Conditional Response Types and the Identification of Multivalued Treatment Effects

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Abstract

I study treatment effects under multiple options that lack a clear ranking. When the identifying variation stems from multiple instruments, agents can switch into different options and from many initial states. I discuss how to define and employ conditional response types (*i.e.*, combinations of potential choices given by one instrument that differ depending on the variation of other instruments) to identify the shares of agents switching at well-defined margins of choice and their treatment effects. I present an empirical strategy consistent with this framework and apply it to three settings: subsidies for malaria treatment in Kenya, childcare choice and children's development in Colombia, and merit- and need-based scholarships and higher education in Colombia. While standard methods would identify the local average treatment effect of one option *versus* the next-best (*i.e.*, a combination of fallback alternatives), I show how combining multiple sources of variation and defining conditional response types can help identify effects of pairwise combinations of the available options across these settings.

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1 Introduction

Economic decisions often require individuals to choose among multiple options, such as selecting healthcare or childcare provider and pursuing different higher education paths. When agents can endogenously choose from multiple unordered alternatives, standard instrumental variables methods identify a combination of local treatment effects with negative weights, or, using the variation from one instrument alone, the effect of one option *versus* the next-best (*i.e.,* a mixture of other options that the agent would have chosen in the absence of her preferred option).[1] Although the effect of an option versus the next-best can answer policy questions in some contexts, it often masks important heterogeneity for agents with distinct fallback alternatives.[2] If the fallback option is observed (*e.g.,* using rankings), pairwise treatment effects can be identified under additional testable behavioral assumptions (Kirkeboen, Leuven, and Mogstad, 2016; Heinesen, Hvid, Kirkebøen, Leuven, and Mogstad, 2024). Otherwise, identification might require multiple continuous instruments (Mountjoy, 2022) with large support (Heckman et al., 2008), or additional assumptions on potential outcomes (Kline and Walters, 2016; Hull, 2018; Lee and Salanié, 2024).

I study the treatment effects of multiple unordered options in scenarios where discrete or continuous instruments are available, but option rankings are not observed. I propose an identification strategy that combines the variation of multiple discrete and/or continuous instruments such that, under some conditions, the set of next-best states changes as the instruments change (without requiring direct observation of fallback options or rankings). To fix ideas, suppose that the researcher has access to experimental variation that encourages agents to choose option 1 instead of 2 or 3, but only if they face lower costs. In turn, when costs are higher, the responses between option 1 and 2 disappear. In this scenario, as costs increase, the set of next-best states goes from containing options 2 and 3 to containing only option 3. Therefore, within my framework, I allow for the response to the variation in one instrument (*e.g.*, random assignment to subsidies encouraging households to use drug shops) to differ depending on other instruments (*e.g.*, proximity to health care centers) that affect the same choice margins. I formalize this notion by defining *conditional response types* consisting of combinations of potential choices given by one instrument that differ depending on the variation of other instruments. I derive conditions under which *conditional response types* help identify pairwise treatment effects

[1] On the particular issue of standard IV methods (namely, two-stage least squares, 2sls) assigning negative weights or leading to estimates lacking clear interpretations see Bhuller and Sigstad (2024). In terms of the effect of one option *versus* the next-best and developments on identification and estimation see, for example, Heckman, Urzua, and Vytlacil (2006); Heckman, Urzúa, and Vytlacil (2008); Mountjoy (2022).

[2] For instance, in the context of healthcare choices, a researcher may seek to estimate the average treatment effects of different options—for example, do drug shops improve health outcomes relative to healthcare centers or to receiving no care?—rather than the effect of choosing drug shops relative to a scenario in which they are unavailable.

(*i.e.,* local and marginal treatment effects of one option relative to another option).

Recent theoretical and empirical work has focused on the identification and estimation of treatment effects with instrumental variables in contexts where agents can choose from multiple unordered alternatives.[3] Because the options often lack a clear ordering, the variation in the instruments can induce agents to switch into different options and from many initial states (Angrist, Imbens, and Rubin, 1996; Heckman et al., 2006). Importantly, the set of potential responses to variation in (a binary) instrument goes beyond the always-takers, never-takers, compliers, and defiers in Imbens and Angrist (1994). For instance, Kirkeboen et al. (2016) and Heinesen et al. (2024) examine identification combining instrumental variables and rankings with additional assumptions on the set of potential responses, namely, no next-best defiers nor irrelevance defiers.[4] In the absence of rankings, different contexts might require more or less restrictive assumptions on choice behavior,[5] or instruments with enough variation to eliminate some next-best options (Heckman et al., 2006, 2008). While jointly modeling responses to multiple instruments may have identification implications, as in the binary choice-binary IV case in Mogstad, Torgovitsky, and Walters (2021, 2024),[6] current methods for multiple options implicitly assume that the behavior of compliers (or responses) to one instrument is the same across the distribution of other IVs.

I contribute to the literature on multiple unordered treatments in three ways. First, I follow the methodological approach of Heckman and Pinto (2018) in which revealed preference analysis defines vectors used to identify the prevalence of compliers (i.e., agents who change their behavior as the IV changes) and their counterfactuals. I extend this notion to the case of *conditional response types* which are defined by variation in an instrument but can change across the support of other IVs. The building block for defining *conditional response types* is the assumption that instruments affect choices through their effect on potential costs.[7] Following long-standing literature of shape restrictions that

[3]For an overview of recent developments in the literature of unordered treatments and instrumental variables see Mogstad and Torgovitsky (2024). Theoretical work can be found in Heckman and Pinto (2018); Lee and Salanié (2018, 2024); Xie (2020); Caetano and Escanciano (2020); Feng (2024); Kamat, Norris, and Pecenco (2023), and, for identification results with empirical applications see Kline and Walters (2016); Pinto (2019); Mountjoy (2022).

[4]Kirkeboen et al. (2016) and Heinesen et al. (2024) examine the returns to fields of study in Norway and Denmark using admission cutoffs and students' reported rankings. They define next-best defiers (students who would not choose their fallback option when below the cutoff) and irrelevance defiers (students whose cutoff status affects other fields). The authors assess the validity of assuming away these two groups, propose testable implications, and assess the resulting bias. For an alternative approach to estimate local treatment effects when rankings are available, see Nibbering, Oosterveen, and Silva (2022).

[5]For instance, Kline and Walters (2016); Hull (2018); Lee and Salanié (2024) employ assumptions on homogeneity of counterfactuals to disentangle treatment effects along well-defined margins of choice. Kamat (2024) focuses on partial identification of effects of program offers and exploits changes in the choice structure (comparing choice sets with and wihout the offer).

[6]The authors show that for the binary treatment case, the standard monotonicity assumption in Imbens and Angrist (1994) imposes homogeneity in the responses to multiple instruments.

[7]I model agents' decisions with a latent utility model with additive separability between the unobserved preference heterogeneity and the cost function. This is standard in the unobserved heterogeneity

stem from economic theory,[8] I assume that the cost function determining individual's decisions is convex. The role of convexity in identification is twofold. First, convexity imposes restrictions such that once an option becomes too costly its likelihood of being the next-best state goes to zero thereafter. Second, without any restrictions on the shape of the function, multiple instruments can affect the costs in different directions. Convexity imposes a smoothness condition such that, although the instruments enter the cost function nonlinearly, agents who are induced to change their behavior do so in the same direction. As a result, the combinations of potential choices in *conditional response types* are consistent with the restrictions of convexity on the cost function.

Second, I show that *conditional response types* satisfy a weaker version of monotonicity than in Imbens and Angrist (1994). In specific, they satisfy partial (unordered) monotonicity for multiple treatments as defined by Mountjoy (2022).[9] This assumption requires that agents who react to the variation in one instrument do so in the same direction (towards or away from the same choices), conditional on the variation in other IVs. Although this assumption has been previously employed, I further exploit a well-known, but frequently overlooked, property of monotonicity. It requires that changes in an instrument from z to z' induce all agents in the same direction; meanwhile, changes from z' to z'' do not have to induce agents in the same direction as changes in z to z'. Nonetheless, it is common to assume the same patterns of behavior at z to z' and z' to z''. I show how allowing for more flexibility in the responses across multiple values of an IV, while unwarranted for the binary choice case, can aid in identification in contexts of multiple unordered choices. That is, with *conditional response types*, I identify treatment effects for a richer set of compliers along multiple margins of choice that result from allowing agents' responses at z *versus* z' and z' *versus* z'' to differ.

Third, I discuss the role of *conditional response types* to identify shares of compliers at different margins of choice and their treatment effects. To do so, I assume that the set of *conditional response types* changes as the conditioning instrument changes, as implied by the restrictions on convexity of costs. If sufficient next-best states disappear, because under convexity of costs one or several options are becoming too costly as the instruments change, the researcher can identify pairwise treatment effects of one option *versus* the remaining next-best state. Heckman et al. (2006) and Heckman et al. (2008) showed that the multiple choice problem can be reduced to a standard binary choice case provided that,

literature (Vytlacil, 2002). Recently, Heckman and Pinto (2018) extended this notion for unordered choices; Lee and Salanié (2024) model changes in relative mean utility through changes in relative costs.

[8] See, for example, a nonparametric model of multinomial choice Matzkin (1991), with restrictions of concavity and monotonicity to achieve identification. Recent work by Freyberger and Horowitz (2015) impose shape restrictions such as convexity and monotonicity on the functional form of the outcome equation. For a review of shape restrictions in applied work see Chetverikov, Santos, and Shaikh (2018).

[9] Alternative monotonicity assumptions have been proposed in the literature. Das (2005) imposes an assumption conditional on covariates for nonlinear IVs; Heckman et al. (2006) impose conditional monotonicity on a second instrument, for the binary treatment case. More recently, Mogstad et al. (2021, 2024) and Goff (2024) present identification results for the binary treatment case.

as one instrument increases or decreases, the probability of one option being the next-best state goes to one. They employ an identification argument requiring instruments with extreme values. In my framework, this argument arises from incorporating economic theory to the identification problem and provides testable implications to empirically assess the validity of *conditional response types*. Importantly, the more sensitive the cost function is to changes in the instruments, the less extreme values of the IVs might be required for identification. That is, identification can be achieved by conditioning on binary IVs, if under one of the two IV values the costs of choosing one option increase dramatically, or on continuous IVs with marginal changes in costs where identification depends on the slope of the cost function.

Last, the strategy I present can be applied, but is not limited, to experimental designs with noncompliance when costs are also available. Noncompliance is frequent in applied work (e.g., Kline and Walters, 2016; Dean and Jayachandran, 2020; Pinto, 2019), and poses the challenge of identifying counterfactual choices or fallback options that can largely vary across individuals. I show that the strategy can be implemented with a semiparametric approach as in Mountjoy (2022),[10] without imposing restrictions on the relation between the instruments on the choice equation.[11] This approach fits with nonlinear instrumental variables estimation for discrete endogenous variables presented in Das (2005) and, more generally, in Imbens and Newey (2009); Chen, Chernozhukov, Lee, and Newey (2014); D'Haultfœuille and Février (2015) and Chernozhukov, Imbens, and Newey (2007). In particular, I show the identification and estimation of conditional Local Average Treatment Effects (LATEs) and Marginal Treatment Effects (MTEs) for pairwise comparisons of choices.

I use the identification results to empirically assess the effect of: (i) choice of care for illness in Kenya, (ii) childcare choice and children's development, and (iii) higher education enrollment choices on students' labor market outcomes in Colombia. These are all (empirical and policy) relevant settings to analyze IVs in contexts of unordered multivalued treatments because options arguably lack a clear ranking and agents with distinct fallback options might derive different gains, or losses, from their choices. Across the three applications, I combine discrete and continuous IVs that jointly affect the same margins of choice. In particular, I exploit experimental (or quasi-experimental) variation jointly with the geographical distance to one of the options. Consistent with the general framework of this paper, I assume that the instruments affect choices through their effect on costs. I impose a shape restriction of convex and increasing costs on the distance to one

[10] Nonparametric estimation of IV strategies such as 2SLS suffer from the ill-posed inverse problem. Nonetheless, the strategy I present here deals with discrete endogenous variables and does not suffer from this problem.

[11] The method can also be implemented with a linear decision model by incorporating interactions between the instruments. An earlier version of this paper employs a linear estimation approach and explains its implementation in detail. See Chapter 2, Section 2.3 in this link.

option. My framework allows the response to the experimental variation to change with distance, which serves as the building block to define *conditional response types* in each context. Yet, the set of treatment effects that can be identified by merely applying the logic of *conditional response types* differs across these settings. In particular, achieving identification of margin-specific treatment effects depends on the sensitivity of the cost function to the conditioning instrument (namely, distance to one of the options in each application).

In the first application, I focus on the case of subsidies for malaria treatment in Kenya using data from Cohen, Dupas, and Schaner (2015). Randomized assignment provided some households with subsidies to purchase antimalarial artemisinin-based combination therapies (ACTs) at drug shops. When facing an illness episode, being assigned to receive the subsidy induces households towards buying a subsidized drug at the drug-shop, and away from seeking care at a health center or doing nothing (or seeking other type of treatment). The random subsidy alone identifies the effect of drug-shops *versus* the next-best. I combine the experimental variation with the geographic distance to the health center and define conditional response types to identify treatment parameters at two specific margins: seeking care at drug-shops *versus* health centers, and seeking care at drug-shops *versus* no care. Healthcare choices exhibit high sensitivity to the distance to the health center. The share of compliers seeking care at drug-shops *versus* health centers (no care) goes from 20% (0%) when distance to the nearest health-center is very small and drop (rise) towards 0% (5-10%) for distances around 7-9 kilometers. Next, I estimate local average treatment effects and marginal treatment effects across these two margins of choice. I find that households choosing drug-shops but who would have sought care for their health in the absence of the subsidy might be worse off in terms of illness episodes than households who would have seek care at health centers.

Second, I study the case of childcare choices in Colombia and their impact on the cognitive, socio-emotional, and nutritional development of children with a subsample from Bernal, Attanasio, Peña, and Vera-Hernández (2019). In the context of an expansion of public care provision that took place in 2011, the researchers ran a lottery with noncompliance among existing small centers which provided information and encouraged winning parents to switch to large centers. Hence, parents could choose to keep their children in small centers, care for them at home, or send them to large-centers. Response types defined by the experimental variation, conditional on the geographical distance between the child's home and the nearest large center,[12] allow identifying the effect of care at small *versus* large centers; however, additional assumptions (*e.g.*, homogeneity) are necessary to disentangle effects for a second margin of choice: small centers *versus* home

[12]Convenience (i.e., low travel time or distance) has been recognized as an important predictor of childcare choice (Attanasio, Maro, and Vera-Hernández, 2013; Bernal and Fernández, 2013; Hojman and López Bóo, 2019). Therefore, despite winning the lottery, some parents might be discouraged from choosing large centers if the distance from home is relatively large.

care. Estimates of LATEs and MTEs suggest that, on average, switching towards large centers might not benefit children on any developmental dimension. I show that part of the detrimental local effect on children's development of enrolling in a large center is due to a bias term that stems from children who would switch between small centers and into home care due to the variation in the lottery and proximity to the large center.

Last, I apply the logic of conditional response types to higher education enrollment choices in Colombia. In particular, I use a random subsample from Londoño-Vélez, Rodriguez, Sanchez, and Álvarez Arango (2023) to study the first cohort of the *Ser Pilo Paga* program (SPP) which provided scholarships for enrollment in high-quality institutions to high school graduates based on need (*i.e.*, being below a poverty score threshold) and merit (*i.e.*, being above a cutoff on the score of the high school exit exam). Following Londoño-Vélez, Rodríguez, and Sánchez (2020), I divide the sample into two estimating subsamples based on whether students are need-eligible or merit-eligible. To estimate treatment effects of higher education choices, I use the remaining dimension of SPP eligibility in each subsample as a source of exogenous variation combined with variation from the distance between the students' high school and the nearest low-quality higher education institution. I assume that, regardless of the subsample, SPP eligibility would induce students to enroll in high-quality higher education institutions instead of enrolling in low-quality higher education institutions or not enrolling.

Unlike the first two applications, students show little sensitivity to changes in the distance to one of the options (namely, low-quality higher education institutions). However, among need-eligible students, nearly all of the variation comes from those who, in the absence of *Ser Pilo Paga*, would have chosen not to enroll, rather than from those who would have attended low-quality institutions. Thus, conditional response types help identify the effect of non-enrollment *versus* enrollment in a high-quality university among the need-eligible. I also present results for the enrollment margin between low- and high-quality universities among merit-eligible students, which is only separately identified under the homogeneity assumption. Overall, I find that students on the margin between choosing high-quality universities or the next-best benefit from the latter in terms of a higher likelihood of working formally in 2021. Nonetheless, this effect may be weaker among individuals facing greater family or financial constraints that prevent them from choosing high-quality institutions.

This paper is organized as follows. Section 2 presents a general framework of multiple unordered treatment effects and instrumental variables, describes the shape restrictions that secure identification, and the resulting conditional response types. Section 3 provides background on the applications, describes the data, and presents results. Section 4 concludes.

2 General Framework: Multiple Unordered Treatments

Consider a decision maker who can choose from a finite number of alternatives in choice set $\mathcal{K}$. Let k represent an alternative or option, $k \in \mathcal{K}$, and let K denote the total number of choices, with $K > 2$. Each of the options are no better than the others *a priori* (*i.e.*, they are unordered), but agents can have preferences over them. Options in $\mathcal{K}$ with higher values, in contexts of unordered choice, do not represent better alternatives. Unlike settings with only 2 options (*e.g.*, treatment or no treatment) or in which choices are ordered (*e.g.*, years of schooling), where treatment effects most commonly refer to comparisons of counterfactual outcomes across two options or states of the world, in the case of unordered choice we can define treatment effects resulting from agents choosing from different choice sets. One typical candidate is the effect of choosing option k *versus* the next-best (which refers to the option that the agent would have chosen if faced with the choice set that does not contain k). Because options are unordered, the next-best option is likely to differ across agents.

2.1 Set Up

Let Y denote the outcome variable. The researcher is interested in the effect of choosing k on Y *versus* another option $l \in \mathcal{K}$, or *versus* a combination of other options, but k is endogenously chosen. For instance, the treatment effect of choosing option k *versus* option l can be defined as $Y_k - Y_l$ for $k \neq l$, where Y_k (Y_l) denotes the counterfactual outcome that the agent would derive from choosing option k (l). I refer to this type of counterfactual contrasts, $Y_k - Y_l$, as the treatment effect of pairwise combinations of options in $\mathcal{K}$. We can also define the treatment effect of option k *versus* the next-best as $Y_k - Y_{\mathcal{K}\setminus k}$, where $Y_{\mathcal{K}\setminus k}$ denotes the potential outcome that the agent would have obtained if option k was not available. That is, $\mathcal{K}\setminus k$ refers to the choice set containing all options in $\mathcal{K}$ except k. Other treatment effects can be defined, as in Heckman et al. (2006) and Heckman and Vytlacil (2007). In what follows, I assume that both $Y_k - Y_l$ and $Y_k - Y_{\mathcal{K}\setminus k}$ hold economic content for the researcher and, hence, her goal is to identify their associated treatment parameters.

As in the standard potential outcomes framework, Y_k is only observed for those who choose k. To model said choices, assume that agents select the option in choice set $\mathcal{K}$ with the highest latent utility. That is, assume that agents preferences can be represented by a discrete choice problem where the latent utility from choosing option $k \in \mathcal{K}$ is

$$U_k(Z) = \mu_k - V_k(Z),$$

where μ_k represents unobserved preference heterogeneity for choice k, and $V_k(Z)$ is the disutility or cost of choosing k. Z is a random vector and contains L instrumental variables, such that $Z = \{Z_1, ..., Z_L\}$ where each Z_l takes values in $\text{supp}(Z_l)$. There are no restrictions on the support of each Z_l, which can be continuous or discrete, nor on the joint support of the instruments in Z denoted as $\mathcal{Z}$. For simplicity, I refer to an element $z \in \mathcal{Z}$ as a combination of evaluation points, $(Z_1 = z_1, ..., Z_L = z_l)$.

Let $D_{\mathcal{K},k}$ be a binary variable indicating whether option k is chosen from choice set $\mathcal{K}$,

$$D_{\mathcal{K},k} = \mathbf{1}[U_k(Z) \geq \max_{l \neq k}\{U_l(Z)\} \; \forall l \in \mathcal{K}],$$

and, hence, the observed outcome is $Y = \sum_{k \in \mathcal{K}} D_{\mathcal{K},k} Y_k$. Define $D_{\mathcal{K}}(z)$ as a categorical variable containing potential choices at value z of the instruments, i.e. the choice agents would select from choice set $\mathcal{K}$ when faced with value z. That is,

$$D_{\mathcal{K}}(z) = \underset{k \in \{1,..,K\}}{\text{argmax}} \left(\mu_k - V_k(z)\right), \tag{1}$$

which depends on Z only through V_k, or costs. Hence, changes in the instruments shift costs but do not alter the underlying preferences of agents for choice k.[13] Costs in V_k can depend on one or many instruments. In settings of multiple unordered choices and IVs, we are interested in agents who would change their choices as the instruments vary and the margins at which they would change their behavior.

Throughout the paper, I maintain the following assumptions:

- A1 *Conditional Independence* - As in Imbens and Angrist (1994), the instruments in Z satisfy $(\{Y_k\}_{k \in 1,..,K}, \{D_{\mathcal{K}}(z)\}_{z \in \mathcal{Z}}) \perp\!\!\!\perp Z | X$, where X denotes a vector of covariates.

