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 pioneering 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. MTO experienced significant noncompliance, making it difficult to determine the causal effect of relocating families from one type of neighborhood to another. Most of the literature on MTO 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 properly evaluate the net effect of the experiment, 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 counterfactual outcomes. An interpolation argument secures the point-identification of the causal effects across neighborhood types. This method enhances understanding of the MTO intervention. I show that TOT parameters evaluate a mixture of neighborhood effects. Even though the overall TOT estimates of labor market outcomes are not statistically significant, components of it corresponding to neighborhood effects of families that are most responsive to the vouchers are statistically and economically significant. This result reconciles evidence from the 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.

JEL codes: H43, I18, I38, J38.

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1 Introduction

William Julius Wilson's seminal book (1987) presents a compelling case that disadvantaged neighborhoods are a primary cause of poverty among African Americans. The book stimulated substantial research on neighborhood effects in the 1990s (Sampson et al., 2002). Despite the abundance of observational studies, the empirical evidence on neighborhood effects has remained elusive (Aliprantis, 2007). Most research is tainted with the issue of residential sorting (Jencks and Mayer, 1990; Sampson, 2008), which hinders the ability to determine the causal effect of neighborhood quality on family outcomes(Durlauf, 2004). Some researchers argued that only a housing experiment could settle the question whether neighborhoods matter (Tienda, 1991).

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 low-income 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 require families to use the vouchers. A significant share of families did not comply with the voucher incentives. Nearly half of the households that received vouchers did not use them to relocate, whereas one-fifth of the control families relocated to better communities. Noncompliance generates the problem of selection bias, which prevents the identification of neighborhood effects by simply comparing the outcomes 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 the causal effect of being offered a voucher. It evaluates the mean difference of the outcomes between families that received a voucher and those that did not. The TOT parameter is calculated by dividing the ITT by the voucher take-up rate.

This scales up the voucher effect by the proportion of families who use the vouchers.

The ITT/TOT are informative parameters to assess the housing policy itself. However, there is considerable disagreement on how to interpret these parameters in terms of the causal effects of neighborhood types (Aliprantis, 2007; Sampson, 2008). This debate 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 for capturing neighborhood effects. This paper addresses the question 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 into the MTO intervention.

This paper exploits the choice incentives induced by the MTO experiment to move beyond ITT/TOT analyses. It employs revealed preference analysis to convert MTO incentives into choice restrictions, which, in turn identify the latent distribution of counterfactual choices and most counterfactual outcomes.

A rigorous analysis of the MTO intervention requires a choice model in which the voucher assignment serves as an instrumental variable (IV) influencing neighborhood choices. MTO's design supports a model with three neighborhood choices and a three-valued instrument. A natural approach to identification 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.

Revealed preference analysis is better suited for exploiting the choice incentives of the MTO intervention. It provides a set of choice restrictions that subsume standard monotonicity conditions. These restrictions determine seven response types that characterize the choice behaviors that are economically justifiable. The response types enable the identification of most of the counterfactual outcomes. They also imply the unordered monotonicity condition of Heckman and Pinto (2018), which allows for writing the counterfactual outcomes as a function of choice probabilities (propensity scores). Interpolation of these response functions guarantees the point-identification of neighborhood effects.

The identification strategy presented here is consistent with Kline and Walters (2016), who uses revealed preference analysis to investigate the Head Start Program through a three-choice model with a two-valued independent variable. Kirkeboen et al. (2016) investigate a three-choice model with an instrument that takes on three values. Their model differs from MTO in terms of choice incentives.[1] Nevertheless, identification results are comparable to MTO: standard monotonicity conditions fail to identify causal effects but revealed preference analysis can deliver a causal interpretation for the Two-stage Least Squares (2SLS) estimator.[2]

The identification method presented here enables a deeper understanding of the MTO intervention. It allows decomposing neighborhood effects across the latent response types that are economically justified. This provides new insights into the experiment. For instance, it shows that the most disadvantaged families do not move regardless of the MTO incentives. In contrast, the least disadvantaged households are those who relocate to low-poverty neighborhoods, irrespective of voucher assignments. The method also enables to characterize the type of family most responsive to MTO incentives, which helps design more effective housing policies. From a scientific perspective, assessing neighborhood effects creates fundamental knowledge of how neighborhoods promote economic prosperity – the original goal of the MTO experiment. To conclude, the method provides a clean interpretation of the TOT parameter as a weighted average of neighborhood effects across a selection of latent types.

Previous MTO research has found significant results on adult outcomes such as 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 are 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).

[1] Section 4.2 compares the identification results generated by the choice incentives of MTO to the choice incentives examined in Kirkeboen et al. (2016).

[2] Kirkeboen et al. (2016) develop a clever identification strategy that exploits additional information on the ranking of agents' choices. A benefit of their approach is that it applies to more than three choices. The causal interpretation generated by revealed preference analysis is limited to the case of a three-choice model.

This paper reexamines the labor market outcomes of MTO. Similar to Kling et al. (2007), I find weak TOT effects. This paper shows that the TOT parameter is a mixture of neighborhood effects that compare low- versus high- and also low- versus medium- poverty neighborhoods. Some of these effects are imprecisely estimated, contributing to the overall lack of significance of the TOT estimates. Nevertheless, the neighborhood effects of moving from high- to a low-poverty neighborhoods for families that are most responsive to the voucher incentives are statistically and economically significant. Families that 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.[3] These findings also offer a potential explanation to the question raised by Harding et al. (2021), who discuss the mismatch between the statistically insignificant economic result of Kling et al. (2007) and statistically significant effects on labor market outcomes of previous observational studies (e.g. (Elliott, 1999; Fauth et al., 2004; Shang, 2014)).

The findings presented here lead to two primary conclusions regarding the evaluation of neighborhood effects in MTO. The first is that the economic analysis of MTO incentives plays a crucial role in moving beyond TOT analyses. The revealed preference analysis was essential in devising a framework that explores MTO noncompliance, usually perceived as an econometric problem, as a valuable source of identifying information.[4] The framework enables us to decompose, isolate and estimate the neighborhood effects that are jointly evaluated by the TOT parameter. This approach contributes to a recent but well-established literature that uses revealed preference analysis to identify treatment effects (Feller et al., 2016; Kamat, 2021; Kline and Tartari, 2016; Kline and Walters, 2016; Mountjoy, 2021).[5]

[3]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.

[4]An early 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 toward leisure.

[5]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 use the assumption of rational choices to determine the bounds of the demand function. Examples in this literature are

The second conclusion is that weak TOT effects on labor market outcomes do not necessarily imply that the MTO intervention failed to improve the economic well-being of its participants. As mentioned, the economic impact of MTO on families that respond to its housing incentives is substantial. This finding helps reconcile the statistically insignificant effects reported in early MTO literature 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).

This paper adds to the literature on empirical evaluations that examine unordered choices (Hull, 2018; Kirkeboen et al., 2016; Mountjoy, 2021) and also offers some methodological contributions to the literature on unordered choice models (Heckman et al., 2006, 2008; Lee and Salanié, 2018). Specifically, this paper introduces the concept of an incentive matrix and explains how to translate choice incentives into identification conditions. It examines the estimation of IV models under unordered monotonicity, which is not addressed in Heckman and Pinto (2018). Finally, it investigates the problem of partial identification that is common in multiple-choice models with categorical instruments. This analysis contributes to a growing body of work addressing the identification constraints imposed by discrete instruments (Brinch et al., 2017; Kline and Walters, 2019; Mogstad et al., 2018; Mogstad and Torgovitsky, 2018).

The paper proceeds as follows. Section 2 describes the MTO intervention and investigates what can and cannot be identified by the exogenous variation of MTO vouchers. Section 3 discusses the IV assumptions and previous evaluation methods. Section 4 uses revealed preference analysis to investigate how MTO incentives affect the neighborhood choices. Section 5 presents identification results and estimation procedures. Section 6 reanalyzes MTO data and Section 7 summarizes the paper's main conclusions.

2 The MTO Experiment: Data, Design and Limitations

The MTO 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).[6] Eligible households consisted of low-income families with children

Blundell et al. (2014); Kitamura et al. (2018); Kline and Tartari (2016).

[6]The intervention was motivated by the positive results of the Gautreaux initiative, which provided housing vouchers that enabled poor families to relocate from extreme segregated public housing in Chicago (Polikoff, 2006).

under 18 years living in the most impoverished housing projects of five US cities: Baltimore, Boston, Chicago, Los Angeles, and New York. The MTO sample totals 4,248 families. Three-quarters of these were on welfare, and only a third had a high school diploma. African Americans comprised 62% and Hispanics 30% of the sample. Females headed 92% of the households.

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 (i.e. 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 helped 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%.

Table 1 presents a statistical description of the 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 the 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 the baseline characteristics of experimental families that used the voucher with those that did not.

Based on the estimates presented in Table 1, it can be inferred that families who utilized the voucher tended to be smaller in size, had fewer teenagers, and had a lower likelihood of having a household member with disabilities. These families also had fewer social connections, fewer friends, and were less likely to engage in activities such as chatting with neighbors or looking out for their neighbor's children. Additionally, these families were more likely to be victims of crime and 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 that a similar though less pronounced pattern emerges.

Neighborhood Types

The design of MTO intervention recognizes 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 neighborhoods t_m comprise 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 communities. The Section 8 voucher incentivizes low (t_l) or medium-poverty (t_m) neighborhoods and families that used this voucher decided between these two neighborhood types. Families that decided to use the voucher had to relocate within six months of 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 that did move decided between low (t_l) or medium-poverty (t_m) neighborhoods.[7]

Outcomes

This paper focuses on labor market outcomes collected at the interim evaluation in 2002. Figure 1 presents a statistical description of the estimated mean income in thousand dollars for the

[7] Appendix B provides a detailed description of neighborhood choices. Figure A.3 in Appendix B displays a diagram of the MTO intervention.

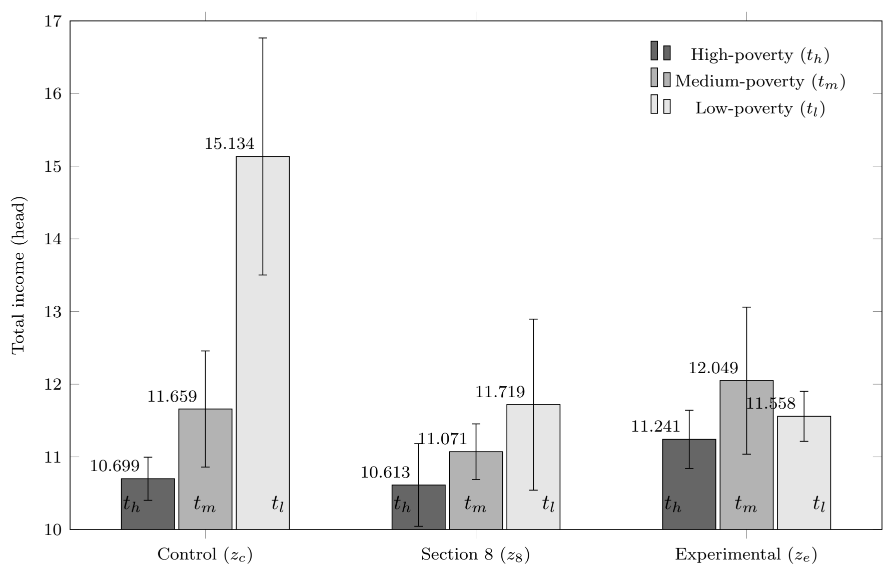
Table 1: Baseline Variables of MTO by Voucher Assignment and Voucher Usage

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's 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.

household head conditined on neighborhood type and voucher assignment. The first three bars of the figure display the outcomes for families assigned to the control group (z_c). The average income for families who chose high (t_h), medium (t_m), and low-poverty (t_l) neighborhoods are \$10.699, \$11.659, and \$15.134 thousand dollars per year respectively. The mean difference between low- and high-poverty neighborhoods is $\$15.134 - \$10.699 = \$4.435$. This difference is not causal as families that decide to move differ from those who do not.

