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

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Abstract

Moving to Opportunity (MTO) is a primary housing experiment in the US. It offered housing vouchers that incentivized disadvantaged families to move from high-poverty neighborhoods to either low or medium-poverty neighborhoods. The intervention has suffered from significant noncompliance, making it difficult to determine the causal effect of relocating families from one type of neighborhood to another. Most of the MTO literature assesses noncompliance by reporting the Intention-to-treat (ITT) the causal effect of being offered a voucher and the treatment-on-the-treated (TOT) the ITT divided by the voucher take-up rate. Although these parameters successfully evaluate the experiment itself, it is unclear how they relate to the causal effect of residing in different neighborhood types. This paper exploits the choice incentives induced by the MTO experiment to go beyond the ITT/TOT analysis. Revealed preference analysis yields choice restrictions that identify the distribution of counterfactual choices and most of the counterfactual outcomes. An interpolation argument secures the point-identification of the causal effects across neighborhood types. This method enables novel analyses that enhance the understanding of the MTO intervention. It shows that the TOT parameters evaluate a mixture of neighborhood effects. Even though the overall TOT estimates of labor market outcomes are not significant, the TOT-components corresponding to neighborhood effects of families that are most responsive to the vouchers are statistically and economically significant. This result reconciles MTO with a growing literature on the importance of neighborhood quality in shaping the lives of its residents.

Keywords: Moving to Opportunity, Randomization, Social Experiment, Causal Effects, Identification, Revealed Preference Analysis.

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1 Introduction

Wilson's 1987 seminal book presents a compelling case that disadvantaged neighborhoods are a primary cause of inner-city poverty. The book spiked substantial research on neighborhood effects in the 90s (Sampson et al., 2002). Despite the abundance of observational studies, the empirical evidence on neighborhood effects remained elusive (Aliprantis, 2007). Most research dealt with the issue of residential sorting (Jencks and Mayer, 1990; Sampson, 2008) and are unlikely to produce definitive evidence on the efficacy of neighborhood effects (Durlauf, 2004). Some researchers argued that only a housing experiment could settle the inquiry over neighborhood effects (Tienda, 1991).

The Moving to Opportunity (MTO) is a housing experiment intended to provide a conclusive assessment regarding neighborhood effects (Ludwig et al., 2008; Sampson, 2008). MTO used the method of randomized controlled trials to investigate the causal effect of relocating disadvantaged families living in high-poverty neighborhoods to more affluent areas (Orr et al., 2003). It targeted over 4,200 low-income households living in high-poverty housing projects across five US cities from 1994 to 1997. Participating families were randomly assigned to one of three groups: *experimental*, *section 8*, or *control*. The *experimental* group received a voucher that subsidized rent in low poverty neighborhoods. The *section 8* group received a voucher that subsidized rent in either medium or low poverty neighborhoods; and the *control* group did not receive any voucher.

MTO did not compel families to use the vouchers, resulting in significant noncompliance. For instance, nearly half of the households that received vouchers did not use them to relocate, whereas one-fifth of the control family relocated to better communities. Noncompliance generates the problem of selection bias, which prevents the identification of neighborhood effects by comparing the outcome of families living in different neighborhood types.

Most of the MTO literature addresses the problem of noncompliance by reporting the intention-to-treat (ITT) and the treatment-on-the-treated (TOT) effects (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). The ITT is a voucher effect. It evaluates the mean difference of the outcomes between families who received a voucher and those who did not. The TOT parameter is calculated by dividing the ITT by the voucher take-up rate, which effectively scales up the voucher effect by the proportion of families who use the vouchers.

The ITT/TOT are primary parameters that successfully evaluate the housing policy itself. However it is not clear how to interpret these parameters in terms of the causal effects between neighborhood types (Aliprantis, 2007; Sampson, 2008). This question culminated in a symposium published in the American Journal of Sociology in 2008. On one side, Ludwig et al. (2008) claim that both parameters are informative regarding the existence of neighborhood effects. On the opposite side, Clampet-Lundquist and Massey (2008) make the case that neither of the two parameters is well suited to capturing neighborhood effects. This paper addresses the question that is at the core of this debate: *How to exploit the exogenous variation of randomized vouchers to identify neighborhood effects?* This study determines the causal content of the TOT parameters and enables new analyses and novel insights on the MTO intervention.

This paper exploits the choice incentives induced by the MTO experiment to move beyond the ITT/TOT analysis. It employs revealed preference analysis to convert MTO incentives into choice restrictions, which, in turn identify the latent distribution of counterfactual choices and most, but not all, counterfactual outcomes.

The design of the MTO intervention calls for an IV model with three choices model and the three instrumental values. A natural identification approach is to extend the local average treatment effects (LATE) framework of Imbens and Angrist (1994) from the binary choice model to the three-choice model of MTO. Unfortunately, standard monotonicity conditions that successfully identify causal effects in the binary choice model fail to identify causal parameters in the three-choice model of MTO.[1]

Revealed preference analysis is better suited to assess the choice incentives of the MTO intervention. The analysis provides a set of choice restrictions that subsume standard monotonicity conditions. These restrictions determine seven pattern of counterfactual choices that are economically justified.

identify the majority of the counterfactual outcomes. Choice restrictions also imply the unordered monotonicity condition of Heckman and Pinto (2018). Their results are used extensively.

Unordered monotonicity enables us to express the counterfactual outcomes of each treatment as a response function of its propensity scores. The interpolation of these response functions secures

[1]The method presented here can be extended to the case of the general case of an IV model with multiple choices and categorical instrumental variable.

the identification of neighborhood effects.

The identification strategy is consistent with Kline and Walters (2016b) who uses revealed preference analysis to evaluate the Head Start Program. They examine a three-choice model with a two-valued IV. Kirkeboen et al. (2016), on the other hand, examine a three-choice model with an instrument that takes on three values. The choice incentives they investigate differ from those of MTO. Nevertheless, the identification results are comparable. Similar to MTO, they show that standard monotonicity conditions also fail to identify causal effects. Their identification strategy employs a clever strategy that exploits additional information on the ranking of the agents' choices. Alternatively, revealed preference analysis could deliver a causal interpretation to the Two-stage Least Squares (2SLS) estimator if the additional information were not available.

The identification method enables a deeper understanding of the MTO intervention. The method renders seven latent types that characterize the counterfactual choice behaviors that are economically justifiable. Decomposing neighborhood effects across family types provides new insights into the experiment. For instance, it is possible to show that the most disadvantaged families are precisely those not persuaded to move. On the other hand, the least disadvantaged families are those who move to low-poverty neighborhoods regardless of the voucher assignment. These findings helps design more efficient policies by characterizing the type of family most responsive to MTO incentives. From a scientific point of view, assessing neighborhood effects builds fundamental knowledge on how neighborhoods promote economic prosperity, which was the original goal of the MTO experiment. Finally, the method offers a clear interpretation of the TOT parameter in terms of causal effects between neighborhood types. It shows that the TOT parameter evaluates a weighted average of neighborhood effects across a selection of latent types.

Previous MTO research has found significant results on adult outcomes such risky behavior and psychological well-being (Clampet-Lundquist and Massey, 2008; Gennetian et al., 2012; Katz et al., 2001; Kling et al., 2007, 2005; Ludwig et al., 2012, 2013, 2001, 2011). However this literature finds little or no significant impact on adult labor market outcomes such as earnings and employment (Kling et al., 2007; Sanbonmatsu et al., 2006, 2011). Such findings were widely interpreted as evidence that neighborhood quality has little impact on economic well-being of poor families (Aliprantis, 2007; Clampet-Lundquist and Massey, 2008; Ludwig et al., 2008; Sampson, 2008).

This paper reexamines the labor market outcomes of MTO. Similar to Kling et al. (2007), I find weak TOT effects. I show that the TOT parameter is a mixture of neighborhood effects that compare low versus high and low versus medium poverty neighborhoods. Some of these effects are imprecise, contributing to the overall lack of significance of the TOT estimates. Nevertheless, the neighborhood effects of moving from 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% rise in employment, and a 34% reduction of being in poverty.

These empirical results corroborate the findings of Clampet-Lundquist and Massey (2008) and Aliprantis and Richter (2020) who employ alternative identification strategies to evaluate the effect of neighborhood quality on labor market outcomes of MTO families.[2] This paper offers a potential explanation to the question raised by Harding et al. (2021), who discuss the mismatch between the insignificant economic result of Kling et al. (2007) and significant effects on labor market outcomes of previous observational studies (e.g. Elliott (1999); Fauth et al. (2004); Shang (2014)). The empirical results also help to reconcile the statistically insignificant effects reported in early MTO literature with recent evidence that claims the importance of neighborhood quality in affecting residents' lives (Chetty et al., 2017, 2016; Chyn, 2016; Galiani et al., 2015).

In broader terms, this paper adds to the IV literature that invokes revealed preference analysis to identify treatment effects (Feller et al., 2016; Kamat, 2021; Kline and Tartari, 2016; Kline and Walters, 2016b).[3] A benefit of this framework is that noncompliance, usually perceived as an econometric problem, becomes a useful source of identifying information. A seminal work on this topic is Heckman (1974), who 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.

This paper also contributes to the literature on empirical evaluations that examine the case

[2]Both works seek to evaluate the causal effect of neighborhood quality on economic outcomes. Clampet-Lundquist and Massey (2008) uses the cumulative time spent in different neighborhood environments as a measure of neighborhood quality. In contrast, Aliprantis and Richter (2020) uses the neighborhood poverty level as a proxy for neighborhood quality.

[3]A large literature uses revealed preference analysis to evaluate choice models (Matzkin, 2007). A common goal in this literature is to test whether rational preferences can generate observed choices. Another goal is to baud demand functions under the assumption of rational choices. Examples in this literature are Blundell et al. (2014); Kitamura et al. (2018); Kline and Tartari (2016).

of unordered choices (Hull, 2018; Kirkeboen et al., 2016; Mountjoy, 2021) and also offers some contributions to the theoretical literature on unordered choice models (Heckman et al., 2006, 2008; Lee and Salanié, 2018). Specifically, this paper examines the estimation of the IV model under unordered monotonicity, which is not addressed in Heckman and Pinto (2018). It also examines the problem of partial identification that is common in multiple-choice models with categorical instruments. Lastly, this paper adds to a growing body of work addressing the identification constraints imposed by discrete instruments (Kline and Walters, 2019; Mogstad et al., 2018; Mogstad and Torgovitsky, 2018).

The paper proceeds as follows. Section 2 describes the MTO intervention. Section 3 describes the identification strategy. Section 4 presents identification results and estimation procedures. Section 5 reanalyses MTO data. Section 6 concludes.

2 The MTO Experiment: Data, Design and Previous Works

In 1976, Dorothy Gautreaux led a class-action lawsuit against the extreme racial segregation experienced by public housing residents in Chicago. Her initiative compelled the Department of Housing and Urban Development (HUD) and the Chicago Housing Authority (CHA) to provide housing vouchers that enable families to relocate to less segregated neighborhoods (Polikoff, 2006).

The positive results of the Gautreaux initiative set the stage for the MTO intervention. The experiment incentivized socially disadvantaged families to relocate from economically deprived areas to better neighborhoods. The experiment was conducted between June 1994 and July 1998 (Orr et al., 2003). Eligible households consisted of low-income families with children under 18 years living in the most impoverished housing projects of five US cities: Baltimore, Boston, Chicago, Los Angeles, and New York. MTO sample totals 4,248 families. Three-quarters of these 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.

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Participants in the MTO study were randomly assigned to one of the three groups: Section 8 (28%), experimental (41%), and control (31%). *Section 8* families received a regular rent-subsidy voucher that could be used if the family consented to relocate from their high poverty neighborhood to eligible private-market dwellings. *Experimental* families received a voucher that could be used only in low poverty neighborhoods, that is, neighborhoods with less than 10% of their households below the poverty line, according to the 1990 US Census. *Control* families did not receive any voucher.

The Department of Housing and Urban Development (HUD) set the subsidy amount and unit eligibility based on the Applicable Payment Standard (APS). Landlords could not discriminate against a voucher recipient, and leases were automatically renewed. 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.

Local nonprofit counseling organizations help to recruit families for MTO. HUD expected that experimental families would face difficulties finding suitable housing units in a low poverty location. HUD's solution was to use these nonprofit organizations to help experimental families to locate and lease units in a timely manner (Orr et al., 2003). Despite these efforts, MTO Noncompliance was substantial. The take-up rate for the experimental voucher was 47%, while the take-up rate for Section 8 was 59%.[4]

Table 1 presents a statistical description of baseline variables at the onset of the intervention. Column 2 presents control means, and 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. As expected, the baseline variables are reasonably balanced across voucher assignments. Columns 7–12 of Table 1 show evidence of selection bias on voucher compliance. Column 8 compares baseline characteristics of experimental families that used the voucher with those that did not. 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 were also more

[4]Figure A.6 in Appendix B displays a diagram of the voucher assignments and compliance patterns for the MTO experiment.

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 Types

The design of MTO intervention renders three neighborhood types: (1) high poverty neighborhoods t_h are the baseline housing projects targeted by the intervention; (2) low poverty neighborhoods t_l are the neighborhoods targeted by the experimental voucher; and (3) medium poverty t_m comprises the remaining eligible neighborhoods that the families may choose.

The experimental voucher (z_e) incentivizes families to choose a low poverty neighborhood (t_l). Families who used this voucher relocated to low poverty neighborhoods (t_l). The Section 8 voucher incentivizes low (t_l) or medium (t_m) poverty neighborhoods, and families who used this voucher decided between these two neighborhood types. Families that decided to use the voucher were required to relocate within six months after receiving their vouchers. This period, however, was extended to nearly a year to allow families to find housing.

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.[5]

Outcomes

This paper focuses on labor market outcomes collected at the interim evaluation in 2002. Figure 1 presents a statistical description of the mean estimates for the household head's income in thousand dollars by neighborhood type and voucher assignment. 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.

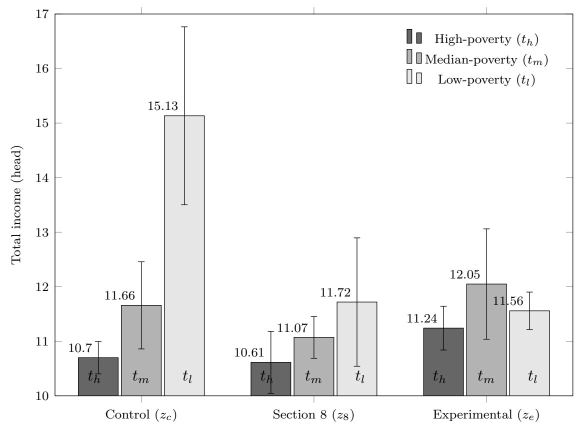
[5]Appendix B provides a detailed description of neighborhood choices. Figure A.6 in Appendix B displays a diagram of the MTO intervention.

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

Columns 2–6 present the arithmetic means for selected baseline variables conditional on voucher assignments. Column 2 presents the control mean. Column 3 displays the difference in means between the Experimental and Control groups. Column 4 shows the double-sided single-hypothesis p-value for the mean equality test using bootstrap. 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 and did not use the voucher. Column 9 shows the double-sided p-value for the mean equality test using bootstrap. Finally, columns 10–12 analyze the families assigned to the Section 8 group, similarly to 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.

The bars 4–6 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 per year. This difference is only a quarter of the estimate for the control group (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 bars 7–9 of Figure 1 display 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, namely, $\$11.56 - \$11.24 = \$0.32$ thousand 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 of lower-income families switches from high to low poverty neighborhoods. This behavior decreases the average income for low poverty neighborhoods from $15.13 to $11.56.