- A2 *Conditional (Partial) Monotonicity* - Let z_k, z'_k be two values in $\text{supp}(Z_k)$, with $Z_k, Z_l \in Z$. For all $k \in \{1, ..., K\}$ either $D_{k,\mathcal{K}}(z_k, Z_l) \geq D_{k,\mathcal{K}}(z'_k, Z_l)$ for all agents, or $D_{k,\mathcal{K}}(z_k, Z_l) \leq D_{k,\mathcal{K}}(z'_k, Z_l)$ for all agents. This a weaker version of monotonicity in Imbens and Angrist (1994).[14,15]

As is standard in the IV literature, *A1* states that, conditional on baseline variables, the instruments are independent of potential outcomes and choices. Meanwhile, *A2* relaxes the monotonicity assumption in Imbens and Angrist (1994) such that changes in an instrument are required to induce agents towards, or against, the same choices conditional

[13] The assumption of separability between μ_k and V_k in equation (1) is standard in latent index selection models (Vytlacil, 2002; Heckman et al., 2006; Lee and Salanié, 2024).

[14] Monotonicity in Imbens and Angrist (1994) states that for any values z, z' in $\text{supp}(Z_l)$ either $D(z) \geq D(z')$ for all agents, or $D(z) \leq D(z')$ for all agents. It is a stronger assumption, since it has to hold regardless of changes in instruments other than Z_l.

[15] Das (2005) employs a conditional monotonicity assumption to the case of nonlinear IV. The author shows that, conditioning on covariates, nonparametric estimation can recover a conditional LATE parameter.

on a second instrument. For binary treatment, Mogstad et al. (2021) employs this assumption for identification. Similarly for binary treatment, Heckman et al. (2006) show that conditioning on other instruments can produce one-way flows in the variation of a selected IV. Mountjoy (2022) extends partial monotonicity to the case of multiple unordered options, and secures identification with an additional assumption of comparable compliers. The latter requires that compliers induced along the same margin of choice by two different instruments would be comparable in terms of average potential outcomes. Instead, in my framework, I secure identification by imposing restrictions on the cost function such that changes in the IVs would satisfy *A2*.

Next, I begin by defining the standard set of treatment parameters that can be identified using instrumental variables (IVs) in contexts involving multiple unordered options, *i.e.*, the effect of option k *versus* the next-best. This is followed by a decomposition into target parameters, *i.e.*, pairwise treatment effects, which I will subsequently demonstrate in Section 2.2 can be identified using conditional response types.

Next-best Treatment Effects: Observed outcomes in the multiple unordered options framework can be expressed as in the standard binary choice setup by using the approach in Heckman et al. (2006) and Heckman et al. (2008). That is, Y can be partitioned into two, rather than K components:

$$Y = D_{\mathcal{K},k} Y_k + (1 - D_{\mathcal{K},k}) Y_{\mathcal{K}\setminus k},$$

where $Y_{\mathcal{K}\setminus k}$ is the potential outcome that would have been observed if option k would have not been available, $Y_{\mathcal{K}\setminus k} = \sum_{l \neq k} \frac{D_{\mathcal{K},l}}{1 - D_{\mathcal{K},k}} Y_l$. Consider two values, $z_k, z'_k \in Z_k$, such that Z_k is a binary IV, or such that the researcher is considering marginal increases in Z_k. Assume that Z_k satisfies *A1* and *A2*. Then, the unconditional Wald estimator (left-hand side in the equation below) that results from employing Z_k as an IV while controlling for Z_l,

$$\frac{E[Y|Z_k = z'_k, Z_l] - E[Y|Z_k = z_k, Z_l]}{E[D_{\mathcal{K},k}|Z_k = z'_k, Z_l] - E[D_{\mathcal{K},k}|Z_k = z_k, Z_l]} = E[Y_k - Y_{\mathcal{K}\setminus k} | D_{\mathcal{K},k}(z'_k, Z_l) = 1, D_{\mathcal{K},k}(z_k, Z_l) = 0],$$

identifies the local average treatment effect (LATE) of k *versus* the next-best (right-hand side), which can be decomposed into pairwise treatment effects,

$$\frac{E[Y|z'_k, Z_l] - E[Y|z_k, Z_l]}{E[D_{\mathcal{K},k}|z'_k, Z_l] - E[D_{\mathcal{K},k}|z_k, Z_l]} = \sum_{l \in \mathcal{K}\setminus k}^{K-1} \frac{\Pr(D_{\mathcal{K},k}(z'_k, Z_l) = 1, D_{\mathcal{K}\setminus k,l}(z_k, Z_l) = 1)}{\Pr(D_{\mathcal{K},k}(z'_k, Z_l) = 1, D_{\mathcal{K},k}(z_k, Z_l) = 0)} \times E[Y_k - Y_l | D_{\mathcal{K},k}(z'_k, Z_l) = 1, D_{\mathcal{K}\setminus k,l}(z_k, Z_l) = 1]. \tag{2}$$

See Appendix A.4 for the identification of the LATE of k *versus* the next-best, and the derivation of the decomposition. The right-hand side of equation (2) is a weighted average of pairwise treatment effects with weights given by the prevalence of compliers across each margin, summed over $K-1$ next-best states. That is, the first term inside the summation denotes the share of compliers switching into k out of next-best state l, among all compliers switching into option k, as Z_k goes from z_k to z'_k. The second term corresponds to the (pairwise) average treatment effect of option k *versus* l for compliers switching along that margin, as Z_k goes from z_k to z'_k.

Plus, imposing additional regularity conditions as in Heckman et al. (2006) for continuous instruments and Brinch, Mogstad, and Wiswall (2017) for binary instruments, the marginal treatment effect (MTE) of option k *versus* the next-best can be identified:

$$\begin{aligned}\text{MTE}_{k,\mathcal{K}\setminus k} &= E[Y_k - Y_{\mathcal{K}\setminus k}|Z=z, U_k(z) = U_{\mathcal{K}\setminus k}(z)] \\ &= \sum_{l\in\mathcal{K}\setminus k}\{\Pr(D_{\mathcal{K}\setminus k,l}=1|Z=z, U_k(z)=U_{\mathcal{K}\setminus k}(z)) \\ &\qquad\qquad \times E[Y_k - Y_l|Z=z, U_k(z)=U_{\mathcal{K}\setminus k}(z), D_{\mathcal{K}\setminus k,l}=1]\},\end{aligned}$$

where the second line further decomposes the next-best-MTE into pairwise marginal treatment effects. See Appendix A.4 for the identification of the MTE of k *versus* the next-best, and the derivation of the decomposition for the specific case of binary instruments. Note that, both in the case of the LATE as well as for the MTE, if sufficient next-best states are unlikely to be chosen (for instance, all except option l), then the pairwise effect of k *versus* l would be identified.[16]

2.2 Identification of Pairwise Treatment Effects Using Conditional Responses

In what follows, I present a generalized set of restrictions stemming from economic theory under which some next-best states would disappear. In particular, to understand how agents switch into, and away, from choices in $\mathcal{K}$ as the instruments vary the researcher can define a set of rules of behavior. These rules stem directly from the properties of costs in $V_k(Z)$, and how they affect the relative mean utility of the different options. For instance, if changes in the distance to option 1 make this option more costly relative to other options then the researcher could assume that changes in distance move agents away from choosing 1. In the case of binary treatment with one binary instrument, agents can either move into (i.e., compliers) or away from (i.e., defiers) treatment as the instrument

[16]Note that the conditional LATEs and MTEs will generally depend on the evaluation point in Z as the weights given to each option $l \in \mathcal{K}\setminus k$ depend on Z. That is, the pairwise treatment effects will be given different weights at different evaluation points in Z (Heckman and Vytlacil, 2007).

varies.[17]

I focus on settings where, for example, the researcher has access to several costs for an option, such as tuition, fees, travel time or distance. In addition, experimental variation can also be available along with information on the costs of different options. Heckman et al. (2006); Mogstad et al. (2021, 2024) and Mountjoy (2022) show that if the researcher simultaneously increases one instrument (e.g. tuition) while decreasing another (e.g. travel time), agents can move towards, and away from, the same option. This motivates exploiting the variation in one instrument, while keeping the other instrument(s) fixed.

2.2.1 Cost Restrictions

To determine how the composition of the agent's choice set varies across different values of the instruments, I propose imposing restrictions on the cost or disutility of choosing an option. Rooted in this idea is the logic of instruments as cost-shifters, such that as the cost of option l increases (as a result of, for instance, an increase in the value of an instrument) the likelihood of option l belonging to set $\mathcal{K}\backslash k$ decreases. How rapidly the increase in the cost of l rules out said option as belonging to the next-best largely depends on the shape of the cost function, $V_l(Z)$. By imposing restrictions on the shape of the cost function, the researcher can rule out some states as next-best alternatives and hence reduce the combinations of potential choices in order to determine which margins of choice would prevail across the distribution of Z. I impose the following restrictions:

- R1 *(Convex costs)* Let $V_l(Z)$ represent the costs of alternative $l \in \mathcal{K}\backslash k$, which depend on instruments in Z. Let $Z_l \in Z$ and define Z_{l-} as an instrument in Z other than Z_l. $V_l(Z)$ is (weakly) element-wise convex in $Z_l \in Z$ iff $\frac{\partial^2 V_l(Z_l, Z_{l-})}{\partial Z_l^2} \geq 0$.
  - R1.1 *(Choice set dependence)* There is at least one option $l \in \mathcal{K}\backslash k$ such that: (i) $V_l(Z)$ satisfies R1 for an instrument $Z_l \in Z$, (ii) $V_l(z_l) = \min_{m\in\mathcal{K}\backslash k}\{V_m(z_l)\}$ for some $z_l \in \text{supp}(Z_l)$ and, (iii) $V_l(z_l') = \max_{m\in\mathcal{K}\backslash k}\{V_m(z_l')\}$ for some $z_l' \neq z_l \in \text{supp}(Z_l)$. Under these conditions, denote Z_l as a conditioning instrument.
  - R1.2 *(Exclusion Restriction for Multiple Treatments)* Let Z_k be a set of instruments that affect choice k. Let Z_{k-} represent the set of instruments that affect choices other than k. There exist at least one instrument in Z_k and not in Z_{k-} such that it does not affect choices other than k.

[17] For example, suppose that treatment is enrolling, or not, in any college. The instrument is a variable that takes the value of one if the student grew up in a county with any college (as in Card, 1995). Always-takers (Never-takers) are students who would choose (not) to enroll in college whether or not they grew up in a county with any college. Neither always-takers nor never-takers respond to changes in the presence of college; they don't provide any variation to estimate treatment effects. Compliers are students who would enroll in college when their county had a college, and would choose to not enroll when there is no college present. Lastly, defiers are students who choose to enroll in college if they grew up with a college in their county, and to enroll if there was no college.

Note that the restriction *R1.1* on the cost function is defined for the set $\mathcal{K}\backslash k$ (*i.e.*, the choice set the agent would have to face if option k was not available), given that the goal is to define conditions under which some options in set $\mathcal{K}\backslash k$ would not be chosen (would not be part of the next-best states). *R1* introduces the definition of a convex cost function used hereafter, which need only be weakly element-wise convex on Z_l rather than on all elements in Z. Assuming (weak) convexity of costs is frequent in economic theory and can be extended, as is the case of this paper, to applications that employ exogenous variation in cost-shifters as instrumental variables. Moreover, the condition of weak convexity is necessary for a concave objective function, and therefore for a unique solution to the utility maximization problem. *R1.1* requires that at least one option in $\mathcal{K}\backslash k$ satisfies weak convexity of costs for an instrument Z_l, and that for some evaluation regions of Z_l option l is chosen (given that it had the minimum cost) whereas it is the least preferred option for some other evaluation regions of Z_l (and, therefore not in $\mathcal{K}\backslash k$ for that region of Z_l). Overall, *R1.1* implies that choice set $\mathcal{K}\backslash k$ is not constant across Z_l. Namely, the composition of the next-best states in $\mathcal{K}\backslash k$ differs across evaluation points of Z_l.

The restriction of convexity on the cost function serves two main purposes. To see its role, suppose that the cost function is not convex but fluctuates over different values of Z_l (increasing and then decreasing for some values and vice versa). The argument that increasing costs would rule out some options as next-best states would then depend on the evaluation points in Z_l, and the composition of $\mathcal{K}\backslash k$ could vary in an unspecified pattern. That is, some next-best states would enter and exit set $\mathcal{K}\backslash k$ in a manner unpredictable for the researcher. In turn, convexity imposes restrictions such that once an option becomes too costly to be in set $\mathcal{K}\backslash k$ its likelihood of being the next-best state goes to zero thereafter. Second, convexity and the additional conditions on *R1* impose restrictions such that agents who would be induced to change their choices because of a change in Z_l would do so towards, or away from, the same options. The latter states that the assumption of convex costs translate into combinations of counterfactual choices that satisfy *A2*. Lastly, *R1.2* restricts the number of instruments that can affect multiple options simultaneously, in a way akin to IV restrictions for unordered choices in Heckman et al. (2006, 2008). It states that there should be at least one instrument that affects choice k but not other choices. Importantly, if the restrictions in *R1* hold, then the instruments satisfy conditional (partial) monotonicity and the researcher can identify a set of local treatment effects.

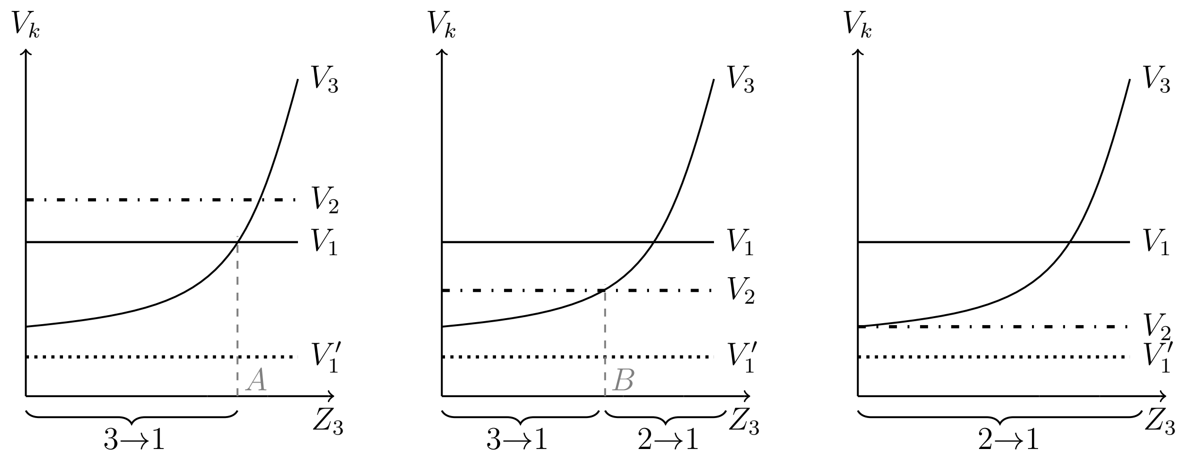
Thus, if the above conditions hold then Z_k, which shifts the cost of option k, satisfies *A2* conditional on Z_l. See Appendix A.3 for the proof of this result.

Example To illustrate how changes in costs affect different margins of choice and, hence, the composition of the next-best set, consider the case of three choices, k =

$\{1, 2, 3\}$, and two IVs, $Z = \{Z_1, Z_3\}$. Suppose that Z_1 is a discrete instrument which denotes random assignment with noncompliance to a treatment 1, and Z_3 refers to a measure of cost (e.g., price, travel time, travel distance). Let $V_k(Z)$ represent the cost of choosing option k which is a function of the instruments. Figure 1 depicts sets of costs for option 1, 2, and 3 under different orderings. V_3 is the cost of choosing option 3 and its convex in Z_3, while options 1 and 2 are unaffected by this instrument. V_1 (V_1') refers to the cost of option 1 evaluated at $Z_1 = 0$ ($Z_1 = 1$) with $V_1 > V_1'$ such that changing Z_1 reduces the cost of choosing 1, while not affecting options 2 and 3.

Figure 1: Example of relative costs that induce agents along the $2 - 1$ and $3 - 1$ margins

(a) 3 is the next-best — (b) 2 and 3 are the next-best — (c) 2 is the next-best



Each panel in Figure 1 displays a decrease in the cost of option 1 ($V_1 > V_1'$, as $Z_1 = 0 \to 1$) such that agents with the cost structures depicted in each Panel would switch out of choosing options 2 or 3 and into choosing option 1. Moreover, as Z_3 increases so does the cost of choosing 3 such that other options (2 in this example) are more likely to be the next-best alternative. Panel (a) of Figure 1 illustrates the case where an agent who would change her choice towards option 1 would do so by substituting away from option 3 (up to point A, thereafter the agent would be an option 1−always-taker). If all agents changing their choices because of changes in Z_1 have this type of cost structure, the next-best state would always be option 3. In contrast, Panel (b) shows the case where at relatively low realizations of Z_3 (below point B) an agent would substitute option 3 for 1 but as Z_3 increases (above point B) the agent would substitute option 2 for 1. Last, Panel (c) presents a case where the cost of option 3 is not only convex but always above the cost of option 2 and hence an agent with these costs would switch out of 2 and into 1 at all values of Z_3.

Note that the costs depicted in Panel (c) do not satisfy all the conditions in *R1*, and in this case convexity plays no role on reducing the number of next-best states. Hence, assuming that V_3 is convex but always above the costs of other options has the same behavior implications as those of assuming that V_3 is constant over Z_3. Whether the researcher should expect the patterns displayed in either panel depends on the sensitivity of costs to the instrument: if V_3 has a small slope, points A and B would be farther away to the right on the horizontal axis making it less likely to eliminate option 3 from the next-best set. In contrast, in combination with *R1.1*, the higher the slope of the cost function of option 3, the closer points A and B would be to the origin, and the more likely is option 2 to be the next-best state.[18] In the next section, I formalize the implications of the restrictions on the cost function.

2.2.2 Conditional Response Types

The restrictions on costs translate into admissible potential choices that agents could make as a response to changes in an instrument Z_k, or rules of behavior, conditional on an instrument Z_l. With binary or discrete IVs, there are limited states of the world (*i.e.*, values of the IVs) that the researcher has to analyze to define potential choices, and in turn complier groups.[19] However, unless the researcher controls for the variation in a second instrument, Z_l, she can only identify the next-best effect. With this challenge in mind, I employ the approach and econometric model in Heckman and Pinto (2018) in which rules of behavior from revealed preference analysis define *vectors* that are used to identify the prevalence of response-types (*e.g.*, always-takers and compliers) and their counterfactuals. In this section, I extend their framework to the case of *conditional vectors* defined by an instrument Z_k, conditional on Z_l. The combinations of potential choices in these *conditional vectors* changes along the support of a second instrument Z_l.

The *conditional vectors* consist of combinations of potential choices at different realizations, z_k, of instrument Z_k, conditional on Z_l. Let $D(z_k|z_l)$ denote potential choices when the agent faces value $Z_k = z_k$ given $Z_l = z_l$. Combinations of $D(z_k|z_l)$ form conditional response vectors denoted by $S_k(Z_l)$. Consider z_{lk}, z'_k two realizations in supp(Z_k),[20] a response vector $S_k(z_l)$ denotes a combination of potential choices at z_k and z'_k given $Z_l = z_l$. The response vector varies depending on Z_l, or is a function of Z_l, which means that the combinations of potential choices in S_k can depend on the realization of the

[18]Note that Z_1 and Z_3 do not affect the cost of the same options. Suppose that instead of Z_3 the researcher has available Z_2 which affects the cost of choosing option 1 jointly with Z_1. Assume that V_1 is convex in Z_2, and Z_1 has the same role as in the example above such that both V_1 and V'_1 are convex curves and $V_1 > V'_1$ always. As Z_2 increases option 1 would become more costly but the change in Z_1 also makes agents more likely to choose option 1 at all values of Z_2 from any next-best state. Hence, combining instruments that affect the same option would not necessarily rule out next-best states.

[19]For contexts where the instruments available are discrete, Heckman and Pinto (2018) show that there are subsets of switcher groups that are justified by the mechanisms of the instruments and it is possible to identify treatment effects. Similarly, Lee and Salanié (2024) show that if there are choices targeted by the discrete instruments (e.g., Z_1 increases the mean relative utility of option 1), it is possible to estimate treatment effects for different complier groups.

[20]For binary variables, z_k, z'_k correspond to 0 and 1. For continuous variables, rather than defining potential responses at all, infinite, values of the continuous IV the researcher can place restrictions on choice behavior at marginal increases of the instrument.

conditioning instrument, Z_l. Formally, $S_k(z_l) = [D(z_k|z_l), D(z'_k|z_l)]'$. The total number of conditional response vectors, N_{S,z_l}, depends on the total possible choice combinations that follow from *R1* and satisfy *A2* at a given $Z_l = z_l$.[21]

Sets of *conditional response vectors* that satisfy *A2* can be pooled in a matrix $R_k(Z_l)$, which varies with a second instrument Z_l. The matrix $R_k(Z_l)$ contains all the combinations of potential choices that satisfy *A2*, and it describes the type of responses induced by changes in Z_k. For instance, in the binary-treatment-binary-IV case R_k would contain always-takers, never-takers, and compliers. The dimension of $R_k(Z_l)$ is $w \times N_{S,z_l}$, where w is the number of values of the instrument at which agents' potential behavior is evaluated. For a binary instrument, w is equal to two. Similarly, for continuous instruments the researcher could analyze marginal changes in the instrument such that $w = 2$. For discrete instruments with more than two possible realizations, such as assignment to multiple treatment arms, $w > 2$.

To illustrate, see Panel (b) of Figure 1 where as Z_3 increases (decreases) it is less (more) likely that option 3 is the next best. Table 1 below presents the combination of potential choices as $Z_3 \to z_3^{\text{min}}$ and $Z_3 \to z_3^{\text{max}}$ implied by the restrictions on costs displayed in Panel (b) of Figure 1. Each column denotes a response vector, or a combination of potential choices at the two values of Z_1. Regardless of the value of Z_3, g_1, g_2, and g_3 are option 1, 2 and 3−always-takers, respectively. While g_4^- are $3-1$ compliers (more prevalent as Z_3 is approaching its minimum value) and g_5^+ are $2-1$ compliers (more prevalent at higher values of Z_3).