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 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. In addition, estimates are weighted according to the Interim Impacts Evaluation manual, 2003; Appendix B. Error bars denote estimated standard errors obtained by a stratified bootstrap procedure that resamples the entire data set by site.

The three middle bars of Figure 1 display the mean incomes for families assigned to the Section 8 voucher (z_8). The average income for families that decide for high (t_h), medium (t_m) and low-poverty (t_l) neighborhoods are \$10.613, \$11.701, and \$11.719 thousand dollars per year respectively. The difference in income between low- and high-poverty neighborhoods is $\$11.719 - \$10.613 = \$1.106$ 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 when assigned to the control group, may decide for medium- and low-poverty neighborhoods when assigned to Section 8.

The last three bars of Figure 1 display the mean incomes for families assigned to the experimental voucher (z_e). It shows the lowest income difference between low- and high-poverty neighborhoods, namely, \$11.558 − \$11.241 = \$0.317 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 \$15.134 to \$11.558 thousand dollars per year.

Table 2 presents the statistical description of labor market outcomes surveyed in 2002. The first three 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;[8] (2) *Employed without welfare* indicates if the sample adult is working and not receiving welfare; (3) *Food Stamps* indicates whether the family receives the benefit; (4) *Currently on welfare* indicates if the family regularly receives welfare benefits;[9] (5) *Job tenure* indicates if the sample adult had been employed for more than one year.

Table 2 suggests a negative selection pattern similar to the one observed in Figure 1. Consider the labor-market outcomes of families that choose to live in low-income areas (t_l). The mean estimate of the sum of spouses' income for families assigned to the control group (z_c) is \$15.134 thousand per year. The estimate for experimental families (z_e) is \$11.558 thousand per year. Thus, annual income reduces by 24% when comparing control versus experimental families that choose to live in low-poverty neighborhoods. In the case of total household income, the reduction is 32%. Moreover, a share 0.552 of the control families living in low-poverty neighborhoods were above the poverty line. 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.

Limitations of the MTO Intervention

[8] The survey considers the following welfare benefits: the Aid to Families with Dependent Children (AFDC), the Temporary Assistance for Needy Families (TANF), Food Stamps, Supplemental Security Income (SSI), or Medicaid.

[9] The survey considers AFDC/TANF regular welfare benefits.

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_8, z_e) 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 the following: (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 family income sources. Income is measured in thousands of dollars per year. 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 were 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, namely: the Aid to Families with Dependent Children (AFDC), the Temporary Assistance for Needy Families (TANF), Food Stamps, Supplemental Security Income (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 the family receives regular welfare benefits (AFDC/TANF). (5) *Job tenure* indicates if employed for more than one year. The last row examines the poverty level of the neighborhood chosen by the family.

MTO vouchers play the role of an IV that incentivizes residential mobility. As a result, the type of neighborhood effect that can be identified by the exogenous variation of the vouchers is bounded by the geographical regions determined by the voucher incentives.[10] Unfortunately, MTO vouchers justify only a coarse characterization of three neighborhood types.[11] Vouchers alone are not suitable for identifying the effects of a particular neighborhood feature. Instead, the neighborhood effects refer to the bundle characteristics associated with each neighborhood type.[12]

Ludwig et al. (2008) and Sampson (2008) point 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.[13]

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.

3 Assessing the IV Assumptions and Previous Analyses

Most MTO evaluations utilize the voucher assignment as an IV to address the issue of noncompliance of neighborhood choices. Some notation is in order to examine the validity of the IV assumptions. 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 denoted by $\boldsymbol{X}$ and is kept implicit for notational simplicity. Let

[10] 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).

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

[12] In particular, MTO vouchers alone cannot identify the causal effect 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.

[13] Several works invoke functional form assumptions that enable 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).

$T(z)$ denote the counterfactual choice 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 $D_z = \mathbf{1}[Z = z]; z \in \{z_c, z_8, z_e\}$ 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 have:

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

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

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

The exclusion restriction signifies that the vouchers can only influence the outcomes through neighborhood choices. The assumption is imperative for the IV model to work properly. Consequently, HUD, the agency sponsoring the experiment, 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.[14] 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 remaining assumptions of the IV model are less contentious. IV exogeneity states that the instrument Z is independent of the counterfactuals $Y(t), T(z)$. The assumption arises from the voucher randomization, which ensures that the voucher assignment is independent of the family's unobserved characteristics that cause the choice T and the outcome Y. IV relevance means that vouchers influence neighborhood decisions, namely Z and T are not statistically independent.

Previous Analyses

As previously stated, the MTO literature typically uses the ITT and TOT parameters to assess the effectiveness of the MTO intervention.[15] These are well-known statistical methods used to

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

[15]Some seminal works on the MTO literature that report ITT and TOT effects are 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).

report findings of randomized control trials which experience noncompliance issues (Begg et al., 1996; Gupta, 2011). The estimation of the ITT effect for experimental versus control families, π_e, is done by the following linear regression:[16]

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

where D_{z_e} is the binary indicator for the experimental voucher, $\boldsymbol{X}$ denotes baseline covariates including site fixed effects. The ITT estimator in (4) is the sample analog of the covariate-adjusted difference in means between experimental versus control groups, $ITT_e = E(Y|Z = z_e) - E(Y|Z = z_c)$. IV exogeneity (2) implies that the ITT_e identifies the causal effect of being offered the experimental voucher, that is, $E(Y(z_e) - Y(z_c))$.[17]

It is challenging to interpret ITT parameter in terms of neighborhood effects since the parameter does not distinguish families that used the vouchers from families that did not. The TOT parameter solves this issue by using the voucher assignment as an IV for the voucher take-up. The TOT parameter that compares the experimental versus control group, γ_e, is commonly estimated by the following 2SLS regression:[18]

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

where C_e indicates the experimental voucher compliance and D_{z_e} is used as an instrument for C_e. The TOT estimator of γ_e evaluates the sample analog of the following ratio:

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

which is the ITT_e divided by the regression-adjusted take-up rate.[19] The TOT parameter scales-up the voucher effects by the voucher compliance rate. It differs from the typical IV model as TOT uses information on voucher usage rather than on neighborhood choices.

Bloom (1984) investigates the causal content of the TOT using a simpler type of intervention that randomly assigns families into two groups, experimental or control, and families can only move if they use the experimental voucher. This experiment only has two types of families: *compliers*, who move from high to low-poverty neighborhoods if assigned to the experimental voucher, and *non-*

[16]The linear regression in equation (4) utilizes data from the experimental and control groups only.

[17]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}.

[18]The two-stage least squares (2SLS) regression in equation (5) utilizes data from the experimental and control groups only.

[19]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.

compliers, who remain in high-poverty neighborhoods regardless of the voucher assignment. Bloom (1984) shows that the TOT parameter of this stylised intervention identifies the neighborhood effect of moving from high- to low-poverty neighborhoods for compliers.[20]

Unfortunately, Bloom's argument cannot be applied to MTO, as both control families and families that do not use the vouchers can choose amongst high-, medium-, and low-poverty neighborhoods. Without additional assumptions, the TOT parameter assesses a combination of various and possibly conflicting neighborhood effects. For instance, a family type could choose a high-poverty neighborhood under the control group but opt for a medium-poverty neighborhood under the experimental voucher. Without additional assumptions, we cannot rule out the existence of another family type that makes the opposite choices. In this case, it is impossible to assign a causal interpretation to the TOT parameter since it evaluates a weighted average of the causal effect of medium- versus high-poverty neighborhoods for some families, as well as the causal effect of high- versus medium-poverty for other families.

To understand the causal content of the TOT parameter, it is necessary to examine the identification problem in MTO. This analysis involves considering counterfactual decisions that are economically justified by MTO incentives. This topic is explored in the following section.

4 The MTO Identification Problem

The IV Assumptions (1)–(3) alone are insufficient to identify causal effects.[21] Identification depends on additional assumptions the instrument affects the treatment choice. It is useful to revisit the well-known LATE model of Imbens and Angrist (1994) in order to introduce the identification challenges posed by the MTO intervention.

Consider a simplified version of the MTO model in which families choose between low- (t_l) and high-poverty (t_h) neighborhoods. In this toy model, each family i 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. Let the *response vector* $\boldsymbol{S}_i = [T_i(z_c)\ ,\ T_i(z_e)]'$ be the 2×1 vector of counterfactual choices that a family i would take if it were assigned to either z_c or z_e

[20]See Appendix C for a proof.

[21]See Angrist and Imbens (1991); Heckman (1990) for a discussion on this topic.

respectively. The support of $\boldsymbol{S}$ consists of 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 is expressed by the following inequality for all families i:

$$\mathbf{1}[T_i(z_c) = t_l] \leq \mathbf{1}[T_i(z_e) = t_l]. \tag{7}$$

Condition (7) implies that if a family i chooses a low-poverty neighborhood (t_l) under the control (z_c), $\mathbf{1}[T_i(z_c) = t_l] = 1$, then it must also choose a low-poverty neighborhood (t_l) under the experimental voucher, $\mathbf{1}[T_i(z_e) = t_l] = 1$. 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 cannot be properly analyzed using a binary LATE model since the instrument Z, and the choice T take three values instead of two. The response vector of MTO is now given by $\boldsymbol{S} = [T(z_c), T(z_8), T(z_e)]'$. It is a 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 a high-poverty neighborhood if assigned to the control $(T_i(z_c) = t_h)$, a medium-poverty neighborhood if assigned to Section 8 $(T_i(z_8) = t_m)$, and a low-poverty neighborhood if assigned to the experimental voucher $(T_i(z_e) = t_l)$. The response vector enables us to connect observed quantities with unobserved causal parameters by the following equation:[22]

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

The left-hand side of (8) consists of two observed quantities: the outcome expectation $E(Y|T = t, Z = z)$ and the propensity score $P(T = t|Z = z)$, which is probability of choosing t given the IV-value 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 that we seek to recover: 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 as a linear

[22] See Heckman and Pinto (2018) or Appendix A.1 for proof.

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) clarifies 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 equations consisting of nine equalities. The number of unknown parameters, $P(\boldsymbol{S}=\boldsymbol{s})$, is given by the number of response types $\boldsymbol{s}\in supp(\boldsymbol{S})$. In 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.[23]

A natural approach to eliminating 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 neighborhoods while Section 8 z_8 incentivizes both low- and medium-poverty 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 induces families toward low-poverty neighborhoods t_l. The inequality in (10) implies that if family i chooses t_l when assigned to control z_c, that is $\mathbf{1}[T_i(z_c)=t_l]=1$, then $\mathbf{1}[T_i(z_e)=t_l]=1$ must hold, which means that family i chooses t_l under z_e. On the other hand, if family i does not choose t_l under control z_c, then the family may or may not choose t_l under z_e since $\mathbf{1}[T_i(z_c)=t_l]=0 \Rightarrow \mathbf{1}[T_i(z_e)=t_l]\in\{0,1\}$. In summary, monotonicity condition (10) states that a family that chooses t_l under z_c also chooses t_l under z_e.[24] The condition eliminates the six response types in which $T_i(z_c)=t_l$ and $T_i(z_e)\neq t_l$.[25] Condition (11) states that a change from z_c to z_8 induces families toward either t_l or t_m, while condition (12) states that a

[23] Appendix D explains how the use of response types enables us to control for the unobserved characteristics that generates bias.

[24] The condition is equivalently stated by the choice restriction $T_i(z_c)=t_l \Rightarrow T_i(z_e)=t_l$.

[25] The response types are: $[t_l,t_h,t_h]'$, $[t_l,t_m,t_h]'$, $[t_l,t_l,t_h]'$, $[t_l,t_h,t_m]'$, $[t_l,t_m,t_m]'$, and $[t_l,t_l,t_m]'$.

change from z_e to z_8 induces families toward medium-poverty neighborhoods t_m. These conditions eliminate additional response types.

