 displays the estimates for the expected values of the baseline variables conditioned on response-types. It shows a sharp contrast in baseline means between high-poverty always-takers $\boldsymbol{s}_{ah}$ and full compliers $\boldsymbol{s}_{fc}$. Families of type $\boldsymbol{s}_{ah}$ are more likely to have disabled persons and teenagers among household members. On the other hand, $\boldsymbol{s}_{fc}$-families are less likely to have teenagers and household heads are less likely to be married, suggesting lower mobility constraints.

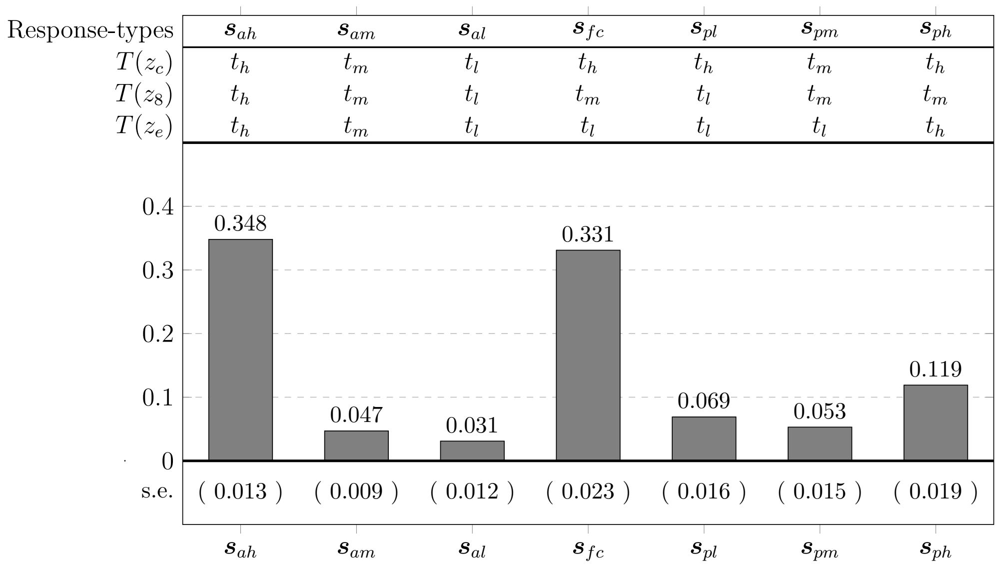
Families of type s_{ah} are less likely to be victims of a crime in the neighborhood. These families show the lowest level of neighborhood dissatisfaction and are more likely to perceive their neighborhood as safe. Families of type $\boldsymbol{s}_{fc}$, who are more responsive to voucher in-

[40] See Davison and Hinkley (1997). The inference method is robust to heteroscedasticity and site clustered errors.

[41] Regression (48) can be understood as the empirical counterpart of the equation $\boldsymbol{P}_Z(t) = \boldsymbol{B}_t \boldsymbol{P}_S$ for $t = t_h, t_m, t_l$. This method is only valid when all response-type probabilities are identified, which occurs if and only if the stacked matrices $[\boldsymbol{B}'_{t_h}; \boldsymbol{B}'_{t_m}; \boldsymbol{B}'_{t_l}]'$ have full column-rank.

[42] Response-type probabilities are estimated by $\boldsymbol{\beta}_P$ in the regression $D_{t,i} = \boldsymbol{B}_{t,i}\boldsymbol{\beta}_P + \boldsymbol{K}_i\boldsymbol{\gamma}_t + \epsilon_{t,i}$ across all $t \in \{t_l, t_m, t_h\}$.

Figure 5: Response-type Probabilities



The figure lists the counterfactual choices of each response-types and their estimated probabilities. Estimates account for the person-level weight for adult survey of the interim analyses as described in the MTO Interim Impacts Evaluation manual, 2003, Appendix B. Standard errors are computed using bootstrap.

centives, show higher levels neighborhood dissatisfaction and are more likely to perceive the neighborhood as unsafe.

Families of type $\boldsymbol{s}_{ah}$ have the lowest level of schooling among all response types. These families are also less likely to have a car. On the other hand, $\boldsymbol{s}_{al}$-families, the low-poverty always-takers, have the highest level of schooling, the highest probability of having a car and the lowest level of welfare usage. $\boldsymbol{s}_{al}$-families are also more likely to have been victimized and show highest level of neighborhood dissatisfaction. These families constitute a small fraction of the sample, which explains the high standard error of the estimates.

MTO incentives are not sufficient to incite the relocation of high-poverty always-takers $\boldsymbol{s}_{ah}$, who constitute a third of the families targeted by the experiment. Data suggests that these families face higher mobility constraints and are less disturbed by neighborhood criminality. Unfortunately, these are also the most disadvantaged families and could potentially benefit the most from relocating. We observe strong positive selection on baseline variables. Families that always move to low-poverty neighborhoods $\boldsymbol{s}_{al}$ are, on average, the most privileged families in the sample. Data also shows that family characteristics play an important role in determining which families are more likely to respond to relocation incentives.