Table 1: Example: Z_1-responses at different evaluation points of Z_3

Response Types as $Z_3 \to z_3^{\text{min}}$					Response Types as $Z_3 \to z_3^{\text{max}}$				
Z_1	g_1^-	g_2^-	g_3^-	g_4^-	Z_1	g_1^+	g_2^+	g_3^+	g_5^+
0	1	2	3	3	0	1	2	3	2
1	1	2	3	1	1	1	2	3	1

Following the combinations of potential choices above, there would be two matrices containing conditional rules of behavior. Let $R_1(Z_3 \to z_3^{\text{min}})$ and $R_1(Z_3 \to z_3^{\text{max}})$ denote the rules of behavior as Z_3 decreases and increases, respectively. Hence,

$$R_1(Z_3 \to z_3^{\text{min}}) = \begin{vmatrix} 1 & 2 & 3 & 3 \\ 1 & 2 & 3 & 1 \end{vmatrix},$$

[21] Heckman and Pinto (2018) show that the total number of response vectors cannot exceed $1 + [(K-1) \times w]$ where K are the total number of choices and w the number of values of the instrument that define the response vectors (e.g., $w = 2$ for a binary instrument). In my case, this number can depend on the evaluation point $Z_l = z_l$.

and,

$$R_1(Z_3 \to z_3^{\max}) = \begin{vmatrix} 1 & 2 & 3 & 2 \\ 1 & 2 & 3 & 1 \end{vmatrix}.$$

Moreover, for a realization $z_3 \in (z_3^{\min}, z_3^{\max})$ the response matrix denoted as $R_1(z_3)$ is the same as the unconditional response matrix,

$$R_1(z_3) = \begin{vmatrix} 1 & 2 & 3 & 3 & 2 \\ 1 & 2 & 3 & 1 & 1 \end{vmatrix},$$

which contains all possible combinations of potential choices induced by Z_1. In addition, if agents' costs follow scenarios as those depicted in Panel (c) of Figure 1 or where point B in Panel (b) is very close to $z_3^{\min}$, $R_1(Z_3 \to z_3^{\min})$ could contain responses along $2-1$. Whether the next-best state changes as drastically as in the example in Panel (b) of Figure 1 is an empirical question testable by following the empirical strategy in Section 3.[22]

Next, I formalize the role of $R_k(Z_l)$ in the identification of treatment effects.

2.2.3 Identification of Treatment Effects

Generally, *conditional vectors* could reduce the number of next-best states if sufficient instruments satisfying *R1* change rendering a set of options less likely to be in set $\mathcal{K}\backslash k$. To see this, take the unconditional response matrix R_k containing as many as $1+[(K-1)\times w]$ response-types of which $(w-1)\times(K-1)$ are compliers or types of agents that, as Z_k changes, would change choices towards option k and away from $K-1$ next-best states (as indicated by the superscript in the summation above). Suppose that the costs of option l satisfy *R1.1* for Z_l, and focus on the case of decreasing Z_l towards its minimum value. Assume that as $Z_l \to z_l^{\min}$ no agent would have chosen options other than l, or the next-best state would be l. That is, as $Z_l \to z_l^{\min}$, $\Pr(D_{\mathcal{K},k}(z_k', Z_l) = 1, D_{\mathcal{K}\backslash k,m}(z_k, Z_l) = 1) \to 0, \forall m \in \mathcal{K}\backslash\{k,l\}$ (*i.e.*, the choice set containing all options in $\mathcal{K}$ other than k and l). The *conditional response vector* $R_k(Z_l \to z_l^{\min})$ would contain only one complier group (namely, those switching along the k vs. l margin). Evaluated at $z_l^{\min}$, the Wald estimator in equation (2) identifies the pairwise treatment effect of k *versus* l,

$$\frac{E[Y|z_k', z_l^{\min}] - E[Y|z_k, z_l^{\min}]}{E[D_{\mathcal{K},k}|z_k', z_l^{\min}] - E[D_{\mathcal{K},k}|z_k, z_l^{\min}]} = E[Y_k - Y_l|D_{\mathcal{K},k}(z_k', z_l^{\min}) = 1, D_{\mathcal{K}\backslash k,l}(z_k, z_l^{\min}) = 1].$$

[22] One could define a threshold where the next-best composition changes (*e.g.*, point B in the example) such that the conditional matrix changes. However, different agents can have distinct cost structures which can complicate the definition of a unique threshold. Instead, I propose following the theoretical implications of the assumptions on costs and evaluating effects as the conditioning instrument increases or decreases.

See Appendix A.4 for the derivation of this result using conditional response vector, $R_k(Z_l \to z_l^{\min})$.

In contrast, even if the costs of option l satisfy *R1.1* for Z_l, increasing Z_l alone would reduce the dimension of $R_k(Z_l)$ at evaluation point $z_l^{\max}$ by one such that $\dim[R_k(Z_l \to z_l^{\max})] = (K-1)\times w$ and the number of compliers decreases to $[(w-1)\times(K-1)]-1$. That is, if l becomes too costly among all next-best states, it is less likely that option l would have been chosen instead of k as $Z_l \to z_l^{\max}$. That is, as $Z_l \to z_l^{\max}$, $\Pr(D_{\mathcal{K},k}(z_k', Z_l) = 1, D_{\mathcal{K}\backslash k,l}(z_k, Z_l) = 1) \to 0$. The Wald estimator in equation (2) identifies a weighted average of treatment effects for option k *versus* options in $\mathcal{K}\backslash k$ other than l,

$$\begin{aligned}\frac{E[Y|z_k', z_l^{\max}] - E[Y|z_k, z_l^{\max}]}{E[D_{\mathcal{K},k}|z_k', z_l^{\max}] - E[D_{\mathcal{K},k}|z_k, z_l^{\max}]} &= \\ \sum_{m\in\mathcal{K}\backslash\{k,l\}}^{K-2} &\frac{\Pr(D_{\mathcal{K},k}(z_k', z_l^{\max}) = 1, D_{\mathcal{K}\backslash\{k,l\},m}(z_k, z_l^{\max}) = 1)}{\Pr(D_{\mathcal{K},k}(z_k', z_l^{\max}) = 1, D_{\mathcal{K},k}(z_k, z_l^{\max}) = 0)} \\ &\times E[Y_k - Y_m | D_{\mathcal{K},k}(z_k', z_l^{\max}) = 1, D_{\mathcal{K}\backslash\{k,l\},m}(z_k, z_l^{\max}) = 1].\end{aligned}$$

Note that, unless $K = 3$, such reduction is not sufficient to identify treatment effects of pairwise combinations of the options; *i.e.*, there would be more than one complier group remaining even after conditioning on Z_l.[23]

Alternatively, consider the case where Z_M denotes a vector of instruments for M options in $\mathcal{K}\backslash k, l$ (*i.e.*, the choice set containing all options in $\mathcal{K}$ other than k and l) and assume that all elements in Z_M satisfy *R1.1*. Then, only one complier remains for response matrix $R_k(z_m^*)$, where z_m^* denotes an evaluation point such that each instrument in Z_M is evaluated at its maximum value, meaning that all other M options are too costly to be the next-best state, and the pairwise treatment effect of option k vs. option l can be identified. A similar argument could be made if M and L correspond to sets of options each with mutually exclusive characteristics (*e.g.*, M (L) denotes publicly (privately) provided options) and in that case the researcher could identify effects of option k vs. the next-best public (or private) option, depending on the incentives of the instruments.[24] Last, in the application in Section 3.3 I show how conditioning on more than one IV can also reduce the number of next-best states.

Similar arguments follow for the identification of pairwise marginal treatment effects

[23]In scenarios where conditional response types only rule out one complier group, the researcher could impose an assumption of homogeneity on counterfactuals as in Kline and Walters (2016); Hull (2018); Lee and Salanié (2024). Formally,

$$E[Y_k|D_{\mathcal{K},k}(z_k', z_l^{\max}) = 1, D_{\mathcal{K}\backslash\{k,l\},m}(z_k, z_l^{\max}) = 1] = E[Y_k|D_{\mathcal{K},k}(z_k', z_l^{\max}) = 1, D_{\mathcal{K}\backslash\{k,l\},j}(z_k, z_l^{\max}) = 1],$$

for all $j \in \mathcal{K}\backslash\{k,l\}$. In general, this assumption states that that the potential outcome from choosing k would have been the same, on average, regardless of the next-best option.

[24]Appendix A.4 embeds the logic of conditional response vectors within the econometric model of Heckman and Pinto (2018), which extends to the case of $w > 2$, for discrete IVs taking on more than two values.

(MTEs). For instance, as $Z_l \to z_l^{\min}$,

$$\lim_{Z_l \to z_l^{min}} E[Y_k - Y_{\mathcal{K}\setminus k} | Z = z, U_k(z) = U_{\mathcal{K}\setminus k}(z)] =$$
$$E[Y_k - Y_l | Z = z, U_k(z) = U_{\mathcal{K}\setminus k}(z), D_{\mathcal{K}\setminus k, l} = 1].$$

In the next section, I present three empirical applications which illustrate the role of conditional response types across distinct settings and detail the empirical strategy.

3 Empirical Applications

In this section, I present three empirical applications. First, I focus on subsidies for malaria treatment in Kenya where households could choose to care for their health at drug-shops, health centers, or seek no care at all. I show that, in this first case, conditional response types allow identifying two treatment parameters (*i.e.*, the effect of seeking care at drug-shops vs. health centers, and of seeking care at drug-shops vs. no care) in addition to the treatment effect of care at drug-shops vs. the next-best. In the second application, I study the case of childcare choices in Colombia and their impact on the cognitive, socio-emotional, and nutritional development of children. Parents could choose to care for their children at home, or send them to small– or large-centers. Conditional response types allow identifying the effect of care at small *versus* large centers; however, additional assumptions (*e.g.*, homogeneity) are necessary to disentangle effects for a second margin of choice: small centers *versus* home care.

Last, in the third application I focus on the case of merit- and need-based scholarships and higher education outcomes in Colombia. In particular, I study the first cohort of the *Ser Pilo Paga* program which provided scholarships to high school graduates of 2014 based on need (*i.e.*, being below a poverty score threshold) and merit (*i.e.*, being above a cutoff on the score of the high school exit exam). Students could either choose not to enroll, or enroll in high-quality or low-quality higher education institutions. Conditioning on two instrumental variables, rather than one as in the previous cases, allows identifying the effect of not enrolling *versus* enrolling in a high-quality university. I also show results for the margin of low– *versus* high-quality universities enrollment which is only identified after imposing the homogeneity assumption.

3.1 Subsidies for malaria treatment in Kenya

For my first application, I employ data from Cohen et al. (2015) who run a field experiment to study the targeting vs. access trade-off of subsidizing antimalarial drugs in Kenya. Households were randomly assigned to receive subsidies to purchase an antimalarial (artemisin combination therapies - ACTs) at drug-shops. For these households, I study their health care choices for their first illness episode after subsidy provision and the effect of this choice on total illness episodes at endline.[25] Households can choose between three alternatives: buying a subsidized drug at the drug-shop (s), go to a formal health facility (h), and do nothing or seek other type of treatment (n).

There are three reasons why this setting is a good candidate for employing conditional response vectors to identify treatment effects of healthcare choices. First, we cannot assume that all households have the same ranking of preferences over these options. While h has medical professionals, it also has long waiting lines, stockouts of ACTs, as well as fees for diagnosis and treatment. In turn, s lacks medical staff and diagnosis tools but is, on average, more easily accessible to households (Cohen et al., 2015). Second, there are two measures of, arguably, exogenous variation available: the random subsidy and the distance to the nearest health center. Third, subsidy provision was solely for purchases of ACTs at s which can divert households from either seeking treatment at h or n and into choosing s. Arguably, households switching on the "intensive" margin might not benefit from choosing s in terms of their overall health while those who are on the "extensive" margin (entering the health care system via s) might benefit the most from seeking appropriate care for their illness. Therefore, disentangling treatment effects at each margin is policy-relevant.

3.1.1 Data

I use data from the replication package of Cohen et al. (2015), which contains information on baseline characteristics and health related behaviors of households as well as subsidy assignment and endline variables (*e.g.*, records on illness episodes). It also contains information on choice of health care (s, h, or n) for all illness episodes. To define the choice variable, I assign households to either s, h, or n based on their health care choice for the first illness episode after subsidy provision. The estimating sample consists of 2,471 households of which 5% belong to the control (no subsidy) group and 95% received an ACT subsidy. In terms of health care choice, 61.4% of households choose s, followed by 20% in h and 18.6% in n (see Table 5).

Households choice of health care is correlated with their characteristics and health behaviors at baseline. Table 5 shows that, on average, households who chose h have younger and more educated household heads than those who chose s and n. In terms of health behaviors at baseline, households who chose n are, on average, less likely to have had malaria episodes, own less bednets, and are less likely to visit s or h for prior illnesses compared to households who chose s and h. At endline, households who choose s report

[25]To apply the logic of conditional response types and estimate treatment effects, I depart from the original question in Cohen et al. (2015). While other outcomes, such as household wealth or labor market participation might be potentially more interesting, I focus on the set of endline variables collected in the original study which pertain mainly to illness episodes and treatment seeking behavior.

on average a higher number of illness episodes than those who choose h or n. Last, Table 6 shows that there is a higher share of subsidy recipients among households who choose s than among those who choose h or n. It also shows that, on average, households who choose h are closer to these options (row "Distance to h, in km") than households who choose n.

3.1.2 Conditional Response Types for Health Care Choices

Let k denote household choice of health care, with $k \in \{s, h, n\}$. This choice, k, affects households' illness episodes at endline denoted by Y_i. X_i contains exogenous covariates, measured at baseline prior to the decision between s, h, and n. These baseline variables include household size, presence of children in the household, and distance to the drug shop. Furthermore, let $Z_i \in \{Z_1, Z_2\}$ contain instrumental variables where Z_1 is a binary variable and Z_2 is a continuous variable. Specifically, Z_1 is the outcome of the random subsidy assignment and Z_2 is the distance to the nearest h. Denote z_i as a realization of Z_i; for instance, z_1 could be either zero or one.

Potential outcomes and choices are denoted by Y_{ki} and $D_i(z_1, z_2)$, respectively. The former represents illness episodes that household i would experience from choosing option k, the latter denotes what household i would choose if facing instrument values (z_1, z_2). I assume that A1 and A2 hold.[26] To define potential choices at different values of the IVs, and illustrate the role of A3, let $V_{ik}(z_1, z_2)$ represent the disutility of choosing k at values $Z_1 = z_1$ and $Z_2 = z_2$ of the instruments. Assume that $V_s(0, z_2) \geq V_s(1, z_2)$, such that obtaining a subsidy to purchase ACTs at s lowers the cost of choosing s while the costs of h and n remain unaffected (*i.e.*, $V_h(0, z_2) = V_h(1, z_2)$ and $V_n(0, z_2) = V_n(1, z_2)$). Last, increases in Z_2 increase $V_{ih}(Z_1, z_2)$ but do not affect directly the costs of s and n.

Following the scenarios depicted in Figure 1, replace option 3 with h, option 2 with n, and option 1 with s. I use these cost structures to define potential combinations of health care choices as the subsidy assignment changes which, following the assumptions on costs, only directly affects V_s (shown in the Figure as the dotted line). Below A and B, households would choose h in the absence of the subsidy but would choose s if they obtain the subsidy (that is, they would switch towards the cheapest option). In contrast, above B households would switch from n and towards s as the subsidy assignment changes. Note that there are other cost structures that satisfy the assumptions, however the main implications on households behavior would remain the same: first, once the cost of choosing h is very high, such that the utility from choosing h becomes smaller, it is less

[26] Distance to the health center might be correlated with other factors that determine households' overall health. While the variation to estimate treatment effects stems from the random subsidy, conditional on distance, violations of the exclusion restriction for Z_2 threaten identification if one group disappearing as the IV changes does so due to changes in gains from treatment that might correlate with the shifts in the distance. I recognize this limitation of the application, but assume in what follows that Z_2 is conditionally exogenous for illustration purposes.

likely that households switch along the $h - s$ margin; second, if the cost of choosing h is very low (near zero) households experiencing large decreases in the cost of choosing s are more likely to switch along the $h - s$ margin. These implications motivate the responses in Table 2 which contains combinations of potential choices when Z_2 approaches zero (right Panel) and when Z_2 approaches its maximum value (left Panel). In both cases, g_1, g_2, and g_3 are always-takers while g_4 (g_5) are switchers along the $h - s$ ($n - s$) margin. At any other point in the distribution of Z_2 we would observe both g_4 and g_5 with some probability.

Table 2: Z_1-responses at different evaluation points of Z_2

Response Types as $Z_2 \to 0$					Response Types as $Z_2 \to z_2^{\max}$				
Z_1	g_1^-	g_2^-	g_3^-	g_4^-	Z_1	g_1^+	g_2^+	g_3^+	g_5^+
0	s	h	n	h	0	s	h	n	n
1	s	h	n	s	1	s	h	n	s

In what follows, I test empirically whether the behavior implied by Figure 1 and formalized in Table 2 hold in this setting. Next, I use the strategy in Section A.1 to estimate local average treatment effects and MTEs.

3.1.3 Exploratory Analysis and Implementation

First stage: I estimate propensity scores locally around evaluation points of Z_2 with the following semiparametric regression:

$$\left\{\widehat{\beta}_1^k(z_2), \widehat{\beta}_2^k(z_2), \widehat{\beta}_X^k(z_2)\right\} = \text{argmin} \sum_{i=1}^{N} K\left(\frac{Z_{2i} - z_2}{h}\right)\left(D_{ki} - \beta_1^k Z_{1i} - \beta_2^k Z_{2i} - \beta_X^k \mathbf{X}\right) \quad (3)$$

where $\mathbf{X}$ denotes baseline variables such as number of young children in the household, other household members, and distance to the nearest drug-shop. I estimate the equation for each choice separately with an Epanechnikov kernel with bandwidth 4.5km, and compute mean contrasts at each evaluation point, z_2, of $Z_1 = 1$ vs. $Z_1 = 0$ to obtain estimates of $\widehat{\beta}_1^k(z_2)$. I employ equation (7) to estimate the probabilities of always-takers and compliers in Table 2.

First stage estimates: Panel A of Figure 2 presents results for $\widehat{\beta}_1^k(z_2)$ at different evaluation points, z_2 for $k \in \{s, h, n\}$. In line with the implications for health care choice from the cost structure in the previous section, the effect of the subsidy on the probability of choosing h is negative (as households are less likely to choose it if they receive the subsidy) but decreases in magnitude as Z_2 increases. In particular, for $Z_2 > 7$km the effect approaches zero and it is not statistically significant. On the other hand, the effect of the subsidy on the probability of choosing n is small and negative at smaller Z_2 but increases in magnitude as Z_2 increases. Hence, these results go in line with the definition of response types in Table 2.

Treatment Effects: For each vector in $Y_o \in \{Y, YD_H, YD_S, YD_L\}$, I estimate the following semiparametric regression:

$$\left\{\widehat{\beta}_1^{Y_o}(z_2), \widehat{\beta}_2^{Y_o}(z_2), \widehat{\beta}_X^{Y_o}(z_2)\right\} = \text{argmin} \sum_{i=1}^{N} K\left(\frac{Z_{2i} - z_2}{h}\right)\left(Y_{oi} - \beta_1^{Y_o} Z_{1i} - \beta_2^{Y_o} Z_{2i} - \beta_X^{Y_o} X\right) \tag{4}$$

and I compute the counterfactuals for always-takers and compliers with equation (6). The following parameters can be identified: (i) s vs. the next-best, $E(Y_s - Y_{s_-}|g_4, g_5, Z_2 = z_2)$, (ii) s vs. h, $E(Y_s - Y_h\,|g_4, Z_2 \to 0)$, and (iii) s vs. n, $E(Y_s - Y_n\,|g_5, Z_2 \to z_2^{max})$. Moreover, the following marginal treatment effects (MTEs) can be identified:

$$\lim_{Z_2 \to 0} \; E\left(Y_s - Y_{s_-}|Z_2, U_s(Z_1) = U_{k\backslash s}(Z_1)\right) = E\left(Y_s - Y_h|Z_2, U_s(Z_1) = U_h(Z_1)\right), \text{ and}$$

$$\lim_{Z_2 \to z_2^{max}} E\left(Y_s - Y_{s_-}|Z_2, U_s(Z_1) = U_{k\backslash s}(Z_1)\right) = E\left(Y_s - Y_n|Z_2, U_s(Z_1) = U_n(Z_1)\right),$$

where s_- denotes the next-best alternative, and $U_{k\backslash s}$ denotes the value of choosing options different than s.

To estimate the MTEs, I exploit additional price variation in Z_1 embedded into Cohen et al. (2015)'s experiment. That is, rather than using a binary indicator for subsidy assignment, I use a categorical variable that takes on 4 values (control - no subsidy, and 80%, 88%, and 92% subsidy). I then follow Brinch et al. (2017) and Mogstad et al. (2021) to estimate the MTEs using a categorical IV. First, I estimate the propensity score for s, denoted by p, with the first stage specification for s. Panel (a) of Figure 9 in the Appendix B.1 shows the common support, which is set as the interval $p \in [0.28, 0.8]$. Then I estimate the following semiparametric regression:

$$\begin{aligned}\left\{\widehat{B}^{Y}(z_2)\right\} = \text{argmin} \sum_{i=1}^{N} K_2\left(\frac{Z_{2i} - z_2}{h_2}\right) K_p\left(\frac{P_i - p}{h_p}\right)(Y_i - \beta_1^Y p_i \\ - \beta_2^Y p_i^2 - \beta_3^Y Z_{2i} - \beta_X^Y \mathbf{X} * p),\end{aligned} \tag{5}$$

where $K_2(.)$ and $K_p(.)$ denote the Epanechnikov kernel function and triangular kernel function, respectively. I evaluate the MTE at $z_2 \in \{0, 4.5, 8.5\}$, and at the sample average of the covariates in $\mathbf{X}$.