Panel A of Table 3 displays the 27 possible response types in MTO. Panel B indicates the response types eliminated by each monotonicity condition in (10)–(12). In total, these conditions 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 response types on a case-by-case basis.[26] 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 monotonicity conditions (10)–(12). Second, it invokes elementary choice axioms grounded on economic theory, which are simpler and more intuitive than the case-by-case study. Finally, revealed preference analysis is more flexible than the case-by-case study as it can be used to investigate choice incentives other than those of MTO.[27]

4.1 Exploiting MTO Incentives

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

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

Each response matrix entry $\boldsymbol{L}[z,t]$ refers to the relative incentive of the IV-value z (row) toward the choice t (column). The control assignment z_c in the first row of $\boldsymbol{L}$ is set to zero, serving as the baseline level of choice incentives. The Section 8 voucher z_8 in the second row incentivizes the choice of medium- (t_m) or low-poverty (t_l) neighborhoods. The experimental voucher z_e in the last

[26]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 the no voucher assignment ($T_i(z_c) = t_m$), but switches to a high-poverty with the experimental voucher ($T_i(z_e) = t_h$). The switch lacks justification as neither of these vouchers subsidizes high- or medium-poverty neighborhoods.

[27]Section 4.2 applies revealed preference analysis to the choice incentives investigated by Kirkeboen, Leuven, and Mogstad (2016).

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 Types 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 Types Eliminated by Choice Restrictions (22)–(28)**																										
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 (22)–(28) 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 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	$T_i(z_c) \neq t_h$	$\Rightarrow$	$T_i(z_8) = T_i(z_c)$

row incentivizes the choice of low-poverty neighborhoods (t_l) only.

The potential choices of a family i can be understood as the result of a utility maximization problem:

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

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 consumption goods $g \in \mathcal{G}$. The *potential budget set* $\mathcal{B}_i(z,t) \subset \mathcal{G}$ is the counterfactual set of consumption goods for family i when the neighborhood type is *set* to $t \in \{t_h, t_m, t_l\}$ and the voucher is *set* to $z \in \{z_c, z_8, z_e\}$.[28] Family i has nine potential budget sets $\mathcal{B}_i(z,t)$ as (z,t) ranges in $\{z_c, z_8, z_e\} \times \{t_h, t_m, t_l\}$. Vouchers incentivize neighborhood choices by providing rent subsidies. Given a choice t, IV-values associated with greater incentives correspond to larger budget sets:

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

Applying equation (15) to Incentive matrix (13) generates the following relationships among the potential budget sets:

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

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

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

Equation (16) compares the potential budget sets across voucher assignments when the choice is fixed at high-poverty neighborhoods t_h. The budget sets remain the same since the subsidy of vouchers z_e and z_8 do not apply to high-poverty neighborhoods t_h.[29] Equation (17) compares the potential budget sets for medium-poverty neighborhoods t_m. Section 8 voucher z_8 subsidizes t_m while the remaining vouchers do not. Thus $\mathcal{B}_i(z_8, t_m)$ is larger than $\mathcal{B}_i(z_c, t_m)$ and $\mathcal{B}_i(z_e, t_m)$. The final 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 budget set relations enable us to use the Weak Axiom of Revealed Preferences[30] (WARP)

[28] 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.

[29] The equality $\mathcal{B}_i(z_c, t_h) = \mathcal{B}_i(z_e, t_h)$ means that, when the neighborhood choice is fixed to t_h, agent i faces the same potential budget set of consumption goods if assigned to either z_c or z_e.

[30] 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, $(t,g) \succ_i^d (t',g') \Rightarrow (t',g') \not\succ_i^d (t,g)$. A sufficient condition for WARP is that utility $u_i(t,g)$ represents rational preferences.

to generate choice restrictions. WARP states that if a family prefers a bundle (t, g) when (t', g') is affordable, then that family will never choose (t', g') whenever (t, g) is available. If a family i chooses t instead of t' when assigned to z, then there exists a 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 under z' the bundle (t, g^*) is available, i.e. $\mathcal{B}_i(z, t) \subseteq \mathcal{B}_i(z', t)$, and the budget set for t' does not increase, i.e. $\mathcal{B}_i(z, t') \supseteq \mathcal{B}_i(z', t')$, then $(t, g^*) \in \mathcal{B}_i(z', t)$ 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', in short, $T_i(z) = t \Rightarrow T_i(z') \neq t'$.

Another applicable axiom is *Normal Choice* defined below:

$$(t \succ_i t')|z \text{ and } \boldsymbol{L}[z', t] - \boldsymbol{L}[z, t] \; = \; \boldsymbol{L}[z', t'] - \boldsymbol{L}[z, t'] \text{ then } (t' \not\succ_i t)|z', \tag{19}$$

where $(t \succ_i t')|z$ means that family i ranks choice t above choice t' under voucher z. Normal Choice states that if a family prefers t instead of t' under z, and, under voucher z', the change in incentives for choosing either t or t' is the same, then the family will not switch their preference from t to t'.[31] These choice axioms enable us to generate a choice rule that converts choice incentives into choice restrictions:

Proposition P.1. Under budget relationships (15), WARP and Normal Choice (19), the following choice rule holds:

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

Proof. See Appendix A.2. □

Choice Rule **P.1** captures a fundamental principle of rational choice theory, whereby if an agent prefers one option over another, it will not alter its preference unless there is a significant incentive to do so. Specifically, the rule states that if a family chooses t over t' under z, and z' offers incentives toward t that are at least as compelling as the incentives toward t', then the family will not choose t' under z'. To fix ideas, consider the standard binary LATE model in which families choose between low- and high-poverty neighborhoods and are randomly assigned to either the experimental voucher (z_e), which subsidizes low-poverty neighborhoods, or the control voucher

[31] Normal Choice is a no-crossing condition on the ranking of choice preferences that maintains the relative rank of two choices that share the same incentives. Normal choice is related to the notion of normal goods. Consider an agent that debates between two goods a and b. Suppose a discount of d dollars is applied to both goods. This discount can be understood as an increase in income of d dollars since the agent will benefit from it regardless of his choice. An increase in income does not decrease the consumption of a normal good. Thereby if the agent had decided to buy a under no discount, then it will continue to consume one unit of good a when the discount is available.

(z_c) that offers no incentives. The corresponding incentive matrix is:

$$\textbf{LATE Incentive Matrix } \boldsymbol{L} = \begin{array}{cc} t_h & t_l \\ \left[\begin{array}{cc} 0 & 0 \\ 0 & 1 \end{array}\right] & \begin{array}{c} z_c \\ z_e \end{array} \end{array} \tag{20}$$

Applying **P.1** to response matrix (20) produces the following implication:

$$T_i(z_c) = t_l \text{ and } \boldsymbol{L}[z_e, t_h] - \boldsymbol{L}[z_c, t_h] = 0 \leq 1 = \boldsymbol{L}[z_e, t_l] - \boldsymbol{L}[z_c, t_l] \Rightarrow T_i(z_e) \neq t_h. \tag{21}$$

The equation above produces the choice restriction $T_i(z_c) = t_l \Rightarrow T_i(z_e) \neq t_h$, which means that if the family chooses low-poverty neighborhood under no incentives, then the family still chooses low-poverty neighborhood when incentives to do so are available. This restriction is equivalently described by the monotonicity condition (7), that is, $\mathbf{1}[T_i(z_c) = t_l] \leq \mathbf{1}[T_i(z_e) = t_l]$. Either representation eliminates the defiers and enables the identification of LATE.

Applying **P.1** to all pairwise combinations of neighborhood choices $(t, t') \in \{t_h, t_m, t_l\}^2$ and IV values $(z, z') \in \{z_c, z_8, z_e\}^2$ generates the following choice restrictions:[32]

Proposition P.2. Budget relationships (15), WARP and Normal Choice (19) imply the following choice restrictions:

$$\begin{aligned}
&\text{Restriction 1: } T_i(z_c) = t_l && \Rightarrow && T_i(z_e) = t_l \text{ and } T_i(z_8) \neq t_h && (22)\\
&\text{Restriction 2: } T_i(z_c) = t_m && \Rightarrow && T_i(z_e) \neq t_h \text{ and } T_i(z_8) \neq t_h && (23)\\
&\text{Restriction 3: } T_i(z_e) = t_m && \Rightarrow && T_i(z_c) = t_m \text{ and } T_i(z_8) = t_m && (24)\\
&\text{Restriction 4: } T_i(z_e) = t_h && \Rightarrow && T_i(z_c) = t_h \text{ and } T_i(z_8) \neq t_l && (25)\\
&\text{Restriction 5: } T_i(z_8) = t_h && \Rightarrow && T_i(z_c) = t_h \text{ and } T_i(z_e) = t_h && (26)\\
&\text{Restriction 6: } T_i(z_8) = t_l && \Rightarrow && T_i(z_e) = t_l && (27)\\
&\text{Restriction 7: } T_i(z_c) \neq t_h && \Rightarrow && T_i(z_c) = T_i(z_8) && (28)
\end{aligned}$$

Proof. See Appendix A.3. □

The first choice restriction in **P.2** 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

[32] Choice restrictions in **P.2** emerge from the combining WARP with the potential budget set relations (16)–(18), which are based on the incentives design of the MTO experiment. Those restrictions hold for each family i regardless whether budget sets are observed or not. The restrictions also hold regardless of family's voucher assignment Z_i, neighborhood choice T_i, or whether the family uses its assigned voucher to relocate.

subsidized by z_8. Appendix A.4 shows that the choice restrictions (22)–(24) subsume the three monotonicity conditions in (10)–(12). The choice restrictions in **P.2** 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 choice restrictions in **P.2**. WARP alone is responsible for the first six choice restrictions in **P.2**. Altogether, these restrictions eliminate 18 out of the 27 possible response types. Normal choice generates the last restriction that eliminates two additional response types. The response types that survive the revealed preference analysis are organized as columns of the following response matrix:

Proposition P.3. Choice restrictions (22)–(28) generate the following response matrix:

$$\begin{array}{cccccccccc} & & \boldsymbol{s}_{ah} & \boldsymbol{s}_{am} & \boldsymbol{s}_{al} & \boldsymbol{s}_{fc} & \boldsymbol{s}_{pl} & \boldsymbol{s}_{pm} & \boldsymbol{s}_{ph} & \\ \boldsymbol{R} = & \left[\begin{array}{c} \\ \\ \\ \end{array}\right. & \begin{array}{c} t_h \\ t_h \\ t_h \end{array} & \begin{array}{c} t_m \\ t_m \\ t_m \end{array} & \begin{array}{c} t_l \\ t_l \\ t_l \end{array} & \begin{array}{c} t_h \\ t_m \\ t_l \end{array} & \begin{array}{c} t_h \\ t_l \\ t_l \end{array} & \begin{array}{c} t_m \\ t_m \\ t_l \end{array} & \begin{array}{c} t_h \\ t_m \\ t_h \end{array} \left.\begin{array}{c} \\ \\ \\ \end{array}\right] & \begin{array}{c} T_i(z_c) \\ T_i(z_8) \\ T_i(z_e) \end{array} \end{array} \tag{29}$$

Proof. See Panel C of Table 3. □

The response matrix of MTO has a richer taxonomy of response types than LATE, sice it involves three choices instead of two. Response types $\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}, \boldsymbol{s}_{al}$ are *always-takers*.[33] 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*, corresponding to families that choose a high-poverty neighborhood if assigned to control, a medium-poverty neighborhood under Section 8, and a low-poverty neighborhood 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 areas (t_l) when subsidized (z_8 or z_e) and high-poverty neighborhoods (t_h) under no subsidy (z_c). Families of type $\boldsymbol{s}_{pm} = [t_m, t_m, t_l]'$ choose low-poverty neighborhoods (t_l) if this is the only available subsidy (z_e), and choose medium-poverty neighborhoods (t_m) otherwise (z_c or z_8). Families of type $\boldsymbol{s}_{ph} = [t_h, t_m, t_h]'$ chose medium-poverty neighborhoods when subsidized (z_8) and high-poverty communities (t_h) otherwise (z_c or