Counterfactual Mean Outcomes

I use equation (45) to estimate the counterfactual outcome means. I do so in three steps: (1) estimate the propensity score $P_{t,i}(z) \equiv P(T = t|Z = z, \boldsymbol{X} = \boldsymbol{X}_i, \boldsymbol{K} = \boldsymbol{K}_i)$ for choice $t \in \{t_h, t_l, t_m\}$ given $z \in \{z_c, z_8, z_e\}$ conditioned on baseline characteristics of family i; (2) estimate the expected value of the interaction YD_t as a function of the propensity

Table 8: Pre-program Variables Means by Response-types

	Variable Mean	Always-takers			Compliers			
		s_{ah}	s_{am}	s_{al}	s_{fc}	s_{pl}	s_{pm}	s_{ph}
Disabled Household Member	0.16	**0.20**	0.09	0.12	0.12	0.17	0.23	0.16
(s.d.)	0.01	0.02	0.06	0.12	0.02	0.07	0.10	0.06
p-value		**0.02**	0.27	0.75	0.08	0.87	0.47	0.96
No teens (ages 13-17) at baseline	0.61	**0.55**	0.76	0.58	**0.72**	0.57	0.40	0.55
(s.d.)	0.01	0.02	0.08	0.18	0.03	0.10	0.14	0.08
p-value		**0.00**	0.06	0.83	**0.00**	0.66	0.12	0.43
Never married	0.62	0.61	0.66	0.49	**0.68**	0.64	0.59	0.48
(s.d.)	0.01	0.02	0.08	0.18	0.03	0.10	0.13	0.08
p-value		0.56	0.57	0.43	**0.02**	0.79	0.84	0.08
Victim last 6 months	0.42	0.38	0.39	0.54	0.43	0.45	0.50	0.41
(s.d.)	0.01	0.02	0.08	0.18	0.03	0.10	0.13	0.08
p-value		0.07	0.71	0.49	0.62	0.74	0.50	0.90
Unsafe at night	0.50	**0.43**	0.57	0.31	**0.55**	0.52	0.53	0.51
(s.d.)	0.01	0.02	0.08	0.18	0.03	0.10	0.14	0.08
p-value		**0.00**	0.35	0.27	**0.04**	0.76	0.80	0.85
Neighborhood Dissatisfaction	0.47	**0.39**	0.53	0.70	**0.54**	0.44	0.49	0.41
(s.d.)	0.01	0.02	0.08	0.18	0.03	0.10	0.13	0.08
p-value		**0.00**	0.41	0.20	**0.01**	0.77	0.84	0.46
Car Owner	0.16	**0.13**	0.15	0.36	0.17	0.22	0.14	0.18
(s.d.)	0.01	0.01	0.06	0.14	0.02	0.08	0.10	0.06
p-value		**0.01**	0.81	0.15	0.67	0.44	0.77	0.73
Completed High School or Has a GED	0.56	**0.51**	0.59	0.69	0.57	0.62	0.60	0.61
(s.d.)	0.01	0.02	0.08	0.18	0.03	0.10	0.13	0.08
p-value		**0.01**	0.76	0.44	0.84	0.56	0.74	0.51
AFDC/TANF Recepient	0.75	0.71	0.67	0.56	0.78	0.82	0.78	0.77
(s.d.)	0.01	0.02	0.08	0.16	0.03	0.09	0.12	0.07
p-value		0.07	0.30	0.23	0.22	0.45	0.78	0.74

The first column lists pre-program variables surveyed at the intervention onset. The second column presents the unconditional variable mean across all response-types. The remaining seven columns present the variable mean conditioned on response-types. The table presents the variable mean conditioned on the response-type, its standard error and the p-value that tests the null hypothesis that the baseline mean conditional on the response-type is equal to the unconditional baseline mean. Bold values statistically differ from the unconditional mean at significant level of 5%. All estimates are conditioned on the site of intervention and account for the person-level weight for adult survey of the interim analyses (Interim Impacts Evaluation manual, 2003, Appendix B). The sample size is 4227.

scores P_t for choice t conditional on baseline characteristics of family i, that is, $M_{t,i}(p) = E(YD_t|P_t = p, \boldsymbol{X} = \boldsymbol{X}_i, \boldsymbol{K} = \boldsymbol{K}_i)$; and (3) estimate the counterfactual outcome mean $E(Y(t)|\boldsymbol{S} = \boldsymbol{s})$ corresponding to the propensity scores interval $[P_t, P'_t]$ by the mean difference $M_{t,i}(P_{t,i}) - M_{t,i}(P'_{t,i})$ divided by the mean difference of propensity scores $P_{t,i} - P'_{t,i}$ across families i.