3.1.4 Results

Panel B of Figure 2 shows the average prevalence of always-takers and compliers induced by the variation in the subsidy, at different evaluation points of the distance to the health center. The group with the largest share corresponds to $s-$always-takers (represented by the light blue diamonds), which goes from around 35% to above 50% as the distance to h increases. In contrast, the share of $h-$always-takers (that is, households who would have chosen the health center regardless of the subsidy assignment) decrease from 30% to 20% as the distance to h increases. Such behavior is consistent with the role of distance as a cost-shifter and households substituting h for relatively cheaper options. More important, the share of compliers along the $h-s$ $(n-s)$ margin decreases (increases) as the distance to h increases which supports the definition of conditional response types in the previous section.

The top panel of Figure 3 shows estimates of local average treatment effects on the number of illness episodes experienced by the households 4 months after the subsidy provision took place. The figure presents estimates for standard LATEs (in gray) and subLATEs for each margin recovered by imposing an assumption of homogeneity.[27] Following the identification results from Section 3.1.2, as the distance to h approaches zero (nine, which is the maximum distance in this setting), the LATE estimates in gray reflect the effect for the $h-s$ $(n-s)$ margin. Hence, households who would switch from h and towards s as the subsidy assignment changes experience virtually no difference in illness episodes, on average. On the other hand, choosing s due to receiving the subsidy when the fallback option is n increases illness episodes by 1-1.5. Note that the results of the standard LATE, in gray, differ from those imposing the homogeneity assumption for the s vs. h margin (in blue) with the former being smaller than the latter. This is in line with households in the $h-s$ margin having a lower expected outcome from choosing s than those in the $n-s$ margin (if switching into s means lower quality care than h), which would result in the homogeneity assumption overestimating the effect of s vs. h.

The bottom panel of Figure 3 shows results of estimating the marginal treatment effect for s vs. the next-best, as well as for the separate margins of $h-s$ and $n-s$. Higher values along the horizontal axis represent a lower likelihood to choose s, the vertical axis measures the effect on the number of illness episodes at endline. The black line shows estimates of the MTE for s vs. the next-best which show that households

[27] I include homogeneity estimates to compare the results for this application to those of the other two applications. In this case, the homogeneity assumption states that the mean potential outcome of choosing s would have been the same regardless of the original state (h or n). Note that separate identification of pairwise treatment effects does not rely on this assumption in this case. Nonetheless, I also present estimates of average of baseline variables for complier groups to assess the validity of homogeneity in Figure 11 of Appendix B.3 which shows that households who would have chosen h in the absence of the subsidy are on average more concerned about their health despite having a similar likelihood of experiencing malaria episodes, compared to households who would have chosen n in the absence of the subsidy.

who are more likely to choose s (lower p values) rather than the next-best alternative experience less illness episodes. A similar pattern emerges for s vs. h, depicted by the blue dashed line. However, when the fallback option is h (the orange dotted line), only those with the highest likelihood of choosing s would benefit from seeking care at the drug-shop; households with $p > 0.4$ would lose from choosing s.[28] These results highlight the importance of disentangling effects at the different margins as those in the margin of indifference between s and n might be worse off in terms of illness episodes than households who are choosing s instead of seeking care at health centers.

3.2 Parental choice of childcare in Colombia

In this second application, I study parental choices of childcare for children between the ages of six months to five years in the context of an expansion of public care provision that took place in Colombia during 2011. From the 1980s to 2011, small nurseries (s) were the main providers of public childcare for low income families. Small nurseries are run by one caretaker that serves 12-15 children in the same space, typically the home of the provider. In 2011 the public provision of childcare was expanded to offer services through both s and large centers (l). The latter serve around 300 children who receive care in age-specific classrooms, with one teacher per 25 children, a nutritionist and a psychologist in each center, and administrative staff.[29]

Despite the fact that l centers offer nutritional and psychological services and have better infrastructure than s centers, there are other factors that could improve or deter children's development. Age-specific classrooms may improve cognitive development, but higher teacher to student ratios may have a negative impact. Having a nutritionist could be beneficial for children at risk, but they can be supervised more closely in smaller classrooms. The heterogeneity of the potential benefits of s and l makes it difficult to rank them *a priori*. For instance, parents with preferences for centers that provide nutritional services could prefer l over s, while those concerned with socio-emotional development could rank s (where children of all ages are interacting) above l. Also, parents with strong preferences for low caretaker to children ratios could prefer to take care of their child at home than either at s or l. Rather than imposing a rank that would restrict parent's preference heterogeneity, I assume that these alternatives are unordered (e.g., l centers are no better than s ones across all dimensions of children development).

[28]Panel (a) of Figure 10 in Appendix B.2 presents estimates of the weights that the IV estimator would place on the MTEs at each value of p. In this case, IV places more weight on households less likely to choose drug-shops when s is compared vs. the next-best. When the fallback option is h, there is more weight on the left of the distribution meaning that households less likely to choose s receive relatively more weight than when the fallback option is n.

[29]For further details on the supply of childcare in Colombia and the characteristics of each center, see Bernal et al. (2019) and Bernal and Ramírez (2019).

3.2.1 Data

I exploit rich data containing a random sample of children who were enrolled in s, before l was available (see Bernal et al., 2019). That is, all children in my sample were enrolled in s at baseline and I observe their enrollment at follow-up which could either be home care (h), s, or l. The dataset contains socioeconomic variables collected at baseline such as children's age and sex, mother's years of education, number of children in the household, and household income. It also has age-standardized measures of child development on cognitive, socio-emotional, and nutritional dimensions, which were collected before and after l was available. At follow-up, more than half of the children in the sample attend l, compared to 32% in s and 13% who receive care at home (h) (see Table 7).

In order to estimate treatment effects, I exploit two sources of exogenous variation: an experiment aimed at providing information to families about the supply of centers, and the geographical distance between the child's home and the different options. The former is a lottery assigned at the s level that offered the chance to transfer to l, for caretakers and children at winner s. The lottery did not provide financial incentives to transfer. Instead, it increased the likelihood of being informed about l and transferring to l. This transfer was not enforced. Distance to l is the straight line distance from the child's home to the nearest l center, measured in kilometers.

About 74% of children in the sample were randomly assigned to transfer with their caretaker directly from s to l ("Wins lottery", Column 5 in Table 8), while the remaining 26% are control children who did not win the lottery. Information on this transfer opportunity was given to caretakers in winner s centers, who could decide: (i) whether or not to contact and inform parents, and (ii) whether to switch to work at l centers since both s and l are publicly funded. Neither caretakers nor parents at winner centers were required to transfer, and caretakers and parents in control s centers could also choose to switch to the nearest l. In this sense, there is noncompliance in the parental response to the lottery and some parents might have lost their original s center if the caretaker decided to work for l.

3.2.2 Conditional Response Types for Childcare Choices

Let k denote parental choice of childcare, with $k \in \{h, s, l\}$. The choice of childcare, k, affects children development denoted by Y_i. I focus on three dimensions: cognitive, socio-emotional, and nutritional. X_i contains exogenous covariates, measured at baseline prior to the decision between h, s, and l. These baseline variables include children characteristics such as age in months, sex, and measures of development (cognitive, socio-emotional, and nutritional). It also includes household income and mother's years of education. Furthermore, let $Z_i \in \{Z_1, Z_2\}$ contain instrumental variables where Z_1 is a binary variable and Z_2 is a continuous variable. Specifically, Z_1 is the outcome of the random lottery and Z_2 is the distance to l. I assume that the instruments in Z_i satisfy A1 and A2.

In a similar manner to the previous application, I assume that parents choose the option with the highest latent utility and that IVs affect choices through their effects on costs. In particular, as the distance to the large center increases (and because some careworkers in winning s centers transition to work at l centers) parents would choose s in the absence of the lottery but would either switch to h or l when winning the lottery. In contrast, when distance to l decreases parents would have strong incentives to switch out of h and s and into l centers due to the lottery outcome.[30]

Table 3: Z_1-responses at different evaluation points of Z_2

Response Types as $Z_2 \to 0$						Response Types as $Z_2 \to z_2^{\max}$					
Z_1	g_1^-	g_2^-	g_3^-	g_4^-	g_5^-	Z_1	g_1^+	g_2^+	g_3^+	g_4^+	g_5^+
0	h	s	l	h	s	0	h	s	l	s	s
1	h	s	l	l	l	1	h	s	l	h	l

In contrast with the case of subsidies for malaria in Kenya, the combination of the experimental variation plus the institutional context (where the lottery also changes the supply of childcare) generate sets of pairs of complier groups across the distance to l, rather than unique groups at different evaluation points. Moreover, pooling all the variation from the lottery would result in a violation of monotonicity since some parents would be induced towards– and away– from h as the lottery outcome changes. In what follows, I empirically establish that as $Z_2 \to 0$, the share of households along the $h - l$ margin is negligible such that, for low values of Z_2, the pairwise LATE of $s - l$ can be identified. In contrast, as $Z_2 \to z_2^{\max}$, to achieve identification of pairwise treatment parameters, conditional response types need to be implemented in combination with assumptions of homogeneity.

3.2.3 Exploratory Analysis and Implementation

First stage: I estimate propensity scores locally around evaluation points of the distance to the large center (Z_2) with the semiparametric regression in equation (3), with an Epanechnikov kernel with bandwidth 0.8km. Baseline variables included in $\mathbf{X}$ are child's age in months, sex, a binary variable to indicate lowest income level, years of education of the mother, number of children 0-5 years of age living at home, binary variables for birth order, cognitive, socio-emotional, and nutritional development. Estimates of $\widehat{\beta}_1^k(z_2)$ for

[30] An earlier version of this paper, which focused exclusively on the childcare application, explains in more detail the assumptions behind the conditional response types presented in Table 4 (available here, Chapter 2, Section 2.3).

$k \in \{h, s, l\}$ are obtained in a similar manner as in the previous example. With equation (7), I estimate the probabilities of always-takers and compliers in Table 4.

First stage estimates: Panel A of Figure 4 shows results for $\widehat{\beta}_1^k(z_2)$ at different evaluation points of distance to l, with each column referring to a childcare choice (l, s, and h). I observe that the effect of the lottery outcome on the probability of choosing l (s) is positive (negative) and relatively constant at all values of the distance. In contrast, winning the lottery increases the probability of choosing h for values of the distance below 1.25km but loses magnitude and significance after 1.7km. These patterns are consistent with the conditional response types in Table 4, and provide empirical support to assume that $\Pr(g_4^-) = 0$ since the lottery outcome only increases the probability of choosing h in the subsample and its effect is not statistically significant for low values of Z_2.

Treatment Effects: I estimate semiparametric regressions in equation (4) for each vector in $Y_o \in \{Y, YD_L, YD_S, YD_H\}$, and compute the counterfactuals for always-takers and compliers with equation (6). Note that variation in the lottery outcome induces parents to switch along the $s - l$ and $s - h$ margins, which implies that univariate IV (*i.e.*, using only Z_1 as instrument) would identify the effect of l vs. s plus a bias component arising from the s vs. h margin. The same result holds for estimating effects using Z_1 and conditioning on different points of Z_2, in particular:

$$\frac{E[Y|Z_1 = 1, Z_2] - E[Y|Z_1 = 0, Z_2]}{E[D_l|Z_1 = 1, Z_2] - E[D_l|Z_1 = 0, Z_2]} = E[Y_l - Y_s|g_5, Z_2] + \frac{E[Y_h - Y_s|g_4^+, Z_2]\Pr(g_4^+|Z_2)}{\Pr(g_5|Z_2)},$$

where the right-hand side of the equation above corresponds to the Wald estimator, evaluated at different values of distance to l. To separately identify LATEs for different margins I assume homogeneity, *i.e.* that potential children's development at s centers would have been the same, on average, regardless of their next-best option: $E[Y_s|\text{Complier:}s - l, Z_2] = E[Y_s|\text{Complier:}s - h, Z_2]$, which can be identified from the ratio of $\beta_1^{YD_s}(z_2)$, in equation (4), over $\beta_1^s(z_2)$, in equation (3). Last, from the first-stage estimates it can be assumed that $\Pr(g_4^+|Z_2 < 0.25) = 0$ and $\Pr(g_4^+|Z_2 > 1.7) = 0$ such that, at those intervals of Z_2, $E[Y_l - Y_s|g_5, Z_2]$ can be separately identified.

Since the lottery outcome induced compliers along the $s - l$ and $s - h$ margins, in what follows and for the purpose of interpretation of effects, I focus on the choice of s vs. the next-best (l or n) or vs. l. The following marginal treatment effects (MTEs) can be identified:

$$E\left(Y_s - Y_{s_-}|Z_2, U_s(Z_1) = U_{k\backslash s}(Z_1)\right), \text{and}$$

$$\lim_{Z_2 \to z_2} E\left(Y_s - Y_{s_-}|Z_2, U_s(Z_1) = U_{k\backslash s}(Z_1)\right) = E\left(Y_s - Y_l|Z_2, U_s(Z_1) = U_l(Z_1)\right),$$

for $z_2 = 0$ and $z_2 = z_2^{\max}$. Where s_- denotes the next-best alternative, and $U_{k\backslash s}$ denotes the value of choosing options different than s. To estimate the MTEs using a binary IV, I follow Brinch et al. (2017) and Mogstad et al. (2021) as in the previous application. I first estimate the propensity score for s, and denote it as p, with the first stage specification for s. Panel (b) of Figure 9 in the Appendix B.1 shows the common support, which is set as the interval $p \in [0.16, 0.76]$. Then, I follow the semiparametric regression in equation (5) and evaluate the MTE at $z_2 \in \{0, 1.25, 1.9\}$, and at the sample average of the covariates in $\mathbf{X}$.

3.2.4 Results

Panel B of Figure 4 shows that, as distance to l increases, the fraction of l-always-takers decreases (from 50% to 10%) while the fraction of s-always-takers increases (from about 20% to almost 60%). This is consistent with parents substituting their childcare choices towards the relatively cheaper option; in this case, as distance to l increases it becomes more costly in relative terms to bring children to l. The fraction of compliers along the $s - l$ margin is around $10 - 20\%$, while the share of $s - h$ compliers is below 10% and tends towards zero for distances below 0.7km and above 1.5km.

The top row of Figure 5 presents local average treatment effects for cognitive, socio-emotional, and nutritional development. Estimates using the variation in the lottery outcome, evaluated at different points of distance to l, recover the effect of s vs. l plus a bias component from the s vs. h margin (denoted as "Standard LATE" in each subfigure). I employ the homogeneity assumption to decompose subLATEs for each of those margins (s vs. l in blue, and s vs. h in orange).[31] Overall, the results indicate no benefit for children switching away from s centers and into home care. For the s vs. l margin, the effect of large centers is negative on cognitive development but positive on socio-emotional and, for some children, on nutritional development. While the results lack predictive power, they are indicative of sizable differences in the effects of choosing alternative childcare choices.

The bottom row of Figure 5 presents marginal treatment effects for cognitive, socio-emotional, and nutritional development. Higher values on the horizontal axis denote a lower propensity to choose small centers. The gray line denotes the MTE of s vs. the next-best (evaluated nonparametrically at $Z_2 = 1.25$km) where half of compliers switch along $s - h$ and the other half along $s - l$. The blue dashed and dotted lines evaluate nonparametrically the MTE at Z_2 equal to 0.1km and 1.9km, where the share of $s - h$ compliers goes to zero. Those more likely to choose s (with low values of p) would lose in terms of cognitive and socio-emotional development and slightly benefit in terms of

[31] In Appendix B.3, I present estimates of average of baseline variables for compliers along the $s - l$ and $s - h$ margin. Figure 12 shows that $s - l$ compliers have, on average, more educated mothers but lower baseline levels of cognitive and socio-emotional development compared to $s - h$ compliers. This finding casts doubt on the validity of the homogeneity assumption in this context.

nutrition, regardless of the fallback option. However, comparisons of the estimates for the MTE of s vs. l and s vs. the next-best suggest that the fallback option matters for those unlikely to choose s (with high values of p): if the fallback option is l, children less likely to choose s would gain in terms of cognitive development but lose in terms of socio-emotional and nutritional development; if the fallback option is either l or n, the cognitive benefits disappear, the behavioral problems remain, with minor gains on nutrition. Last, note that those with values of p in the interval (0.35,0.55) seem to do better across all development dimensions, in particular if the fallback option is l.[32]

3.3 Higher education choices in Colombia

The last application focuses on the case of the *Ser Pilo Paga* program (SPP, henceforth), which provided scholarships for attending any 4 or 5-year higher education program in any high quality university in Colombia. Eligibility was need (*i.e.*, being below a poverty score) and merit (*i.e.*, being above a cutoff score in the high school exit exam) based. To analyze this case, I use an anonymized subsample of eligible students from the universe of high school graduates in 2014 from Londoño-Vélez et al. (2023). The results I present here are not intended to evaluate SPP in any dimension, which has been documented rigorously by Londoño-Vélez et al. (2020) and Londoño-Vélez et al. (2023), rather they illustrate the role of conditional response types in the context of higher education choices. To do so, I deviate from identifying the impact of SPP on access to higher education and labor market outcomes with a Regression Discontinuity Design, and instead estimate the effect of choosing a higher education option (*i.e.*, not enrolling in higher education, enrolling in a low quality university, or enrolling in a high quality university) on the probability of working in 2021 using SPP eligibility as an instrumental variable.[33]

3.3.1 Data

The subsample from Londoño-Vélez et al. (2023) contains student level information for the first cohort of SPP on test scores in the high school exit exam, the poverty score, socioeconomic characteristics such as household size and mother's educational level. All these variables are measured in 2014, prior to the higher education enrollment choice and to the announcement of SPP by the government. It also contains the higher education enrollment choice students made which I categorize into three alternatives: not enrolling in higher education (n), enrolling in a low quality university (l), and enrolling in a high

[32]Panel (b) of Figure 10 in Appendix B.2 presents estimates of the weights that the IV estimator would place on the MTEs at each value of p. In this case, IV places more weight on households less likely to choose small centers.

[33]That is, the central research question for this application pertains to estimating the labor market effects of choosing a high vs. low-quality program, or vs. not enrolling, rather than estimating the impact of financial aid on higher education access and on long-term student outcomes.

quality university (h). Following the logic of the previous applications, I assume that these options are unordered such that one is not better than the other *for all* students.

I split the data into two estimating subsamples based on whether students are need-eligible (*i.e.*, below the poverty score cutoff for SPP) or merit-eligible (*i.e.*, above the high school exit exam score cutoff for SPP), as has been done in other studies analyzing SPP. To estimate treatment effects of higher education choices, I use the remaining dimension of SPP eligibility in each subsample as a source of exogenous variation. That is, for the need-eligible (merit-eligible) students I construct a binary indicator, Z_1, taking the value of one if the student is above the high school exit exam cutoff (below the poverty score cutoff), and its zero otherwise. In both groups, being eligible for SPP would induce students towards enrolling in h instead of choosing l or n. Moreover, I georeference all higher education institutions in the country and compute the geographic distance from the student's high school to the nearest low– and high–quality university. I define Z_2, the second instrument, as the distance to the nearest l.

Table 9 shows average characteristics at baseline, average outcomes, and the distribution of enrollment choices for the need– and merit–eligible subsamples. About 70% (36%) of need-eligible (merit-eligible) students do not enroll in a higher education program, while 17% (18%) enroll in a low-quality program, and 14% (47%) enroll in a high-quality program. Regardless of the subsample, students choosing h are on average younger, less likely to be female, and more likely to have more educated mothers, than those choosing n. As expected, those in the need-eligible subsample are about twice as likely to belong to the lowest socio-economic level than those in the merit-based subsample. In terms of outcomes, students who choose h are more likely to be formally employed in 2021 (7 years after completing high school) than those choosing l or n. Among the need-eligible, students choosing h are 6 percentage points more likely to work formally than those choosing l, while these difference is only of 4 p.p. between l and n. In contrast, h merit-eligible students are only 2 p.p. more likely to work while these difference increases to 14 p.p. between l and n students.

Table 10 shows the average of Z_1 and of the distance to the nearest h and l, for the subsamples of merit- and need-based eligible students. More than two thirds of students choosing h satisfy both eligibility criteria for SPP (72% among the need-eligible, and 75% among the merit-eligible), as expected given that the program covers full tuition for a program at a high-quality university. In terms of distance to h and l, regardless of the subsample, students choosing h (l) are on average at least as near to those options than students choosing l or n (h or n). Moreover, l universities are on average closer than h universities regardless of the subsample, and need-eligible students are on average farther away from any type of HEIs than merit-eligible students.