[33] Alternatively, one can interpret $\boldsymbol{s}_{ah}$ as never-takers, while $\boldsymbol{s}_{am}, \boldsymbol{s}_{al}$ remain the t_m-always-takers and the t_l-always-takers respectively.

z_e).[34]

Despite its intuitive appeal, the revealed preference approach is not without criticism. Violations of the monotonicity condition of the binary LATE also undermine the credibility of the revealed preference analysis. For example, the discrimination and stigmatization that those who use housing vouchers may experience is a potential threat to the model's validity.[35]

4.2 Comparing MTO to a Benchmark Design

MTO stands out from conventional experimental designs because it incorporates an innovative incentive structure in which an IV-value (z_8) incentivizes two choices (t_m and t_l). It is instructive to understand how MTO differs from a more familiar design involving three treatment options (t_0, t_1, t_2) and three randomized arms (z_0, z_1, z_2), where control group (z_0) has no incentives, while z_1 incentivizes choices t_1 and z_2 incentivizes t_2.[36] This design was investigated by Kirkeboen, Leuven, and Mogstad (2016) and is characterized by the following incentive matrix:

$$\boldsymbol{L} = \begin{array}{c} \begin{array}{ccc} t_0 & t_1 & t_2 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{array} \begin{array}{c} \\ z_0 \\ z_1 \\ z_2 \end{array} \tag{30}$$

The MTO incentive matrix justifies three monotonicity conditions, whereas the incentive matrix above justifies only two:

$$\mathbf{1}[T_i(z_0) = t_1] \leq \mathbf{1}[T_i(z_1) = t_1], \quad \text{and} \quad \mathbf{1}[T_i(z_0) = t_2] \leq \mathbf{1}[T_i(z_2) = t_2]. \tag{31}$$

The first condition states that an IV-change from z_0 to z_1 induces agents to shift their choice toward t_1 while the second condition states that a change from z_0 to z_2 induces agents toward t_2. Kirkeboen et al. (2016) show that these conditions lead to an IV estimate that does not have a causal interpretation.[37] This is further corroborated in Appendix E.6, which shows that the two monotonicity conditions eliminate 12 out of the 27 possible response types. This elimination is

[34] See Figure A.4 of Appendix A.5 for a diagram of the mapping between observed and unobserved variables generated by the response matrix (29).

[35] Further investigation into this matter is presented in Appendices E.4 and E.5, which consider the violation of the Normal Choice Assumption and the misrepresentation of choice incentives, respectively.

[36] This setup is called the three-arm parallel-group design in the literature of clinical trials (Turner, 2013).

[37] The authors use a clever identification strategy that exploits additional information on the rankings of students' preferences among college majors. Their solution applies to more than three choices. They use the three-choice model only to explain that standard monotonicity conditions fail to secure identification.

insufficient to point-identify any of the response type probabilities or counterfactual outcomes.

Similar to MTO, the revealed preference analysis subsumes and outperforms the monotonicity conditions. Appendix E.6 shows that applying WARP to incentive matrix (30) generates five choice restrictions that eliminate 19 out of the 27 possible response types. The response types that survive this elimination process are:

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

The response matrix of MTO has seven response types, while the response matrix above has eight. This is beneficial for MTO, as fewer response types mean fewer causal parameters must be identified from the observed data. On the other hand, the response matrix (32) has the advantage of satisfying the monotonicity condition of Angrist and Imbens (1995) for treatment values such that $t_1 < t_0 < t_2$. To understand this property, 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 rows of (32) according to sequence z_1, z_0, z_2 to obtain the following response matrix:

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

The values in each column of equation (33) are weakly increasing as we move down the rows. This implies that $T_i(z_1) \leq T_i(z_0) \leq T_i(z_2)$ holds for any agent i regardless of their type. This 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 $T_i(z) \geq T_i(z') \, \forall \, i$.

A major benefit of the monotonicity condition proposed by Angrist and Imbens (1995) is that it allows for the causal interpretation of the Two-Stage Least Squares (2SLS) estimator. The condition is typically invoked when treatment choices have a natural order, such as in the case of

MTO.[38] Unfortunately, MTO does not satisfy this condition since the entries of MTO response matrix cannot be weakly increasing.[39] Therefore, the 2SLS interpretation of Angrist and Imbens (1995) does not apply to MTO, and further investigation is needed to understand what can and cannot be identified according to MTO response matrix. Such analysis is presented in the following section.

5 Identifying the Causal Parameters of MTO

The response matrix characterizes the fundamental components of the IV model. In the case of MTO, it comprises 12 counterfactual outcomes associated with seven response types. The complete model evaluation requires assessing all response-type probabilities and counterfactual outcomes. However, complete model identification is seldom possible in IV models with multiple treatments and categorical IVs. Therefore, most policy evaluations report a single policy-relevant parameter, such as the TOT. Examining the model components, nonetheless, allows for a much deeper and more comprehensive understanding of the intervention.

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

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

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[40] of $\boldsymbol{B}_t$ and $\boldsymbol{b}(\mathcal{S}) = [\mathbf{1}[\boldsymbol{s}_1 \in \mathcal{S}], ..., \mathbf{1}[\boldsymbol{s}_k \in \mathcal{S}]]'$ is the binary vector that indicates which response type belongs to $\mathcal{S}$.[41] Theorem **T.1** applies this result to MTO.

[38] (Vytlacil, 2006) shows that the Angrist and Imbens (1995) monotonicity condition is equivalent to assuming an ordered choice model with random thresholds.

[39] Appendix E.1 shows that the choice incentives induced by the MTO vouchers are incompatible with the monotonicity condition of Angrist and Imbens (1995). On the other hand, Appendix E.2 uses revealed preference analysis to describe the type of choice incentives that justify Angrist and Imbens (1995) monotonicity condition.

[40] The Moore-Penrose matrix $\boldsymbol{B}^{+}$ of a matrix $\boldsymbol{B}$ is 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 $\boldsymbol{B}$. If $\boldsymbol{B}$ has full column-rank, then its pseudo inverse is given by $\boldsymbol{B}^{+} = (\boldsymbol{B}'\boldsymbol{B})^{-1}\boldsymbol{B}'$.

[41] Moreover, if $E(Y(t)|\boldsymbol{S} \in \mathcal{S})$ is identified, then it can be evaluated by the expression $E(Y(t)|\boldsymbol{S} \in \mathcal{S}) = \frac{\boldsymbol{b}(\mathcal{S})'\boldsymbol{B}_t^{+}(\boldsymbol{Q}_Z(t) \odot \boldsymbol{P}_Z(t))}{\boldsymbol{b}(\mathcal{S})'\boldsymbol{B}_t^{+}\boldsymbol{P}_Z(t)}$, where $\boldsymbol{P}_Z(t) \equiv [P(T = t|Z = z_1), ..., P(T = t|Z = z_n)]'$ is the vector of propensity scores and $\boldsymbol{Q}_Z(t) \equiv [E(Y|T = t, Z = z_1), ..., E(Y|T = t, Z = z_n)]'$ is the vector of observed conditional outcome means.

Theorem T.1. The following counterfactual outcomes are identified given the IV assumptions (1)–(3) and the MTO response matrix (29):

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. □

Theorem **T.1** states that nine counterfactual outcomes are identified. These include the three counterfactual outcomes for always-takers (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 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 assumptions.

The identification results in **T.1** stem from a central property of response matrix (29): 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 (29) such that choice t lies in the *lower triangular* portion of the matrix. The following matrix displays the lower triangular version of the response matrix $\boldsymbol{R}$ for choice t_l :

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

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 $P(\boldsymbol{S}=\boldsymbol{s}_{al})$ and the counterfactual outcome $E(Y(t_l)|\boldsymbol{S}=\boldsymbol{s}_{al})$ 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 $\boldsymbol{s}_{pl}$. 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 $E(Y(t_l)|\boldsymbol{S}=\boldsymbol{s}_{pl})$:

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

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

where $P_{t_l}(z_8) - P_{t_l}(z_c)$ is 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 $E(Y(t_l)|\boldsymbol{S}\in\{\boldsymbol{s}_{fc},\boldsymbol{s}_{pm}\})$:

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

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

Matrix $\boldsymbol{R}_h$ (42) reorders rows and columns of the response matrix $\boldsymbol{R}$ in (29) 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 :

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

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

Matrices $\boldsymbol{R}_h$ and $\boldsymbol{R}_m$ enable us to identify the counterfactual outcomes for t_h and t_m in the same fashion that the triangular property of $\boldsymbol{R}_l$ enables us to identify the counterfactuals for t_l. For instance, the first row of $\boldsymbol{R}_h$ identifies 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 $\boldsymbol{R}_m$ in (43) identify $E(Y(t_m)|\boldsymbol{S} = \boldsymbol{s}_{am})$, $E(Y(t_m)|\boldsymbol{S} = \boldsymbol{s}_{pm})$, and $E(Y(t_m)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{ph}\})$.

It is possible to characterize all the identification results of counterfactual outcomes by the following equation:[42]

$$E(Y(t)|\boldsymbol{S} \in \mathcal{S}_t(z')\Delta\mathcal{S}_t(z)) = \frac{E(YD_t|Z = z') - E(YD_t|Z = z)}{P_t(z') - P_t(z)}, \tag{44}$$

where $\mathcal{S}_t(z)$ denotes the set of response types that take value t given z, and Δ is the symmetric difference of two sets. For example, the response types that take value t_l given z_e are $\mathcal{S}_{t_l}(z_e) = \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}, \boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}$, while the response types that take value t_l given z_8 are $\mathcal{S}_{t_l}(z_8) = \{\boldsymbol{s}_{al}, \boldsymbol{s}_{pl}\}$. The difference between these sets is $\mathcal{S}_{t_l}(z_e)\Delta\mathcal{S}_{t_l}(z_8) = \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}$. Thus, equation (44) tell us that LATE parameter for t_l that uses the IV values z_8 and z_e identifies $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$. This representation will be handy later in this section.

Identification of the response type probabilities 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 the first two 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 the probabilities sum to one. Theorem **T.2** formalizes this result.

Theorem T.2. Under the IV assumptions (1)–(3) and the response matrix (29), 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. □

[42] This property stems from the triangular property of the MTO response matrix. Appendix F examines additional properties of the response matrix. Appendix F.1 displays a mapping between counterfactual outcomes and the observed data. Appendix F.2 provides the closed-form solutions for each identified counterfactual. Appendix F.3 relates these results with the IV literature on binary treatments. It shows that each identified counterfactual outcome can be estimated by a 2SLS regression under a suitable transformation of the observed data.

5.1 Interpreting the TOT Parameter

MTO response matrix enables a clear interpretation of the TOT parameter in terms of neighborhood effects.

Proposition P.4. Given the IV assumptions (1)–(3) and the MTO response matrix (29), the TOT parameter in (6) identifies the following mixture of neighborhood effects:

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

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

Proof. See Appendix A.7. □

Parameter TOT_e compares the experimental and the control groups.[43] Its content stems from the difference between the first (z_c) and last (z_c) rows of the response matrix $\boldsymbol{R}$ in (29). According to **P.4**, TOT_e consists of two terms. The first term is a mixture of three neighborhood effects: low- versus medium-poverty neighborhoods for the response type $\boldsymbol{s}_{pm}$; and low- versus high-poverty neighborhoods for response types $\boldsymbol{s}_{fc}$ and $\boldsymbol{s}_{pl}$. The second term ξ_e is a 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.[44]

The TOT decomposition relates to the analysis of Kline and Walters (2016), who studied a preschool experiment that randomly offered Head Start day-care services to children. They decompose the LATE parameter into a mixture of two sub-effects: Head Start versus other center-based preschools, and Head Start versus home care. The decomposition also relates to Heckman and Urzúa (2010) who study the causal interpretation of LATE parameters.