Table 2 presents the statistical description of labor market outcomes surveyed in 2002. The three first variables are the income of the family head, the sum of the head's and spouse's income, and total household income. All income variables are measured in thousands of dollars per year. The five remaining variables are economic indicators: (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 suggests a selection pattern similar to the one observed in Figure 1. Consider the labor-market outcomes of families who choose to live in low-income areas. The mean estimate of the sum of spouses' income for families assigned to the control group is $15.1 thousand per year. The estimate for experimental families is $11.6 thousand per year. Thus, annual income reduces by 24% when comparing control versus experimental families who choose to live in low poverty neighborhoods. In the case of total household income, the reduction is 32%. Moreover, 55% the control families living in low poverty neighborhoods were above the poverty line in 2002. In contrast, only 32% of experimental families that decided for low poverty neighborhoods were above the poverty line in 2002. This pattern is likely to be explained by a negative selection bias. The larger the incentive to move to high-poverty neighborhoods, the smaller the mean outcome estimates.

2.1 What Can and Cannot be Identified by the MTO experiment?

There are limitations on the type of neighborhood effects that can be identified by the exogenous variation of the voucher assignments.[6] Vouchers play the role of an IV that incentivizes residential mobility. Therefore, the type of neighborhood effects that can be identified is bounded by the geographical regions determined by the voucher incentives. Unfortunately, MTO vouchers justify only a coarse characterization of three neighborhood types.[7]

The voucher alone cannot identify the causal effect of a particular neighborhood feature. Instead, the neighborhood effects of MTO refer to the bundle characteristics associated with each neighborhood type. In particular, MTO vouchers are not suitable for identifying the causal effect

[6] A sizeable share of the MTO literature investigates the type of neighborhood effects that voucher assignments can identify. See, for instance, Aliprantis (2007); Aliprantis and Richter (2020); Clampet-Lundquist and Massey (2008); Ludwig et al. (2008); Sampson (2008).

[7] Medium poverty neighborhoods, for instance, comprise a remarkably heterogeneous set of eligible dwellings.

Table 2: Labor 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 labor outcome variables by voucher assignment (z_c, z_m, z_l) and neighborhood choice (t_l, t_m, t_h). Estimates are obtained via Least Squares regressions that control for site fixed effects and standardized baseline variables listed in Table 1. 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.

of neighborhood characteristics such as the quality of public schools or the level of criminal activity since voucher incentives do not directly target these characteristics.[8] Moreover, Ludwig et al. (2008) and Sampson (2008) points out that the MTO incentivizes families to move to better neighborhoods instead of improving the neighborhoods themselves. Consequently, MTO is not suitable for experimentally separating the impact of the act of relocation from the change in neighborhood characteristics.

The intervention also suffers from limited external validity, a common problem among social experiments. MTO findings only apply to the population targeted by the intervention and should not be interpreted as broad implications concerning neighborhood effects. Finally, the neighborhood types refer to relocation choices at the onset of the experiment and do not account for eventual relocations after the mandatory waiting period. Fortunately, less than two percent of families that used the experimental voucher returned to their original neighborhood.

Assessing the IV Assumptions

Most MTO evaluations address the problem of noncompliance by using the vouchers as an IV affecting neighborhood choices. Some notation is in order to examine the validity of the IV assumptions in MTO. Let Z denote the voucher assignment taking values in $supp(Z) = \{z_c, z_8, z_e\}$; let T denote neighborhood choice taking values in $supp(T) = \{t_h, t_m, t_l\}$; and let Y denote an outcome of interest. The vector of baseline covariates is given by $\boldsymbol{X}$ denote, which is suppressed for now in the sake of notational simplicity. Let $T(z)$ and $Y(z)$ denote the counterfactual choice and the counterfactual outcome when the instrument Z is fixed to $z \in supp(Z)$. Let $Y(z,t)$ be the counterfactual outcome Y when (Z,T) are fixed to $(z,t) \in supp(Z) \times supp(T)$, and let $Y(t)$ be the counterfactual outcome when T is fixed to $t \in supp(T)$. Let $D_t = \mathbf{1}[T = t]; t \in \{t_h, t_m, t_l\}$ and $D_z = \mathbf{1}[T = z]; z \in \{z_c, z_8, z_e\}$ denote binary indicators for neighborhood choices and IV values respectively. In this notation, the IV assumptions state that for all $(z,t) \in supp(Z) \times supp(T)$ we

[8] Several works use the MTO data has been used to identify the causal effect of indexes of neighborhood quality on family outcomes Aliprantis and Richter (2020); Clampet-Lundquist and Massey (2008); Kling et al. (2007), but the identification strategy invokes additional functional form assumptions.

have that:

$$\textbf{Exclusion Restriction:} \quad Y(z,t) = Y(t). \tag{1}$$

$$\textbf{Exogeneity Condition:} \quad Z \perp\!\!\!\perp (Y(t), T(z), Y(z)). \tag{2}$$

$$\textbf{IV relevance:} \quad E\left([D_{z_c}, D_{z_8}, D_{z_e}]'[D_{t_l}, D_{t_m}, D_{t_h}]\right) \text{ has full rank.} \tag{3}$$

The Exclusion Restriction (1) means that the vouchers affect the outcomes only through neighborhood choices. The restriction is critical to the identification of neighborhood effects. Therefore, HUD implemented some measures to ensure its validity. HUD paid rent directly to the landlord and required that households pay 30% of their monthly adjusted gross income to offset the cost of rent and utilities.[9] On the other hand, HUD allowed for a considerable range of counseling practices offered by local agencies. Counseling focused primarily on housing mobility (Orr et al., 2003). However, some agencies offered non-housing assistance (Feins et al., 1997), which is a potential threat to the validity of the exclusion restriction in the MTO literature. The assumptions of exogeneity (2) and relevance (3) are less contentious. Exogeneity (2) implies that MTO voucher are independent of the family unobserved characteristics. IV relevance (3) means that vouchers influence neighborhood decisions, namely Z and T .

It is natural to perceive the MTO as an example of IV model with ordered choices. This type of model is examined by Angrist and Imbens (1995), who show that the Two-Stage Least Squares (2SLS) estimator has a causal interpretation whenever their monotonicity condition is satisfied. Unfortunately, their monotonicity condition is equivalent to assuming an ordered choice model[10] which is not compatible with the choice incentives induced by the MTO vouchers. See Appendix F for a discussion on the type of incentives that justify Angrist and Imbens (1995) model.

2.2 Previous Analyses

As mentioned, most of the MTO literature addresses the problem of noncompliance by reporting the intention-to-treat (ITT) and the treatment-on-treated (TOT) parameters.[11] The ITT effect for experimental versus control families is typically estimated by the parameter π_e in equation (4) via

[9] The 30% rent cap is a common practice among landlords that provide low-income housing.

[10] See Vytlacil (2004).

[11] For examples of these analyses, see Chetty et al. (2017, 2016); 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).

the ordinary least squares regression that uses data from experimental and control groups:

$$Y = \alpha + D_{z_e}\pi_e + \boldsymbol{X}\beta + \epsilon, \tag{4}$$

where D_{z_e} is the binary indicator for the experimental voucher and $\boldsymbol{X}$ denotes baseline covariates including site fixed effects. The ITT estimate in (4) is the sample analog of the covariate-adjusted difference in means between experimental versus control groups, $ITT_e = E(Y|Z = z_e) - E(Y|Z = z_c)$. According to the IV Assumption (2), the ITT_e identifies the causal effect of being offered the experimental voucher, that is, $E(Y(z_e) - Y(z_c))$. The ITT for Section 8 versus control, $ITT_8 = E(Y|Z = z_8) - E(Y|Z = z_c)$, is estimated by replacing the voucher indicator D_{z_e} in (4) by D_{z_8}.

It is challenging to interpret ITT parameters in terms of neighborhood effects since the parameters do not distinguish families who used the vouchers from families that did not. The TOT parameter solves this issue by using the voucher assignment as an instrumental variable for the voucher take-up. The TOT parameter that compares the experimental versus control group is usually estimated by the parameter γ_e in equation (5) via the Two Stage Least Squares (2SLS) regression that uses data from experimental and control families:

$$Y = \alpha + C_e\gamma_e + \boldsymbol{X}\beta + \epsilon, \tag{5}$$

where C_e indicates the experimental voucher compliance and D_{z_e} is used as an instrument for C_e. The TOT estimate in (5) is the sample analog of the ITT_e divided by the regression-adjusted take-up rate:

$$TOT_e = \frac{ITT_e}{P(C_e = 1|Z = z_e)} = \frac{E(Y|Z = z_e) - E(Y|Z = z_c)}{P(C_e = 1|Z = z_e)}. \tag{6}$$

The TOT parameter that compares Section 8 and control families is obtained by replacing the terms C_e, Z_e and D_{Z_e} in (6) and (5) with the terms C_8, Z_8 and D_{Z_8} corresponding to the Section 8 voucher.

The TOT parameter conflates voucher effects with the voucher compliance rate. It differs from the typical IV model as TOT uses the information on voucher compliance rather than the neighborhood choices. The parameter is motivated by a simpler intervention studied by Bloom (1984). Consider a version of the MTO intervention that randomly assigns families to the experimental or the control group. Suppose that the investigators can ensure that the only families that move are those who use the experimental voucher. This experiment admits two types of families. *Compliers* are families who intend to use the voucher. These families move to a low poverty neighborhood if assigned to the experimental voucher and remain in a high poverty neighborhood if assigned to control. *Non-compliers* are families that do not intend to use the experimental voucher. These families remain in high poverty neighborhoods regardless of the voucher assignment. Bloom (1984) shows that the TOT parameter of this intervention identifies the neighborhood effect of low versus high poverty neighborhoods for compliers. See Appendix C for a proof.

Unfortunately, identifying neighborhood effects break down when families are allowed to move. In MTO, control families can choose among high, medium, and low poverty neighborhoods. Experimental families that do not comply with the voucher can also choose among these three neighborhood types. Without additional assumptions, the TOT parameter evaluates a mixture of several and perhaps conflicting neighborhood effects. For instance, we cannot rule out a type of family that chooses high poverty neighborhood under control assignment and medium poverty neighborhood under the experimental voucher or vice-versa. The precise definition of what TOT estimates requires a deeper investigation of the counterfactual choices that are economically justified by MTO incentives.

3 Examining the Identification Problem of MTO

The IV assumptions (1)–(3) alone are not sufficient to identify any causal effect.[12] The nonparametric identification of causal parameters requires additional constraints on how the instrument affects the treatment choice. This paper uses the familiar LATE model of Imbens and Angrist (1994) as a leading example to examine the identification challenge in MTO.

3.1 Exploring Monotonicity Conditions

Consider a binary choice model where families choose between low (t_l) and high (t_h) poverty neighborhoods. Each family is randomly assigned to either the experimental voucher (z_e), which subsidizes low-poverty neighborhoods, or the control group (z_c), which does not offer any subsidy. The *response vector* $\boldsymbol{S} = [T(z_c)\ ,\ T(z_e)]'$ denotes the 2×1 vector of counterfactual choices that families would take if it were assigned to either z_c or z_e respectively. The support of $\boldsymbol{S}$ comprises

[12]See Heckman (1990) and Angrist and Imbens (1991) for a discussion.

four *response-types*: (*i*) never-takers $\boldsymbol{s}_{nt} = [t_h, t_h]'$; (*ii*) compliers $\boldsymbol{s}_c = [t_h, t_l]'$; (*iii*) always-takers $\boldsymbol{s}_{at} = [t_l, t_l]'$; and (*iv*) defiers $\boldsymbol{s}_d = [t_l, t_h]'$. Imbens and Angrist (1994) invokes a *monotonicity condition* stating that a change in the instrument from z_c to z_e induces families to choose low-poverty neighborhoods t_l. This condition an be expressed by the following inequality:

$$\mathbf{1}[T_i(z_c) = t_l] \leq \mathbf{1}[T_i(z_e) = t_l] \text{ for all families } i. \tag{7}$$

The condition implies that if a family i chooses low-poverty neighborhood (t_l) under control (z_c) then it must also choose low poverty neighborhood (t_l) under the experimental voucher. This choice restriction *eliminates the defiers* and enables the identification of the Local Average Treatment Effect (LATE), $E(Y(t_h) - Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_c)$, which is the causal effect of low versus high poverty for compliers.

MTO differs from the binary LATE since Z, and T take three values instead of two. The response vector of MTO is given by $\boldsymbol{S} = [T(z_c), T(z_8), T(z_e)]'$. It is the 3×1 vector of potential neighborhood choices that a family takes when assigned to z_c, z_8, and z_e respectively. If family i has *response-type* $\boldsymbol{S}_i = [t_h, t_m, t_l]'$, then it chooses high-poverty neighborhood if assigned to control ($T_i(z_c) = t_h$), medium-poverty neighborhood if assigned to Section 8 ($T_i(z_8) = t_m$), and low-poverty neighborhood if assigned to the experimental voucher ($T_i(z_e) = t_l$).

The response vector is central to the identification analysis.[13] It enable us to connect observed quantities with unobserved causal parameters.

Proposition P.1. The following equation holds under IV assumptions (1)–(3):

$$\underbrace{E(Y|T=t, Z=z)\, P(T=t|Z=z)}_{\text{Observed}} = \sum_{\boldsymbol{s} \in supp(\boldsymbol{S})} \underbrace{\mathbf{1}[T=t|\boldsymbol{S}=\boldsymbol{s}, Z=z]}_{\text{Deterministic}} \underbrace{E(Y(t)|\boldsymbol{S}=\boldsymbol{s})\, P(\boldsymbol{S}=\boldsymbol{s})}_{\text{Unobserved}}. \tag{8}$$

Proof. See Heckman and Pinto (2018) or Appendix A.1 for proof. □

The left-hand side of (8) consists of two observed quantities: the outcome expectation $E(Y|T = t, Z = z)$ and the propensity score $P(T = t|Z = z)$. The right-hand side of (8) consists of a deterministic indicator $\mathbf{1}[T = t|\boldsymbol{S} = \boldsymbol{s}, Z = z]$, and two unobserved quantities: the expected value of the counterfactual outcome conditioned on the response-types $E(Y(t)|\boldsymbol{S} = \boldsymbol{s})$ and the response-type probabilities $P(\boldsymbol{S} = \boldsymbol{s})$. Setting $Y = 1$ yields an equation that expresses the propensity scores

[13] See Appendix D for a discussion on how the response vector helps to control for unobserved characteristics that generate selection bias.

as a linear function of response-type probabilities:

$$\underbrace{P(T=t|Z=z)}_{\text{Propensity Scores}} = \sum_{\boldsymbol{s}\in supp(\boldsymbol{S})} \mathbf{1}[T=t|\boldsymbol{S}=\boldsymbol{s}, Z=z] \underbrace{P(\boldsymbol{S}=\boldsymbol{s})}_{\text{Response-type Probabilities}}. \tag{9}$$

Equation 9 is helpful to clarify the identification problem in MTO. As (Z,T) ranges in $\{z_c, z_8, z_e\} \times \{t_h, t_m, t_l\}$, the equation provides a linear system of nine equalities. The number of unknowns is equal to the number of response-types $\boldsymbol{s} \in supp(\boldsymbol{S})$. In the MTO, the response vector consists of three counterfactual choices $T(z_c), T(z_8), T(z_e)$ that can take any of the three neighborhood types t_h, t_m, t_l. This yields a total of 27 possible response-types. An identification problem arises as the number of unobserved parameters exceeds the number of equations. Identifying causal parameters requires eliminating some response types in the same fashion that eliminating defiers in the LATE model identifies the causal effect for compliers.