Propensity scores are estimated by the linear probability model (50), which uses the interaction between IV values and baseline characteristics:

$$D_{t,i} = \sum_{z\in\{z_c,z_8,z_e\}} \mathbf{1}[Z_i = z] \cdot \Big(\alpha_{t,z} + \boldsymbol{X}_i\boldsymbol{\theta}_{t,z} + \boldsymbol{K}_i\gamma_{t,z}\Big) + \epsilon_{t,i}; t \in \{t_l, t_m, t_h\}. \tag{50}$$

Equation (50) is used to estimate propensity scores. It differs from equation (48), whose parameter $\boldsymbol{\beta}$ estimates the response-type probabilities.

Estimated propensity scores are $\hat{P}_{t,i}(z) = \hat{\alpha}_{t,z} + \boldsymbol{X}_i\hat{\boldsymbol{\theta}}_{t,z} + \boldsymbol{K}_i\hat{\boldsymbol{\gamma}}_{t,z}$.[43] The full complier probability of equation (46) for family i is $\hat{P}_i(\boldsymbol{s}_{fc}) = \Big(\hat{P}_{t_h,i}(z_8) - \hat{P}_{t_h,i}(z_e)\Big) - \Big(\hat{P}_{t_m,i}(z_c) - \hat{P}_{t_m,i}(z_8)\Big)$. Let $\hat{P}_{t,i} \equiv \hat{P}_{t,i}(Z_i)$ be the propensity score estimate corresponding to the voucher assigned to family i. Outcome equation (51) evaluates YD_t as a local polynomial of propensity score estimates:

$$Y_i \cdot D_{t,i} \;=\; \sum_{k=0}^{3} \alpha_k \cdot \big(\hat{P}_{t,i}\big)^k + \Big(\hat{P}_{t,i} \cdot \boldsymbol{K}_i\Big)\boldsymbol{\xi}_t + \Big(\hat{P}_{t,i} \cdot \boldsymbol{X}_i\Big)\boldsymbol{\psi}_t + \boldsymbol{K}_i\boldsymbol{\gamma}_t + \boldsymbol{X}_i\boldsymbol{\theta}_t + \epsilon_{t,i} \tag{51}$$

$M_{t,i}(p)$ is estimated by $\hat{M}_{t,i}(p) = \sum_{k=0}^{3} \hat{\alpha}_k \cdot p^k + p(\boldsymbol{K}_i\hat{\boldsymbol{\xi}}_t + \boldsymbol{X}_i\hat{\boldsymbol{\psi}}_t) + \boldsymbol{K}_i\hat{\boldsymbol{\gamma}}_t + \boldsymbol{X}_i\hat{\boldsymbol{\theta}}_t$. The counterfactual outcome $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ in equation (43) corresponds to the propensity score interval $[P_{t_l}(z_8), P_{t_l}(z_8) + P(\boldsymbol{s}_{fc})]$ and is estimated by the empirical counterpart of equation (45):

$$\hat{E}(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc}) = \frac{\sum_i \Big(\hat{M}_{t_l,i}\big(\hat{P}_{t_l,i}(z_8) + \hat{P}_i(\boldsymbol{s}_{fc})\big) - \hat{M}_{t_l,i}\big(\hat{P}_{t_l,i}(z_8)\big)\Big) \cdot W_i}{\sum_i \hat{P}_i(\boldsymbol{s}_{fc}) \cdot W_i} \tag{52}$$