Proposition **P.4** states that TOT evaluates an interpretable mixture of neighborhood effects. Assessing each of these effects promotes a deeper understanding of the TOT parameter and the MTO intervention. The causal effects for full-compliers, $\boldsymbol{s}_{fc}$, are of particular interest since this response type corresponds to the families most responsive to MTO incentives and makes up the largest share of compliers. To assess these neighborhood effects, one must address the problem of

[43] 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. The term $P(\boldsymbol{s})$ is a short-hand notation for the response-type probability $P(\boldsymbol{S}=\boldsymbol{s})$.

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

partial identification of the counterfactual outcomes in **T.1**.

It is noteworthy that partial identification is a pervasive issue in multiple-choice models with categorical IVs. To give some perspective, consider applying the well-known monotonicity condition of Angrist and Imbens (1995) to the three-choice model with a three-valued IV, as seen in the MTO study. Appendix E.3 shows that this monotonicity condition generates a response matrix with ten response types. Only two of the ten response type probabilities are point-identified. These ten response types comprise 18 counterfactual outcomes. Again, only two of the 18 counterfactuals are point-identified.

As mentioned, the monotonicity condition of Angrist and Imbens (1995) does not apply to MTO.[45] Instead, MTO incentives give rise to a response matrix containing only seven response types. The response matrix enables us to point-identify all the response type probabilities (**T.2**) and nine counterfactual outcome means. Six of the nine counterfactuals are point-identified, while the remaining three are partially identified. These substantial identification results motivate us to seek solutions to the partial identification problem.

There are two main approaches to addressing the partial identification problem. One option is to forsake the goal of point identification in favor of constructing bounds on the partially identified parameters. Unfortunately, this approach commonly produces wide bounds that are rarely informative (Brinch et al., 2017; Heckman and Vytlacil, 2007). The analysis of MTO is no exception, as documented in Appendix G.1. The alternative option is to adopt a functional or parametric framework that enables point identification. This solution entails examining which monotonicity conditions hold for MTO.

5.2 From Choice Restrictions to Monotonicity Conditions

The following theorem converts the choice restrictions in MTO into monotonicity conditions:

Theorem T.3. The choice restrictions (22)–(28) are equivalently and uniquely represented by the following monotonicity conditions:

[45] See discussion on Section 4.2.

	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. $\square$

Theorem **T.3** demonstrates that nine monotonicity conditions generate the same response matrix as the seven choice restriction in (22)–(28). 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 this monotonicity representation is that each condition in **T.3** corresponds to a propensity score inequality that can be verified from observed data:

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

Table 4 shows that the direction of each monotonicity conditions in **T.3** matches its corresponding propensity score inequality.[46] There are 336 possible sets of nine propensity score inequalities with different directions. Revealed preference analysis justifies only one of these sets – 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	$P(T = t_l\|Z = z_e) = 0.49$	$>$	$0.03 = P(T = t_l\|Z = z_c)$

The monotonicity conditions in **T.3** satisfy the unordered monotonicity criterion of Heckman

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

and Pinto (2018).[47] This criterion states that a change in the instrument induces all agents toward or against a choice t.[48] Formally, for any two IV-values z, z' and each choice t, we have that:

$$\mathbf{1}[T_i(z) = t] \geq \mathbf{1}[T_i(z') = t] \text{ for all } i \in \mathcal{I} \text{ or } \mathbf{1}[T_i(z) = t] \leq \mathbf{1}[T_i(z') = t] \text{ for all } i \in \mathcal{I}. \tag{45}$$

Heckman and Pinto (2018) show that unordered monotonicity is equivalent to assuming that the equation that governs the treatment choice is separable in terms of the observed instrument and the unobserved variables that generate bias. The following theorem builds on their ideas to describe useful properties of the MTO model:[49]

Theorem T.4. Given the IV assumptions (1)–(3) and the MTO response matrix (29), 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 :

$$D_t = \mathbf{1}[P_t(Z) \geq U_t], \tag{46}$$

where $P_t(Z) \equiv P(T = t|Z)$ denotes the propensity score 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). The counterfactual outcome means can be expressed as:

$$E(Y(t)|\boldsymbol{S} \in \mathcal{S}_t(z')\Delta\mathcal{S}_t(z)) = \frac{E(YD_t|Z = z') - E(YD_t|Z = z)}{P_t(z') - P_t(z)} = \frac{\int_{P_t(z)}^{P_t(z')} E(Y(t)|U_t = u)du}{P_t(z') - P_t(z)}, \tag{47}$$

where $E(Y(t)|U_t = u)$ is the marginal response function of the counterfactual outcome $Y(t)$ given the unobserved variable $U_t = u \in [0, 1]$, and $P_t(z') > P_t(z)$.

Proof. See Appendix A.9. □

Item (i) of **T.4** states that neighborhood choices can be expressed as a threshold crossing inequality that is separable on the propensity $P_t(Z)$ and an unobserved variable U_t that is uniformly distributed in $[0, 1]$. In general, the choice indicator of multiple choice models is a function of all propensity scores (Heckman et al., 2008; Lee and Salanié, 2018). The central property of equation (46) 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. Item (ii) of **T.4** complements equation (44). It states

[47] Heckman and Pinto (2018) demonstrate that the triangular property displayed by matrices (35), (42) and (43) are necessary and sufficient 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, which means that each binary element $\boldsymbol{B}_t[z, t]$ of the matrix $\boldsymbol{B}_t$ can be fully determined by the matrix's 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).

[48] Unordered monotonicity does not imply or nor is it implied by Angrist and Imbens (1995) monotonicity condition.

[49] The 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.

that the LATE parameter for t that compares two IV-values z, z', identify a counterfactual outcome mean that can be expressed as an integral of the marginal response function $E(Y(t)|U_t = u)$ over the interval $[P_t(z), P_t(z')]$ in the support of the unobserved variable U_t.

Theorem **T.4** is closely related to well-known results in the IV literature on binary choice models. If the treatment is binary, $T \in \{0,1\}$, the unordered monotonicity (45) becomes 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 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.

5.3 Addressing the Problem of Partial Identification

This section investigates additional assumptions for identifying the components of the partially identified counterfactual outcomes in **T.1**. In the case of t_l, this means disentangling $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$, into $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm})$ and $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$. Theorem **T.4** helps understand this identification problem. According to the theorem, $E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\})$ can be represented as an integral of the response function $E(Y(t_l)|U_{t_l} = u)$ over the interval $[P_{t_l}(z_8), P_{t_l}(z_e)]$:

$$E(Y(t_l)|\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}) = \frac{E(YD_{t_l}|Z=z_e) - E(YD_{t_l}|Z=z_8)}{P_{t_l}(z_e) - P_{t_l}(z_8)} = \frac{\int_{P_{t_l}(z_8)}^{P_{t_l}(z_e)} E(Y(t_l)|U_{t_l} = u)du}{P_{t_l}(z_e) - P_{t_l}(z_8)}, \tag{48}$$

where the first equality is due to (40) and the second due to item (ii) of **T.4**. The counterfactual outcomes $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{al})$ in (37) and $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pl})$ in (39) correspond to integrals over the intervals $[0, P_{t_l}(z_c)]$ and $[P_{t_l}(z_c), P_{t_l}(z_8)]$ respectively. Figure 2 displays these expressions.

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

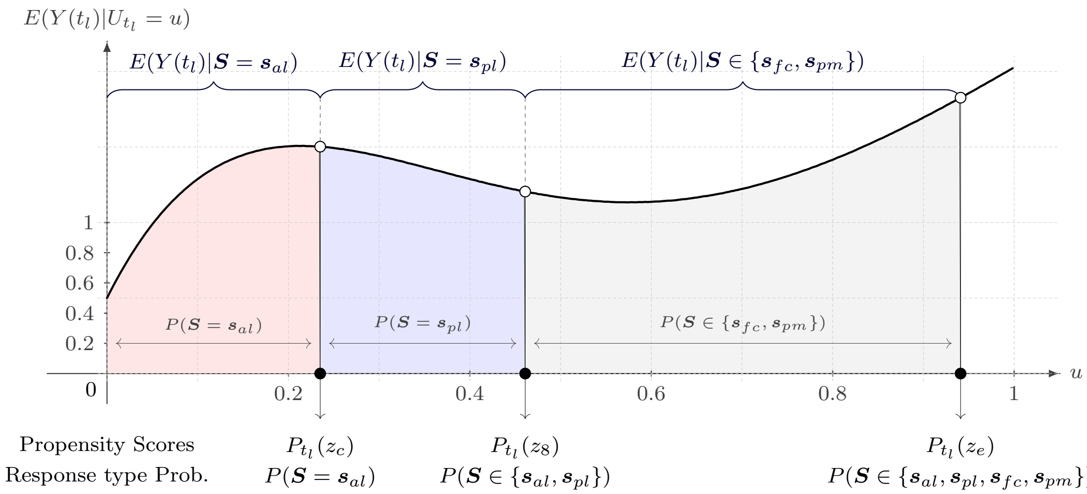


Figure 2 maps the response types $\boldsymbol{s}_{al}$, $\boldsymbol{s}_{pl}$, and $\{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}$ to the propensity score intervals $[0, P_{t_l}(z_c)]$, $[P_{t_l}(z_c), P_{t_l}(z_8)]$, and $[P_{t_l}(z_8), P_{t_l}(z_e)]$, respectively. The length of each interval is equal to its corresponding response type probability. In particular, $P(\boldsymbol{S} \in \{\boldsymbol{s}_{fc}, \boldsymbol{s}_{pm}\}) = P_{t_l}(z_e) - P_{t_l}(z_8)$.[50] Split the interval $[P_{t_l}(z_8), P_{t_l}(z_e)]$ into $[P_{t_l}(z_8), P_{t_l}(z_8) + P(\boldsymbol{S} = \boldsymbol{s}_{fc})]$, corresponding to $\boldsymbol{s}_{fc}$, and $[P_{t_l}(z_8) + P(\boldsymbol{S} = \boldsymbol{s}_{fc}), P_{t_l}(z_e)]$, corresponding $\boldsymbol{s}_{pm}$.[51] From **T.4**, we obtain the following identification equations:

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc}) = \frac{\int_{P_{t_l}(z_8)}^{p^*} E(Y(t_l)|U_{t_l} = u)du}{P(\boldsymbol{S} = \boldsymbol{s}_{fc})} = \frac{E(YD_{t_l}|P_{t_l} = p^*) - E(YD_t|P_{t_l} = P_{t_l}(z_8))}{p^* - P_{t_l}(z_8)}, \quad (49)$$

$$E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm}) = \frac{\int_{p^*}^{P_{t_l}(z_e)} E(Y(t_l)|U_{t_l} = u)du}{P(\boldsymbol{S} = \boldsymbol{s}_{pm})} = \frac{E(YD_{t_l}|P_{t_l} = P_{t_l}(z_e)) - E(YD_t|P_{t_l} = p^*)}{P_{t_l}(z_e) - p^*}, \quad (50)$$

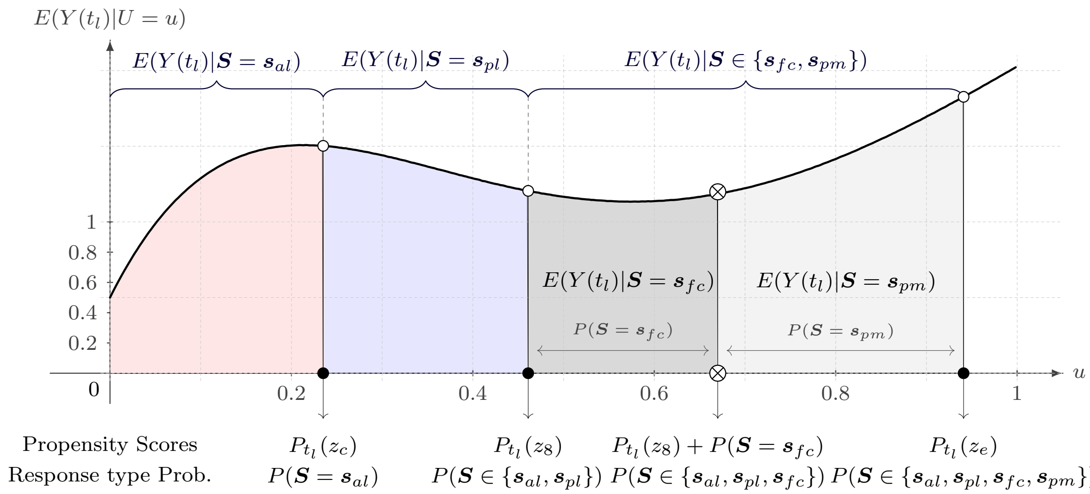
where $P_{t_l} \equiv P(T = t_l|Z)$ is the propensity score and $p^* = P_{t_l}(z_8) + P(\boldsymbol{S} = \boldsymbol{s}_{fc})$. (51)

The first equality in (49) and (50) states that 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 integrals of the response function $E(Y(t_l)|U_{t_l} = u)$ over their corresponding intervals. The following figure displays a diagram of these equations.