A natural approach to eliminate response-types is to extend the monotonicity condition of LATE to the case of multiple choices of MTO. Recall that the experimental voucher z_e incentivizes low-poverty t_l neighborhoods while Section 8 z_8 incentivizes both low t_l and medium-poverty t_m neighborhoods. These incentives justify three monotonicity conditions:

$$\mathbf{1}[T_i(z_c)=t_l] \leq \mathbf{1}[T_i(z_e)=t_l] \tag{10}$$

$$\mathbf{1}[T_i(z_c)\in\{t_m, t_l\}] \leq \mathbf{1}[T_i(z_8)\in\{t_m, t_l\}] \tag{11}$$

$$\mathbf{1}[T_i(z_e)=t_m] \leq \mathbf{1}[T_i(z_8)=t_m] \tag{12}$$

Condition (10) states that a change from z_c to z_e induce families toward low-poverty neighborhoods (t_l). Condition (11) states a change from z_c to z_8 induce families toward either t_l or t_m. Finally, condition (12) states that a change from z_e to z_8 induce families toward medium-poverty t_m.

Panel A of Table 3 display the 27 possible response-types in MTO. Panel B indicates the response-types eliminated by each monotonicity condition in (10)–(12). For example, condition (10) implies that if a family i chooses t_l under z_c, then it also choose t_l under z_e. This condition eliminates the six response-types in which $T_i(z_c)$ is equal to t_l and $T_i(z_e)$ differs from t_l. In total, the monotonicity conditions (10)–(12) eliminate 13 out of the 27 response-types. This quantity, however, is insufficient to secure the identification of causal parameters.

One approach to eliminate additional response-types is to scrutinize each of the remaining 14

Table 3: 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 (10)–(12)**																										
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 Choice Restrictions (21)–(27)**																										
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. Panel B describes an elimination process based on the three monotonicity conditions displayed in equations (10)–(12). Panel C describes an elimination process based on the seven choice restrictions (21)–(27) generated by the revealed preference analysis. The monotonicity condition and the choice restrictions are also displayed below to be easily accessed.. Check mark ✓ indicates that the response-type does not violate the restriction while The cross sign ✗indicates that the response-type violates the monotonicity condition or the choice restriction and should be eliminated. The check mark ✓ indicates that the response-type does not violate the condition. The last row in each panel presents the response-types that survive the elimination process.

Monotonicity Conditions

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	$\mathbf{1}[T_i(z_e) = t_m]$	$\leq$	$\mathbf{1}[T_i(z_8) = t_m]$

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	$T_i(z_c) \neq t_h$	$\Rightarrow$	$T_i(z_8) = T_i(z_c)$

response-types on a case-by-case basis.[14] This is a cumbersome task. An alternative approach is to use revealed preference analysis to exploit the information on the choice incentives of MTO. Revealed preference analysis offers several advantages. First, it subsumes the monotonicity conditions (10)–(12). Second, it invokes elementary choice axioms grounded on economic behavior, which are simpler and more intuitive than the case-by-case study. Finally, revealed preference analysis is more general than the case-by-case study as it can be applied to choice incentives other than those of MTO.[15]

3.2 Exploiting MTO Incentives

This paper uses a simple economic model to exploit the choice incentives of MTO. It is convenient to represent these incentives though an *incentive matrix* $\boldsymbol{L}$ displayed below:

$$\boldsymbol{L} = \begin{array}{c} \\ \\ \\ \end{array}\begin{array}{ccc} t_h & t_m & t_l \\ \end{array} \\ \boldsymbol{L} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \begin{array}{c} z_c \\ z_8 \\ z_e \end{array} \tag{13}$$

Each entry $\boldsymbol{L}[z,t]$ in (13) refers to the relative incentive of the instrumental value z (row) towards the choice t (column). The control assignment (z_c) in the first row of $\boldsymbol{L}$ is the baseline comparison. The Section 8 voucher (z_8) in the second row incentivizes medium (t_m) and low (t_l) poverty neighborhoods. The experimental voucher (z_e) in the last row incentivizes low poverty neighborhoods (t_l).

The counterfactual choice of a family i can be understood as the result of a utility maximization problem:[16]

$$T_i(z) = \underset{t\in\{t_l,t_m,t_h\}}{\arg\max} \left(\max_{g\in\mathcal{B}_i(z,t)} u_i(t,g) \right), \tag{14}$$

where $u_i(t,g)$ is the utility function of a family i over the neighborhood types $t \in \{t_h, t_m, t_l\}$ and

[14] 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.

[15] Section 3.3 applies revealed preference analysis to the choice incentives investigated by Kirkeboen, Leuven, and Mogstad (2016).

[16] This formulation is only used for didactic exposition. The rationality implied by the existence of an utility function is not invoked as an assumption in any of the proofs.

consumption goods $g \in \mathcal{G}$. Let $\mathcal{B}_i(z,t) \subset \mathcal{G}$ denotes 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 $z \in \{z_c, z_8, z_e\}$.[17] Greater incentives correspond to larger budget sets for a fixed neighborhood t. Notationally, we have that:

$$\boldsymbol{L}[z,t] \leq \boldsymbol{L}[z',t] \quad \Rightarrow \quad \mathcal{B}_i(z,t) \subseteq \mathcal{B}_i(z',t). \tag{15}$$

Thus, the incentive matrix (13) generates the following budget set relationships:

$$\text{High poverty neighborhood } t_h : \mathcal{B}_i(z_c,t_h) = \mathcal{B}_i(z_e,t_h) = \mathcal{B}_i(z_8,t_h). \tag{16}$$

$$\text{Medium poverty neighborhood } t_m : \mathcal{B}_i(z_c,t_m) = \mathcal{B}_i(z_e,t_m) \subset \mathcal{B}_i(z_8,t_m). \tag{17}$$

$$\text{Low poverty neighborhood } t_l : \mathcal{B}_i(z_c,t_l) \subset \mathcal{B}_i(z_e,t_l) = \mathcal{B}_i(z_8,t_l). \tag{18}$$

Equation (16) compares budget sets for high poverty neighborhood (t_h) across voucher assignments. Family budget sets remain the same as none of the vouchers incentivize t_h. Equation (17) compares budget sets for t_m, $\mathcal{B}_i(z_8,t_m)$ is the largest because z_8 is the only voucher that subsidizes t_m. Lastly, equation (18) compares budget sets for t_l. Budget sets $\mathcal{B}_i(z_e,t_l), \mathcal{B}_i(z_8,t_l)$ are larger than $\mathcal{B}_i(z_c,t_l)$ because vouchers z_8 and z_e subsidize t_l while z_c does not.

The Weak Axiom of Revealed Preferences[18] (WARP) states that if a family i chooses the bundle (t,g^*) when it could choose (t',g'), then the family would not choose (t',g') whenever (t,g^*) is available. WARP is useful to generate choice restrictions that are economically justified. Consider a family i that decides for t instead of t' when assigned to z. This means that there exists an unobserved bundle (t,g^*) for some $g^* \in \mathcal{B}_i(z,t)$ that is preferred to all the bundles $(t',g'); g' \in \mathcal{B}_i(z,t')$. If the budget set of choice t under z' does not decrease, $\mathcal{B}_i(z,t) \subseteq \mathcal{B}_i(z',t)$, then (t,g^*) remains available. Moreover, if the budget set for t' does not increase, $\mathcal{B}_i(z,t') \supseteq \mathcal{B}_i(z',t')$, then (t,g^*) is still preferred to all bundles (t',g') in $\mathcal{B}_i(z',t')$. In this case, family i does not chose t' under z'. Proposition **P.2** formalizes this rationale.

Proposition P.2. WARP and the budget relation (15) produce the following choice rule:

$$\text{If } T_i(z) = t \text{ and } \boldsymbol{L}[z',t'] - \boldsymbol{L}[z,t'] \leq 0 \leq \boldsymbol{L}[z',t] - \boldsymbol{L}[z,t] \text{ then } T_i(z') \neq t'.$$

Proof. See Appendix A.2 for proof. ☐

[17] 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.

[18] 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 (t',g') cannot be revealed preferred to (t,g), namely, $(t,g) \succ_i^d (t',g') \Rightarrow (t',g') \not\succ_i^d (t,g)$.

Proposition P.2 states that if a family chooses t instead of t' under z, and z' offers at least as much incentives towards t than t', then the family will not choose t' under z'.

It is instructive to apply this methodology to the binary LATE model discussed at the beginning of this section. Suppose families could only choose between low (t_l) and high (t_h) poverty neighborhoods and are randomly assigned to either the experimental voucher (z_e), which subsidizes low-poverty neighborhoods, or the control voucher (z_c) that offers no incentives. The corresponding incentive matrix is:

$$\boldsymbol{L} = \begin{array}{c} \\ \end{array}\begin{matrix} t_h & t_l \\ \end{matrix}$$
$$\boldsymbol{L} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{matrix} z_c \\ z_e \end{matrix} \quad \text{(columns } t_h, t_l\text{)} \tag{19}$$

Applying P.2 to the response matrix (19) produces the following restriction:

$$T_i(z_c) = t_l \text{ and } \boldsymbol{L}[z_e, t_h] - \boldsymbol{L}[z_c, t_h] = 0 \leq 1 = \boldsymbol{L}[z_e, t_l] - \boldsymbol{L}[z_c, t_l] \Rightarrow T_i(z_e) \neq t_h. \tag{20}$$

Choice restriction $T_i(z_c) = t_l \Rightarrow T_i(z_e) \neq t_h$ in (20) is equivalently described by the monotonicity condition (7), that is, $\mathbf{1}[T_i(z_c) = t_l] \leq \mathbf{1}[T_i(z_e) = t_l]$. Indeed, if the choice of low poverty neighborhood is revealed preferred to high poverty neighborhood under no incentives, then the family still chooses low poverty neighborhood when incentives to do so are available.

In the case of MTO, P.2 can be applied to all pairwise combination of neighborhood choices $(t, t') \in \{t_h, t_m, t_l\}^2$ and IV values $(z, z') \in \{z_c, z_8, z_e\}^2$. Next proposition lists the choice restrictions generated by WARP:

Proposition P.3. The choice restrictions generated by applying WARP to MTO incentive matrix (13) are:

$$\begin{aligned}
&\text{Restriction 1: } T_i(z_c) = t_l && \Rightarrow && T_i(z_e) = t_l \text{ and } T_i(z_8) \neq t_h && (21)\\
&\text{Restriction 2: } T_i(z_c) = t_m && \Rightarrow && T_i(z_e) \neq t_h \text{ and } T_i(z_8) \neq t_h && (22)\\
&\text{Restriction 3: } T_i(z_e) = t_m && \Rightarrow && T_i(z_c) = t_m \text{ and } T_i(z_8) = t_m && (23)\\
&\text{Restriction 4: } T_i(z_e) = t_h && \Rightarrow && T_i(z_c) = t_h \text{ and } T_i(z_8) \neq t_l && (24)\\
&\text{Restriction 5: } T_i(z_8) = t_h && \Rightarrow && T_i(z_c) = t_h \text{ and } T_i(z_e) = t_h && (25)\\
&\text{Restriction 6: } T_i(z_8) = t_l && \Rightarrow && T_i(z_e) = t_l && (26)
\end{aligned}$$

Proof. See Appendix A.4 for proof. □

The first choice restriction in **P.3** 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 would not choose high-poverty t_h under z_8, but may choose t_l or t_m, which are indeed subsidized by z_8. Appendix A.3 shows that the choice restrictions (21)–(23) subsume the three monotonicity conditions in (10)–(12). The choice restrictions in **P.3** hold for each family i regardless if budget sets are observed or if the family utilizes the voucher to relocate. Panel C of Table 3 displays the response-types eliminated by each of the six choice restrictions in **P.3**. Altogether, these restrictions eliminate 18 out of the 27 possible response-types.

We can exploit the concept of a *Normal Choice* to generate additional choice restrictions. Normal Choice impose a no-crossing condition across the rankings of choice preferences. If family i prefers t to t' under z, and the incentive gain from switching to z' is the same for both choices, then the relative rank of these choices remains the same.[19] Normal choice generates the following choice restriction:

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

Normal Choice relates with the notion of a normal good. Consider a family i that debates between moving to either a low t_l or a medium t_m poverty neighborhood. Suppose that the voucher changes from z_c to z_8. The control voucher offers no subsidy, while Section 8 subsidizes both neighborhood choices considered by the family. Thus this voucher change can be interpreted as an increase in the family's income. If the neighborhood choice were a normal good, then an increase in income does not decrease its consumption. Otherwise stated, if family i prefers a low instead medium poverty neighborhood under z_c, it will maintain its preference under z_8. Normal choice generates an additional choice restriction in MTO:

$$T_i(z_c) \neq t_h \Rightarrow T_i(z_8) = T_i(z_c). \tag{27}$$

This restriction eliminates two additional response-types. The response-types that survive the revealed preference analysis are organized as columns of the following response matrix:

[19] Notationally we can define normal choice as:

$$(t \succ_i t')|z \text{ and } \boldsymbol{L}[z,t] - \boldsymbol{L}[z,t] = \boldsymbol{L}[z,t'] - \boldsymbol{L}[z',t] \text{ then } (t' \not\succ_i t)|z',$$

where $(t \succ_i t')|z$ means that family i ranks choice t above choice t' under voucher z.

Proposition P.4. Choice restrictions (21)–(27) generate the following response matrix:

$$\boldsymbol{R} = \begin{array}{c} \begin{matrix} \boldsymbol{s}_{ah} & \boldsymbol{s}_{am} & \boldsymbol{s}_{al} & \boldsymbol{s}_{fc} & \boldsymbol{s}_{pl} & \boldsymbol{s}_{pm} & \boldsymbol{s}_{ph} \end{matrix} \\ \begin{bmatrix} t_h & t_m & t_l & t_h & t_h & t_m & t_h \\ t_h & t_m & t_l & t_m & t_l & t_m & t_m \\ t_h & t_m & t_l & t_l & t_l & t_l & t_h \end{bmatrix} \end{array} \begin{array}{c} \\ T_i(z_c) \\ T_i(z_8) \\ T_i(z_e) \end{array} \tag{28}$$

Proof. See Panel C of Table 3. □

Response-types $\boldsymbol{s}_{ah}, \boldsymbol{s}_{al}, \boldsymbol{s}_{al}$ are *always-takers*. They correspond to families that choose the same neighborhood type regardless of the voucher assignment. 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. Response-types $\boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{ph}$ are called *partial-compliers*. They 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 subsidized (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).[20]

3.3 Comparing MTO to a Conventional Experimental Design

The MTO program has an unusual pattern of choice incentives when compared to other experimental designs. A more traditional approach involving three treatment statuses t_0, t_1, t_2 consists of three randomized arms z_0, z_1, z_2 in which z_1, z_2 incentivize choices t_1, t_2 respectively, and z_0 stands for a control that has no incentives. This model has been investigated by Kirkeboen, Leuven, and Mogstad (2016) (henceforward referred to as KLM) and is characterized by the following incentive

[20]See Figure A.7 of Appendix A.5 for a diagram of the mapping between observed and unobserved variables generated by the response matrix (28).

matrix:

$$
\boldsymbol{L} = \begin{array}{c} \\ \end{array}\begin{array}{c} \begin{matrix} t_0 & t_1 & t_2 \end{matrix} \\ \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{array} \begin{matrix} \\ z_0 \\ z_1 \\ z_2 \end{matrix} \tag{29}
$$

The incentive matrix (29) differs from the MTO as z_1 incentivizes a single choice t_1, while z_8 in (13) incentivizes two choices, t_m and t_l. Incentive matrix (29) justifies only two monotonicity conditions:

$$
\mathbf{1}[T_i(z_0) = t_1] \leq \mathbf{1}[T_i(z_1) = t_1] \tag{30}
$$

$$
\mathbf{1}[T_i(z_0) = t_2] \leq \mathbf{1}[T_i(z_2) = t_2]. \tag{31}
$$

Condition (30) states that a change in the instrument from z_0 to z_1 induces agents to shift their choice towards t_1 while (31) states that a change from z_0 to z_2 induces agents towards t_2. Table A.5 of Appendix E shows that the monotonicity conditions (30)–(31) eliminate 12 out of the 27 possible response-types. The remaining 15 response-types do not render the identification of counterfactual outcomes or response-type probabilities.These results corroborate the analysis of KLM, who show that monotonicity conditions (30)–(31) yields an IV estimate that lacks causal interpretation.