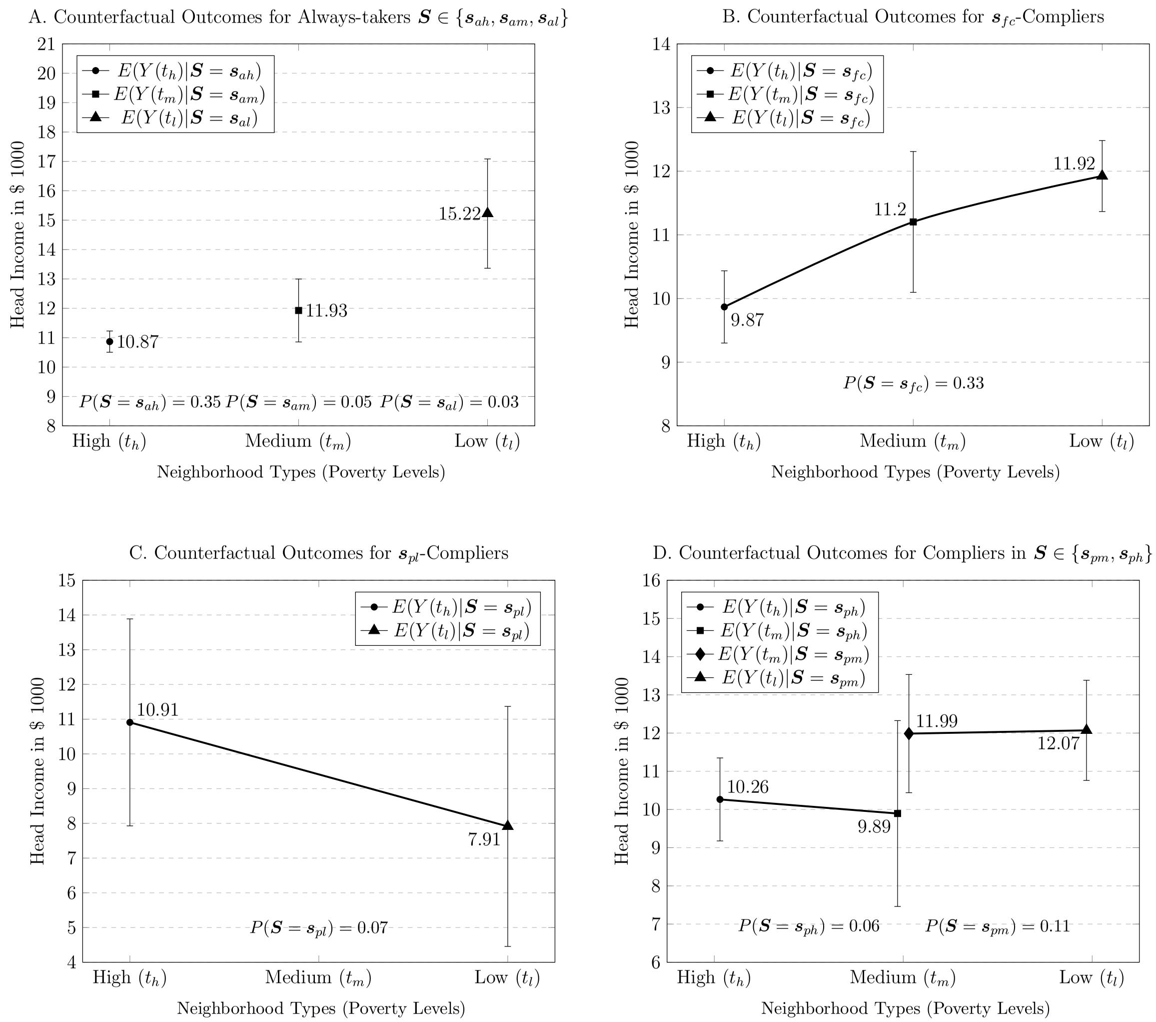
where W_i denotes the MTO weights. Each counterfactual outcome mean is estimated by evaluating equation (52) at the corresponding propensity score interval.

Figure 6 displays the estimated counterfactual outcome means for the income of the head of the family. Graph A shows the counterfactual income estimates for the always-takers. Estimates increase as the neighborhood choice ranges across high, median and low-poverty. Income differences across response-types are not causal as family characteristics differ.

The lowest mean income belongs to the families that always choose high-poverty neighborhoods ($\boldsymbol{s}_{ah}$), which are also the most disadvantaged. The precision of the estimates, displayed by error bars, is inversely proportional to sample share of each of the response-type. Graph B displays the estimates for full-compliers $\boldsymbol{s}_{fc}$. It shows a steep increase in income as families move to better neighborhoods. The income difference across neighborhood types constitutes a causal effect as we control for unobserved characteristics of the

[43] The fact that baseline variables $\boldsymbol{X}, \boldsymbol{K}$ are standardized to have mean zero assures that the estimates for propensity scores $\hat{P}_{t,i}(z_c), \hat{P}_{t,i}(z_8), \hat{P}_{t,i}(z_e)$ sum to one for each family i. The linear probability model does not impose positive probabilities. Appendix H evaluates the propensity scores using the multinomial logistic regression. The empirical results using the logistic model are closely related to the ones presented in this section.

Figure 6: Counterfactual Outcome Estimates for Income of the Head of the Family



This figure displays the estimates of the counterfactual outcomes for income of the head of the family. Graph A displays the counterfactual outcome estimates for always-takers $(\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}, \boldsymbol{s}_{al})$; Graph B examines response-type $\boldsymbol{s}_{fc}$; Graph C investigates type $\boldsymbol{s}_{pl}$, and Graph D presents results for response-types $\boldsymbol{s}_{pm}$ and $\boldsymbol{s}_{ph}$. Estimations are conditional on site and baseline variables. All estimates account for the person-level weight for adult survey of the interim analyses as described in the MTO Interim Impacts Evaluation manual, 2003, Appendix B. Error bars denote the standard error associated with each estimate.

families.

Graph C of Figure 6 shows the mean income of $\boldsymbol{s}_{pl}$-families while Graph D examines families of type $\boldsymbol{s}_{pm}$ and $\boldsymbol{s}_{ph}$. These families account for a small share of the sample and estimates lack statistical precision. As a consequence, the differences of income estimates between neighborhood-types are not statistically significant.

Table 9 presents estimates of counterfactual means for the economic outcomes described in Section 2. Greater values of the counterfactual means denote a desirable result for all outcomes except for currently on welfare.