3.3.2 Conditional Response Types for Higher Education Choices

Let k denote the higher education enrollment choice, with $k \in \{n, l, h\}$. I assume that these options are unordered, meaning that one is not better than the other *for all* students. Higher education enrollment choice, k, affects the probability of working in the formal sector in 2021 given by Y_i. X_i contains student characteristics measured prior to the enrollment choice. Let $Z_i \in \{Z_1, Z_2\}$ contain instruments where Z_1 is a binary variable of eligibility (either being above the Saber 11 or Sisben cutoff) and Z_2 is the distance to the nearest low quality HEI (measured at baseline). I assume that the instruments in Z_i satisfy A1 and A2.[34]

Since SPP required students to secure a slot at any h, I assume that satisfying the eligibility criteria would shift students across two margins of choice: n *versus* h, and l *versus* h. That is, being eligible for SPP would shift students away from not enrolling in higher education or enrolling in a low-quality university, and into enrolling in a high-quality university. Moreover, following the logic of cost-shifters and applying it to the second instrument, Z_2, as distance to l increases it is more costly to choose l relative to h or n. Using the variation from Z_1 conditional on Z_2, one would expect that as distance to l increases the probability of observing students switching along the $l - h$ margin, because of changes in SPP eligibility, decreases (see Table 4 below).

Table 4: Z_1-responses at different evaluation points of Z_2 (distance to nearest low-quality university)

Response Types as $Z_2 \to 0$					Response Types as $Z_2 \to z_2^{\max}$				
Z_1	g_1^-	g_2^-	g_3^-	g_4^-	Z_1	g_1^+	g_2^+	g_3^+	g_5^+
0	n	l	h	l	0	n	l	h	n
1	n	l	h	h	1	n	l	h	h

However, in contrast with previous applications, students might be less sensitive to distance, and a considerable fraction usually migrates across the country to pursue a higher education degree even in the absence of SPP. If students are insensitive to the distance to the HEI, then restriction R1 does not hold, the cost function of enrolling in higher education does not depend on Z_2, and the set of conditional response types would be the same as the set of unconditional response types. Moreover, note that the sensitivity of students to Z_1 and Z_2 might differ for those who are need– vs. merit–eligible: need-eligible students have higher constraints and have on average less access to

[34] That is, the instruments should be uncorrelated with potential outcomes and potential choices. They must also satisfy the exclusion restriction, such that the instruments can only affect outcomes through their effect on choices. While SPP eligibility satisfies these conditions, distance tends to be correlated with other factors that can determine labor market outcomes. Similarly to the previous applications, I assume that Z_2 is exogenous for illustration purposes.

HEIs, which implies that regardless of changes in eligibility for SPP or if the distance to l were to decrease, they would be less likely to attend l or h and more likely to choose n in the absence of SPP than merit-eligible students. Hence, conditioning on meeting the need-based criteria leads to a low likelihood of option l belonging to the set of next-best states which, implicitly, results from following the logic of conditional response types.

3.3.3 Exploratory Analysis and Implementation

First stage: I estimate propensity scores locally around evaluation points of the distance to the nearest low-quality university (Z_2) with the semiparametric regression in equation (3), with an Epanechnikov kernel with bandwidth 20km. Baseline variables included in $\mathbf{X}$ are student's age, sex, family size, mother's educational level, distance to the nearest h, and a cubic polynomial in the high school exit exam (poverty) score for the need-eligible (merit-eligible) subsample. Estimates of $\widehat{\beta}_1^k(z_2)$ for $k \in \{n, l, h\}$ are obtained in a similar manner as in the previous examples. With equation (7), I estimate the probabilities of always-takers and compliers in Table 4.

First stage estimates: Figure 6 shows results for $\widehat{\beta}_1^k(z_2)$ at different evaluation points of distance to the nearest l, with each column referring to an enrollment choice (h, l, and n) for the need-eligible students (in Panel A) and the merit-eligible students (in Panel B). First, Panel A shows that the effect of SPP eligibility on enrollment in h is of about 60 percentage points for the need-eligible subsample (column "Probability of choosing high-quality HEI (h)") and most of this effect (around 90%) comes from a decrease on the probability of choosing n rather than on the probability of choosing l. In contrast, for the merit-eligible subsample (in Panel B) SPP increases the probability of choosing h by about 40 percentage points and 60% of this effect comes from reductions on the probability of choosing n while the remaining effect stems from reductions on the probability of choosing l. In both subsamples, the effect of SPP eligibility is constant across different values of distance to l, $Z_2 \in \{0\text{km}, 77\text{km}\}$, implying that students are not sensitive to changes in this instrument. Unlike the previous applications, changes in the prevalence of complier groups do not stem from a single additional instrument, Z_2, but on analyzing distinct subsamples of students, resulting from combinations of IVs of SPP eligibility, with more, or less, binding constraints.

Treatment Effects: For each vector in $Y_o \in \{Y, YD_n, YD_l, YD_h\}$, I estimate the following semiparametric regression in equation (4) and I compute the counterfactuals for always-takers and compliers with equation (6). Regardless of the subsample, the following parameters can be identified: (i) h vs. the next-best, $E(Y_h - Y_{h_-} | g_4, g_5, Z_2)$ where h_- denotes the next-best alternative. In order to separately identify effects at distinct margins, I employ the homogeneity assumption which allows identifying: (i) n vs. h,

$E(Y_h - Y_n\,|g_5, Z_2)$, and (ii) l vs. h, $E(Y_h - Y_l\,|g_4, Z_2)$. In this case, homogeneity assumes that labor market participation from choosing h would have been the same, on average, regardless of the next-best option: $E[Y_h|\text{Complier:}h-l, Z_2] = E[Y_h|\text{Complier:}h-n, Z_2]$, which can be identified as the ratio of $\beta_1^{YD_h}(z_2)$, in equation (4), over $\beta_1^h(z_2)$, in equation (3). It is worth noting that, among the need-eligible students, $Pr(g_4^-|Z_2)$ is very small such that $E(Y_h - Y_{h_-}\,|g_4, g_5, Z_2)$ mostly captures the effect of n vs. l.

The marginal treatment effect (MTE) of h vs. the next-best can be identified, $E\left(Y_h - Y_{h_-}|Z_2, U_h(Z_1) = U_{k\backslash h}(Z_1)\right)$ where h_- denotes the next-best alternative and $U_{k\backslash h}$ denotes the value of choosing options different than h. Rather than employing an homogeneity assumption, I evaluate MTEs at the minimum and maximum values of Z_2 in each subsample to illustrate how a modest increase in the $Pr(g_4^-|Z_2)$ might affect the shape and range of the MTE. That is, I estimate two additional MTE parameters:

$$\text{MTE (lower limit)} = \lim_{Z_2 \to z_2^{min}} E\left(Y_s - Y_{s_-}|Z_2, U_s(Z_1) = U_{k\backslash s}(Z_1)\right), \text{ and,}$$

$$\text{MTE (upper limit)} = \lim_{Z_2 \to z_2^{max}} E\left(Y_s - Y_{s_-}|Z_2, U_s(Z_1) = U_{k\backslash s}(Z_1)\right).$$

I estimate the MTEs using a binary IV in a similar manner as in the previous applications, by first estimating the propensity score for h, denoted by p, with the first stage specification for h. Panels (c) and (d) of Figure 9 in the Appendix B.1 shows the common support for each subsample, which is set as the interval $p \in [0.12, 0.8]$. Then I estimate the semiparametric regression in equation (5). I evaluate the MTE at $z_2 \in \{7, 15, 65\}$ for the need-eligible subsample (and at $z_2 \in \{7, 9, 65\}$ for the merit-eligible subsample) where each value corresponds to the minimum, average, and maximum of Z_2 respectively, and at the sample average of the covariates in $\mathbf{X}$.

3.3.4 Results

Figure 7 show the estimates of always-takers and compliers for the subsample of need-eligible students (in Panel A) and merit-eligible students (in Panel B) at different values of Z_2. The share of $l-$ and n$-$always-takers (in black and gray, resp.) is of about 30% and 10% across values of the distance to l, regardless of the subsample. In contrast, the share of h-always-takers (*i.e.*, students who would have chosen h regardless of SPP eligibility) is of less than 5% among the need-eligible compared to $20-30\%$ among the merit-eligible. Moreover, the majority of students among the need-eligible are $n-h$ compliers (about 50% at different values of Z_2) and less than $5-10\%$ are compliers along the $l-h$ margin. Among the merit-eligible, the share of $n-h$ compliers is $20-30\%$ and the share of $l-h$ compliers is $15-20\%$.

The first row of Figure 8 shows estimates of LATEs for the need-eligible (in column A) and merit-eligible (in column B) subsamples. The effect of h vs. the next-best is denoted as "Standard LATE" in the first row of subfigures, and is positive such that choosing a high-quality program instead of l or n increases the probability of working in the formal labor market in 2021 by about 10p.p., irrespective of the subsample. Among the need-eligible, the estimates of h vs. the next-best (in gray) closely follow those of the effect of n vs. h (in orange) identified by imposing the homogeneity assumption; the estimates of h vs. l (in blue) are negative for some values of Z_2 but it is worth noting that the share of compliers along this margin is small and might render these estimates less informative. Among the merit-eligible (first subfigure in Panel B), the estimates of h vs. the next-best are a combination of estimates for the $n-h$ and $l-h$ (a byproduct of employing the homogeneity assumption) but the magnitude and sign of the subLATEs changes after 49km of distance to the nearest l. For $Z_2 < 49$km, the effect of choosing h instead of l is negative on the probability of working formally in 2021 while the effect for $n-h$ compliers is positive and between 10-20 percentage points. After 49km, the latter effect decreases up to zero while the effect for $l-h$ compliers increases to around 20 percentage points.[35]

The second row of Figure 8 shows estimates of MTEs for the need-eligible (in column A) and merit-eligible (in column B) subsamples. Higher values along the horizontal axis represent a lower likelihood to choose h, while the vertical axis measures the effect on the probability of working formally in 2021. Among the need-eligible (Panel A), those with a very low, or very high, likelihood of choosing h vs. the next-best would experience a higher likelihood of working formally in 2021 (the gray and dashed blue line) and note that this effect is largely driven by the n vs. h margin. Meanwhile, when the share of $l-h$ compliers increases marginally the effect for those who are more likely to choose h instead of the next-best is negative (the upper limit MTE in the blue dotted line). This might reflect effects for students who would have been better off by choosing l than h. Among the merit-eligible, the MTE is positive regardless of whether it is evaluated at the minimum (the dashed blue line), the average (in gray), or the maximum (the blue dotted line) of distance to l. In practice, students on the margin between choosing h or the next-best benefit from choosing a high-quality program in terms of a higher likelihood of working formally in 2021. This effect nonetheless decreases as individuals become less likely to choose h (which intuitively would denote individuals with higher family or financial constraints to choose h).[36]

[35] Differences on the subLATEs across evaluation points of Z_2 for the merit-eligible subsample might be explained by differences in their average characteristics at baseline, or by changes in the composition of the groups. Figure 12 in Appendix B.3 shows that compliers along the $n-h$ have similar average shares of female students but are older, on average, than $l-h$ compliers. Moreover, for $Z_2 < 49$km both groups seem comparable in average household size, maternal education, with some differences in terms of SES in favor of $n-h$ compliers. However, for $Z_2 > 49$km $n-h$ compliers are on average less vulnerable with more educated mothers while the share of $l-h$ compliers belonging to low SES households increases.

[36] Panels (c) and (d) of Figure 10 in Appendix B.2 present estimates of the weights that the IV estimator would place on the MTEs at each value of p for the need-eligible and the merit-eligible subsamples, respectively. In the need-eligible subsample, IV places more weight on students more likely to choose

4 Concluding Remarks

In this paper, I study the identification and estimation of treatment effects in contexts where agents can choose between multiple options, and the researcher has access to multiple instrumental variables that can affect the same options. I focus on settings with two main features. First, agents can have preferences over the alternatives and self-select into their preferred choice. The latter motivates employing IVs as an estimation strategy. Second, the options are unordered, meaning that we cannot say that one option is better than the other, *a priori*. As a result, agents can have different fallback options and derive different gains or losses from their choices.

The IV approach has limitations. It estimates local effects for agents who change their behavior as the IV changes (i.e., compliers). In the presence of multiple unordered choices, compliers are heterogeneous, and agents can switch along many margins. For instance, if households receive a subsidy for purchases at drug shops, they could switch between healthcare centers and drug shops, or seeking no care and drug shops. The set of compliers becomes more complex when multiple instruments are available. In the first application I show that healthcare choices are highly sensitive to the availability of alternative options, and whether households respond to the subsidy by switching to drug shops depends on their proximity to the nearest health center. While this type of joint response to multiple instruments has been recognized in the literature, current methods implicitly assume that the behavior of compliers (or responses) to one instrument is the same across the distribution of other instruments. Furthermore, the case of multiple instruments that affect the same margins of choice is relevant for many empirical applications.

My main contribution is to present an identification strategy that addresses some of these challenges. First, I account for the joint effects of multiple instruments on the probability of choosing an option. That is, I allow for the response to the variation in one instrument (for example, an subsidy for drug shop purchases) to differ depending on other instruments (for example, proximity to the health center) that affect the same margins of choice. To do so, I employ a latent utility framework and model responses to the instruments through their effect on the costs of each option. I impose restrictions on the shape of the cost function. In particular, I assume that the cost function is convex. The latter allows me to define *conditional response types* that satisfy partial unordered monotonicity, locally.

I apply these tools to the contexts of healthcare and childcare choices, as well as decisions about pursuing different higher education paths. I show the scope of conditional response types in identifying treatment effects across these settings, which differ in their sources of variation and institutional features. Namely, I combine experimental or quasi-experimental variation with the distance to one of the options available. An important

high-quality HEI while the opposite holds for the merit-eligible subsample.

takeaway from the applications' results is that achieving identification of margin-specific treatment effects depends on the sensitivity of the cost function to the conditioning instrument–namely, distance to one of the options in each application. Notably, while healthcare and childcare choices exhibit strong sensitivity to distance, higher education decisions are less affected. A considerable proportion of students usually migrates to pursue a degree even in the absence of financial aid or incentives. In such contexts, researchers might need to supplement *conditional response types* with the standard homogeneity assumption or derive bounds of the estimates to account for the weaker role of the available conditioning instrument.

The application results underscore important caveats of the proposed identification strategy. First, it requires combining variation from multiple instrumental variables which might be prohibitive as researchers often have access to a single source of variation. Second, the estimated effects are inherently local, as they are evaluated at specific values or ranges of the conditioning instrument. However, in the context of multiple treatments, (local) evaluation points of the instruments define the set of next-best states. As a result, the results I present can be informative of treatment effects under different combinations of next-best states. Third, the evaluation points are often defined at extreme values of the conditioning instrument, but in practice changes in the composition of *conditional response types* depend on the slope of the cost function. That is, not every context will require extreme values as evident from the first two applications.

Moreover, the strategy rests on the standard no-defiers assumption but, as shown by Kirkeboen et al. (2016) and Heinesen et al. (2024) in the case of observed next-best alternatives, the estimates can be biased if unordered defiers are prevalent. Similarly, the standard limitations apply to employing the distance to options as an IV as it might be correlated with other factors that can affect potential outcomes. In this case, the conditioning IV serves an illustration purpose and the results I present are not intended to evaluate or provide evidence on the effectiveness of each policy scenario. That is, I focus on each application context to show the role of *conditional response types* and why they matter in the estimation of effects in complex settings. Last, while my results pertain to identification without inference (which remains an important direction for future research), they are indicative of the importance of uncovering variation along different margins of choice in the estimation of multivalued treatment effects.

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Tables and Figures

Table 5: Average characteristics, by type of health care

Variable	Drug-shop (s)	Health center (h)	Nothing (n)
Age of hh head	38.338	37.015	43.170
Years of educ of hh head	5.536	5.878	4.311
Household size	5.558	5.455	4.730
Health at baseline			
Number of bednets owned	1.867	1.879	1.483
Any malaria episode in hh	0.719	0.735	0.558
Drugs from drug-shop	0.309	0.345	0.214
Drugs from health center	0.361	0.305	0.235
Outcomes			
Illness episode reported at endline	3.314	3.139	2.174
%	61.4	20	18.6
N	1,517	495	459

Source: subsample from Cohen et al. (2015).
Note: The sample consists of households in control and ACT subsidies groups, excluding those who also received testing subsidies. All socioeconomic variables were collected at baseline.

Table 6: Average of instruments, by type of health care

Variable	Drug-shop (s)	Health center (h)	Nothing (n)
ACT Subsidy	0.950	0.915	0.913
Distance to the health center (h), in km	6.471	6.563	6.623
Distance to the drug-shop (s), in km	1.647	1.646	1.670
N	1,517	495	459

Source: subsample from Cohen et al. (2015).
Note: The sample consists of households in control and ACT subsidies groups, excluding those who also received testing subsidies.

Table 7: Average characteristics, by type of childcare

Variable	Large centers (l)	Small centers (s)	Home care (h)
Age (months)	36.980	36.241	37.553
Male	0.515	0.526	0.465
Children 0-5 at home	1.477	1.536	1.730
Mother's years of education	8.986	8.697	7.791
Low income household	0.409	0.442	0.535
Distance to small center (s), in km	0.299	0.331	0.290
Children development at baseline			
Cognitive	0.027	-0.094	0.121
Socio-emotional	-0.022	0.091	-0.135
Nutritional	0.035	0.068	-0.323
Outcomes [Obs.]			
Cognitive [1231]	0.166 [674]	-0.021 [401]	-0.662 [156]
Socio-emotional [1238]	-0.064 [678]	-0.035 [403]	0.368 [157]
Nutritional [927]	0.127 [513]	0.007 [299]	-0.584 [115]
%	54.9	32.34	12.76
N	684	403	159

Source: subsample from Bernal et al. (2019).
Note: The sample consists of children who were initially at small centers. All socioeconomic variables were collected at baseline. Cognitive development is a composite of scores from the ASQ. Socio-emotional development is a composite of behavioral components of the ASQ. All scores from the ASQ are age standardized. Nutritional development corresponds to z-scores for weight-for-age, height-for-age, and weight for height.

Table 8: Average of instruments, by type of childcare

Variable	Large centers (l)	Small centers (s)	Home care (h)	All
Wins lottery	0.805	0.615	0.802	0.743
Distance to large center (l), in km	0.668	1.125	0.912	0.848

Source: subsample from Bernal et al. (2019).
Note: The sample consists of children who were initially at small centers. Each column represents a childcare choice; the last column presents averages for the full sample for comparison. The row "Wins lottery" refers to the fraction of households that where assigned to received information and the option to transfer to large centers. Distance to large centers is the geographic distance from the child's home to the nearest large center, in km.

Table 9: Average characteristics, by enrollment choice and eligibility sample

	Need-eligible			Merit-eligible		
Variable	High-quality HEI (h)	Low-quality HEI (l)	Not enrolled (n)	High-quality HEI (h)	Low-quality HEI (l)	Not enrolled (n)
Age at Saber 11	16.875	16.937	17.476	16.807	16.767	17.499
Female	0.469	0.538	0.526	0.437	0.423	0.445
Household size	4.520	4.611	4.739	4.380	4.232	4.329
Mother's educ: primary	0.208	0.222	0.359	0.155	0.137	0.191
Mother's educ: secondary	0.472	0.485	0.485	0.439	0.444	0.464
Mother's educ: 2-year college	0.168	0.150	0.093	0.181	0.196	0.159
Mother's educ: 4-year college+	0.152	0.143	0.062	0.225	0.223	0.186
Household SES: lowest	0.304	0.385	0.386	0.178	0.147	0.141
Outcomes						
Formally employed in 2021	0.549	0.484	0.443	0.583	0.568	0.428
%	13.7	16.8	69.5	46.7	17.7	35.6
N	11,926	14,607	60,608	6,842	2,599	5,217

Source: subsample from Londoño-Vélez et al. (2023).

Note: The sample consists of students belonging to the first cohort of SPP, and all the socioeconomic variables are measured in 2014 prior to the enrollment choice and the SPP announcement. Household SES consists of 6 socioeconomic stratum, with strata 1 denoting the lowest socioeconomic level. The outcome is a binary variable that indicates if the student was working in the formal labor market in 2021 which is measured by whether the student contributed to social security and was recorded in PILA during that year. Need-eligible (merit-eligible) denotes students who were below the poverty score cutoff for SPP (above the high school exit exam score cutoff for SPP).