KLM solution exploits additional information on the students' preferences among college majors. An alternative approach is to use revealed prefference analysis. Similar to MTO, revealed preference analysis subsumes and outperform the monotonicity conditions (30)–(31). Appendix E shows that the WARP rule of Proposition **P.2** provides five choice restrictions:

1	$T_i(z_0) = t_0$	$\Rightarrow$	$T_i(z_1) \neq t_2$	and	$T_i(z_2) \neq t_1$
2	$T_i(z_0) = t_1$	$\Rightarrow$	$T_i(z_1) = t_1$	and	$T_i(z_2) \neq t_0$
3	$T_i(z_0) = t_2$	$\Rightarrow$	$T_i(z_1) \neq t_0$	and	$T_i(z_2) = t_2$
4	$T_i(z_1) = t_2$	$\Rightarrow$	$T_i(z_0) = t_2$	and	$T_i(z_2) = t_2$
5	$T_i(z_2) = t_1$	$\Rightarrow$	$T_i(z_0) = t_1$	and	$T_i(z_1) = t_1$

The second and third restrictions subsume the monotonicity conditions (30)–(31). Table A.5 of Appendix E shows that the five choice restrictions above eliminate 19 out of the 27 possible response-types. The eight remaining response-types are:

$$\boldsymbol{R} = \begin{array}{c} \begin{matrix} \boldsymbol{s}_1 & \boldsymbol{s}_2 & \boldsymbol{s}_3 & \boldsymbol{s}_4 & \boldsymbol{s}_5 & \boldsymbol{s}_6 & \boldsymbol{s}_7 & \boldsymbol{s}_8 \end{matrix} \\ \begin{bmatrix} t_1 & t_1 & t_0 & t_0 & t_2 & t_0 & t_0 & t_2 \\ t_1 & t_1 & t_1 & t_1 & t_1 & t_0 & t_0 & t_2 \\ t_1 & t_2 & t_0 & t_2 & t_2 & t_0 & t_2 & t_2 \end{bmatrix} \end{array} \begin{matrix} T_i(z_0) \\ T_i(z_1) \\ T_i(z_2) \end{matrix} \tag{32}$$

Response matrix (32) has a peculiar property: it satisfies the monotonicity condition of Angrist and Imbens (1995) whenever $t_1 < t_0 < t_2$. Let t_0, t_1, t_2 denote years of college education where $t_1 = 0$ denotes no college, $t_0 = 2$ denotes a 2-year college degree and $t_2 = 4$ denotes a 4-year college degree. We can reorder the rows of (32) according to sequence z_1, z_0, z_2 without loss of generality. The resulting response matrix is:

$$\boldsymbol{R} = \begin{array}{c} \begin{matrix} \boldsymbol{s}_1 & \boldsymbol{s}_2 & \boldsymbol{s}_3 & \boldsymbol{s}_4 & \boldsymbol{s}_5 & \boldsymbol{s}_6 & \boldsymbol{s}_7 & \boldsymbol{s}_8 \end{matrix} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 2 & 2 & 4 \\ 0 & 0 & 2 & 2 & 4 & 2 & 2 & 4 \\ 0 & 4 & 2 & 4 & 4 & 2 & 4 & 4 \end{bmatrix} \end{array} \begin{matrix} T_i(z_1) \\ T_i(z_0) \\ T_i(z_2) \end{matrix} \tag{33}$$

Note that the values of each of the columns in (33) are weakly increasing as we move from one row to the next. This means that $T_i(z_1) \leq T_i(z_0) \leq T_i(z_2)$ holds for any agent i regardless of its type. This property satisfies the monotonicity condition of Angrist and Imbens (1995) which states that for any $z, z' : T_i(z) \leq T_i(z') \forall i$ or $T_i(z) \geq T_i(z') \forall i$. Consequently, the results of Angrist and Imbens (1995) apply. In particular, they show that the standard 2SLS estimate has a causal interpretation.

4 Identification of Causal Parameters

Heckman and Pinto (2018) present the necessary and sufficient conditions for identifying counterfactual outcomes in multiple-choice models with categorical instrumental variables. They show that for any response matrix $\boldsymbol{R} = [\boldsymbol{s}_1, ..., \boldsymbol{s}_N]$ and any subset of response-types $\mathcal{S} \subset \{\boldsymbol{s}_1, ..., \boldsymbol{s}_N\}$,

$$E(Y(t)|\boldsymbol{S} \in \mathcal{S}) \text{ is identified if and only if } \boldsymbol{b}(\mathcal{S})'(\boldsymbol{I} - \boldsymbol{B}_t^{+}\boldsymbol{B}_t)\boldsymbol{b}(\mathcal{S}) = 0, \tag{34}$$

where $\boldsymbol{I}$ is the identity matrix, $\boldsymbol{B}_t \equiv \mathbf{1}[\boldsymbol{R} = t]$ is a binary matrix of same dimension of $\boldsymbol{R}$ that indicates which elements in $\boldsymbol{R}$ are equal to t, $\boldsymbol{B}_t^+$ is the Moore-Penrose pseudo-inverse[21] of $\boldsymbol{B}_t$ and $\boldsymbol{b}(\mathcal{S}) = [\mathbf{1}[\boldsymbol{s}_1 \in \mathcal{S}], ..., \mathbf{1}[\boldsymbol{s}_{N_S} \in \mathcal{S}]]'$ is the binary vector that indicates which response-type belongs to $\mathcal{S}$.[22] Theorem **T.1** applies this result to MTO.

Theorem T.1. The following counterfactual outcomes are identified given the IV assumptions (1)–(3) and the MTO response matrix (28):

Neighborhood Choice	High Poverty t_h	Medium Poverty t_m	Low Poverty t_l
Always-takers	$E(Y(t_h)\|\boldsymbol{S}=\boldsymbol{s}_{ah})$	$E(Y(t_m)\|\boldsymbol{S}=\boldsymbol{s}_{am})$	$E(Y(t_l)\|\boldsymbol{S}=\boldsymbol{s}_{al})$
Partial-compliers	$E(Y(t_h)\|\boldsymbol{S}=\boldsymbol{s}_{ph})$	$E(Y(t_m)\|\boldsymbol{S}=\boldsymbol{s}_{pm})$	$E(Y(t_l)\|\boldsymbol{S}=\boldsymbol{s}_{pl})$
Partially identified	$E(Y(t_h)\|\boldsymbol{S}\in\{\boldsymbol{s}_{fc},\boldsymbol{s}_{pl}\})$	$E(Y(t_m)\|\boldsymbol{S}\in\{\boldsymbol{s}_{fc},\boldsymbol{s}_{ph}\})$	$E(Y(t_l)\|\boldsymbol{S}\in\{\boldsymbol{s}_{fc},\boldsymbol{s}_{pm}\})$

Proof. See Appendix A.5 for proof. □

Theorem **T.1** states that nine counterfactual outcomes are identified. These include the three counterfactual outcomes for always-takes (first-row) and three counterfactual outcomes for partial-compliers (second-row). These counterfactuals are said to be point-identified since they are conditioned on a single response-type. The last row displays three counterfactual outcomes are said that to be partially identified since they are conditioned on a set of two response-types. Although $E(Y(t_h)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\})$ is identified, we cannot disentangle it into $E(Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ and $E(Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{pl})$ without additional model assumptions.

The identification results in **T.1** stem from a central property of the response matrix (28): for each of the neighborhood choices $t \in \{t_h, t_m, t_l\}$, it is possible to reorder rows and columns of the response matrix (28) such that choice t lies in the *lower triangular* portion of the matrix. Matrix $\boldsymbol{R}_l$ in (35) displays the lower triangular response matrix for choice t_l :

$$\boldsymbol{R}_l = \begin{array}{c} \begin{matrix} \boldsymbol{s}_{al} & \boldsymbol{s}_{pl} & \boldsymbol{s}_{fc} & \boldsymbol{s}_{pm} & \boldsymbol{s}_{ah} & \boldsymbol{s}_{am} & \boldsymbol{s}_{pl} \end{matrix} \\ \begin{bmatrix} t_l & t_h & t_h & t_m & t_h & t_m & t_h \\ t_l & t_l & t_m & t_m & t_h & t_m & t_m \\ t_l & t_l & t_l & t_l & t_h & t_m & t_h \end{bmatrix} \end{array} \begin{matrix} z_c \\ z_8 \\ z_e \end{matrix} \tag{35}$$

The first row of $\boldsymbol{R}_l$ shows that the response-type of families that choose t_l under z_c is $\boldsymbol{s}_{al}$, i.e., low-poverty always-takers. Equations (8) and (9) enable us to identify the response-type probability

[21]The Moore-Penrose matrix $\boldsymbol{B}^+$ of a matrix $\boldsymbol{B}$ characterized by four properties: (1) $\boldsymbol{B}\boldsymbol{B}^+\boldsymbol{B} = \boldsymbol{B}$; (2) $\boldsymbol{B}^+\boldsymbol{B}\boldsymbol{B}^+ = \boldsymbol{B}^+$; (3) $\boldsymbol{B}^+\boldsymbol{B} = (\boldsymbol{B}^+\boldsymbol{B})'$; and (4) $\boldsymbol{B}\boldsymbol{B}^+ = (\boldsymbol{B}\boldsymbol{B}^+)'$. Matrix $\boldsymbol{B}^+$ is unique and always exists for any real-valued matrix $\boldsymbol{B}$.

[22]Moreover, if $E(Y(t)|\boldsymbol{S} \in \mathcal{S})$ is identified, then it can be evaluated by the expression $E(Y(t)|\boldsymbol{S} \in \mathcal{S}) = \frac{\boldsymbol{b}(\mathcal{S})'\boldsymbol{B}_t^+(\boldsymbol{Q}_Z(t)\odot\boldsymbol{P}_Z(t))}{\boldsymbol{b}(\mathcal{S})'\boldsymbol{B}_t^+\boldsymbol{P}_Z(t)}$.

$P(\boldsymbol{S} = \boldsymbol{s}_{al})$ and the counterfactual outcome $E(Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{al})$ by the following expressions:

$$P(\boldsymbol{S} = \boldsymbol{s}_{al}) = P_{t_l}(z_c), \tag{36}$$

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{al}) = \frac{E(Y \cdot D_{t_l}|Z = z_c)}{P_{t_l}(z_c)}, \tag{37}$$

where $D_{t_l} = \mathbf{1}[T = t_l]$ is the indicator for treatment choice t_l, and $P_{t_l}(z_c) = P(T = t_l|Z = z_c)$ denotes the propensity score.

The second row of $\boldsymbol{R}_l$ shows that families that choose t_l under z_8 are of two types: $\boldsymbol{s}_{al}$ or $\boldsymbol{s}_{al}$. The difference between the second row (z_8) and first row (z_c) singles out the response-type $\boldsymbol{s}_{pl}$, which enables us to identify the response-type probability $P(\boldsymbol{S} = \boldsymbol{s}_{pl})$ and the counterfactual outcome $E(Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{pl})$:

$$P(\boldsymbol{S} = \boldsymbol{s}_{pl}) = P_{t_l}(z_8) - P_{t_l}(z_c), \tag{38}$$

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl}) = \frac{E(YD_{t_l}|Z = z_8) - E(YD_{t_l}|Z = z_c)}{P_{t_l}(z_8) - P_{t_l}(z_c)}, \tag{39}$$

where $P_{t_l}(z_8) - P_{t_l}(z_c)$ denotes the difference between propensity scores.

A similar argument applies to the third row of $\boldsymbol{R}_l$. The difference between the third row (z_e) and second row (z_8) singles out the response-types $\boldsymbol{s}_{fc}$ and $\boldsymbol{s}_{pm}$, which enable us to identify $P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$ and $E(Y(t_h)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$:

$$P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}) = P_{t_l}(z_e) - P_{t_l}(z_8), \tag{40}$$

$$E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}) = \frac{E(YD_{t_l}|Z = z_e) - E(YD_{t_l}|Z = z_8)}{P_{t_l}(z_e) - P_{t_l}(z_8)}. \tag{41}$$

Matrix $\boldsymbol{R}_h$ (42) reorders rows and columns of the response matrix (28) such that choices t_h lie in the *lower triangular* portion of the matrix. Matrix $\boldsymbol{R}_m$ (43) displays the lower triangular response matrix for choice t_m :

$$\boldsymbol{R}_h = \begin{array}{c} \begin{array}{ccccccc} \boldsymbol{s}_{ah} & \boldsymbol{s}_{ph} & \boldsymbol{s}_{fc} & \boldsymbol{s}_{pl} & \boldsymbol{s}_{pm} & \boldsymbol{s}_{am} & \boldsymbol{s}_{al} \end{array} \\ \left[\begin{array}{ccccccc} \boxed{t_h} & t_m & t_m & t_l & t_m & t_m & t_l \\ \boxed{t_h} & \boxed{t_h} & t_l & t_l & t_l & t_m & t_l \\ \boxed{t_h} & \boxed{t_h} & \boxed{t_h} & \boxed{t_h} & t_m & t_m & t_l \end{array}\right] \end{array} \begin{array}{c} z_8 \\ z_e \\ z_c \end{array}, \tag{42}$$

$$\boldsymbol{R}_m = \begin{array}{c} \begin{array}{ccccccc} \boldsymbol{s}_{am} & \boldsymbol{s}_{pm} & \boldsymbol{s}_{fc} & \boldsymbol{s}_{ph} & \boldsymbol{s}_{pl} & \boldsymbol{s}_{ah} & \boldsymbol{s}_{al} \end{array} \\ \left[\begin{array}{ccccccc} \boxed{t_m} & t_l & t_l & t_h & t_l & t_h & t_l \\ \boxed{t_m} & \boxed{t_m} & t_h & t_h & t_h & t_h & t_l \\ \boxed{t_m} & \boxed{t_m} & \boxed{t_m} & \boxed{t_m} & t_l & t_h & t_l \end{array}\right] \end{array} \begin{array}{c} z_e \\ z_c \\ z_8 \end{array} \tag{43}$$

Matrices $\boldsymbol{R}_h$ and $\boldsymbol{R}_m$ enable us to identify the counterfactual outcomes for t_h and t_m in the same way as for t_l. For instance, the first row of matrix $\boldsymbol{R}_h$ in (42) enables us to identify the outcome counterfactual for always-takers $E(Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{ah})$. The difference between the second and first rows identifies $E(Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{ph})$. The difference between the third and second rows identifies $E(Y(t_h)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\})$. Analogous arguments applied to matrix $\boldsymbol{R}_m$ in (43) identify $E(Y(t_m)|\boldsymbol{S} = \boldsymbol{s}_{am})$, and $E(Y(t_m)|\boldsymbol{S} = \boldsymbol{s}_{pm})$. Appendix G.1 displays a mapping between counterfactual outcomes and the observed data. Appendix G.2 provides the closed-form solutions for each identified counterfactual. Appendix G.3 shows that each identified counterfactual outcomes can be estimated by a 2SLS regression under a suitable transformation of the observed data.