We observed a common pattern among always-takers $\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}$ and $\boldsymbol{s}_{al}$. Counterfactual outcomes improve as the neighborhood types change from high to medium and from medium to low-poverty. A similar pattern is observed for full-compliers $\boldsymbol{s}_{fc}$. $\boldsymbol{s}_{fc}$-families are better off in low-poverty neighborhoods than high-poverty neighborhoods across all outcomes. The estimates for partial-compliers ($\boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{ph}$) have large standard errors due to their small sample shares. As expected, the comparisons between these counterfactual means is less informative.

The last row of Table 9 displays the poverty levels means across response-types and neighborhood types. The difference in poverty levels between medium and high poverty always-takers ($\boldsymbol{s}_{am}$ and $\boldsymbol{s}_{ah}$) is below four percentage points, while the difference between low-poverty and medium poverty always-takers ($\boldsymbol{s}_{al}$ and $\boldsymbol{s}_{am}$) is above 30 percentage points. Counterfactual estimates agree with this pattern. The difference of counterfactual means between $\boldsymbol{s}_{am}$ and $\boldsymbol{s}_{ah}$ is less pronounced than the difference between $\boldsymbol{s}_{al}$ and $\boldsymbol{s}_{am}$.

The difference of poverty levels between neighborhood types for full compliers $\boldsymbol{s}_{fc}$ is larger than the corresponding difference for partial compliers. The difference between t_l and t_h for $\boldsymbol{s}_{fc}$ is 33.25 percentage points; the analogous difference for $\boldsymbol{s}_{pl}$ is 26.37. The difference between t_l and t_m for $\boldsymbol{s}_{fc}$ is 20.39, while the difference for $\boldsymbol{s}_{pm}$ is 18.00. Lastly, the difference between t_m and t_h for $\boldsymbol{s}_{fc}$ is 12.87, while the difference for $\boldsymbol{s}_{ph}$ is 7.88. Thus, there are two reasons to expect most significant effects when comparing low versus high-poverty neighborhoods for full-compliers. Full-compliers have the largest sample share among all compliers and the low versus high comparison for $\boldsymbol{s}_{fc}$ corresponds to the largest average difference in neighborhood poverty levels.

Causal Effects for Full Compliers $\boldsymbol{s}_{fc}$

Table 10 displays the causal effects of neighborhood types on economic outcomes for full-compliers $\boldsymbol{s}_{fc}$. Most of the neighborhood effects for low versus high-poverty neighborhoods are statistically significant. None of the remaining effects that compare low versus median or median versus low-poverty neighborhoods is significant at a 5% level. The last row of the table evaluates neighborhood poverty levels.

The first three outcomes in Table 10 investigate family income. Full-compliers who move from high to low-poverty neighborhoods experience an average additional annual income of the head of \$ 2056, which corresponds to a 20% increase. The estimated neighborhood effect on the total income of the family is \$ 1902 per year, which accounts for a 14% increase in the household income. Both results are statistically and economically significant.

Table 9: Counterfactual Mean Outcomes

	Always-takers			**Full Complier**			**Partial Compliers**					
Response-types	$\boldsymbol{s}_{ah}$	$\boldsymbol{s}_{am}$	$\boldsymbol{s}_{al}$	$\boldsymbol{s}_{fc}$			$\boldsymbol{s}_{pl}$		$\boldsymbol{s}_{pm}$		$\boldsymbol{s}_{ph}$	
Choices	t_h	t_m	t_l	t_h	t_m	t_l	t_h	t_l	t_m	t_l	t_h	t_m
Income of Family Head	10.867	11.927	15.244	9.868	11.203	11.924	10.908	7.912	11.986	12.071	10.263	9.894
(s.e.)	0.362	1.071	1.860	0.567	1.060	0.558	2.980	3.465	1.574	1.311	1.086	2.433
Income of Head and Spouse	11.779	12.802	16.213	11.533	11.062	12.411	14.962	9.594	12.986	12.127	11.389	12.222
(s.e.)	0.392	1.091	1.840	0.655	1.185	0.501	3.536	2.346	1.918	1.462	1.236	2.693
Total household income	14.474	15.474	17.541	12.844	12.296	14.747	17.925	10.396	13.320	13.186	13.000	14.796
(s.e.)	0.436	1.211	1.960	0.698	1.167	0.548	3.807	2.645	2.349	1.707	1.412	2.893
Above Poverty Line	0.285	0.345	0.578	0.239	0.303	0.347	0.308	0.105	0.403	0.294	0.285	0.138
(s.e.)	0.019	0.063	0.095	0.031	0.059	0.027	0.160	0.164	0.105	0.087	0.055	0.142
Employed without welfare	0.473	0.501	0.601	0.414	0.392	0.527	0.545	0.417	0.446	0.306	0.431	0.529
(s.e.)	0.024	0.071	0.110	0.035	0.067	0.031	0.184	0.152	0.121	0.108	0.075	0.187
Currently on welfare	0.227	0.216	0.111	0.351	0.256	0.229	0.431	0.309	0.340	0.515	0.275	0.344
(s.e.)	0.020	0.058	0.086	0.033	0.060	0.027	0.155	0.127	0.114	0.099	0.067	0.154
Job tenure	0.373	0.428	0.494	0.343	0.324	0.431	0.289	0.224	0.348	0.315	0.420	0.527
(s.e.)	0.022	0.067	0.093	0.033	0.066	0.032	0.174	0.182	0.131	0.085	0.069	0.160
Economic self-sufficiency	0.187	0.186	0.306	0.155	0.235	0.220	0.292	0.092	0.162	0.163	0.142	0.153
(s.e.)	0.017	0.051	0.082	0.025	0.052	0.023	0.122	0.117	0.091	0.071	0.045	0.115
Neighborhood Poverty	40.582	37.058	5.647	39.948	27.078	6.692	35.240	8.865	27.973	9.971	43.739	35.857
(s.e.)	0.722	1.818	0.783	0.973	1.767	0.354	5.848	1.061	3.833	1.024	2.378	6.100