[50] Moreover, according to (36)–(38), we have that $P(\boldsymbol{S} = \boldsymbol{s}_{al}) = P_{t_l}(z_c)$, and $P(\boldsymbol{S} = \boldsymbol{s}_{pl}) = P_{t_l}(z_e) - P_{t_l}(z_8)$.

[51] Recall that the probability $P(\boldsymbol{S} = \boldsymbol{s}_{fc})$ is identified since all response type probabilities are identified (**T.2**).

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



The second equality in (49) and (50) shows that $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ and $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{pm})$ are identified by LATE-type parameters that require evaluating the expectation of $Y \cdot D_{t_l}$ conditioned on propensity scores.[52] The expectations $E(YD_{t_l}|P_{t_l} = P_{t_l}(z_8))$ and $E(YD_{t_l}|P_{t_l} = P_{t_l}(z_e))$ can be evaluated from observed data. The probability $P_{t_l}(z_8) + P(\boldsymbol{S} = \boldsymbol{s}_{fc})$ can also be evaluated since $P(\boldsymbol{S} = \boldsymbol{s}_{fc})$ is identified.[53] However, the expectation $E(YD_{t_l}|P_{t_l} = P_{t_l}(z_8) + P(\boldsymbol{S} = \boldsymbol{s}_{fc}))$ cannot be properly assessed from available data.

The typical approach to this type of problem involves adopting a functional structure for the expectation $E(YD_{t_l}|P_{t_l} = p)$.[54] For instance, a simple solution consists in fitting the expectation $E(YD_{t_l}|P_{t_l} = p)$ as a polynomial of the three observed propensity scores and then evaluate this polynomial at $P_{t_l} = P_{t_l}(z_8) + P(\boldsymbol{S} = \boldsymbol{s}_{fc})$. A better fit is obtained by exploiting the variation of baseline variables $\boldsymbol{X}$. Specifically, let $P_{t_l}(z, \boldsymbol{x}) = P(T = t_l|Z = z, \boldsymbol{X} = \boldsymbol{x})$ be the propensity score conditioned on the baseline variables $\boldsymbol{X} = \boldsymbol{x}$ for $z \in \{z_c, z_8, z_e\}$, and let $M_t(p, \boldsymbol{x}) = E(Y \cdot D_{t_l}|P_{t_l} = p, \boldsymbol{X} = \boldsymbol{x})$ be the expected value of the interaction $Y \cdot D_{t_l}$ conditioned on the propensity score $P_{t_l} = p$ and baseline variables $\boldsymbol{X} = \boldsymbol{x}$. In this notation, the counterfactual outcome $E(Y(t_l)|\boldsymbol{S} = \boldsymbol{s}_{fc})$ in

[52] The identification of the response function itself, namely $E(Y(t_l)|U_{t_l} = u)$, is not possible since MTO has a categorical instrument. If the propensity score $P_{t_l}(Z)$ were continuous around a value $u \in (0, 1)$, then the response function $E(Y(t_l)|U_{t_l} = u)$ could be identified by $\frac{\partial E(YD_{t_l}|P_{t_l}=p)}{\partial p}|_{p=u}$.

[53] The response type probability for the full-compliers ($\boldsymbol{s}_{fc}$) is identified by $P(\boldsymbol{S} = \boldsymbol{s}_{fc}) = \big(P_{t_h}(z_8) - P_{t_h}(z_e)\big) - \big(P_{t_m}(z_c) - P_{t_m}(z_8)\big)$.

[54] Examples of works that study the adoption of functional form assumptions to go beyond standard LATE-type parameters are Brinch et al. (2017); Kline and Walters (2016, 2019). See also Mogstad et al. (2018); Mogstad and Torgovitsky (2018) for a general approach that adopts functional structures to evaluate causal parameters in IV models with categorical instruments.

(49) is identified by the following expression:[55]

$$E(Y(t_l)|\boldsymbol{S}=\boldsymbol{s}_{fc}) = \frac{\int \big(M_{t_l}(P_{t_l}(z_8,\boldsymbol{x})+P_{fc}(\boldsymbol{x}),\boldsymbol{x}) - M_{t_l}(P_{t_l}(z_8,\boldsymbol{x}),\boldsymbol{x})\big)dF_{\boldsymbol{X}}(\boldsymbol{x})}{\int P_{fc}(\boldsymbol{x})dF_{\boldsymbol{X}}(\boldsymbol{x})}, \tag{52}$$

$$\text{where } P_{fc}(\boldsymbol{x}) = \big(P_{t_h}(z_8,\boldsymbol{x}) - P_{t_h}(z_e,\boldsymbol{x})\big) - \big(P_{t_m}(z_c,\boldsymbol{x}) - P_{t_m}(z_8,\boldsymbol{x})\big). \tag{53}$$

Equation (52) can be evaluated by a propensity score estimator (Frölich, 2007). The method for doing so comprises three steps: (*i*) estimate the propensity scores $P_{t_l}(z,\boldsymbol{x})$ as a parametric function of the IV-values z and covariates $\boldsymbol{x}$; (*ii*) use the fitted values of the propensity scores to estimate the conditional expectation $M_{t_l}(p,\boldsymbol{x})$ as a polynomial of the propensity scores p and covariates $\boldsymbol{x}$; and (*iii*) evaluate the empirical counterpart of equations (52)–(53) by:

$$\hat{E}(Y(t_l)|\boldsymbol{S}=\boldsymbol{s}_{fc}) = \frac{\sum_i \Big(\hat{M}_{t_l}\big(\hat{P}_{t_l}(z_8,\boldsymbol{X}_i)+\hat{P}_i(\boldsymbol{s}_{fc}),\boldsymbol{X}_i\big) - \hat{M}_{t_l}\big(\hat{P}_{t_l}(z_8,\boldsymbol{X}_i),\boldsymbol{X}_i\big)\Big)\cdot W_i}{\sum_i \hat{P}_i(\boldsymbol{s}_{fc})\cdot W_i}, \tag{54}$$

$$\text{s.t. } \hat{P}_i(\boldsymbol{s}_{fc}) = \big(\hat{P}_{t_h}(z_8,\boldsymbol{X}_i) - \hat{P}_{t_h}(z_e,\boldsymbol{X}_i)\big) - \big(\hat{P}_{t_m}(z_c,\boldsymbol{X}_i) - \hat{P}_{t_m}(z_8,\boldsymbol{X}_i)\big), \tag{55}$$

where $\hat{M}_{t_l}\big(p,\boldsymbol{x}\big)$ is the estimated function for $E(YD_{t_l}|Z=z,\boldsymbol{X}=\boldsymbol{x})$, $\hat{P}_t\big(z,\boldsymbol{x}\big); t \in \{t_h,t_m,t_l\}$ denotes the propensity score estimator, $\boldsymbol{X}_i$ consists of the baseline covariates of family i, and W_i is the MTO adult sampling weights (Orr et al., 2003). The estimator can also be used to evaluate the remaining mean counterfactual outcomes of MTO, since they are all identified by LATE-type parameters. Appendix G provides additional information on the identification and estimation of counterfactual outcomes.[56]

6 A New Empirical Analysis of MTO

This section uses the analytical framework of Section 5 to move beyond the TOT analysis frequently seen in the empirical research on MTO. The framework allows us to decompose the TOT parameters into a weighted average of well-defined causal effects between neighborhood types. Additionally, it enables us to evaluate the fundamental causal components of the MTO choice model, including response-type probabilities, baseline variables, and counterfactual outcomes conditioned

[55] See Appendix G.3 for this derivation.

[56] Appendix G.2 describes the decompositions of the partially-identified outcomes of all three neighborhood choices in greater detail. Appendix G.3 describes the general properties of the propensity score estimator. Appendix G.4 presents the equations that are the basis for the propensity score estimator for all counterfactual outcomes in MTO. Appendix G.5 provides a detailed description of the empirical strategy to estimate counterfactual outcomes using the propensity score estimator.

on response types. These new analyses promote a greater comprehension of the MTO intervention and can be used to guide the designing of more effective housing policies.

Section 6.1 estimates the share of families that belong to each response type, that is the response type probabilities. It shows that almost half of families are always-takes who choose the same type of neighborhood regardless of any MTO incentives. The most responsive families make up a third of the sample. Section 6.2 evaluates the baseline characteristics are closely associated with each family type.[57] Families who do not move regardless of MTO incentives have less education and face significant mobility restrictions. They are also less affected by the level of criminality in high-poverty neighborhoods. Families that respond to MTO incentives have fewer mobility restrictions, are more likely to be victims of crime, and report greater dissatisfaction while living in high-poverty neighborhoods. Altogether, these analyses give new insights into the decision-making processes of MTO families.

Section 6.3 reports the estimates of the counterfactual outcomes of MTO. The section provides an informative characterization of labor market outcomes across the 12 counterfactual outcomes and the seven response types of MTO. Section 6.4 focuses on the neighborhood effects for the full-compliers. That section gives a detailed picture of how the different neighborhood types affect the labor market outcomes of the families that respond to voucher incentives. It shows that families who relocate from high-poverty to low-poverty neighborhoods significantly improve their economic outcomes.

Section 6.5 links the novel empirical analyses to traditional MTO evaluations. The section presents a decomposition of the TOT estimates of labor market outcomes into weighted averages of the neighborhood effects. The results demonstrate that the neighborhood effects of families most responsive to the voucher are statistically and economically significant. Moreover, it shows that the TOT parameter is often statistically insignificant because it dilutes the large and significant effects of the full-compliers with weaker neighborhood effects of other response types that lack statistical precision.