The identification of the response-type probabilities also stems from the triangular property displayed in (35), (42), and (43). The first and second rows of matrix $\boldsymbol{R}_l$ identify $P(\boldsymbol{S} = \boldsymbol{s}_{al})$ in (36), and $P(\boldsymbol{S} = \boldsymbol{s}_{pl})$ in (38). In a similar fashion, the first two rows of $\boldsymbol{R}_h$ identify $P(\boldsymbol{S} = \boldsymbol{s}_{ah})$ and $P(\boldsymbol{S} = \boldsymbol{s}_{ph})$, and two first rows of $\boldsymbol{R}_m$ identify $P(\boldsymbol{S} = \boldsymbol{s}_{am})$ and $P(\boldsymbol{S} = \boldsymbol{s}_{pm})$. The last response-type probability, $P(\boldsymbol{S} = \boldsymbol{s}_{fc})$, is identified because response-type probabilities sum up to one. Theorem **T.2** formalizes this result.

Theorem T.2. Given the IV assumptions (1)–(3) and the MTO response matrix (28), we have that:

(i). All response-type probabilities $P(\boldsymbol{S} = \boldsymbol{s}); \boldsymbol{s} \in \{\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}, \boldsymbol{s}_{al}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{ph}\}$ are identified.

(ii). Also, the expected values of baseline variables $\boldsymbol{X}$ conditioned on response-types, $E(\boldsymbol{X}|\boldsymbol{S} = \boldsymbol{s}); \boldsymbol{s} \in \{\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}, \boldsymbol{s}_{al}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{ph}\}$ are identified.

Proof. See Appendix A.6 for proof. □

4.1 Interpreting the TOT Parameter

The response matrix provides a clear interpretation of the TOT parameter as a mixture of causal effects among neighborhood types.

Proposition P.5. Given the IV assumptions (1)–(3) and the MTO response matrix (28), the TOT parameter in (6) identifies the following mixture of neighborhood effects:

$$TOT_e = \frac{E(Y(t_l) - Y(t_h)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\})\, P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\}) + E(Y(t_l) - Y(t_m)|\boldsymbol{S} = \boldsymbol{s}_{pm})\, P(\boldsymbol{S} = \boldsymbol{s}_{pm})}{P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}\})} \cdot \xi_e$$

$$\text{s.t. } \xi_e = \frac{P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}\})}{P(C_e = 1|Z = z_e)}$$

Proof. See Appendix A.7 for proof. □

Parameter TOT_e compares the experimental and the control groups.[23] Its content stems from the difference between the first (z_c) and last (z_c) rows of the response matrix $\boldsymbol{R}$ in (28). According to **P.5**, TOT_e comprises two terms. The first term is a mixture of two neighborhood effects: (1) low versus high poverty neighborhoods for response-types $\boldsymbol{s}_{fc}$ and $\boldsymbol{s}_{pl}$; and (2) low versus medium poverty neighborhoods for the response-type $\boldsymbol{s}_{pm}$. The second term ξ_e is ratio between the probability of response-types $\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}$ and the take-up rate for the experimental voucher. This term is positive and less than one.[24]

The TOT decomposition relates to Kline and Walters (2016a), who studied a preschool experiment that randomly offered Head Start day-care services to children. They decompose LATE parameter into a mixture of two sub-effects: Head Star versus other center-based preschools, and Head Start versus home care.

Proposition **P.5** states that TOT evaluates an interpretable mixture of neighborhood effects.

[23]See Appendix A.7 for the decomposition of the TOT parameter that compares the Section 8 and the control groups as a mixture of neighborhood effects.

[24]If all the experimental families that relocated to low poverty neighborhoods had use the voucher, the second term would be given by $\xi_e = 1 - P(\boldsymbol{S} = \boldsymbol{s}_{al}|\boldsymbol{S} \in \{\boldsymbol{s}_{al}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}\})$.

Nevertheless, it is desirable to disentangle the parameter into its causal components in order to accurately evaluate the effect of its response-types. In addition, assessing neighborhood effects for each response-type allows for a deeper understanding of the MTO intervention. The causal effects for full-compliers, $\boldsymbol{s}_{fc}$, are of particular interest. This response-type consists of families that are most responsive to MTO incentives. It accounts for the majority of the families that change their neighborhood choices across voucher assignments. These analyses requires us to address the problem of partial identification of the counterfactual outcomes in (**T.1**).

4.2 Addressing the Problem of Partial Identification

Partial identification is a common problem in multiple-choice models with categorical IVs. To give some perspective, consider applying the well-known monotonicity criterion of Angrist and Imbens (1995) to the three-choice model with a three-valued IV as in MTO. Appendix F.2 shows this monotonicity criterion generates a response matrix with ten response-types and only two out of the ten response-types probabilities are point-identified. Moreover, the response matrix comprises 18 counterfactual outcomes. Again, only two out of these 18 counterfactuals are point-identified.

Appendix F explains that the MTO incentives do not justify the monotonicity criterion of Angrist and Imbens (1995). Instead, MTO incentives generate choice restrictions that result in a response matrix containing only seven response-types. These response-types enable us to point-identify all the response-type probabilities. In addition, the response-types identify nine counterfactual outcomes, but only six of them are point-identified. This section addresses the partial identification problem of the remaining three counterfactual outcomes. The solution to this problem entails converting the choice restrictions of MTO into the following set of monotonicity conditions:

Theorem T.3. The choice restrictions (21)–(27) are equivalently and uniquely represented by the following monotonicity conditions:

	Z-pairs	T	Unordered Monotonicity Conditions		
1	(z_c, z_8)	t_h	$\mathbf{1}[T_i(z_c) = t_h]$	$\geq$	$\mathbf{1}[T_i(z_8) = t_h]$
2	(z_8, z_e)	t_h	$\mathbf{1}[T_i(z_8) = t_h]$	$\leq$	$\mathbf{1}[T_i(z_e) = t_h]$
3	(z_e, z_c)	t_h	$\mathbf{1}[T_i(z_e) = t_h]$	$\leq$	$\mathbf{1}[T_i(z_c) = t_h]$
4	(z_c, z_8)	t_m	$\mathbf{1}[T_i(z_c) = t_m]$	$\leq$	$\mathbf{1}[T_i(z_8) = t_m]$
5	(z_8, z_e)	t_m	$\mathbf{1}[T_i(z_8) = t_m]$	$\geq$	$\mathbf{1}[T_i(z_e) = t_m]$
6	(z_e, z_c)	t_m	$\mathbf{1}[T_i(z_e) = t_m]$	$\leq$	$\mathbf{1}[T_i(z_c) = t_m]$
7	(z_c, z_8)	t_l	$\mathbf{1}[T_i(z_c) = t_l]$	$\leq$	$\mathbf{1}[T_i(z_8) = t_l]$
8	(z_8, z_e)	t_l	$\mathbf{1}[T_i(z_8) = t_l]$	$\leq$	$\mathbf{1}[T_i(z_e) = t_l]$
9	(z_e, z_c)	t_l	$\mathbf{1}[T_i(z_e) = t_l]$	$\geq$	$\mathbf{1}[T_i(z_c) = t_l]$

Proof. See Appendix A.8 for proof. □

Theorem **T.3** presents nine monotonicity conditions generate the same response matrix as the seven choice restriction in (21)–(27). Moreover, these monotonicity conditions are unique in the sense that changing the direction of any of the inequalities generate a different response matrix.

One advantage of the monotonicity representation is that each condition in **T.3** corresponds to a propensity score inequality that can be estimated from observed data, namely

$$\underbrace{\mathbf{1}[T_i(z) = t] \leq \mathbf{1}[T_i(z') = t]}_{\text{Monotonicity Condition}} \Rightarrow \underbrace{P(T = t|Z = z) < P(T = t|Z = z')}_{\text{Propensity Score Inequality}} \text{ for any } t, z, z'.$$

Table 4 shows that the direction of each monotonicity conditions in **T.3** matches its corresponding propensity score inequality.[25] There are 336 possible sets of nine propensity score inequalities with different directions. Revealed preference analysis justifies only one of these sets, which is precisely the one corroborated by the observed data.

Table 4: Propensity Scores Inequalities Corresponding to Each Monotonicity Condition in **T.3**

	Z-pairs	T	Propensity Score Inequalities		
1	(z_c, z_8)	t_h	$P(T = t_h\|Z = z_c) = 0.82$	$>$	$0.34 = P(T = t_h\|Z = z_8)$
2	(z_8, z_e)	t_h	$P(T = t_h\|Z = z_8) = 0.34$	$<$	$0.44 = P(T = t_h\|Z = z_e)$
3	(z_e, z_c)	t_h	$P(T = t_h\|Z = z_e) = 0.44$	$<$	$0.82 = P(T = t_h\|Z = z_c)$
4	(z_c, z_8)	t_m	$P(T = t_m\|Z = z_c) = 0.15$	$<$	$0.57 = P(T = t_m\|Z = z_8)$
5	(z_8, z_e)	t_m	$P(T = t_m\|Z = z_8) = 0.57$	$>$	$0.07 = P(T = t_m\|Z = z_e)$
6	(z_e, z_c)	t_m	$P(T = t_m\|Z = z_e) = 0.07$	$<$	$0.15 = P(T = t_m\|Z = z_c)$
7	(z_c, z_8)	t_l	$P(T = t_l\|Z = z_c) = 0.03$	$<$	$0.09 = P(T = t_l\|Z = z_8)$
8	(z_8, z_e)	t_l	$P(T = t_l\|Z = z_8) = 0.09$	$<$	$0.49 = P(T = t_l\|Z = z_e)$
9	(z_e, z_c)	t_l	$P(T = t_l\|Z = z_e) = 0.49$	$>$	$0.03 = P(T = t_l\|Z = z_c)$

[25] Table 4 relates to Kline and Tartari (2016), who study labor market participation and generate a set of economically justified inequalities of observed response probabilities.

The monotonicity conditions in **T.3** satisfy the unordered monotonicity criterion of Heckman and Pinto (2018).[26] This criterion states that a change in the instrument induce all agents towards or against a choice t.[27] Formally, for any two instrumental values z, z' and each choice t, we have that:

$$\mathbf{1}[T_i(z) = t] \geq \mathbf{1}[T_i(z') = t] \text{ for all } i \in \mathcal{I} \text{ or } \mathbf{1}[T_i(z) = t] \leq \mathbf{1}[T_i(z') = t] \text{ for all } i \in \mathcal{I}. \tag{44}$$

Heckman and Pinto (2018) show that unordered monotonicity is equivalent to assuming a model in the treatment choice is additively separable from the unobserved variables that generate bias. The following theorem builds on their ideas to describe useful properties of MTO model:[28]

Theorem T.4. Given the IV assumptions (1)–(3) and the MTO response matrix (28), the following properties hold:

(i). The choice indicator $D_t = \mathbf{1}[T = t]$ for $t \in \{t_h, t_m, t_l\}$ can be expressed as :

$$D_t = \mathbf{1}[P_t(Z) \geq U_t], \tag{45}$$

where $P_t(Z)$ (or simply P_t) denotes the propensity score $P(T = t|Z)$ and $U_t \sim Unif[0, 1]$ is an unobserved random variable that is uniformity distributed in $[0, 1]$ and statistically independent of $P_t(Z)$.

(ii). It is possible to express a LATE-type parameter regarding the a choice $t \in \{t_h, t_m, t_l\}$ and IV-values $z, z' \in \{z_c, z_8, z_e\}$ such that $P_t(z) < P_t(z')$, as:

$$\frac{E(YD_t|Z = z') - E(YD_t|Z = z)}{P_t(z') - P_t(z)} = \frac{E(YD_t|P_t = P_t(z')) - E(YD_t|P_t = P_t(z))}{P_t(z') - P_t(z)} = \frac{\int_{P_t(z)}^{P_t(z')} E(Y(t)|U_t = u)du}{P_t(z') - P_t(z)}, \tag{46}$$

where $E(Y(t)|U_t = u)$ is the marginal response function of the counterfactual outcome $Y(t)$ given the unobserved variable $U_t = u \in [0, 1]$.

Proof. See Appendix A.9 for proof. □

Equation (45) states that each neighborhood choice t can be expressed by a threshold crossing inequality that is separable on the propensity $P_t(Z)$ and an unobserved variable U_t. Lee and Salanié (2018) study the identification of multi-valued choice models determined by an arbitrary system threshold crossing inequalities. They show that, in general, choice indicators are a function of all

[26] Heckman and Pinto (2018) demonstrate that the triangular property displayed by matrices (35), (42) and (43) are a necessary and sufficient criteria for the unordered monotonicity condition to hold. Specifically, they show that unordered monotonicity holds if and only if each of the matrices $\boldsymbol{B}_t; t \in supp(T)$ is lonesum. That is to say that each binary element of the matrix $\boldsymbol{B}_t$ can be fully determined using the information on the column and row sums. It turns out that a binary matrix is lonesum if and only if it can be transformed into a triangular matrix by row and column permutations. This is precisely the property shown in (35), (42), and (43).

[27] Unordered monotonicity does not imply or is implied by the monotonicity criteria of Angrist and Imbens (1995).

[28] Heckman and Pinto (2018) approach is slightly different than the one used here since their causal framework employs structural equations instead of the language of potential outcomes employed in (1)–(3). See Heckman and Pinto (2022) for a recent discussion on the differences between these causal frameworks.

propensity scores. The central property of equation (45) is that the choice indicator D_t is a function of *only* its own propensity score $P_t(Z)$, instead of the propensity scores of all choices.

Theorem **T.4** is closely related to well-known results in the IV literature on binary choice models. If the treatment were binary, $T \in \{0,1\}$, the unordered monotonicity (44) would be equivalent to the monotonicity condition of Imbens and Angrist (1994), that is, $T_i(z) \geq T_i(z')\forall i$ or $T_i(z) \leq T_i(z')\forall\, i$. Vytlacil (2002) shows that if this monotonicity holds, then treatment choice $T \in \{0,1\}$ can be expressed as $T = \mathbf{1}[P(Z) \geq U]$ where $P(Z) = P(T=1|Z)$ and $U \sim unif[0,1]$. Moreover, Heckman and Vytlacil (1999, 2000) show that given IV-values z, z' such that $P(z) < P(z')$, the LATE parameter in Imbens and Angrist (1994) can be expressed as:

$$\frac{E(Y|Z=z') - E(Y|Z=z)}{P(z') - P(z)} = \frac{\int_{P(z)}^{P(z')} E(Y(1) - Y(0)|U_t = u)du}{P(z') - P(z)}.$$

Theorem **T.4** can be understood as an extension of these results from the binary choice model to the case of multiple choices.