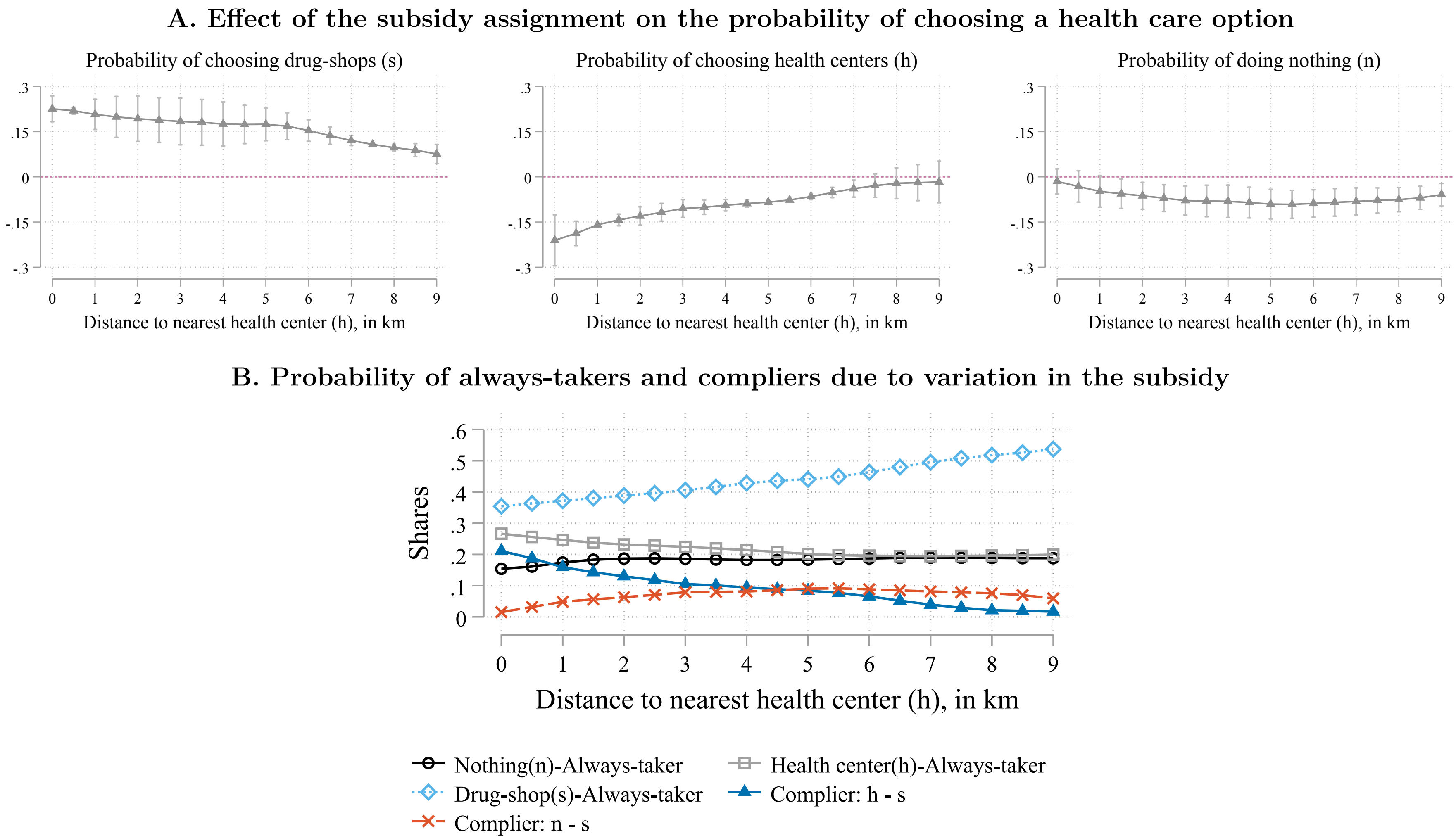
Table 10: Average of instruments, by enrollment choice and eligibility sample

Variable	Need-eligible			Merit-eligible		
	High-quality HEI (h)	Low-quality HEI (l)	Not enrolled (n)	High-quality HEI (h)	Low-quality HEI (l)	Not enrolled (n)
Eligible	0.721	0.108	0.062	0.746	0.317	0.371
Distance to high-quality HEI	50.945	74.091	62.645	38.640	44.032	37.333
Distance to low-quality HEI	12.751	14.572	16.332	10.052	6.901	8.792
N	11,926	14,607	60,608	6,842	2,599	5,217

Source: subsample from Londoño-Vélez et al. (2023).

Note: The sample consists of students belonging to the first cohort of SPP. Need-eligible (merit-eligible) denotes students who were below the poverty score cutoff for SPP (above the high school exit exam score cutoff for SPP). The row "Eligible" for the need-eligible (merit-eligible) refers to the fraction of students above the high school exit exam cutoff (below the poverty score cutoff). Distance to high– and low-quality HEI is the geographic distance from the student's high school to the nearest high– and low-quality HEI respectively, in km.

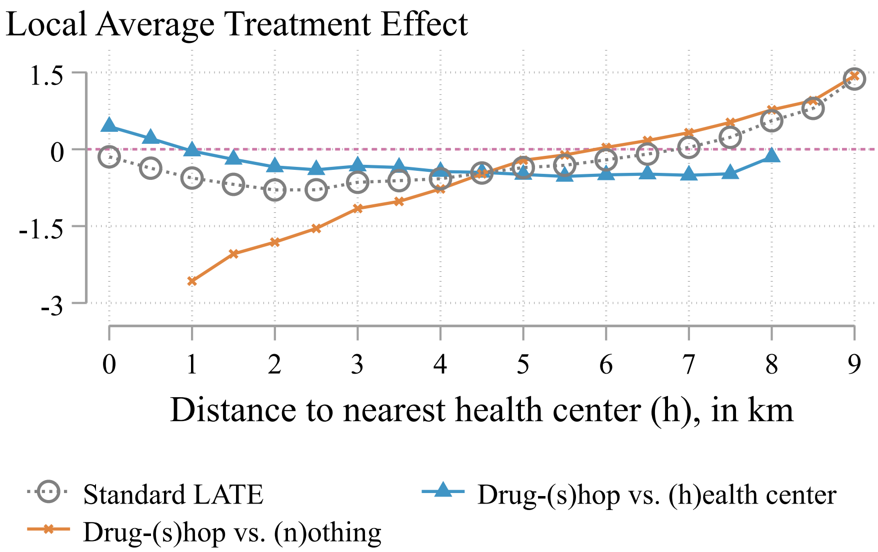
Figure 2: Effect of the subsidy assignment on the probability of choosing a health care option, by distance to the nearest health center

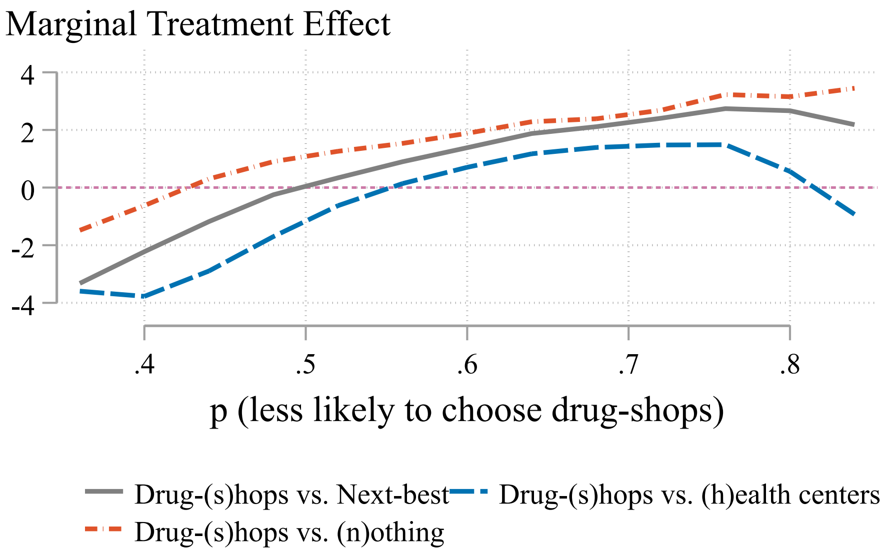


Source: subsample from Cohen et al. (2015).

Note: Panel A. shows the effect of the subsidy on the probability of choosing the drug-shop, health centers, and no care. Effects are computed with a semiparametric regression using an Epanechnikov kernel around different evaluations points of the distance to the nearest health center. All figures show confidence intervals at the 90% level. Panel B. shows the estimated probability of always-takers and compliers induced by the variation of the subsidy assignment, by distance to the nearest health care center.

Figure 3: Treatment Effect of choosing drug-shops on the number of illness episodes at endline, by distance to the nearest health center



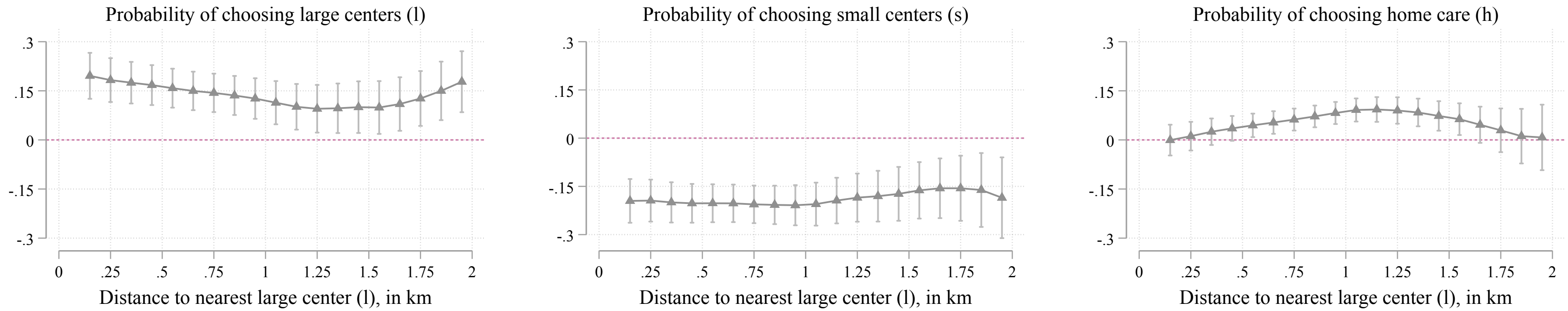


Source: subsample from Cohen et al. (2015).

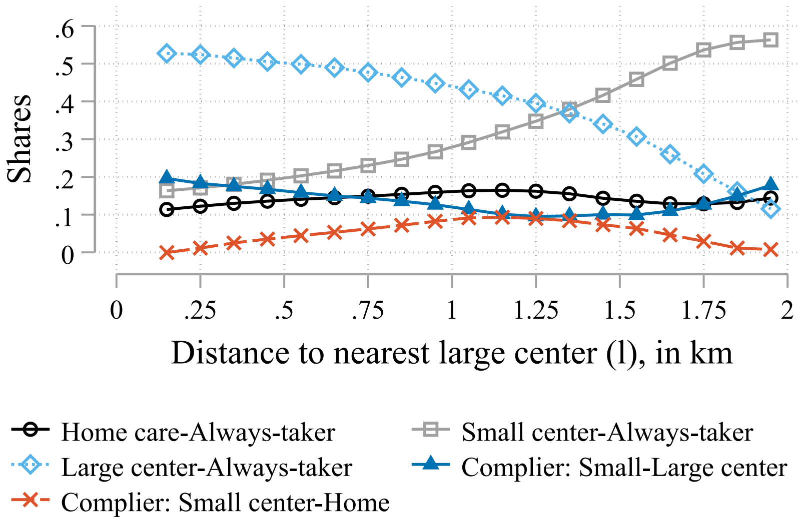
Note: The figure at the top shows the estimated local average treatment effects for compliers induced by the variation of the subsidy assignment, by distance to the nearest health care center. The figure at the bottom shows the estimated marginal treatment effects for s vs. the next-best (in black), s vs. h (in blue), and s vs. n (in red), by distance to the nearest health care center. Higher (lower) values on the horizontal axis represent households who are less (more) likely to choose s. The vertical axis measures effects on the number of illness episodes of the household at baseline.

Figure 4: Effect of the lottery outcome on the probability of choosing a type of childcare, by distance to the nearest large center

A. Effect of the lottery outcome on the probability of choosing a type of childcare

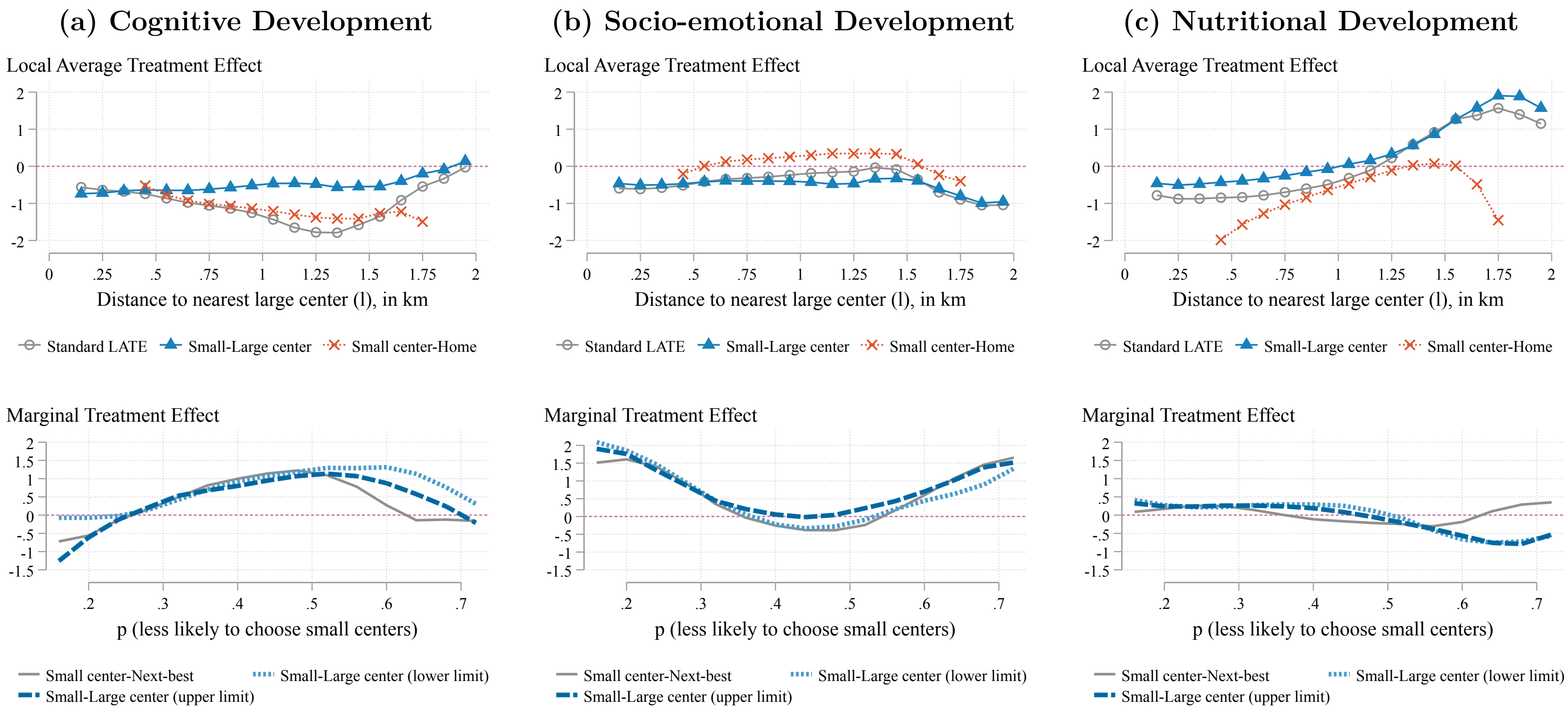


B. Probability of always-takers and compliers due to variation in the lottery outcome



Source: subsample from Bernal et al. (2019).
Note: Panel A. shows the effect of the lottery outcome on the probability of choosing the large centers, small centers, and home care. Effects are computed with a semiparametric regression using an Epanechnikov kernel around different evaluations points of the distance to the nearest large center. All figures show confidence intervals at the 90% level. Panel B. shows the estimated probability of always-takers and compliers induced by the variation of the lottery outcome, by distance to the nearest large center.

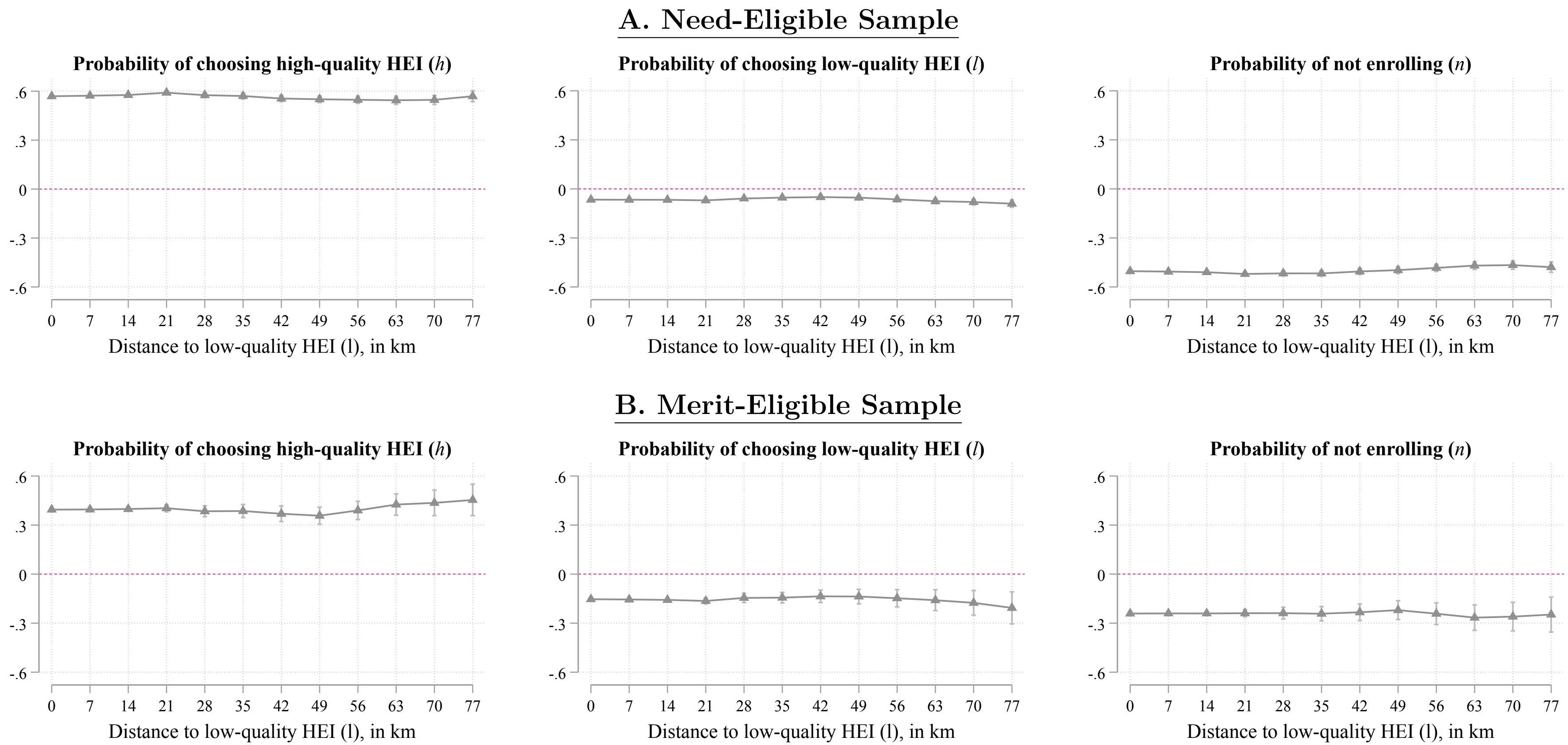
Figure 5: Treatment Effects for compliers along the large *versus* small center margin and the home-care *versus* small center margin, by distance to the nearest large center (l)



Source: subsample from Bernal et al. (2019).

Note: The figure presents estimated treatment effects for cognitive development in column (a), socio-emotional development in column (b), and nutritional development in column (c). Figures in the top row show the estimated local average treatment effects for compliers induced by the variation in the lottery outcome, by distance to the nearest large center. The bottom row shows estimates of MTEs for small-center vs. the next-best and evaluated at the minimum and maximum distances to the large center. Higher (lower) values on the horizontal axis represent households who are less (more) likely to choose small centers. The vertical axis measures effects on standard deviations of developmental measures.

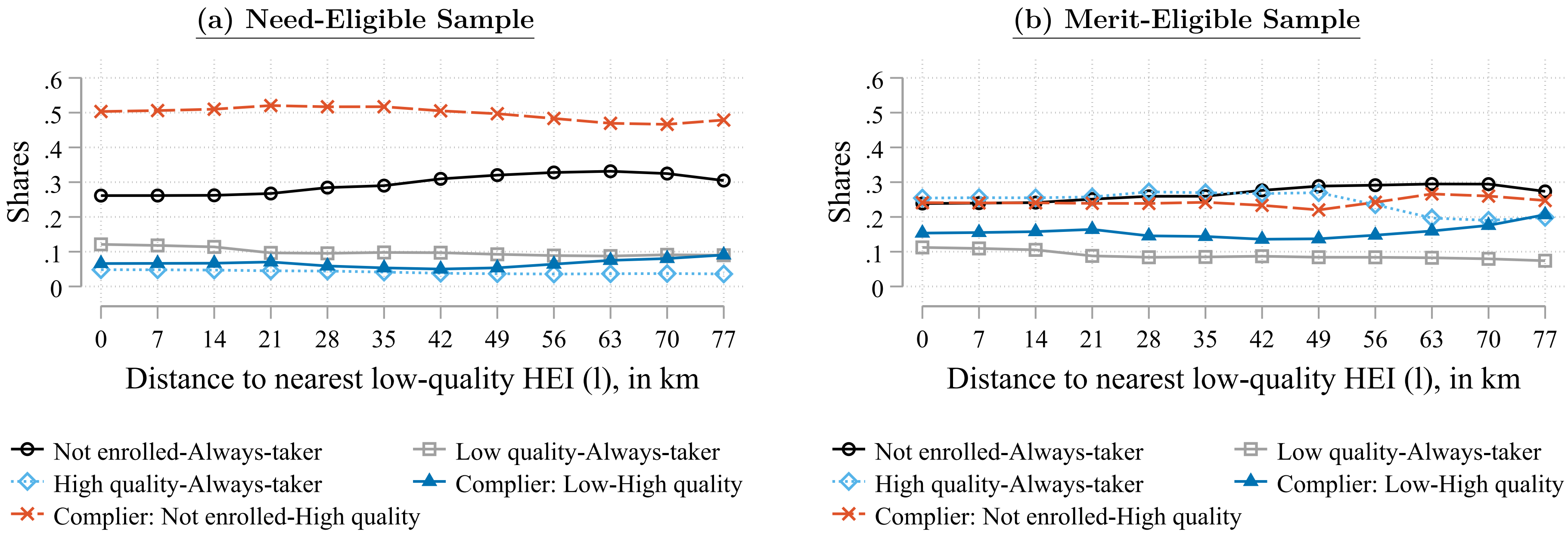
Figure 6: Effect of SPP eligibility on the probability of enrolling in higher ed., by eligibility and distance to the nearest low-quality HEI



Source: subsample from Londoño-Vélez et al. (2023).