The first column lists pre-program variables surveyed at the intervention onset. The second column presents the unconditional variable mean across all response-types. The remaining seven columns present the variable mean conditioned on response-types. The first line displays the estimated variable mean conditioned on the response-type. The second line gives its standard deviation and the third line gives the p-value that tests the null hypothesis that the conditional mean is equal to the unconditional one. All estimates are conditioned on the site of intervention and account for the person-level weight for adult survey of the interim analyses (Interim Impacts Evaluation manual, 2003, Appendix B). The p-values are associated with the double-tailed inference that tests if the estimates are equal to zero. Asterisks indicate the typical p-value thresholds: *** for p-value < 0.01, ** for $0.01 \leq p$-value < 0.05, * for $0.05 \leq p$-value < 0.1.

Table 10 shows that switching from high to low-poverty neighborhoods increases the likelihood that a family is above the poverty line by about 50%. It increases the likelihood of being employed by 27% and reduces welfare dependency by 34%. Neighborhood effects on job tenure and economic sufficiency are positive but significant only at the 10% threshold. The estimated neighborhood effect on job tenure is 0.088, which corresponds to an average increase of 25% of the high-poverty baseline. The estimate for economic self-sufficiency is 0.065, which corresponds to an increase of 40%.

The last row of Table 10 presents the mean difference in poverty levels between the neighborhood types. As expected, the largest difference occurs when comparing low versus high-poverty neighborhood. The differences for the remaining comparisons are statistically significant, but substantially lower. Not surprisingly, neighborhood effects that compare low versus high-poverty neighborhoods are often statistically significant, while the remaining effects are not.

Decomposing TOT Effects

Kling et al. (2007, 2005) show that the TOT parameter (37) that compares the experimental z_e versus control z_c vouchers can be evaluated by a Two-Stage Least Square (TSLS) regression that uses the experimental voucher as the instrumental variable for the voucher take-up.

Equation (38) shows that the TOT parameter can be expressed as a mixture of three neighborhood effects. The main effect, $E(Y(t_l) - Y(t_h)|\boldsymbol{s}_{fc})$, compares the low versus high-poverty neighborhood for full compliers, who are the most responsive families to MTO incentives. The remaining effects, $E(Y(t_l) - Y(t_h)|\boldsymbol{s}_{pl})$ and $E(Y(t_l) - Y(t_m)|\boldsymbol{s}_{pm})$, refer to response-types associated with small sample shares.

Table 11 presents the TOT estimates based on a TSLS regression and on the mixture of the neighborhood effects in (38). The second column of Table 11 presents the estimates of $\mathbf{TOT}(z_e, z_c)$ using TSLS regressions. The third column of the table presents the TOT estimates using the mixture of the neighborhood effects presented in columns 4–6. Although the estimation methods differ substantially, the TOT estimates are very close.

The last row of Table 11 presents the average difference of neighborhood poverty associated with each causal parameter. Both TOT estimates are associated with a decrease in neighborhood poverty of 28 percentage points. As mentioned, the decrease in neighborhood poverty for the causal effect $E(Y(t_l) - Y(t_h)|\boldsymbol{s}_{fc})$ is about 33 percentage points. The estimated value of this causal effect is bigger than the $\mathbf{TOT}(z_e, z_c)$ estimates in each of the outcomes. The neighborhood effect $E(Y(t_l) - Y(t_h)|\boldsymbol{s}_{pl})$ corresponds to a decrease in neighborhood poverty of 26 percentage points. The estimates for this causal effect are quite imprecise as the share of $\boldsymbol{s}_{pl}$-families in the sample is small. The neighborhood effect $E(Y(t_l) - Y(t_m)|\boldsymbol{s}_{pm})$ compares low versus medium-poverty neighborhood types. The effect corresponds to the smallest decrease in neighborhood poverty of 18 percentage points. The share of $\boldsymbol{s}_{pm}$ is also small compared to full-compliers $\boldsymbol{s}_{fc}$. As a consequence, none of the estimates are statistically significant.