Equation (46) in **T.4** enable us to rewrite the three counterfactual outcomes for t_l in (37), (39), and (40) as the following equations:

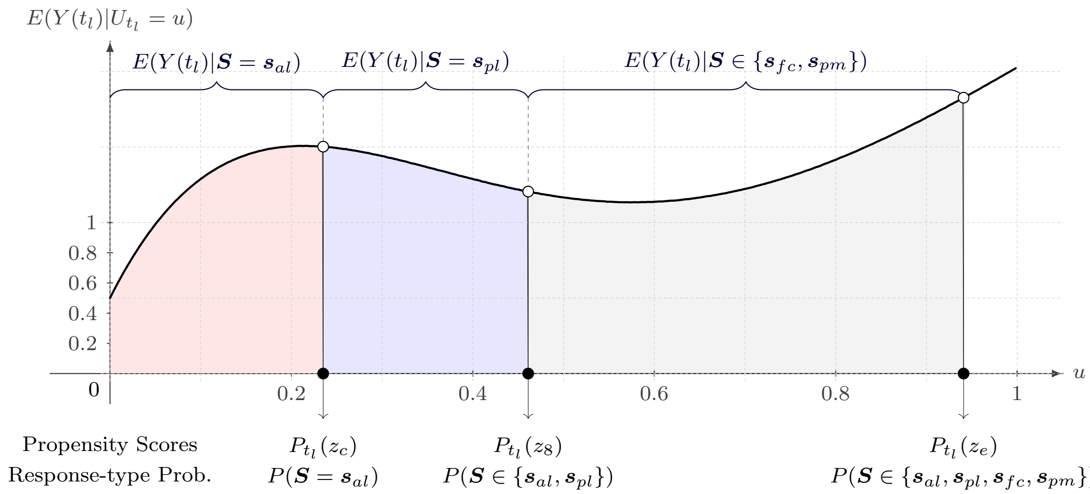
$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{al}) = \frac{\int_0^{P_{t_l}(z_c)} E(Y(t_l)|U_{t_l} = u)du}{P_{t_l}(z_c)}, \tag{47}$$

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl}) = \frac{\int_{P_{t_l}(z_c)}^{P_{t_l}(z_8)} E(Y(t_l)|U_{t_l} = u)du}{P_{t_l}(z_8) - P_{t_l}(z_c)}, \tag{48}$$

$$E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}) = \frac{\int_{P_{t_l}(z_8)}^{P_{t_l}(z_e)} E(Y(t_l)|U_{t_l} = u)du}{P_{t_l}(z_e) - P_{t_l}(z_8)}. \tag{49}$$

Equations (47)–(49) relates the response-types $\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}$ with the consecutive propensity score intervals $[0, P_{t_l}(z_c)]$, $[P_{t_l}(z_c), P_{t_l}(z_8)]$, $[P_{t_l}(z_c), P_{t_l}(z_8)]$, in the $[0,1]$-support of the unobserved variable U_{t_l}. The counterfactual mean $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$ in (49) is the integral of the response function $E(Y(t_l)|U_{t_l} = u)$ over the corresponding propensity score interval $u \in [P_{t_l}(z_8), P_{t_l}(z_e)]$ divided by the interval length, $P_{t_l}(z_e) - P_{t_l}(z_8)$, which also identifies the response-type probability $P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$. The same applies to $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{al})$ in (47) and $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl})$ in (48). Figure 2 presents a diagram of the identification equations (47)–(49).

Figure 2: Graphical Representation of the Identification Results for $Y(t_l)$



In summary, equation 46 implies that if we are able to map the response type $\boldsymbol{s}$ to an interval $[p, p']$ in the support of U_t, then the counterfactual mean $E(Y(t)|\boldsymbol{S}=\boldsymbol{s})$ can be expressed as:

$$E(Y(t)|\boldsymbol{S}=\boldsymbol{s}) = \frac{\int_{P_t(z)}^{P_t(z')} E(Y(t)|U_t=u)du}{P_t(z')-P_t(z)} = \frac{E(YD_t|P_t=p')-E(YD_t|P_t=p)}{p'-p} \tag{50}$$

Equation (50) motivates an identification strategy that employs interpolation of $E(YD_t|P_t=p)$. The strategy consists of estimating the expected value of the interaction $Y \cdot D_t$ as a function of the propensity scores of choice t. Covariates $\boldsymbol{X}$ ensure the variation in propensity scores. The counterfactual outcome $E(Y(t)|\boldsymbol{S}=\boldsymbol{s})$ is obtained by evaluating the estimated function at propensity score values p and p'.

In our leading example, we seek to disentangle $E(Y(t_l)|\boldsymbol{S}\in\{\boldsymbol{s}_{fc},\boldsymbol{s}_{pm}\})$ into $E(Y(t_l)|\boldsymbol{S}=\boldsymbol{s}_{fc})$ and $E(Y(t_l)|\boldsymbol{S}=\boldsymbol{s}_{pm})$. The point identification of these counterfactuals involves two tasks. The first task requires splitting the interval $[P_{t_l}(z_8), P_{t_l}(z_e)]$ of Figure 2 into two intervals associated with the response-types $\boldsymbol{s}_{fc}$ and $\boldsymbol{s}_{pm}$. The second task is to evaluate (50)

integral of the response function $E(Y(t_l)|U_{t_l}=u)$ over each interval.

Task 1: Splitting the Propensity Score Interval

The diagram in Figure 2 displays a coarse mapping between the response types that choose t_l and intervals in the unitary support of U_{t_l}. Specifically, the response types $\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}$, correspond to the intervals $[0, P_{t_l}(z_c)]$, $[P_{t_l}(z_c), P_{t_l}(z_8)], [P_{t_l}(z_c), P_{t_l}(z_8)]$, respectively. The order of response-types traces back to the triangular property of the MTO response matrix. Specifically, the sequence $\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}$ arises when scanning the rows of the response-matrix $\boldsymbol{R}_l$ in (35) for the response-types that take value t_l.

Applying the same procedure to the choice t_h generates a mapping where the response types $\boldsymbol{s}_{ah}, \boldsymbol{s}_{ph}, \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pl}\}$, correspond to the intervals $[0, P_{t_h}(z_8)]$, $[P_{t_h}(z_8), P_{t_h}(z_e)], [P_{t_h}(z_e), P_{t_h}(z_c)]$ in the unitary support of U_{t_h}. In the case of t_m, we have that the response types $\boldsymbol{s}_{am}, \boldsymbol{s}_{pm}, \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{ph}\}$, correspond to the intervals $[0, P_{t_m}(z_e)]$, $[P_{t_m}(z_e), P_{t_m}(z_c)], [P_{t_m}(z_c), P_{t_m}(z_8)]$ in the unitary support of U_{t_m}.

The same approach applies to the choices t_m and t_h. We seek to split the interval $[P_{t_l}(z_8), P_{t_l}(z_e)]$ in Figure 2. This task require us to determine if the full-compliers $\boldsymbol{s}_{fc}$ precede the partial-compliers $\boldsymbol{s}_{pm}$ or not.

In the case of choice t_m, we seek to determine the order of the full-compliers $\boldsymbol{s}_{fc}$ and partial-compliers $\boldsymbol{s}_{ph}$, and in the case of t_l, we seek to determine if the full-compliers $\boldsymbol{s}_{fc}$ precede the partial-compliers $\boldsymbol{s}_{pm}$ or not. The next theorem is useful in determining the ordering of these response-types.

Theorem T.5. Consider the IV model characterized by assumptions (1)–(3) in which the response matrix (28) holds, and each choice indicator is given by equation (45), that is, $D_t = \mathbf{1}[P_t(Z) \geq U_t]; U_t \sim Unif[0,1]$ for $t \in \{t_h, t_m, t_l\}$. If the ordering of the response-types is such that the partial-compliers $(\boldsymbol{s}_{pm}, \boldsymbol{s}_{ph}, \boldsymbol{s}_{ph})$ precede the full-compliers $\boldsymbol{s}_{fc}$ in $(U_{t_l}, U_{t_m}, U_{t_h})$ respectively, then the probability of at least two of the partial-compliers must be zero. On the other hand, the response-type probabilities for all partial-compliers can be strictly positive if the full-compliers $\boldsymbol{s}_{fc}$ precede the partial-compliers $(\boldsymbol{s}_{pm}, \boldsymbol{s}_{ph})$.

Proof. See Appendix A.10 for proof. □

Theorem **T.5** considers an ordering of the response-types in which the partial-compliers precede the full-compliers. This arrangement is only possible if only if the probability of some partial-compliers are zero. I other words, some partial-compliers cannot exist. Such constraint does not apply when full-compliers precede partial-compliers. Moreover, the empirical section shows that the probability of all partial-compliers are positive and statistically different than zero. Thus, it is safe to assume that the full-compliers precede the partial-compliers. In the case of t_l, this means that the interval $[P(t_l(z_8), P(t_l(z_8) + P(\boldsymbol{S}))]$ in the support of U_{t_l} refers to $\boldsymbol{s}_{fc}$, while $[P(t_l(z_8) +$

$P(\boldsymbol{S})), P(t_l(z_e)]$ refers to $\boldsymbol{s}_{pm}$,[29] According to equation (46), the counterfactuals $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ and $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm})$ can be expressed as:

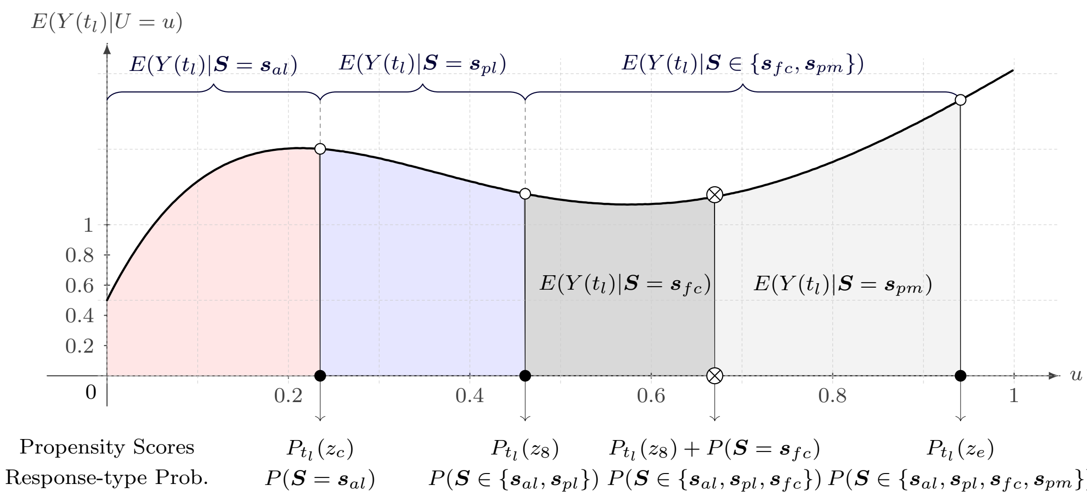
$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc}) = \frac{\int_{P_{t_l}(z_8)}^{p^*} E(Y(t_l)|U_{t_l} = u)du}{P(\boldsymbol{S} = \boldsymbol{s}_{fc})} = \frac{E(YD_{t_l}|P_{t_l}(Z) = p^*) - E(YD_t|P_{t_l} = P_{t_l}(z_8))}{p * - P_{t_l}(z_8)}, \quad (51)$$

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm}) = \frac{\int_{p^*}^{P_{t_l}(z_e)} E(Y(t_l)|U_{t_l} = u)du}{P(\boldsymbol{S} = \boldsymbol{s}_{pm})} = \frac{E(YD_{t_l}|P_{t_l}(Z) = P_{t_l}(z_e)) - E(YD_t|P_{t_l}(Z) = p^*)}{P_{t_l}(z_e) - p^*}, \quad (52)$$

$$\text{where} p^* = P_{t_l}(z_8) + P(\boldsymbol{S} = \boldsymbol{s}_{fc}). \quad (53)$$

The following figure displays a diagram of equations (51) and (52).

Figure 3: 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 $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm})$



Note that each of the four counterfactual means $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}); \boldsymbol{s} \in \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}$ in Figure 3 can be expressed as the ratio of the integral of the marginal response $E(Y(t_l)|U = u)$ over a probability interval $[p, p']$ divided by the interval length, $p' - p$. Moreover, the difference $p' - p$ identifies the response-type probability $P(\boldsymbol{S} = \boldsymbol{s})$. Appendix H.2 provides the decompositions of the partially-identified outcomes of neighborhood choices t_m and t_h.

Task 2: Evaluating the Response Function Integrals

[29]Recall that Theorem (**T.2**) establishes that all the response-type probabilities are identified. In particular, we have that $P(\boldsymbol{S} = \boldsymbol{s}_{fc}) = \big(P_{t_h}(z_8) - P_{t_h}(z_e)\big) - \big(P_{t_m}(z_c) - P_{t_m}(z_8)\big)$.

Theorem T.4 enables us to write the expressions such as (51) and (52) as propensity score estimators (Frölich, 2007). Specifically, let $P_t(z,\boldsymbol{x}) = P(T=t|Z=z,\boldsymbol{X}=\boldsymbol{x})$ be the propensity score conditioned on the baseline variables $\boldsymbol{X}=\boldsymbol{x}$ for $(t,z) \in \{t_h, t_m, t_l\} \times \{z_c, z_8, z_e\}$, and let $M_t(p,\boldsymbol{x}) = E(Y \cdot D_t | P_t = p, \boldsymbol{X}=\boldsymbol{x})$ be the expected value of the interaction $Y \cdot D_t$ conditioned on the propensity score $P_t = p$ and baseline variables $\boldsymbol{X}=\boldsymbol{x}$. In this notation, the counterfactual outcome $E(Y(t_l)|\boldsymbol{S}=\boldsymbol{s}_{fc})$ in (51) is identified by the following expression:

$$E(Y(t_l)|\boldsymbol{S}=\boldsymbol{s}_{fc}) = \frac{\int \big(M_{t_l}(P_{t_l}(z_8,\boldsymbol{x}) + P_{fc}(\boldsymbol{x}), \boldsymbol{X}=\boldsymbol{x}) - M_{t_l}(P_{t_l}(z_8,\boldsymbol{x}), \boldsymbol{X}=\boldsymbol{x})\big) dF_{\boldsymbol{X}}(\boldsymbol{x})}{\int P_{fc}(\boldsymbol{x}) dF_{\boldsymbol{X}}(\boldsymbol{x})}, \tag{54}$$

$$\text{where } P_{fc}(\boldsymbol{x}) = \big(P_{t_h}(z_8,\boldsymbol{x}) - P_{t_h}(z_e,\boldsymbol{x})\big) - \big(P_{t_m}(z_c,\boldsymbol{x}) - P_{t_m}(z_8,\boldsymbol{x})\big). \tag{55}$$

Note that both $P_t(z,\boldsymbol{x})$ and $M_t(p,\boldsymbol{x})$ can be evaluated from data. In summary, the propensity score estimator exploits the variation of baseline variables $\boldsymbol{X}$ to estimate the function $M_t(p,\boldsymbol{x})$, which is then evaluated at the propensity score values that identify the counterfactual outcome of interest. Appendix H.3 describes the propensity score estimator in greater detail. Section 5.3 describes the empirical strategy for estimating $P_t(z,\boldsymbol{x})$ and $M_t(p,\boldsymbol{x})$.

5 Empirical Results

The methodology of Section 4 enables us to expand our understanding of the MTO intervention through novel analyses that supplement the previous literature. Section 5.1 presents the estimates of the MTO response-type probabilities, whereas Section 5.2 reports the expected value of the baseline variables conditioned on the response-types. Together, these sections provide informative characterizations of the MTO families.

Section 5.3 reports the estimates of counterfactual outcomes for all response-types, while Section 5.4 presents estimates of neighborhood effects for the full-compliers. These analyses provide a detailed picture of how the MTO intervention affected the lives of its participants, and are only possible due to identification results in Section 4.2.

Finally, Section 5.5 connects these novel analyses to traditional evaluations by decomposing TOT estimates into weighted averages of the neighborhood effects across response-types.