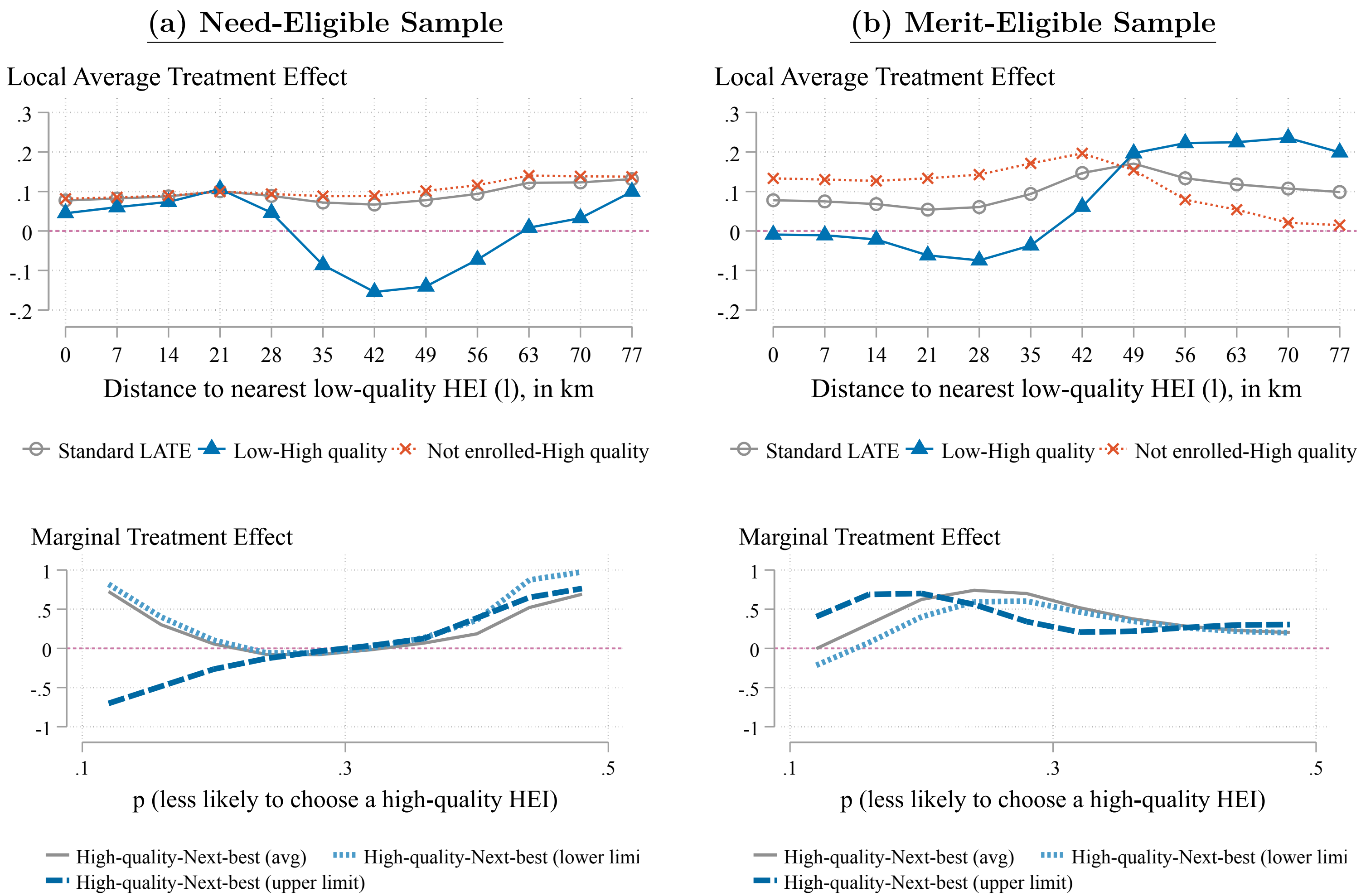
Note: Panel A. shows the effect of being above the high school exit exam cutoff for need-eligible students on the probability of choosing a high-quality HEI, a low-quality HEI, and not enrolling. Panel B. shows the effect of being below the poverty score cutoff for merit-eligible students on the probability of choosing a high-quality HEI, a low-quality HEI, and not enrolling. Effects are computed with a semiparametric regression using an Epanechnikov kernel around different evaluations points of the distance to the nearest high-quality HEI. All figures show confidence intervals at the 90% level.

Figure 7: Probability of always-takers and compliers due to variation in eligibility, by distance to the nearest low-quality HEI (l)



Source: subsample from Londoño-Vélez et al. (2023).
Note: The Figure shows the estimated probability of always-takers and compliers induced by the variation in eligibility, by sample and distance to the nearest low-quality HEI. Panel (a) presents estimates of group shares for the need-eligible students using as IV a binary indicator taking the value of one if the student is above the high school exit exam cutoff, and zero otherwise. Panel (b) presents estimates of group shares for the merit-eligible students using as IV a binary indicator taking the value of one if the student is below the poverty score cutoff, and zero otherwise.

Figure 8: Treatment Effects on the probability of formal employment for compliers along the low *versus* high-quality HEI margin and the margin of not enrolled *versus* high-quality HEI, by distance to the nearest low-quality HEI (l)



Source: subsample from Londoño-Vélez et al. (2023)

Note: The figure presents estimated treatment effects on the probability of formal work. The top row shows the estimated local average treatment effects for compliers induced by the variation in the SPP eligibility, by distance to the nearest low-quality HEI. The hollow gray circles show estimates of the LATE of enrolling in a high-quality HEI vs. the next best. The blue triangles and red x show estimates of LATEs for the high– vs. low-quality HEI margin and the high-qaulity vs. not enrolling margin, respectively. The bottom row shows estimates of MTEs for high-quality HEI vs. the next-best and evaluated at the minimum and maximum distances to the nearest low-quality HEI. Higher (lower) values on the horizontal axis represent students who are less (more) likely to choose high-quality HEI.

Appendix A

A.1 Econometric Model: discrete IVs

This appendix follows the econometric model and identification results in Heckman and Pinto (2018). Assume that instruments in $Z = \{Z_1, ..., Z_L\}$ satisfy *A1*; and that the restrictions in *R1*, which imply *A2*, also hold. I keep implicit the variables in $\mathbf{X}$. For simplification, let $D(z_k, Z_l)$ denote potential choices at $Z_k = z_k$, which satisfy *A2* conditional on Z_l. Combinations of conditional potential choices, $D(z_k|z_l)$, define response vectors $S_k(z_l) = [D(z_k|z_l), D(z'_k|z_l)]'$. Combinations of $S_k(z_l)$ define conditional response matrices, $R_k(Z_l)$ with dimension $w \times N_{S,z_l}$, where w is the number of values of the instrument at which agents' potential behavior is evaluated. Each column in $R_k(Z_l)$ denotes a type of response, denoted as $g \in \{1, ..., N_{S,z_l}\}$. For instance, in the binary-treatment-binary-IV case, g_1 denotes always-takers, g_2 denotes never-takers, and g_3 denotes compliers.

Let $B^k_k(Z_l)$ denote a binary matrix that takes the value of one every time option k is chosen in matrix $R_k(Z_l)$. Define $B_k(Z_l)$ as a matrix that stacks option specific B^k_k such that:

$$B_k(Z_l) = \left(B^1_k(Z_l)', B^2_k(Z_l)', .., B^K_k(Z_l)'\right)'$$

Importantly, matrix $B_k(Z_l)$ depends on Z_l. This matrix weights observed choices and outcomes based on admissible potential responses (i.e., conditional rules of behavior) to changes in the instruments. Appendix A.2 describes how to estimate the probability of each type of response in $R_k(Z_l)$, as well as their average baseline characteristics.

The identification of counterfactuals for each response in matrix $R_k(Z_l)$ depends on the margins and choices agents are induced to choose as a result of variation in Z_k. For instance, if Z_k induces agents away from choosing option 1 and option 2 and towards choosing option 3 there is not enough variation to separately identify the counterfactuals of choosing option 3 along both margins. Therefore, the researcher can identify the counterfactual of option 3 *versus* the next-best (i.e., what the agent would have chosen if option 3 was no longer available).

To define the counterfactuals that can be identified, let $\sum_{k,k}(q|Z_l)$ be a set that contains responses in matrix $R_k(Z_l)$ where k appears q times, with $q \in \{1, ..., w\}$. The first subindex in $\sum_{k,k}(q|Z_l)$ denotes the option, k, and the second subindex denotes the IV, Z_k. Let $b_{k,k}(q|Z_l)$ be a binary vector that takes the value of one every time option k appears q times in matrix $R_k(Z_l)$. Let YD_k denote a vector of interactions between outcome Y and choice $k \in \{1, 2, ..K\}$. Define $L^k_{Yk}(Z_l) = [E[YD_k|z_k, Z_l], E[YD_k|z'_k, Z_l]]'$ as the average of outcome Y when option $k \in \{1, 2, ..K\}$ is chosen, evaluated at realizations z_k, z'_k conditional on Z_l. If assumption *A2* holds, then the following counterfactuals can be identified:

$$E\left(Y_k \mid S \in \sum_{k,k}(q|Z_l)\right) = \frac{b_{k,k}(q|Z_l)B_k^{k+}(Z_l)L_{Yk}^{k}(Z_l)}{b_{k,k}(q|Z_l)B_k^{k+}(Z_l)\mathrm{Pr}_{Z_k}(D=k|Z_l)} \tag{6}$$

where $B_k^{k+}(Z_l)$ is the Moore-Penrose pseudoinverse; and $\mathrm{Pr}_{Z_k}(D=k|Z_l)$ is the propensity score of choice k evaluated at realizations $z_k, z_k' \in \mathrm{supp}(Z_k)$, conditional on Z_l. That is, $\mathrm{Pr}_{Z_k}(D=k|Z_l) = [\mathrm{Pr}_{Z_k}(D=k|z_k, Z_l), \mathrm{Pr}_{Z_l}(D=k|z_l', Z_l)]$. Appendix A.3 formally shows how partial monotonicity in *A2* translates into the identification of conditional counterfactuals in equation (6).

If the set $\sum_{k,k}(q|Z_l)$ contains exactly one element then response specific counterfactuals can be identified. Otherwise, the counterfactuals for k, such that set $\sum_{k,k}(q|Z_l)$ is not unique, are a combination of next-best alternatives. Consequently, in cases as the latter the researcher cannot separately identify local treatment effects for each choice k. Instead, it is possible to estimate local treatment effects of choice k *versus* the next-best.

A.2 Probability of groups and their average baseline characteristics

This appendix follows the identification results in Heckman and Pinto (2018), and the results for response vectors $S_k(z_l)$ and binary matrix $B_k^k(Z_l)$ for choice $k \in \{1, 2, ..., K\}$ in Section A.1. Let $P_{gk}(Z_l)$ represent a vector containing the shares of each type of response in matrix $R_l(Z_l)$. These shares can be identified from:

$$P_g(Z_l) = B_k^+(Z_l)\mathrm{Pr}_{Z_k}(D|Z_l) \tag{7}$$

where $B_k^+(Z_l)$ is the Moore-Penrose pseudoinverse.[37] Vector $\mathrm{Pr}_{Z_k}(D|Z_l)$ contains the propensity score for choices $k \in \{1, 2, ..., K\}$ evaluated at instrument Z_k, conditional on Z_l. I denote the shares as functions of Z_l, to indicate that the prevalence of different types of responses can vary depending on the evaluation point in Z_l. Let $\mathrm{Pr}_{Z_k}(D=k|Z_l) = [\mathrm{Pr}_{Z_k}(D=k|z_k, Z_l), \mathrm{Pr}_{Z_k}(D=k|z_k', Z_l)]$ be the propensity score of choice k evaluated at realizations $z_k, z_k' \in \mathrm{supp}(Z_k)$, conditional on Z_l. Thus,

$$\mathrm{Pr}_{Z_k}(D|Z_l) = [\mathrm{Pr}_{Z_k}(D=1|Z_l), \mathrm{Pr}_{Z_k}(D=2|Z_l), ..., \mathrm{Pr}_{Z_l}(D=K|Z_l)]' \tag{8}$$

and its dimension is $(w \cdot K) \times 1$. Intuitively, the identification of shares of responses is a weighed combination of observed choices and potential behavior at different values of the instruments, given Z_l.

Let $E[X_{gk}(Z_l)]$ denote the average of baseline variables and $E[Y_{gk}(Z_l)]$ the average

[37] For instance, if $B_k(Z_l)$ has full-rank then $B_k^+(Z_l) = (B_k(Z_l)'B_k(Z_l))^{-1} B_k(Z_l)'$.

counterfactuals for response g in matrix matrix $R_k(Z_l)$. To identify the average of baseline variables and counterfactuals of the responses in matrix $R_k(Z_l)$ define $\omega(Z_l) = B_k(Z_l) \circ P_{gk}(Z_l)'$. That is, $\omega(Z_l)$ is the element-wise multiplication of matrix $B_k(Z_l)$ and the shares of responses in $P_{gk}(Z_l)$. Let XD_k denote a vector of baseline variables and choices interactions, for $X \in \mathbf{X}$. For each choice $k \in \{1, ..., K\}$ define $L^k_{Xk}(Z_l) = [E[XD_k|z_k, Z_l], E[XD_k|z'_k, Z_l]]$ which is the observed average of baseline variable X when option k is chosen, evaluated at realizations z_k, z'_k conditional on Z_l. Vector $L_{Xk}(Z_l)$ stacks choice specific $L^k_{Xk}(Z_l)$ such that $L_{Xk}(Z_l) = [L^{k=1}_{Xk}(Z_l), L^{k=2}_{Xk}(Z_l), ..., L^{k=K}_{Xk}(Z_l)]'$. The average of baseline variables for each response, g, in matrix $R_k(Z_l)$ corresponds to:

$$E[X_{gk}(Z_l)] = \omega^+(Z_l)L_{Xk}(Z_l) \tag{9}$$

The shares of responses, g, in equation 7 and their average baseline variables in equation 9 can be identified if $\text{rank}\,(B_k(Z_l)) = N_{S,z_l}$.[38]

A.3 Proofs

Convexity of costs and partial monotonicity Let $k \in \{1, 2, ..., K\}$ and k^- represent choices other than k. Let $U_{ik}(z) = \mu_{ik} - V_{ik}(z)$ denote the utility of choice k evaluated at realization z of the instruments in $\mathbf{Z}$. μ_{ik} represent unobserved preferences for choice k, $V_{ik}(z)$ denote the costs of choosing option k. Let (z_l, z_{l^-}) and (z'_l, z_{l^-}) be two realizations of $Z_l, Z_{l^-} \in \mathbf{Z}$, and suppose $z_l < z'_l$. From element-wise convexity of V_{ik} in R1 it follows that $\frac{\partial^2 V_{ik}(Z_l, z_{l^-})}{\partial Z_l^2} \geq 0$.

For convex and decreasing costs, then $V_{ik}(z_l, z_{l^-}) \geq V_{ik}(z'_l, z_{l^-})\ \forall i$. Suppose that $Z_k \cap Z_{k^-} = \emptyset$, such that the restriction in R1.2 holds and there is no intersection in the instruments that affect each choice (i.e., $\frac{\partial V_{ik^-}(Z_l, z_{l^-})}{\partial Z_l} = 0$). Then, $U_{ik}(z_l, z_{l^-}) \leq U_{ik}(z'_l, z_{l^-})$, and $U_{ik^-}(z_l, z_{l^-}) = U_{ik^-}(z'_l, z_{l^-})$. Thus, $(z_l, z_{l^-}) \to (z'_l, z_{l^-})$ weakly induces agents towards k such that $D_{ik}(z_l, z_{l^-}) \leq D_{ik}(z'_l, z_{l^-})\ \forall i$. Similarly for convex and increasing costs, then $V_{ik}(z_l, z_{l^-}) \leq V_{ik}(z'_l, z_{l^-})\ \forall i$. Suppose $\frac{\partial V_{ik^-}(Z_l, z_{l^-})}{\partial Z_l} = 0$. Then, $U_{ik}(z_l, z_{l^-}) \geq U_{ik}(z'_l, z_{l^-})$, and $U_{ik^-}(z_l, z_{l^-}) = U_{ik^-}(z'_l, z_{l^-})$. Thus, $(z_l, z_{l^-}) \to (z'_l, z_{l^-})$ weakly induces agents away from d such that $D_{ik}(z_l, z_{l^-}) \geq D_{ik}(z'_l, z_{l^-})\ \forall i$.

Consider the case of $Z_k \cap Z_{k^-} \neq \emptyset$ and let $Z_{l^-} \in Z_k \cap Z_{k^-}$, such that there is at least one instrument that affects d and k^-. From R1, it follows that $V_{ik}(Z_l, Z_{l^-})$ and $V_{ik^-}(Z_l, Z_{l^-})$ are element-wise convex. Suppose $\frac{\partial V_{ik}(Z_l, Z_{l^-})}{\partial Z_{l^-}} \leq 0$ and $\frac{\partial V_{ik^-}(Z_l, Z_{l^-})}{\partial Z_{l^-}} \leq 0$ and assume $\frac{\partial^2 V_{ik}(Z_l, z_{l^-})}{\partial Z_l^2} > \frac{\partial^2 V_{ik}(Z_l, z_{l^-})}{\partial Z_l^2}$ such that costs decrease faster for k. Then $V_{ik}(z_l, z_{l^-}) \leq V_{ik}(z'_l, z_{l^-})$ implies $U_{ik}(z_l, z_{l^-}) \geq U_{ik}(z'_l, z_{l^-})$ and $(z_l, z_{l^-}) \to (z'_l, z_{l^-})$

[38] This follows from the identification result in Heckman and Pinto (2018) for unconditional matrix B.

weakly induces agents away from d such that $D_{ik}(z_l, z_{l^-}) \leq D_{ik}(z_l', z_{l^-})$ $\forall i$. Similarly, suppose $\frac{\partial V_{ik}(Z_l, Z_{l^-})}{\partial Z_{l^-}} \geq 0$ and $\frac{\partial V_{ik^-}(Z_l, Z_{l^-})}{\partial Z_{l^-}} \geq 0$ and $\frac{\partial^2 V_{ik}(Z_l, z_{l^-})}{\partial Z_l^2} > \frac{\partial^2 V_{ik}(Z_l, z_{l^-})}{\partial Z_l^2}$. Then $V_{ik}(z_l, z_{l^-}) \leq V_{ik}(z_l', z_{l^-})$ implies $U_{ik}(z_l, z_{l^-}) \geq U_{ik}(z_l', z_{l^-})$ and $(z_l, z_{l^-}) \rightarrow (z_l', z_{l^-})$ weakly induces agents away from k such that $D_{ik}(z_l, z_{l^-}) \leq D_{ik}(z_l', z_{l^-})$ $\forall i$.

Conditional/Partial monotonicity and identification of counterfactuals

Let R denote a response matrix and let $B_k = \mathbf{1}[R = k]$ for $k \in \text{supp}(D)$. That is, B_k is a binary matrix that takes the value of one every time k appears in response matrix R. Heckman and Pinto (2018) define unordered monotonicity such that:

A3 *(Unordered Monotonicity)* For any $z, z' \in \mathcal{Z}$[39] and each $d \in \{1, 2, 3, .., k\}$ either $\mathbb{1}[D_i(z) = k] \geq \mathbb{1}[D_i(z') = k]$ $\forall i$, or, $\mathbb{1}[D_i(z) = k] \leq \mathbb{1}[D_i(z') = k]$ $\forall i$.

Assumption A2 is a weaker version of A3, thus if A3 holds then A2 holds. The opposite does not hold; that is, partial monotonicity does not imply unordered monotonicity. For unconditional response matrix R, Heckman and Pinto (2018) show that R is unordered monotonic if and only if each $B_k = \mathbf{1}[R = k]$ is lonesum such that there are no two-way patterns in any sub-matrix of dimension 2×2. That is, there is no 2×2 sub-matrix in R that takes the form of:

$$\begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} \qquad \begin{vmatrix} 0 & 1 \\ 1 & 0 \end{vmatrix}$$

For the IV Model with A1, unconditional response matrix R is not unordered monotonic. Nonetheless, from A2 it follows that $R_l(Z_{l^-})$ satisfies that each $B_l^k = \mathbf{1}[R_l(Z_{l^-}) = k]$ is lonesum, with $k \in \text{supp}(D)$. Suppose not. If B_l^k is not lonesum, then there is at least one 2×2 sub-matrix that takes either of the following forms:

$$\begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} \qquad \begin{vmatrix} 0 & 1 \\ 1 & 0 \end{vmatrix}$$

Given that $B_l^k = \mathbf{1}[R_l(Z_{l^-}) = k]$, two-way patterns are defined by conditional response matrix $R_l(Z_{l^-})$. By definition of $R_l(Z_{l^-})$, there is a response vector $S_{la}(Z_{l^-})$ and $S_{lb}(Z_{l^-})$ such that $\mathbf{1}[S_{la}(Z_{l^-}) = k] = [1, 0]'$ and $\mathbf{1}[S_{lb}(Z_{l^-})] = [0, 1]'$. Then, $D_{ak}(z, Z_{l^-}) \geq D_{ak}(z', Z_{l^-})$ and $D_{bk}(z, Z_{l^-}) \leq D_{bk}(z', Z_{l^-})$. This contradicts A2. Hence, conditional response matrix $R_l(Z_{l^-})$ and conditional binary matrices for each k, $B_l^k(Z_{l^-})$, are lonesum. Then, applying Theorem T-6 in Heckman and Pinto (2018) to the case of conditional response matrix, the counterfactuals for responses g are identified by:

$$E\left(Y_k \mid S \in \textstyle\sum_{kl}(q|Z_{l^-})\right) = \frac{b_{kl}(q|Z_{l^-}) B_l^{k+}(Z_{l^-}) L_{Yl}^k(Z_{l^-})}{b_{kl}(q|Z_{l^-}) B_l^{k+}(Z_{l^-}) \text{Pr}_{Z_l}(D = k|Z_{l^-})}$$

where $B_l^{k+}(Z_{l^-})$ is the Moore-Penrose pseudoinverse.