Appendix H presents additional evaluations that check the robustness of these findings under various modifications of the baseline model. Estimates across a variety of model perturbations are very close to those presented in Tables 9–11.

Table 10: Causal Effects for Full-Compliers

	$E(Y(t_l) - Y(t_h)\|\boldsymbol{s}_{fc})$		$E(Y(t_l) - Y(t_m)\|\boldsymbol{s}_{fc})$		$E(Y(t_m) - Y(t_h)\|\boldsymbol{s}_{fc})$	
Income of Family Head	2.056	***	0.721		1.334	
(s.e.)	0.810		1.232		1.184	
(p-value)	0.007		0.552		0.257	
Income of Head and Spouse	0.878		1.349		−0.471	
(s.e.)	0.854		1.265		1.359	
(p-value)	0.322		0.318		0.752	
Total household income	1.902	**	2.451	*	−0.549	
(s.e.)	0.900		1.272		1.329	
(p-value)	0.047		0.073		0.698	
Above Poverty Line	0.108	***	0.044		0.064	
(s.e.)	0.041		0.065		0.067	
(p-value)	0.010		0.490		0.342	
Employed without welfare	0.113	**	0.135	*	−0.022	
(s.e.)	0.045		0.073		0.074	
(p-value)	0.017		0.095		0.763	
Currently on welfare	−0.121	***	−0.026		−0.095	
(s.e.)	0.043		0.067		0.068	
(p-value)	0.005		0.683		0.160	
Job tenure	0.088	*	0.107		−0.019	
(s.e.)	0.047		0.073		0.074	
(p-value)	0.063		0.175		0.803	
Economic self-sufficiency	0.065	*	−0.015		0.080	
(s.e.)	0.033		0.060		0.057	
(p-value)	0.057		0.777		0.167	
Neighborhood Poverty	−33.256	***	−20.387	***	−12.869	***
(s.e.)	1.008		1.808		1.955	
(p-value)	0.000		0.000		0.000	

This table evaluates the neighborhood effects for full compliers $\boldsymbol{s}_{fc}$ across several outcomes. The first column lists the outcome variables. The second column evaluates the causal effect between the neighborhood types of low and high-poverty. The third column compares low versus medium-poverty neighborhoods and the last column evaluates the neighborhood effects between medium versus high-poverty types. The results are based on a semi-parametric method that evaluates propensity scores and response-type probabilities using a linear probability model. All estimates are conditioned on the site of intervention and account for the person-level weight for adult survey of the interim analyses (Interim Impacts Evaluation manual, 2003, Appendix B). Inference is obtained by a bootstrap method that employs a weighted sampling scheme. The p-values are associated with the double-tailed inference that tests if the estimates are equal to zero. Asterisks indicate the typical p-value thresholds: *** for p-value < 0.01, ** for $0.01 \leq p$-value < 0.05, * for $0.05 \leq p$-value < 0.1.

7 Summary and Conclusions

MTO is a housing experiment designed to investigate the economic consequences of relocating low-income families living in high-poverty neighborhoods to low-poverty areas. The experiment offered vouchers that subsidised rent for families who agreed to move. About half of the families did not use the vouchers. Noncompliance generates the problem of selection bias which, complicates identification of neighborhood effects. The raw experimental data identifies the treatment-on-the-treated (TOT) effects, but not the causal effects of neighborhood types. The previous literature that reported TOT parameters found little or no effect on labor market outcomes.

This paper goes beyond estimating the impact of offering vouchers on participant outcomes to estimate the effect of actually moving from one type of neighborhood to another. In doing so, I model MTO using an choice model with categorical instruments (voucher assignments) and multiple choices (neighborhood types). I show that standard monotonicity conditions, such as those invoked in LATE, do not identify neighborhood effects. My solution exploits the information in MTO incentives; I use revealed preference analysis to translate MTO incentives into choice restrictions that subsume standard monotonicity conditions and secure the identification of neighborhood effects.

I show that TOT evaluates a mixture of neighborhood causal effects. The causal effects of switching from a medium to a low-poverty neighborhood on labor market outcomes are not statistically significant. This component of the mixture decreases the statistical significance of TOT estimates. On the other hand, most of the estimated neighborhood effects for full-compliers who move from high to low-poverty neighborhoods are statistically and economically significant. On average, these families experience: a 20% increase in the income of the head of the family; a 14% increase in household income; a 50% increase in the likelihood of the family income bing above the poverty line; a 27% increase in employment; and a 34% reduction in welfare dependency. These results help to reconcile MTO with an extensive literature claiming that neighborhood quality significantly influences the lives of its residents (Wilson, 2009).