5.1 Response-type Probabilities

Response-type probabilities are estimated by the parameter $\boldsymbol{\beta}_P$ of the following linear probability model:[30]

$$D_{t,i} = \boldsymbol{B}_{t,i}\boldsymbol{\beta}_P + \boldsymbol{X}_i\boldsymbol{\theta}_t + \boldsymbol{K}_i\boldsymbol{\gamma}_t + \epsilon_{t,i} \text{ across all } t \in \{t_l, t_m, t_h\}, \tag{56}$$

where $D_{t,i} = \mathbf{1}[T_i = t]$ indicates if family i chooses neighborhood $t \in \{t_h, t_m, t_l\}$, $\boldsymbol{X}_i$ denotes the baseline variables displayed in Table 1, $\boldsymbol{K}_i$ denotes the site fixed effects, and $\boldsymbol{B}_{t,i} \equiv \boldsymbol{B}_t[Z_i, \cdot]$ denotes the row of the binary matrix $\boldsymbol{B}_t$ associated with instrumental value Z_i assigned to family i. All the estimations use weighted observations according to the MTO adult weighting scheme described in Orr et al. (2003). Variables $\boldsymbol{X}$ and $\boldsymbol{K}$ are normalized to have zero weighted averages and unitary standard deviations. The inference is based on the stratified bootstrap method that resamples the full data set according to the MTO weights.[31]

Figure 4 presents the estimates of the seven response-type probabilities of MTO. These probabilities partition the sample into latent groups based on the families' choice behavior. For instance, 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 voucher assignment. In particular, about a third of the families always remain in high poverty neighborhoods, $P(\boldsymbol{S} = \boldsymbol{s}_{ah}) = 0.35$. Another third of the sample consists of full-compliers, $P(\boldsymbol{S} = s_{fc}) = 0.31$. These families choose high, medium, and low poverty neighborhoods if assigned to z_c, z_8, and z_e, respectively. Partial compliers account for almost a quarter of the sample, $P(\boldsymbol{S} \in \{\boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{ph}\}) = 0.24$. These comprise the families that choose two out of the three possible neighborhood-types as the instrument varies.

5.2 Conditional Expectation of Baseline Variables

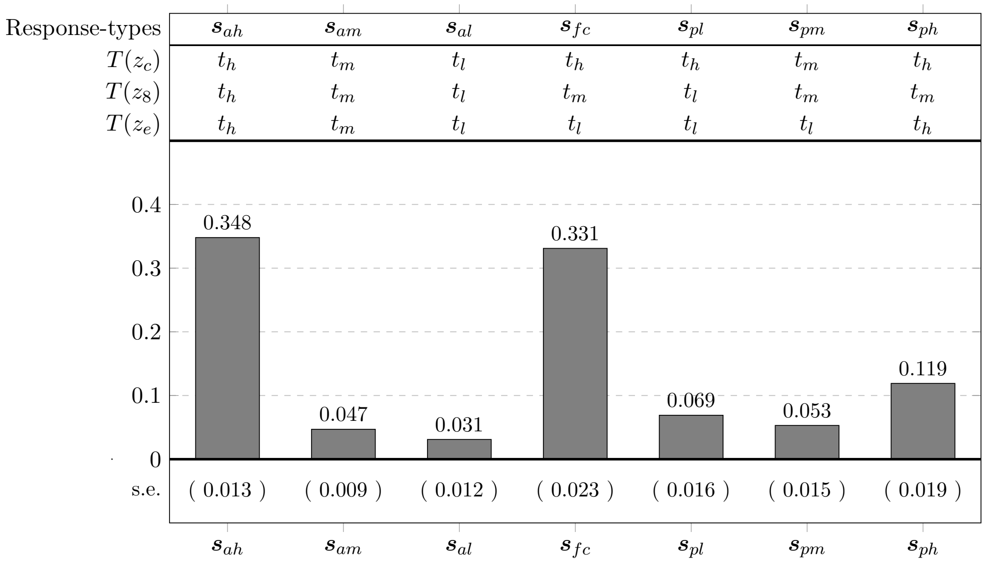
The following model is used to estimate the expected value of baseline variables conditioned on the response-types:

$$X_i D_{t,i} = \boldsymbol{B}_{t,i}\boldsymbol{\beta}_X + \boldsymbol{K}_i\boldsymbol{\theta}_t + \epsilon_{t,i}, \text{ across all } t \in \{t_l, t_m, t_h\}. \tag{57}$$

[30] Regression (56) can be understood as the empirical counterpart of the equation $\boldsymbol{P}_Z(t) = \boldsymbol{B}_t\boldsymbol{P}_S; t \in \{t_h, t_m, t_l\}$ in Appendix A.6. This method is only valid when all response-type probabilities are point-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.

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

Figure 4: Response-type Probabilities



This figure presents the counterfactual choices of each response-types and their estimated probabilities.

Equation (57) replaces the dependent variable $D_{t,i}$ in (56) by the interaction $X_i D_{t,i}$. The parameter $\boldsymbol{\beta}_X$ estimates the 7×1 vector of the parameters $E(X|\boldsymbol{S} = \boldsymbol{s})P(\boldsymbol{S} = \boldsymbol{s})$ across all the response-types. The estimates for $E(X|\boldsymbol{S} = \boldsymbol{s})$ are obtained by dividing the elements of $\boldsymbol{\beta}_X$ by their corresponding response-type probabilities.

Table 5 presents the estimates for the conditional expectation of the baseline variables given the response-types. We observe a sharp contrast of baseline means between the high poverty always-takers $\boldsymbol{s}_{ah}$, which comprise families that always remain in high poverty neighborhoods, and the full-compliers $\boldsymbol{s}_{fc}$, who are the most responsive to the voucher incentives. The families of type $\boldsymbol{s}_{ah}$ are more likely to have disabled persons and teenagers among household members, which is consistent with their reduced neighborhood mobility. On the other hand, $\boldsymbol{s}_{fc}$-families are less likely to have teenage members, and the head of the family is less likely to be married.

The high poverty always-takers $\boldsymbol{s}_{ah}$ are less likely to be victims of a crime in the neighborhood. These families report the lowest level of neighborhood dissatisfaction and are most likely to perceive their neighborhood as safe. In contrast, the full-compliers, $\boldsymbol{s}_{fc}$, report the highest level of neighborhood dissatisfaction and are more likely to perceive the neighborhood as unsafe.

On average, the high poverty always-takes, $\boldsymbol{s}_{ah}$, have the lowest level of schooling and are less likely to have a car. On the opposite side are the low poverty always-takers, $\boldsymbol{s}_{al}$. These families have the highest level of schooling. They are most likely to have a car and the least likely to be a welfare recipient. In addition, the low poverty always-takers, $\boldsymbol{s}_{al}$, are families that are most likely to be victims of criminal activity. Not surprisingly, these are also the families that report the highest level of neighborhood dissatisfaction.

In summary, the data indicates that baseline characteristics play a primary role in shaping how families respond to relocation incentives. For instance, MTO incentives are insufficient to induce the relocation of high poverty always-takers $\boldsymbol{s}_{ah}$. These families face higher mobility constraints and are less disturbed by neighborhood criminality. Unfortunately, these are also the most disadvantaged families and could gain the most from relocation. Note that we observe a strong positive selection on baseline variables, in that the most privileged families always move to low poverty neighborhoods regardless of the voucher incentives.

5.3 Estimating Counterfactual Outcomes

This paper evaluates the counterfactual outcomes using a propensity score estimator summarized by the following steps:

1. Estimate the conditional propensity score $P_{t,i}(z) \equiv P(T = t|Z = z, \boldsymbol{X} = \boldsymbol{X}_i, \boldsymbol{K} = \boldsymbol{K}_i)$ for $(t, z) \in \{t_h, t_l, t_m\} \times \{z_c, z_8, z_e\}$, given the baseline characteristics $\boldsymbol{X}_i, \boldsymbol{K}_i$ of family i;

2. Estimate the conditional expected value of the interaction $M_{t,i}(p) = E(Y \cdot D_t|P_t = p, \boldsymbol{X} = \boldsymbol{X}_i, \boldsymbol{K} = \boldsymbol{K}_i)$ as a function of the propensity scores P_t for choice t, given the baseline characteristics $\boldsymbol{X}_i, \boldsymbol{K}_i$ of family i;

3. Estimate the counterfactual outcome means $E(Y(t)|\boldsymbol{S} = \boldsymbol{s})$ using the empirical counterpart of the propensity score estimator discussed in (51).

The first step estimates the propensity scores using the following linear probability model:

$$D_{t,i} = \sum_{z \in \{z_c, z_8, z_e\}} \mathbf{1}[Z_i = z] \cdot \Big(\alpha_{t,z} + \boldsymbol{X}_i \boldsymbol{\theta}_{t,z} + \boldsymbol{K}_i \boldsymbol{\gamma}_{t,z}\Big) + \epsilon_{t,i}; t \in \{t_l, t_m, t_h\}. \tag{58}$$

Table 5: 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 reposts the p-value that tests the null hypothesis that the baseline mean conditional on the response-type is equal to the unconditional mean. Bold values indicates that the p-value is less than 5%. The sample size is 4227.

The estimate for the propensity score for a family i and IV-value z is given by:[32]

$$\hat{P}_{t,i}(z) = \hat{\alpha}_{t,z} + \boldsymbol{X}_i\hat{\boldsymbol{\theta}}_{t,z} + \boldsymbol{K}_i\hat{\boldsymbol{\gamma}}_{t,z};\ \text{for } (t,z) \in \{t_h, t_l, t_m\} \times \{z_c, z_8, z_e\}.$$

In particular, the estimate for the full-complier probability conditioned on the baseline characteristics of family i is $\hat{P}_i(\boldsymbol{s}_{fc}) = \big(\hat{P}_{t_h,i}(z_8) - \hat{P}_{t_h,i}(z_e)\big) - \big(\hat{P}_{t_m,i}(z_c) - \hat{P}_{t_m,i}(z_8)\big)$.

The second step evaluates the the conditional expectation of the interaction YD_t as a local polynomial of propensity the score estimates:

$$Y_i \cdot D_{t,i} \; = \; \sum_{k=0}^{3} \alpha_k \cdot \big(\hat{P}_{t,i}\big)^k + \Big(\hat{P}_{t,i} \cdot \boldsymbol{K}_i\Big)\boldsymbol{\xi}_t + \Big(\hat{P}_{t,i} \cdot \boldsymbol{X}_i\Big)\boldsymbol{\psi}_t + \boldsymbol{K}_i\boldsymbol{\gamma}_t + \boldsymbol{X}_i\boldsymbol{\theta}_t + \epsilon_{t,i}, \tag{59}$$

where $\hat{P}_{t,i} \equiv \hat{P}_{t,i}(Z_i)$ is the propensity score of family i.[33] The estimate for $M_{t,i}(p)$ is $\hat{M}_{t,i}(p) = \sum_{k=0}^{3} \hat{\alpha}_k \cdot p^k + p(\boldsymbol{K}_i\hat{\boldsymbol{\xi}}_t + \boldsymbol{X}_i\hat{\boldsymbol{\psi}}_t) + \boldsymbol{K}_i\hat{\boldsymbol{\gamma}}_t + \boldsymbol{X}_i\hat{\boldsymbol{\theta}}_t$.

The final step evaluates the conditional expectations of the counterfactual outcomes. For instance, $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ in (51) 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 (54), namely:

$$\hat{E}(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc}) = \frac{\sum_i \Big(\hat{M}_{t_l,i}\big(\hat{P}_{t_l,i}(z_8) + \hat{P}_i(\boldsymbol{s}_{fc})\big) - \hat{M}_{t_l,i}\big(\hat{P}_{t_l,i}(z_8)\big)\Big) \cdot W_i}{\sum_i \hat{P}_i(\boldsymbol{s}_{fc}) \cdot W_i} \tag{60}$$

where W_i denotes the MTO weights.

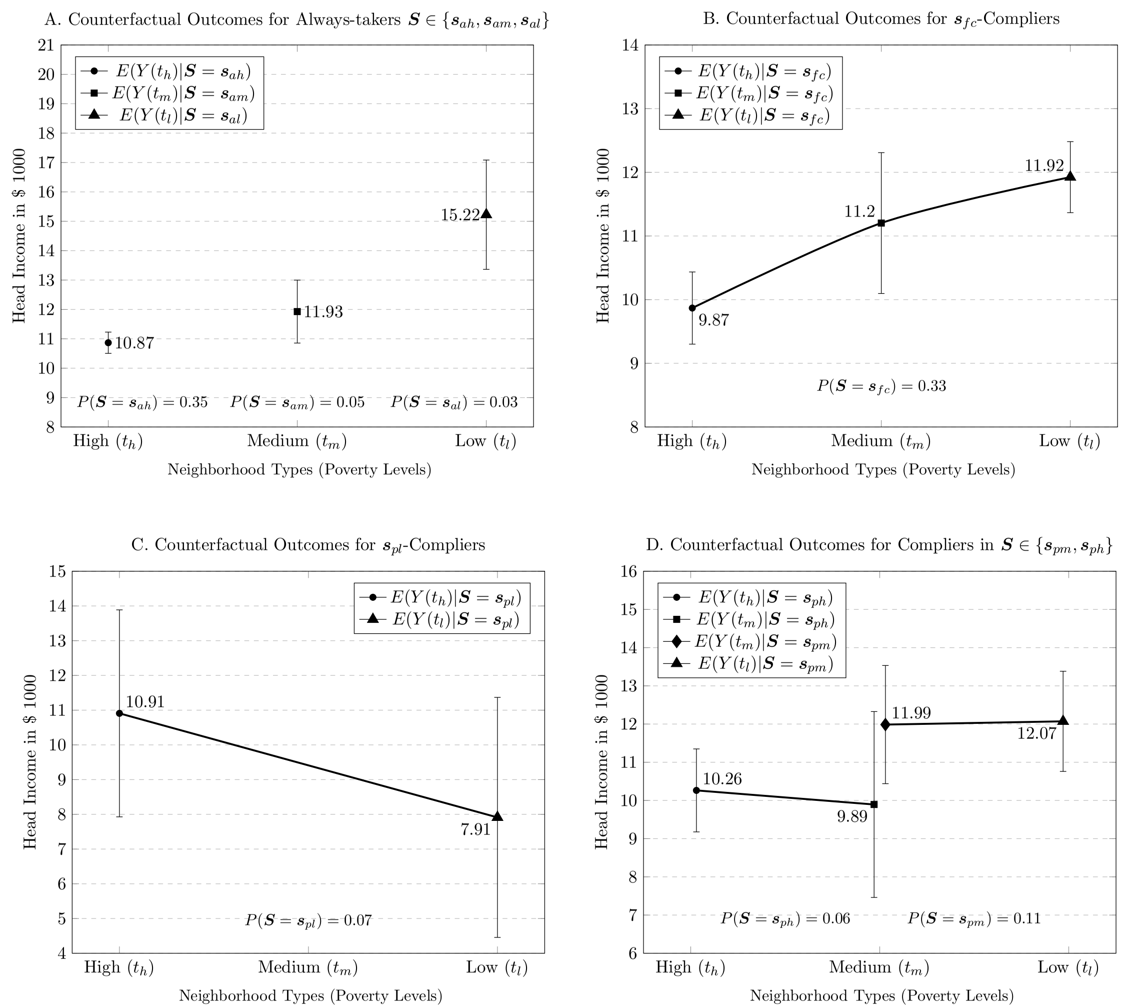
Figure 5 presents the estimated means for the counterfactual outcomes of the income of the head of the family. Figure 5.A shows the counterfactual income estimates for the always-takers. Estimates increase as the neighborhood choice ranges across high, median and low poverty neighborhoods. The difference of the counterfactual outcomes across the always-takes $\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}$ and $\boldsymbol{s}_{al}$ are not causal since family characteristics differ across these response-types. The high poverty always-takes $\boldsymbol{s}_{ah}$ have the lowest income among all always-takes. They are also the most disadvantaged families among the always-takers. The precision of the estimates is inversely proportional to sample share of each of the response-type.

Figure 5.B displays the estimates for the full-compliers $\boldsymbol{s}_{fc}$. It shows a steep increase in income as families move to better neighborhoods. In this case, the income difference across neighborhood

[32] 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.