All estimations presented here weight the observed data according to the MTO adult sampling weights (Orr et al., 2003). Inference is based on the stratified bootstrap method that resamples the

[57] The identification of the distribution of baseline characteristics conditioned on response types also enables estimating the likelihood that a family belongs to each of the response types given its baseline characteristics.

full data set according to the MTO weights.[58]

6.1 Response type Probabilities

Identification of response type probabilities follows from equation (9). The matrix version of the equation is:

$$\boldsymbol{P}_Z(t) = \boldsymbol{B}_t \cdot \boldsymbol{P}_S; \quad t \in \{t_h, t_m, t_l\}, \tag{56}$$

where $\boldsymbol{P}_Z(t) = [P_t(z_c), P_t(z_8), P_t(z_e)]'$ is the 3×1 vector of propensity scores. It is useful to express these propensity scores by the following expectations:

$$\boldsymbol{P}_Z(t) = [E(D_t|Z = z_c), E(D_t|Z = z_8), E(D_t|Z = z_e)]'; \quad t \in \{t_h, t_m, t_l\}. \tag{57}$$

The vector $\boldsymbol{P}_S$ in the right-hand side of (56) is the 7×1 vector of response type probabilities:

$$\boldsymbol{P}_S = [P(\boldsymbol{S} = \boldsymbol{s}_{ah}), P(\boldsymbol{S} = \boldsymbol{s}_{am}), P(\boldsymbol{S} = \boldsymbol{s}_{al}), P(\boldsymbol{S} = \boldsymbol{s}_{fc}). P(\boldsymbol{S} = \boldsymbol{s}_{pl}), P(\boldsymbol{S} = \boldsymbol{s}_{pm}), P(\boldsymbol{S} = \boldsymbol{s}_{ph})]', \tag{58}$$

Finally, $\boldsymbol{B}_t = \mathbf{1}[\boldsymbol{R} = t]$ is the 3×7 binary matrix that indicates which elements in $\boldsymbol{R}$ are equal to $t \in \{t_l, t_m, t_h\}$. If we stack the vectors $\boldsymbol{P}_Z(t)$ and matrices $\boldsymbol{B}_t$ across the neighborhood choices, we get the equation $\boldsymbol{P}_Z = \boldsymbol{B}_T \cdot \boldsymbol{P}_S$, where $\boldsymbol{P}_Z = [\boldsymbol{P}_Z(t_h)', \boldsymbol{P}_Z(t_m)', \boldsymbol{P}_Z(t_l)']'$ and $\boldsymbol{B}_T = [\boldsymbol{B}'_{t_h}, \boldsymbol{B}'_{t_m}, \boldsymbol{B}'_{t_l}]'$. The response type probabilities are identified by $\boldsymbol{P}_S = \boldsymbol{B}_T^+ \boldsymbol{P}_Z$, where $\boldsymbol{B}_T^+ = (\boldsymbol{B}'_T \boldsymbol{B}_T)^{-1} \boldsymbol{B}'_T$ is the Moore-Penrose pseudo-inverse matrix of $\boldsymbol{B}_T$. A simple way to estimate the response type probabilities is to evaluate the vector of propensity scores $\hat{\boldsymbol{P}}_Z$ by taking the sample means from the observed data and calculate the response type probabilities by $\hat{\boldsymbol{P}}_S = \boldsymbol{B}_T^+ \hat{\boldsymbol{P}}_Z$. These estimations are numerically equivalent to the estimates of parameter $\boldsymbol{\beta}_P$ in the following linear regression:[59]

$$D_{t,i} = \boldsymbol{B}_{t,i} \boldsymbol{\beta}_P + \epsilon_{t,i} \text{ for all } t \in \{t_l, t_m, t_h\}, \tag{59}$$

where $D_{t,i} = \mathbf{1}[T_i = t]$ indicates if family i chooses neighborhood $t \in \{t_h, t_m, t_l\}$, 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. We can control for baseline variables by including pre-intervention covariates in the linear

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

[59] 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. See Appendix A.6 for additional discussion on the identification of response type probabilities.

probability model (59). The regression-adjusted model is as follows:

$$D_{t,i} = \boldsymbol{B}_{t,i}\boldsymbol{\beta}_P + \boldsymbol{X}_i\boldsymbol{\theta}_t + \boldsymbol{K}_i\boldsymbol{\gamma}_t + \epsilon_{t,i} \text{ for all } t \in \{t_l, t_m, t_h\}, \tag{60}$$

where $\boldsymbol{X}_i$ denotes the baseline variables displayed in Table 1 and $\boldsymbol{K}_i$ denotes site fixed effects. In order to ensure that the estimated probabilities in $\hat{\boldsymbol{\beta}}_P$ sum to one, it is necessary to normalize the variables $\boldsymbol{X}$ and $\boldsymbol{K}$ to have zero means. These variables are also standardized to have unitary standard deviations.

Figure 4 presents the estimates of MTO's seven response type probabilities. These probabilities partition the sample into latent groups based on the families' choice behavior. The always-takers are families who do not change their neighborhood choice regardless of voucher assignment. These families account for 42.6% of the sample: $P(\boldsymbol{S} \in \{\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}, \boldsymbol{s}_{al}\}) = .348 + .047 + .031 = 0.426$. In particular, a third of the sample consists of high-poverty always-takers $P(\boldsymbol{S} = \boldsymbol{s}_{ah}) = 0.348$, who are families that never move from high-poverty neighborhoods. 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. The remaining families are the partial compliers since they choose two out of the three possible neighborhood types as the instrument varies. They account for almost a quarter of the sample: $P(\boldsymbol{S} \in \{\boldsymbol{s}_{pl}, \boldsymbol{s}_{pm}, \boldsymbol{s}_{ph}\}) = 0.069 + 0.053 + 0.119 = 0.241$.

6.2 Baseline Variables conditioned on Response Types

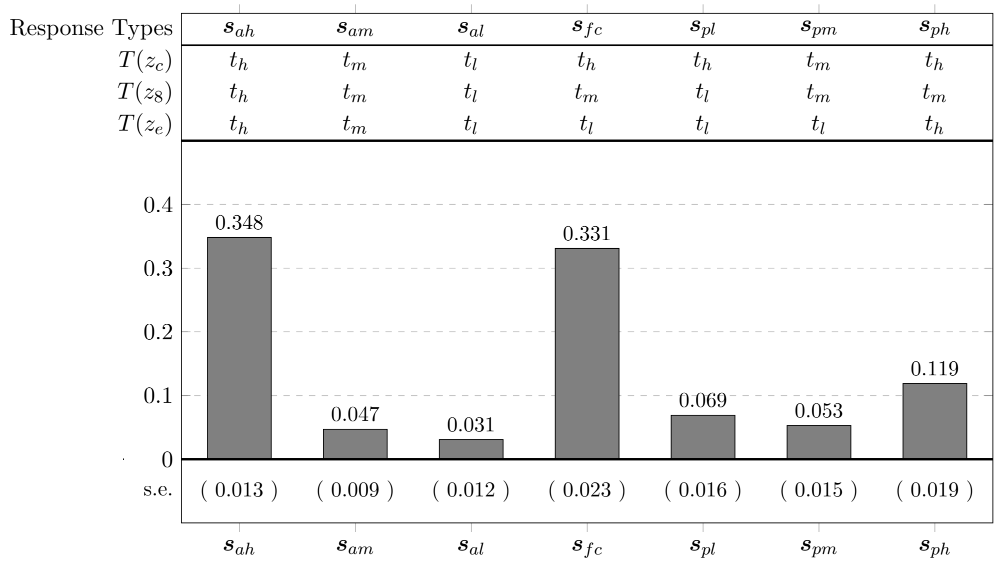
Identification of the expected value of baseline variables X conditioned on response types follows from the following equation:[60]

$$E(X \cdot D_t | Z = z) = \sum_{\boldsymbol{s} \in supp(\boldsymbol{S})} \mathbf{1}[T = t | \boldsymbol{S} = \boldsymbol{s}, Z = z]\, E(X | \boldsymbol{S} = \boldsymbol{s})\, P(\boldsymbol{S} = \boldsymbol{s}). \tag{61}$$

The matrix version of this equation is a variation of $\boldsymbol{P}_Z(t) = \boldsymbol{B}_t \cdot \boldsymbol{P}_S$ in (56) that replaces the entries $E(D_t|Z = z)$ of $\boldsymbol{P}_Z(t)$ in (57) by $E(X \cdot D_t|Z = z)$, and replaces the entries $P(\boldsymbol{S} = \boldsymbol{s})$ of $\boldsymbol{P}_S$ in (58) by $E(X|\boldsymbol{S} = \boldsymbol{s})\, P(\boldsymbol{S} = \boldsymbol{s})$. We can use the same arguments of the previous section to obtain

[60] See Appendix A.6 for the identification proof.

Figure 4: Response Type Probabilities



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

the following linear regression:

$$X_i D_{t,i} = \boldsymbol{B}_{t,i}\boldsymbol{\beta}_X + \boldsymbol{K}_i\boldsymbol{\theta}_t + \epsilon_{t,i}, \text{ across all } t \in \{t_l, t_m, t_h\}. \tag{62}$$

The regression is similar to the linear probability model (60). The regression simply replaces the dependent variable $D_{t,i}$ in (60) by the interaction $X_i D_{t,i}$. The parameter $\boldsymbol{\beta}_X$ is a 7×1 vector that evaluates the value of $E(X|\boldsymbol{S} = \boldsymbol{s})P(\boldsymbol{S} = \boldsymbol{s})$ for all the seven response types. The estimates for $E(X|\boldsymbol{S} = \boldsymbol{s})$ are obtained by dividing the estimates in $\boldsymbol{\beta}_X$ by their corresponding response type probabilities.

Table 5 presents estimates for the conditional expectation of the baseline variables given the response types. There is a sharp contrast between families that always remain in high-poverty neighborhoods, the high-poverty always-takers $\boldsymbol{s}_{ah}$,[61] and those that are most responsive to voucher incentives, the full-compliers $\boldsymbol{s}_{fc}$. Families of type $\boldsymbol{s}_{ah}$ are more likely to have disabled persons and teenagers among household members, consistent with their lower 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 crime in their residential

[61] These families can also be understood as "never-movers" or "stayers."

neighborhoods. 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-takers, $\boldsymbol{s}_{ah}$, have the lowest level of schooling and are less likely to have a car. On the opposite side are the low-poverty always-takers, $\boldsymbol{s}_{al}$, which consists of families that choose low-poverty neighborhoods regardless of the voucher assignment. 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. These families are most likely to be victims of criminal activity and report the highest level of neighborhood dissatisfaction.

Table 5 helps understanding how families respond to the relocation incentives. For instance, MTO incentives are insufficient to induce the high-poverty always-takers $\boldsymbol{s}_{ah}$ to relocate since these families never move from high-poverty neighborhoods. These families also face higher mobility constraints and are less bothered by neighborhood criminality. Unfortunately, they are the most disadvantaged families of the sample and are likely to gain the most from relocation. In general, the data shows a positive selection on the baseline variables. Families that always move to low-poverty neighborhoods despite voucher incentives, the low-poverty always-takers $\boldsymbol{s}_{al}$, are, on average, the most privileged families of the sample.

6.3 Counterfactual Outcomes

The counterfactual mean outcomes of MTO can be expressed as a LATE-type parameter in the form of equation (47). These parameters are evaluated by a conventional propensity score estimator outlined in Section 5.3. See Appendix G.5 for a detailed description of this method. Figure 5 presents the estimates for the counterfactual outcome means of the income of the head of the family conditioned on the response types.

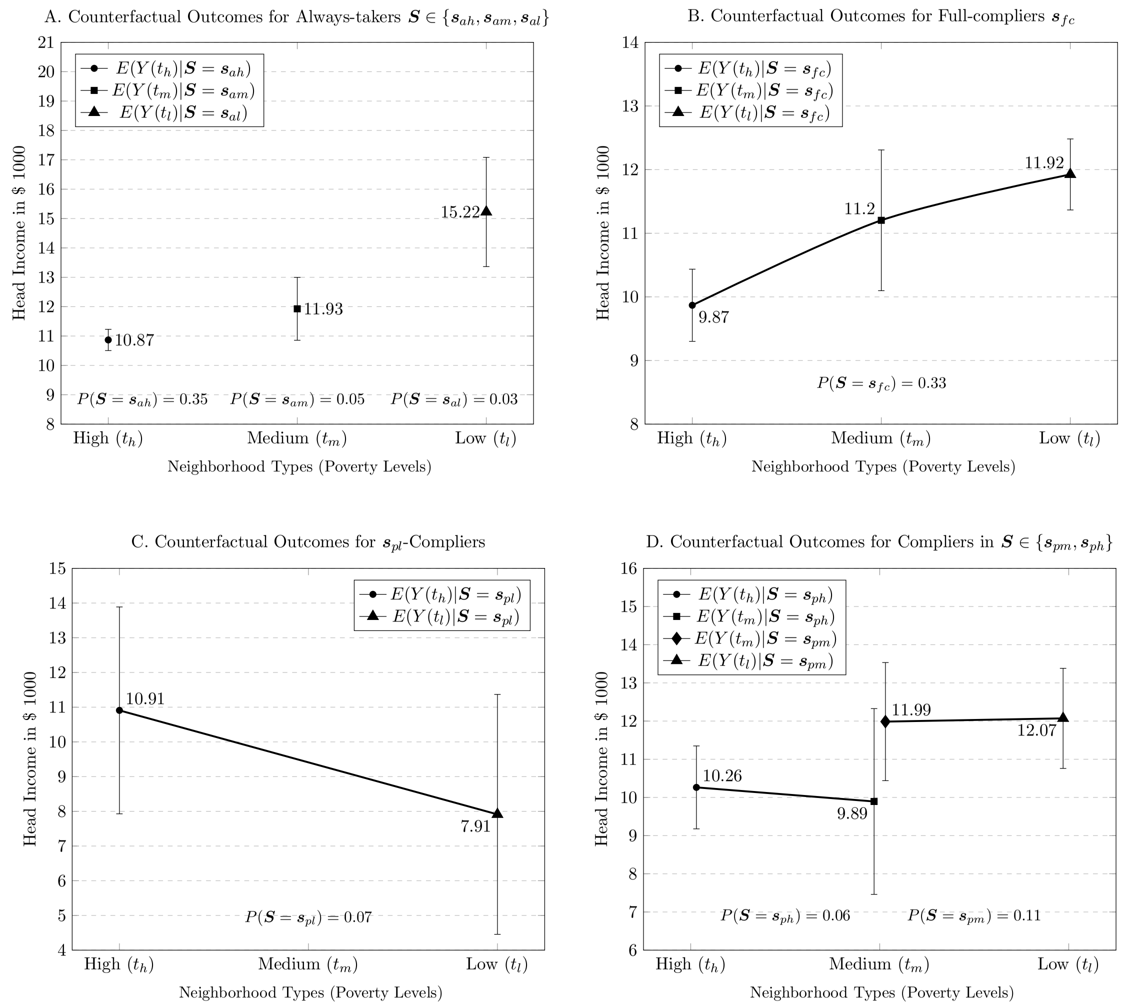
Figure 5.A shows counterfactual income estimates for the three response types corresponding to always-takers. Estimates increase as the neighborhood choice ranges across high-, median- and low-poverty neighborhoods. The difference of the counterfactual outcomes across these response types always-takers $\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}$ and $\boldsymbol{s}_{al}$ are not causal since family characteristics differ across these response types. The high-poverty always-takers $\boldsymbol{s}_{ah}$ have the lowest income among all always-takers. They