This paper contributes to an emerging literature that employs revealed preference arguments to investigate policy parameters in an IV setting (Kline and Tartari, 2016; Kline and Walters, 2016; Manski, 2014). The methods described here can be broadly applied to exploit economic incentives in multiple-choice models with heterogeneous agents and categorical instrumental variables. A benefit of this framework is that noncompliance, usually perceived as an econometric problem, becomes a useful source of identifying information.[44]

[44]Seminal work on this topic by Heckman (1974) uses the information on female nonparticipation in the labor market combined with observed data on wages and labor supply to identify shadow wages and preferences towards leisure.

Table 11: Treatment on the treated decomposition

Outcomes	$TOT(z_e, z_c)$ TSLS		$TOT(z_e, z_c)$ Mixture		Neighborhood effects $E(Y(t_l) - Y(t_h)\|\boldsymbol{s}_{fc})$		$E(Y(t_l) - Y(t_h)\|\boldsymbol{s}_{pl})$		$E(Y(t_l) - Y(t_m)\|\boldsymbol{s}_{pm})$	
Income of Family Head	1.423	**	1.144	*	2.056	***	−2.996		0.086	
s.e. and p-value	0.685	0.038	0.669	0.080	0.810	0.007	4.585	0.407	2.032	0.967
Income of Head and Spouse	0.234		−0.080		0.878		−5.368		−0.860	
s.e. and p-value	0.762	0.759	0.772	0.915	0.854	0.322	4.158	0.165	2.311	0.702
Total household income	0.538		0.568		1.902	**	−7.529		−0.134	
s.e. and p-value	0.838	0.520	0.818	0.488	0.900	0.047	4.500	0.113	2.926	0.960
Above Poverty Line	0.034		0.040		0.108	***	−0.203		−0.109	
s.e. and p-value	0.038	0.376	0.035	0.260	0.041	0.010	0.230	0.338	0.132	0.390
Employed without welfare	0.069	*	0.050		0.113	**	−0.128		−0.140	
s.e. and p-value	0.041	0.092	0.041	0.227	0.045	0.017	0.227	0.573	0.172	0.407
Currently on welfare	−0.072	*	−0.074	*	−0.121	***	−0.122		0.175	
s.e. and p-value	0.037	0.053	0.039	0.060	0.043	0.005	0.197	0.522	0.150	0.233
Job tenure	0.079	*	0.051		0.088	*	−0.065		−0.033	
s.e. and p-value	0.041	0.054	0.041	0.202	0.047	0.063	0.247	0.750	0.154	0.825
Economic self-sufficiency	0.024		0.026		0.065	*	−0.200		0.001	
s.e. and p-value	0.032	0.451	0.029	0.365	0.033	0.057	0.172	0.223	0.114	0.993
Neighborhood Poverty	−28.601	***	−28.184	***	−33.256	***	−26.375	***	−18.003	***
s.e. and p-value	1.082	0.000	1.117	0.000	1.008	0.000	6.071	0.000	3.902	0.002

The first column lists the outcomes being examined. The second column estimates of TOT parameter $TOT(z_e, z_c)$ using the following TSLS regression:

$$\text{First Stage:} \quad C_i = \gamma_1 + \gamma_2 \cdot \mathbf{1}[Z_i = z_c] + \gamma_X \cdot \boldsymbol{X} + \gamma_K \cdot \boldsymbol{K} + \eta_i \text{ for } i\,;\ Z_i \in \{z_c, z_e\}, \tag{53}$$

$$\text{Second Stage:} \quad Y = \beta_0 + \beta_{\text{TOT}} \cdot \hat{C}_i + \beta_X \cdot \boldsymbol{X} + \beta_K \cdot \boldsymbol{K} + \epsilon_i \text{ for } i\,;\ Z_i \in \{z_c, z_e\}, \tag{54}$$

where C_i is a binary variable that indicates if family i uses the voucher and $\boldsymbol{X}$ denotes baseline variables listed in Table 1 and $\boldsymbol{K}$ are site fixed effects. The third column presents the $TOT(z_e, z_c)$ estimates according to equation (38), which employs the mixture of the neighborhood effects presented in columns 4–6. Propensity scores are generated by the linear probability model in (50). The neighborhood effects employ the estimates of the outcome equation (51), which regresses the interaction $Y_i \cdot D_t$ on a local polynomial of propensity scores, baseline variables $\boldsymbol{X}$, site effects $\boldsymbol{K}$ and their interaction with the propensity scores. All estimates are conditioned on the site of intervention and account for the person-level weight for adult survey of the interim analyses (Interim Impacts Evaluation manual, 2003, Appendix B). Inference is obtained by a bootstrap method that employs a weighted sampling scheme. The p-values are associated with the double-tailed inference that tests if the estimates are equal to zero. Asterisks indicate the typical p-value thresholds: *** for p-value < 0.01, ** for $0.01 \leq p$-value < 0.05, * for $0.05 \leq p$-value < 0.1.

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