[33] Appendix I 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 5: 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.

types constitute causal effects since we control for the same response-type.

Figures 5.C and 5.D present the income estimates for partial-compliers. Figure 5.C shows the income estimates for $\boldsymbol{s}_{pl}$-families, while Figure 5.D presents the income estimates for the families of type $\boldsymbol{s}_{pm}$ and $\boldsymbol{s}_{ph}$. These families account for a small share of the sample and the estimates lack the necessary statistical precision for conclusive analyses.

Table 6 presents the estimates for the counterfactual means of the economic outcomes described in Section 2. Note that greater values of the estimates are economically desirable in all outcomes, except currently on welfare.

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

The last row of Table 6 provides the estimates for the poverty levels across response-types. In the case of always-takers ($\boldsymbol{s}_{am}$ and $\boldsymbol{s}_{ah}$), the difference between on poverty levels between medium and high poverty neighborhoods is below four percentage points. In contrast, the difference between low and medium poverty neighborhoods is well above 30 percentage points. This trend is consistent with the counterfactual estimates: the difference in 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. For instance, the difference in poverty levels low and high poverty neighborhoods for full-compliers $\boldsymbol{s}_{fc}$ is 33.25%, while the difference for the partial complier $\boldsymbol{s}_{pl}$ is 26.37. This helps explain why the estimates for the full-compliers are the most significant among all compliers. Full-compliers account for the largest sample share and the largest difference in poverty levels between the neighborhood types.

Table 6: Estimates for the Expected Values of the Counterfactual 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.

5.4 Evaluating the Causal Effects for Full-compliers

This section investigates the neighborhood effects for the full-compliers $\boldsymbol{s}_{fc}$. As mentioned, this response-type comprises families that are most responsive to MTO incentives and accounts for the largest share of families that respond to these incentives. This neighborhood effect can be understood as an instance of the policy-relevant treatment effects (PRTE) of Heckman and Vytlacil (2001, 2005). The PRTE seeks to evaluate a policy question that affects the program participation but does not directly affect the treatment effects of each individual.[34] The average neighborhood effect for the full-compliers corresponds to the PRTE that sets participation probability of full-compliers to one, while setting the participation probability of remaining types to zero.

Table 7 presents the neighborhood effects on economic outcomes for the full-compliers. The first effect compares low versus high poverty neighborhoods, namely, $E(Y(t_l) - Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{fc})$. The second one compares low versus medium, $E(Y(t_l) - Y(t_m)|\boldsymbol{S} = \boldsymbol{s}_{fc})$, and the last one compares medium versus high, $E(Y(t_m) - Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{fc})$. Most of the neighborhood effects for low versus high poverty neighborhoods are statistically significant. On the other hand, none of the 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 the mean difference in the poverty levels of the neighborhood types.

The first three outcomes in Table 7 refer to family income. Full-compliers who move from high to low poverty neighborhoods experience an average rise in the annual income of the head of \$2.056. This accounts for a considerable increase of 20% in household income. The estimated neighborhood effect on the total income of the family is \$1.902 per year, accounting for a 14% increase in the household income. Both results are statistically and economically significant.

The estimates of Table 7 show that switching from a high to a low poverty neighborhood enhances a family's chance of being above the poverty line by about 50%. It also increases the likelihood of being employed by 27% and reduces welfare dependency by 34%. The 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, corresponding to an average increase of 25%. The estimate for the likelihood of being economically self-sufficiency is 0.065, representing a

[34] The full implementation of their method requires a continuous instrument, which is not the case in MTO.

40% rise. It is worth noting that these results refer to a sub-group of MTO families that cannot be assessed using the methodology of prior literature.

The last row of Table 7 presents the mean difference in poverty levels between the neighborhood types. As expected, the largest difference is between low and high poverty neighborhoods. The differences for the remaining comparisons are substantially lower. Not surprisingly, most of the neighborhood effects that compare low and high poverty neighborhoods are statistically significant, while the remaining effects are not.

5.5 Decomposing TOT Effects

The most influential literature on MTO relies on the treatment on the treat parameter to report weak and insignificant TOT effects on the economic outcomes (Kling et al., 2007, 2005; Sanbonmatsu et al., 2006, 2011). Some researchers however have reached different conclusions using alternative identification strategies. For instance, Clampet-Lundquist and Massey (2008) finds significant effects on earnings and employment when controlling for the duration of residing in disadvantaged neighborhoods. Aliprantis and Richter (2020) also finds significant labor market effects when controlling for the neighborhood quality. More recently, Harding et al. (2021) discuss the mismatch between the insignificant economic result of (Kling et al., 2007) and the significant effects on labor market outcomes of several observational studies (e.g. Elliott (1999); Fauth et al. (2004); Shang (2014)). A central contribution of this work is to reconcile these seemingly inconsistent findings in the MTO literature.

Section 2.2 explains that the TOT parameter consists of the causal effect of being offered a voucher divided by the voucher compliance rate. the section shows that the TOT parameter that compares the experimental and the control vouchers can be estimated by a Two-Stage Least Square (2SLS) regression that uses the experimental voucher z_e as the instrumental variable for the voucher take-up.

This paper uses a novel approach to investigate the causal content of the TOT parameter. Its core idea is to use classical economic behavior to exploit the information on the choice incentives of the MTO intervention. The economic analysis generates a causal framework that maps the neighborhood choice into several response-types. This framework renders a deeper understanding

Table 7: Estimates of the Causal Effects for Full-Compliers

	$E(Y(t_l) - Y(t_h) \mid \boldsymbol{s}_{fc})$		$E(Y(t_l) - Y(t_m) \mid \boldsymbol{s}_{fc})$		$E(Y(t_m) - Y(t_h) \mid \boldsymbol{s}_{fc})$	
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 $\boldsymbol{s}_{fc}$. The second column compares low and high poverty neighborhoods, the third column compares low and medium poverty neighborhoods, and the last column compares medium and high poverty neighborhoods. All estimates use the adult weighting scheme of MTO interim evaluation. The p-values test if the estimates are equal to zero are based on a bootstrap method that accounts for weighted scheme. Asterisks *** indicate a p-value < 0.01, ** indicates $0.01 \leq p$-value < 0.05, and * indicates $0.05 \leq p$-value < 0.1.

of the MTO intervention as shown in previous sections. In addition, it enable us to decompose the TOT parameter in terms of the neighborhood effects across the response-types.

Proposition **P.5** reveals that the TOT parameter that compares the experimental z_e with the control z_c vouchers evaluates a weighted average of three neighborhood effects. The most important element of the TOT parameter is the neighborhood effect that compares the low with the high poverty neighborhoods for full-compliers, that is, $E(Y(t_l)-Y(t_h)|\boldsymbol{s}_{fc})$. The second effect compares low and high poverty neighborhoods for the partial-compliers $\boldsymbol{s}_{pl}$, namely, $E(Y(t_l) - Y(t_h)|\boldsymbol{s}_{pl})$. The last effect stems from comparing the low with the medium poverty neighborhoods for the partial-compliers $\boldsymbol{s}_{pm}$, that is, $E(Y(t_l) - Y(t_m)|\boldsymbol{s}_{pm})$. These effects are estimated by the methods described in Sections 5.3–5.4.

The full-compliers account for a large share of the sample and their neighborhood effects are typically highly significant. In contrast, the partial-compliers $\boldsymbol{s}_{pl}$ and $\boldsymbol{s}_{pm}$ account for a smaller share of the MTO sample. Not surprisingly, the neighborhood effects of partial-compliers lack statistical precision. The TOT parameter combines the neighborhood effects of full and partial-compliers. This combination results in weaker estimates that do not share the statistical significance of the neighborhood effects for the full-compliers.

Table 8 presents the decomposition of the TOT estimates. The first column specifies the economic outcomes. The subsequent column presents the TOT estimates using 2SLS. The third column estimates the TOT parameter as a mixture of the three neighborhood effects as described in Proposition **P.5**. The remaining columns present the breakdown of the TOT estimates into the neighborhood effects of the full and the partial-compliers.

Note that the TOT estimates based on the 2SLS and on the weighted average of neighborhood effects are quite similar, despite being estimated by substantially different methods. Column 4 of Table 8 presents the neighborhood effects for the full-compliers. Most of the estimates are statistically significant. Columns 5–6 provides the neighborhood effects for the partial-compliers. As expected, none of the neighborhood effects for the partial-compliers are statically significant. Combining the significant effects of the full-compliers with the insignificant effects of the partial-compliers leads to statistically insignificant TOT effects.

The last row of Table 8 evaluates the average reduction in neighborhood poverty levels. The

Table 8: Decomposition of the Treatment on the Treated Effects

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 2SLS regression:

$$\text{First Stage:} \quad C_i = \gamma_1 + \gamma_2 \cdot \mathbf{1}[Z_i = z_c] + \gamma_X \cdot \boldsymbol{X} + \gamma_K \cdot \boldsymbol{K} + \eta_i \text{ for } i\,;\ Z_i \in \{z_c, z_e\}, \tag{61}$$

$$\text{Second Stage:} \quad Y = \beta_0 + \beta_{\text{TOT}} \cdot \hat{C}_i + \beta_X \cdot \boldsymbol{X} + \beta_K \cdot \boldsymbol{K} + \epsilon_i \text{ for } i\,;\ Z_i \in \{z_c, z_e\}, \tag{62}$$

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 based on the mixture of the neighborhood effects presented in columns 4–6. The p-values test the null hypothesis that the effects are equal to zero. They are obtained by a stratified bootstrap method that employs the MTO weighting scheme for the adult survey of the interim evaluation.

estimates are consistent with the empirical findings of the economic outcomes. The TOT estimate that uses 2SLS is -28.6 percentage points. The TOT estimate that evaluates the weighted average of the poverty reduction for the full and the partial-compliers is also -28.6 percentage points. However, there is considerable variation in poverty reduction among these response-types. The most significant decrease in neighborhood poverty is for the full-compliers $\boldsymbol{s}_{pl}$. The average reduction in neighborhood poverty levels for $\boldsymbol{s}_{fc}$-families that move from high to low-poverty neighborhoods is about 33 percentage points. The decrease of neighborhood poverty for the partial-compliers is significantly smaller. The average decline of poverty levels for the $\boldsymbol{s}_{pl}$-families is about 26 percentage points, while the average reduction for the $\boldsymbol{s}_{pm}$-families is about 18 percentage points. These findings help to explain why the aggregate effect evaluated by the TOT parameters is weaker than the neighborhood effects for the full-compliers.

Appendix I presents additional evaluations that check the robustness of these findings under various modifications of the baseline model. It turns out that the estimates across a variety of model specifications are very similar to the estimates presented in this section.

This section provides two key conclusions regarding the study of the TOT parameter. The first is that the economic analysis of MTO incentives was crucial in moving beyond simply evaluating the TOT. The analysis was essential in devising a method to decompose, isolate and estimate the neighborhood effects of the TOT parameter.

The second conclusion is that insignificant TOT effects on labor market outcomes does not necessarily mean that the MTO intervention failed to improve the economic well-being of its participants. The economic impact of MTO on families who complied with the voucher incentives (the full-compliers) remains economically and statistically significant. This result reconciles the MTO intervention with recent evidence that shows the importance of neighborhood quality in shaping the lives of its residents (Chetty et al., 2017, 2016; Chyn, 2016; Galiani et al., 2015).

6 Summary and Conclusions

The Moving to Opportunity (MTO) is the most influential housing experiments in the United States. It was designed to investigate the impact of relocating low-income families living in high poverty neighborhoods to low poverty areas. The participating families were randomly assigned to one of the three groups. Families assigned to the experimental group receives a housing voucher that subsidized the rent of dwellings located in low poverty neighborhoods. Families assigned to the Section 8 group received a voucher that subsidized the rent of dwellings located in either low or medium poverty neighborhoods. The control group received no voucher.

The MTO noncompliance was substantial. About half of the families that were offered the vouchers did not use them. This noncompliance generates the econometric problem of selection bias, which prevents the identification of the neighborhood effects by simple methods. Most of the MTO literature has addressed the problem of noncompliance by reporting treatment-on-the-treated (TOT) effects, that is the causal effect of being offered the voucher divided by the voucher compliance rate. The studies the that report TOT estimates typically find that the effect of the vouchers on labor market outcomes is not statistically significant.[35] However, several studies that employ other identification strategies have found significant effects on labor market outcomes.[36]

Despite the fact that the MTO intervention has been extensively studied, some questions remain unanswered. For instance, there is considerable disagreement on how to interpret the TOT parameter in terms of the causal effects between neighborhood types (Aliprantis, 2007; Clampet-Lundquist and Massey, 2008; Ludwig et al., 2008; Sampson, 2008). Other works, such as Harding et al. (2021), debates the reasons for the mismatch between the insignificance TOT effects on economic outcomes and the significant effects on labor market outcomes reported by several observational studies.[37]

This paper contributes to the MTO literature by addressing these questions. The MTO intervention is modeled as an IV model in which MTO families decide between three neighborhood types. The voucher assignment plays the role of a three-valued instrumental variable that affects the neighborhood choice. An issue with this approach is that standard monotonicity conditions that identifies LATE-type effects in IV models are not sufficient to secure the identification of neighborhood effects in MTO.

The core innovation of this study is to employ classical economic behavior to exploit the information on the choice incentives of the MTO intervention. Revealed preference analysis yields choice restrictions that subsume standard monotonicity conditions. These choice restrictions determine

[35] See, for instance, (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).

[36] See, for instance, Aliprantis and Richter (2020); Clampet-Lundquist and Massey (2008).

[37] See, for instance, Elliott (1999); Fauth et al. (2004); Shang (2014).

seven response-types that summarize the choice behaviors that are consistent with economic theory. This approach secures the identification of all response-type probabilities and most of the counterfactual outcomes of the MTO intervention. Moreover, it enable us describe the TOT parameter as a weighted average of neighborhood effects with clear causal interpretation. The choice restrictions also imply the unordered monotonicity condition of Heckman and Pinto (2018). I explore the properties of the unordered monotonicity condition to identify the remaining counterfactual outcomes.

This framework promotes novel analysis that enhances the understanding of the MTO intervention. It is possible to investigate the characteristics of the families that belong to each of the seven response-types. The full-compliers consist of the families most responsive to the MTO incentives. These families account for a third of the MTO sample. On the other hand, the always-takers consist of families that do not change their neighborhood choice regardless of their voucher assignment. These families account for over 40% of the MTO sample. The most disadvantaged families in MTO are those who always choose to live in high poverty neighborhoods. In contrast, the families that always choose to live in low poverty neighborhoods present the highest level of schooling and are least likely to be on welfare. The remaining response-type are called partial-compliers and account for a smaller share of the MTO sample.

The empirical analysis shows that the neighborhood effects estimates for the full-compliers who move from high to low poverty neighborhoods are statistically and economically significant. On average, these families experience: (a)a 20% increase in the income of the head of the family; (b)a 14% increase in household income; (c)a 50% increase in the likelihood of the family income being above the poverty line; (d)a 25% increase in employment; and (e)a 34% reduction in welfare dependency. These empirical findings are consistent with a growing body of research demonstrating the importance of neighborhood quality in promoting the economic well-being of its inhabitants (Chetty et al., 2017, 2016; Chyn, 2016; Galiani et al., 2015).

Finally, the method developed here enables us to decompose the TOT parameter into a weighted average of the neighborhood effects of the full and partial-compliers. Although the neighborhood effects for the full-compliers are statistically significant, the effect for partial-compliers are not, leading to TOT estimates that are not statistically significant. This finding helps to explain the apparent inconsistency between the MTO literature that reports insignificant TOT effects and other MTO studies that claim significant effects on labor market outcomes.

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