Table 5: Pre-program Variables Means by Response Types

	Variable	**Always-takers**			**Compliers**			
		Stayers			Movers			
	Mean	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.

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. Appendix G.5 describes the estimation procedure in detail. Error bars denote the standard error associated with each estimate. Income measured in thousand dollars per year.

are also the most disadvantaged families among the always-takers. The precision of the estimates is inversely proportional to sample share of each response type.

Figure 5.B displays the estimates for the same response type, the full-compliers $\boldsymbol{s}_{fc}$, for the high-, medium-, and low-poverty neighborhoods. It shows a steep increase in income as families move to better neighborhoods. In this case, the income difference across neighborhood types constitute a true causal effect since they are assessed 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 any conclusive analysis.

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.

There is common pattern among the always-takers $\boldsymbol{s}_{ah}, \boldsymbol{s}_{am}$ and $\boldsymbol{s}_{al}$. Counterfactual outcomes improve as the neighborhood types change from high- to medium- and from medium- to low-poverty neighborhoods. A similar pattern is observed 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, comparisons across 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 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 $39.948\% - 6.692\% = 33.256\%$, while the difference for the partial complier $\boldsymbol{s}_{pl}$ is $35.240\% - 8.865\% = 26.375\%$. This helps explain why the estimates for the full-compliers are

Table 6: Estimates of the Expected Values of the Counterfactual Outcomes

	Always-takers Stayers			Full Complier Mover			Partial Compliers Movers					
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

This table presents the estimates for the counterfactual outcome means and standard errors for economic variables across all response types. Estimates are conditioned on the site of intervention and baseline variables discussed in Section 2. Observed data is weighted according to the MTO adult sampling weights (Interim Impacts Evaluation manual, Orr et al. (2003), Appendix B). Appendix G.5 describes the estimation procedure in detail. Income is measures in thousand dollars per year. The sample size is 4227.

the most significant among all compliers. Full-compliers account for the largest sample share and the largest difference in poverty levels between neighborhood types.

6.4 Evaluating the Causal Effects for Full-compliers

This section investigates the neighborhood effects for the full-compliers $\boldsymbol{s}_{fc}$. 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.[62]

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-poverty neighborhoods, $E(Y(t_l) - Y(t_m)|\boldsymbol{S} = \boldsymbol{s}_{fc})$, and the last one compares medium- versus high-poverty neighborhoods, $E(Y(t_m) - Y(t_h)|\boldsymbol{S} = \boldsymbol{s}_{fc})$. Most of the neighborhood effects for low- versus high-poverty neighborhoods are statistically significant. However, none of the effects that compare low- versus medium- or medium- versus low-poverty neighborhoods is statistically 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 on average an increase in the annual income of the family head of \$2,056. This accounts for a considerable increase of 20% in income. The estimated neighborhood effect on the total income of the family is \$1,902 per year, accounting for a 14% increase in total income. Both results are statistically and economically significant.

The estimates of Table 7 show that switching from high- to 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 40%

[62]These neighborhood effects can be understood as an instance of the policy-relevant treatment effects (PRTE) of Heckman and Vytlacil (2001, 2005). The PRTE seeks to evaluate policies that affect program participation but does not directly affect the treatment effects of each individual.[63] 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.

rise. It is noteworthy that previous literature was unable to evaluate these results because they pertain to full-compliers, a subgroup of MTO families that could only be characterized through the revealed preference analysis.

The last row of Table 7 presents the mean difference in poverty levels between 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.

6.5 Decomposing TOT Effects

The influential literature on MTO relies on the treatment-on-the-treat (TOT) 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) find significant effects on earnings and employment when controlling for the duration of residence in disadvantaged neighborhoods. Aliprantis and Richter (2020) also find significant labor market effects when controlling for the neighborhood quality. More recently, Harding et al. (2021) investigate the mismatch between the statistically insignificant economic results 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 the current paper is to reconcile these seemingly inconsistent findings in the MTO literature. Section 3 explains that the widely reported TOT parameter consists of the causal effect of being offered a voucher divided by the voucher compliance rate. That 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 for investigating 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

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

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

This table evaluates the neighborhood effects for full-compliers $\boldsymbol{s}_{fc}$. 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 sampling weights of MTO interim evaluation. Appendix G.5 describes the estimation procedure in detail. The p-values test if the estimates are equal to zero are based on a bootstrap method that accounts for sampling weights. Asterisks *** indicate a p-value < 0.01, ** indicates $0.01 \leq p$-value < 0.05, and * indicates $0.05 \leq p$-value < 0.1.

neighborhood choice into several response types. This framework facilitates a deeper understanding of the MTO intervention as shown in previous sections. In addition, it enables us to decompose the TOT parameter in terms of neighborhood effects across the response types.

Proposition **P.4** 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 used in Sections 6.3–6.4.

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 smaller shares of the MTO sample. Not surprisingly, the neighborhood effects of partial-compliers lack statistical precision. The combination of these neighborhood effects dilutes the strong effects of the full-compliers resulting in weak TOT estimates.

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.4**. The remaining columns present the breakdown of the TOT estimates into the neighborhood effects of the full- and the partial-compliers.

The TOT estimates based on the 2SLS and those based 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:

$$\text{First Stage:} \quad C_i = \gamma_1 + \gamma_2 \cdot \mathbf{1}[Z_i = z_c] + \gamma_X \cdot \boldsymbol{X} + \gamma_K \cdot \boldsymbol{K} + \eta_i \text{ for } i\,;\; Z_i \in \{z_c, z_e\}, \tag{63}$$

$$\text{Second Stage:} \quad Y = \beta_0 + \beta_{\text{TOT}} \cdot \hat{C}_i + \beta_X \cdot \boldsymbol{X} + \beta_K \cdot \boldsymbol{K} + \epsilon_i \text{ for } i\,;\; Z_i \in \{z_c, z_e\}, \tag{64}$$

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 poverty due to neighborhood location 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 smaller than the neighborhood effects for the full-compliers.

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

The analysis of this section leads to two key conclusions mentioned in the introduction of this paper. The first is that economic analysis of MTO incentives was crucial in moving beyond simply reporting TOT. The revealed preference analysis was essential for devising a method to decompose, isolate and estimate the neighborhood effects that are jointly evaluated by the TOT parameter.

The second conclusion is that statistically insignificant estimated TOT effects on labor market outcomes does not necessarily mean that the MTO intervention failed to improve the economic outcomes of its participants. The economic impact of MTO on families that complied with the voucher incentives (the full-compliers) is both economically and statistically significant. This result helps make sense of the literature on neighborhood effects since it reconciles the MTO intervention with recent studies that find significant impact of neighborhood quality on the economic outcomes of its residents (Chetty et al., 2017, 2016; Chyn, 2016; Galiani et al., 2015).

7 Summary and Conclusions

MTO is an influential housing experiment that used the method of randomized controlled trials to investigate the causal effects of relocating disadvantaged families living in poor areas to better neighborhoods. The experiment offered rent-subsidized vouchers that incentivize families to move from high-poverty neighborhoods to either low- or medium-poverty neighborhoods. Unfortunately, half of the families that received the vouchers did not use them to relocate. This noncompliance generates the problem of selection bias which prevents the use of simple methods to identify the causal effect of relocating from one type of neighborhood to another.

Most of the MTO literature has addressed the issue of noncompliance by reporting the treatment-on-the-treated (TOT) effect, which is the causal effect of being offered a voucher divided by the voucher compliance rate. Typically, these studies find that the TOT effect on labor market outcomes is not statistically significant (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). However, this conclusion is not shared by all researchers. Some studies employing different identification strategies have found significant effects of MTO on labor market outcomes (Aliprantis and Richter, 2020; Clampet-Lundquist and Massey, 2008).

Despite extensive literature, many questions regarding the effects of MTO remain unanswered. For instance, there is considerable disagreement on how to interpret the TOT parameter in terms of causal effects across neighborhood types (Aliprantis, 2007; Clampet-Lundquist and Massey, 2008; Ludwig et al., 2008; Sampson, 2008). Other studies, such as Harding et al. (2021), call into question the discrepancy between the insignificant TOT effects on economic outcomes and the significant effects on labor market outcomes reported by various observational studies (Elliott, 1999; Fauth et al., 2004; Shang, 2014). This paper provides answers to these long-standing questions.

The MTO intervention consists of a choice model in which families decide among three different types of neighborhoods, and the voucher assignment consists of a three-valued instrumental variable that affects the neighborhood choice. The experimental design takes us well outside the realm of the binary LATE model. In particular, standard monotonicity conditions that identify LATE are not sufficient to secure the identification of neighborhood effects in MTO.

The core innovation of this study is to use classical economic behavior to explore the choice incentives of the MTO intervention. Applying revealed preference analysis yields choice restrictions that encompass standard monotonicity conditions. These restrictions lead to seven response types, allowing us to identify all response type probabilities and most of the counterfactual outcomes of the

MTO intervention. Moreover, this analysis enables us to determine the causal content of the TOT parameter as a weighted average of neighborhood effects. Furthermore, the choice restrictions imply the unordered monotonicity condition of Heckman and Pinto (2018), which is helpful to ensure the point-identification of the counterfactual outcomes that were partially identified.

This framework facilitates novel analyses that enhance 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 those families most responsive to the MTO incentives. These families account for a third of the MTO sample. In contrast, always-takers (or stayers) 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 that always choose to live in high-poverty neighborhoods. Conversely, the families that always choose to live in low-poverty neighborhoods have the highest levels 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 and have characteristics somewhat in between the two archetypes isolated here.

The paper shows that the TOT parameter evaluates a weighted average of the neighborhood effects of the full- and partial-compliers. It demonstrates that weak TOT effects on labor market outcomes do not necessarily imply that MTO fails to improve the economic well-being of its participants. The empirical analysis shows substantial neighborhood effects for full-compliers who move from high to low-poverty neighborhoods. These families tend to have higher income, increased employment, and are more likely to be above the poverty line and less likely to depend on welfare. These empirical findings are both statistically and economically significant. This conclusion aligns 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).

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