[39] Recall $z \in \mathcal{Z}$ is a combination of $(Z_{i,1}, ..., Z_{i,L})$

A.4 Multiple choices and identification of pairwise treatment effects

Let Y_k denote the potential outcome that the agent would derive from choosing option $k \in \{1, 2, .., K\}$, with $\mathcal{K}$ denoting the choice set containing those alternatives, and let $D_{\mathcal{K},k}$ denote a binary variable taking the value of one if option k is chosen from choice set $\mathcal{K}$. Potential choices are denoted as $D_{\mathcal{K},k}(0)$ and $D_{\mathcal{K},k}(1)$, binary variables taking the value of one if the agent would have chosen option k when facing $Z_k = 0$ and $Z_k = 1$, respectively. The observed outcome results from a switching regression model, $Y = \sum_{k=1}^{K} D_{\mathcal{K},k} Y_k$, which can be partitioned into two components:

$$Y = D_{\mathcal{K},k} Y_k + (1 - D_{\mathcal{K},k}) Y_{\mathcal{K}\setminus k},$$

where $D_{\mathcal{K},k}$ is a binary indicator taking the value of one if option k is chosen from choice set $\mathcal{K}$, and $Y_{\mathcal{K}\setminus 1}$ denotes the potential outcome that would have been observed if option 1 would have not been available. That is, $Y_{\mathcal{K}\setminus k} = \sum_{l \in \mathcal{K}\setminus k} \frac{D_{\mathcal{K},l}}{(1-D_{\mathcal{K},k})} Y_l$. Assume that Z_k is a binary IV, which satisfies A1 and A2, that induces agents towards k and away from all other options, $l \in \mathcal{K}\setminus k$. It follows that,

$$\begin{aligned}
E[Y|Z_k = 1] &= E[D_{\mathcal{K},k} Y_k + (1 - D_{\mathcal{K},k}) Y_{\mathcal{K}\setminus k} | Z_k = 1] \\
&= E[D_{\mathcal{K},k} Y_k | Z_k = 1] + E[(1 - D_{\mathcal{K},k}) Y_{\mathcal{K}\setminus k} | Z_k = 1] \\
&= E[Y_k | Z_k = 1, D_{\mathcal{K},k} = 1] \Pr(D_{\mathcal{K},k} = 1 | Z_k = 1) \\
&+ E[Y_{\mathcal{K}\setminus k} | Z_k = 1, D_{\mathcal{K},k} = 0] \Pr(D_{\mathcal{K},k} = 0 | Z_k = 1),
\end{aligned}$$

and,

$$\begin{aligned}
E[Y|Z_k = 0] &= E[D_{\mathcal{K},k} Y_k + (1 - D_{\mathcal{K},k}) Y_{\mathcal{K}\setminus k} | Z_k = 0] \\
&= E[D_{\mathcal{K},k} Y_k | Z_k = 0] + E[(1 - D_{\mathcal{K},k}) Y_{\mathcal{K}\setminus k} | Z_k = 0] \\
&= E[Y_k | Z_k = 0, D_{\mathcal{K},k} = 1] \Pr(D_{\mathcal{K},k} = 1 | Z_k = 0) \\
&+ E[Y_{\mathcal{K}\setminus k} | Z_k = 0, D_{\mathcal{K},k} = 0] \Pr(D_{\mathcal{K},k} = 0 | Z_k = 0).
\end{aligned}$$

By *A1* and *A2*,

$$\begin{aligned}
E[Y|Z_k = 1] = E[Y_k | D_{\mathcal{K},k}(0) = 1, D_{\mathcal{K},k}(1) = 1] \Pr(D_{\mathcal{K},k}(0) = 1, D_{\mathcal{K},k}(1) = 1) \\
+ E[Y_k | D_{\mathcal{K},k}(0) = 0, D_{\mathcal{K},k}(1) = 1] \Pr(D_{\mathcal{K},k}(0) = 0, D_{\mathcal{K},k}(1) = 1) \\
+ E[Y_{\mathcal{K}\setminus k} | D_{\mathcal{K},k}(0) = 0, D_{\mathcal{K},k}(1) = 0] \Pr(D_{\mathcal{K},k}(0) = 0, D_{\mathcal{K},k}(1) = 0),
\end{aligned}$$

and,

$$\begin{aligned}E[Y|Z_k=0] &= E[Y_k|D_{\mathcal{K},k}(0)=1, D_{\mathcal{K},k}(1)=1]\Pr(D_{\mathcal{K},k}(0)=1, D_{\mathcal{K},k}(1)=1)\\ &+E[Y_{\mathcal{K}\backslash k}|D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=0]\Pr(D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=0)\\ &+E[Y_{\mathcal{K}\backslash k}|D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1]\Pr(D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1).\end{aligned}$$

Hence,

$$\begin{aligned}E[Y|Z_k=1]-E[Y|Z_k=0] &= E[Y_k|D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1]\Pr(D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1)\\ &-E[Y_{\mathcal{K}\backslash k}|D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1]\Pr(D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1)\\ &= E[Y_k - Y_{\mathcal{K}\backslash k}|D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1]\Pr(D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1),\end{aligned}$$

where the first term on the right-hand side is the local average treatment effect of choosing option k *versus* the next-best (*i.e.*, what the agent would have chosen if option k was not available).

Similarly, by *A1* and *A2*,

$$\begin{aligned}E[D_{\mathcal{K},k}|Z_k=1] &= \Pr(D_{\mathcal{K},k}=1, Z_k=1)\\ &= \Pr(D_{\mathcal{K},k}(1)=1)\\ &= \Pr(D_{\mathcal{K},k}(0)=1, D_{\mathcal{K},k}(1)=1)\\ &+ \Pr(D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1),\end{aligned}$$

and,

$$\begin{aligned}E[D_{\mathcal{K},k}|Z_k=0] &= \Pr(D_{\mathcal{K},k}=1, Z_k=0)\\ &= \Pr(D_{\mathcal{K},k}(0)=1, D_{\mathcal{K},k}(1)=1)\end{aligned}$$

Thus,

$$E[D_{\mathcal{K},k}|Z_k=1]-E[D_{\mathcal{K},k}|Z_k=0] = \Pr(D_{\mathcal{K},k}(0)=1, D_{\mathcal{K},k}(1)=1).$$

Then, the Wald estimator identifies the local average treatment effect of choosing option k *versus* the next-best alternative,

$$\frac{E[Y|Z_k=1]-E[Y|Z_k=0]}{E[D_{\mathcal{K},k}|Z_k=1]-E[D_{\mathcal{K},k}|Z_k=0]} = E[Y_k - Y_{\mathcal{K}\backslash k}|D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1].$$

In terms of the Marginal Treatment Effect, note that identification relies on the variation of the binary instrument, Z_k. Invoking the identification arguments in Brinch et al. (2017), and explicitly conditioning on X, the MTE of option k vs. the next-best can be identified,

$$\frac{\partial E(Y|P(Z)=p, X=x)}{\partial p} = E[Y_k - Y_{\mathcal{K}\setminus k}|Z=z, U_1(z)=U_{\mathcal{K}\setminus k}(z)]$$
$$= E[Y_k - Y_{\mathcal{K}\setminus k}|X=x, Z=z, \mu_k=p],$$

where p a realization of the propensity score, $P(Z)$, of choosing option k vs. the next-best, and μ_k denotes the unobserved component in the latent utility of choosing option k. That is, using the variation in Z_k and imposing parametric restrictions on the shape of the MTE, the average treatment effect of option k for those on the margin of indifference between choosing k and not choosing it, *i.e.*, $\text{MTE}_{k,\mathcal{K}\setminus k}$, can be identified.

Decomposition into pairwise treatment effects: Note that,

$$\begin{aligned}
E[(1-D_{\mathcal{K},k})Y_{\mathcal{K}\setminus k}|Z_k=1] &= \sum_{l\in\mathcal{K}\setminus k} E\left[D_{\mathcal{K},l}Y_l|Z_k=1\right] \\
&= \sum_{l\in\mathcal{K}\setminus k} E\left[Y_l|Z_k=1, D_{\mathcal{K},l}=1\right]\Pr(D_{\mathcal{K},l}=1|Z_k=1) \\
&= \sum_{l\in\mathcal{K}\setminus k} E\left[Y_l|D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=1\right]\Pr(D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=1)
\end{aligned}$$

Similarly,

$$\begin{aligned}
E[(1-D_{\mathcal{K},k})Y_{\mathcal{K}\setminus k}|Z_k=0] &= \sum_{l\in\mathcal{K}\setminus k} E\left[Y_l|Z_k=0, D_{\mathcal{K},l}=1\right]\Pr(D_{\mathcal{K},l}=1|Z_k=0) \\
&= \sum_{l\in\mathcal{K}\setminus k} E\left[Y_l|D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=1\right]\Pr(D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=1) \\
&\qquad + E\left[Y_l|D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=0\right]\Pr(D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=0)
\end{aligned}$$

Plus,

$$\Pr(D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1) = \sum_{l\in\mathcal{K}\setminus k} \Pr(D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=0)$$

Hence,

$$\begin{aligned}
E[Y|Z_k=1]-E[Y|Z_k=0] &= E[Y_k|D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1]\Pr(D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1) \\
&\quad - \sum_{l\in\mathcal{K}\setminus k} E\left[Y_l|D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=0\right]\Pr(D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=0) \\
&= \sum_{l\in\mathcal{K}\setminus k} E[Y_k - Y_l|D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=0]\Pr(D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=0),
\end{aligned}$$

and the Wald estimator,

$$\begin{aligned}\frac{E[Y|Z_k=1]-E[Y|Z_k=0]}{E[D_{\mathcal{K},k}|Z_k=1]-E[D_{\mathcal{K},k}|Z_k=0]} = \sum_{l\in\mathcal{K}\setminus k} & \frac{\Pr(D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=0)}{\Pr(D_{\mathcal{K},k}(0)=0, D_{\mathcal{K},k}(1)=1)} \\ & \times E[Y_k - Y_l | D_{\mathcal{K},l}(0)=1, D_{\mathcal{K},l}(1)=0].\end{aligned} \tag{10}$$

Similarly, the MTE of option k *versus* the next-best can be decomposed into pairwise MTEs. Recall that the MTE identifies the average treatment effect of option k for those on the margin of indifference between option k and the next-best option, $\text{MTE}_{k,\mathcal{K}\setminus k} = E[Y_k - Y_{\mathcal{K}\setminus k}|Z=z, U_k(z)=U_{\mathcal{K}\setminus k}(z)]$. First, replacing $Y_{\mathcal{K}\setminus k}$ and $1-D_{\mathcal{K},k}=\sum_{l\in\mathcal{K}\setminus k} D_{\mathcal{K},l}$ in $Y_k - Y_{\mathcal{K}\setminus k}$,

$$\begin{aligned}Y_k - Y_{\mathcal{K}\setminus k} &= Y_k - \sum_{l\in\mathcal{K}\setminus k}\frac{D_{\mathcal{K},l}}{1-D_{\mathcal{K},k}} Y_l \cdot \mathbb{1}[D_{\mathcal{K},k}\neq 1] \\ &= \frac{\mathbb{1}[D_{\mathcal{K},k}\neq 1]}{1-D_{\mathcal{K},k}}\left[Y_k(1-D_{\mathcal{K},k}) - \sum_{l\in\mathcal{K}\setminus k} D_{\mathcal{K},l}Y_l\right] \\ &= \frac{\mathbb{1}[D_{\mathcal{K},k}\neq 1]}{1-D_{\mathcal{K},k}}\left[\sum_{l\in\mathcal{K}\setminus k} D_{\mathcal{K},l}Y_k - \sum_{l\in\mathcal{K}\setminus k} D_{\mathcal{K},l}Y_l\right] \\ &= \frac{\mathbb{1}[D_{\mathcal{K},k}\neq 1]}{1-D_{\mathcal{K},k}}\left[\sum_{l\in\mathcal{K}\setminus k} D_{\mathcal{K},l}(Y_k - Y_l)\right] = \sum_{l\in\mathcal{K}\setminus k}\frac{\mathbb{1}[D_{\mathcal{K},k}\neq 1]\cdot D_{\mathcal{K},l}}{1-D_{\mathcal{K},k}}(Y_k - Y_l) \\ &= \sum_{l\in\mathcal{K}\setminus k} D_{\mathcal{K}\setminus k,l}(Y_k - Y_l)\end{aligned}$$

Replacing in the MTE formula,

$$\begin{aligned}&E[Y_k - Y_{\mathcal{K}\setminus k} \mid Z=z, U_k(z)=U_{\mathcal{K}\setminus k}(z)] \\ &\quad = E\left[\sum_{l\in\mathcal{K}\setminus k} D_{\mathcal{K}\setminus k,l}(Y_k - Y_l)\middle| Z=z, U_k(z)=U_{\mathcal{K}\setminus k}(z)\right] \\ &\quad = \sum_{l\in\mathcal{K}\setminus k} E[D_{\mathcal{K}\setminus k,l}(Y_k - Y_l) \mid Z=z, U_k(z)=U_{\mathcal{K}\setminus k}(z)] \\ &\quad = \sum_{l\in\mathcal{K}\setminus k} \Pr(D_{\mathcal{K}\setminus k,l}=1|Z=z, U_k(z)=U_{\mathcal{K}\setminus k}(z)) E[Y_k - Y_l|Z=z, U_k(z)=U_{\mathcal{K}\setminus k}(z)].\end{aligned} \tag{11}$$

Identification of Pairwise Treatment Effects: Define the unconditional response matrix resulting from the variation in Z_k as:

$$R_k = \begin{vmatrix} 1 & \cdots & k & \cdots & K & 1 & \cdots & K \\ 1 & \cdots & k & \cdots & K & k & \cdots & k \end{vmatrix},$$

which contains all possible combinations of potential choices induced by Z_k, where the first K groups are always-takers and the remaining $K-1$ groups are compliers. Following the setting in Section 2.2.3, let Z_l denote an additional IV that meets the restrictions in R1. Assume that as $Z_l \to z_l^{\min}$ no agent would have chosen options other than l, or the next-best state would be l. The *conditional response vector* $R_k(Z_l \to z_l^{\min})$ would contain only one complier group (namely, those switching along the k vs. l margin).

$$R_k(Z_l \to z_l^{\min}) = \begin{vmatrix} 1 & \cdots & k & \cdots & K & l \\ 1 & \cdots & k & \cdots & K & k \end{vmatrix},$$

which implies that $\Pr(D_{\mathcal{K},m}(0) = 1, D_{\mathcal{K},}(1) = 0) = 0$ for $m \neq l \in \mathcal{K}\backslash k$. Hence,

$$\frac{E[Y|Z_k = 1, z_l^{\min}] - E[Y|Z_k = 0, z_l^{\min}]}{E[D_{\mathcal{K},k}|Z_k = 1, z_l^{\min}] - E[D_{\mathcal{K},k}|Z_k = 0, z_l^{\min}]} = E[Y_k - Y_l|D_{\mathcal{K},l}(0, z_l^{\min}) = 1, D_{\mathcal{K},3}(1, z_l^{\min}) = 0].$$

Equivalence to Heckman and Pinto (2018): Here, I follow the notation in Appendix A.1 to show how to identify treatment effects for more general cases (for instance, if Z_k takes on more than 2 values, $w > 2$, or if the researcher is interested in identifying counterfactuals for always-takers or imposing the homogeniety assumption). I focus on the running example in Section 2.2.3 and in this Appendix, for the case when $Z_l \to z_l^{\max}$. In this case, the conditional response matrix resulting from the variation in Z_k evaluated at $Z_l \to z_l^{\max}$ is given by:

$$R_k(Z_l \to z_l^{\max}) = \begin{vmatrix} 1 & \cdots & k & \cdots & K & 1 & \cdots & K \\ 1 & \cdots & k & \cdots & K & k & \cdots & k \end{vmatrix},$$

where each column is a response vector, $S_k(Z_l \to z_l^{\max})$, and $\dim[R_k(Z_l \to z_l^{\max})] = (K-1) \times w < \dim[R_k]$, which means that the number of responses in the conditional matrix is lower than in the unconditional matrix. In particular, the number of compliers decreases to $[(w-1) \times (K-1)] - 1$ *versus* $[(w-1) \times (K-1)]$ for the unconditional matrix. Moreover, binary matrix $B_k^k(Z_l \to z_l^{\max})$ takes the value of one each time k appears in $R_k(Z_l \to z_l^{\max})$. For example,

$$B_k^1(Z_l \to z_l^{\max}) = \begin{vmatrix} 1 & 0 & \cdots & 0 & \cdots & 0 & 1 & \cdots & 0 \\ 1 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \end{vmatrix}.$$

Stacking option-specific B matrices results in:

$$
B_k(Z_l \to z_l^{\max}) = \left|\begin{array}{cccccccccc}
1 & 0 & \cdots & 0 & \cdots & 0 & 1 & 0 & \cdots & 0 \\
1 & 0 & \cdots & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 \\
0 & 1 & \cdots & 0 & \cdots & 0 & 0 & 1 & \cdots & 0 \\
0 & 1 & \cdots & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & \cdots & 1 & \cdots & 0 & 0 & 0 & \cdots & 0 \\
0 & 0 & \cdots & 1 & \cdots & 0 & 1 & 1 & \cdots & 1 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & \cdots & 0 & \cdots & 1 & 0 & 0 & \cdots & 1 \\
0 & 0 & \cdots & 0 & \cdots & 1 & 0 & 0 & \cdots & 0
\end{array}\right|
\begin{array}{l}
\left.\begin{matrix} \\ \\ \end{matrix}\right\} B_k^1 \\
\left.\begin{matrix} \\ \\ \end{matrix}\right\} B_k^2 \\
\\
\left.\begin{matrix} \\ \\ \end{matrix}\right\} B_k^k \\
\\
\left.\begin{matrix} \\ \\ \end{matrix}\right\} B_k^K
\end{array}
$$

Now define $\sum_{k,k}(q|Z_l)$ for $q \in 1, 2$, which denotes sets of responses in $R_k(Z_l \to z_l^{\max})$ where k appears q times. For every $l \in \mathcal{K} \backslash k$, $\sum_{l,k}(1|Z_l) = \{S_{l-k}\}$ and $\sum_{l,k}(2|Z_l) = \{S_l\}$, where S_l denotes option l–always-takers and S_{l-k} denotes $l-k$ compliers. For option k, $\sum_{k,k}(1|Z_l) = \{S_{1-k}, S_{2-k}, \dots, S_{K-k}\}$ and $\sum_{l,k}(2|Z_l) = \{S_k\}$. That is, for option k the set of responses where k appears exactly one time (*i.e.*, compliers) contains $K-1$ elements. It follows that $b_{k,k}(1|Z_l) = [0, 0, \cdots, 0, \cdots, 0, 1, 1, \cdots, 1]$, which indicates which response types belong to $\sum_{l,k}(1|Z_l)$ (in this case, all complier response types), while $b_{k,k}(2|Z_l) = [0, 0, \cdots, 1, \cdots, 0, 0, 0, \cdots, 0]$ where the value of one is associated with the option k–always-taker.

Hence, following Theorem T-6 in Heckman and Pinto (2018), the following counterfactuals are identified:

$$
E\left(Y_k \mid S \in \sum_{k,k}(2|Z_l)\right) = \frac{b_{k,k}(2|Z_l) B_k^{k+}(Z_l) L_{Yk}^k(Z_l)}{b_{k,k}(2|Z_l) B_k^{k+}(Z_l) \Pr_{Z_k}(D = k|Z_l)},
$$

for all groups of always-takers. For instance, for $k = 1$,

$$
\begin{aligned}
E\left(Y_1 \mid S_1\right) &= \frac{b_{1,k}(2|Z_l) B_k^{1+}(Z_l) L_{Y1}^k(Z_l)}{b_{1,k}(2|Z_l) B_k^{1+}(Z_l) \Pr_{Z_k}(D = 1|Z_l)} \\
&= \frac{E(YD_1|z_k', Z_l)}{E(D_1|z_k', Z_l)},
\end{aligned}
$$

which follows from the definition of $B_k^{k+}(Z_l)$, $L_{Y1}^k(Z_l)$, and $\Pr_{Z_k}(D = 1|Z_l)$ in Appendix A.1. Moreover,

$$
\begin{aligned}
E\left(Y_k \mid S \in \sum_{k,k}(1|Z_l)\right) &= \frac{b_{k,k}(1|Z_l) B_k^{k+}(Z_l) L_{Yk}^k(Z_l)}{b_{k,k}(1|Z_l) B_k^{k+}(Z_l) \Pr_{Z_k}(D = k|Z_l)} \\
&= \frac{E(YD_k|z_k', Z_l) - E(YD_k|z_k, Z_l)}{E(D_k|z_k', Z_l) - E(D_k|z_k, Z_l)},
\end{aligned}
$$

which identifies the counterfactual of option k for compliers switching into k, that is,

$\{S_{1-k}, S_{2-k}, \ldots, S_{K-k}\}$; and,

$$\begin{aligned} E\left(Y_l \mid S_{l-k}\right) &= \frac{b_{l,k}(1|Z_l)B_k^{l+}(Z_l)L_{Yl}^k(Z_l)}{b_{l,k}(1|Z_l)B_k^{l+}(Z_l)\Pr_{Z_k}(D=l|Z_l)} \\ &= \frac{E(YD_l|z_k, Z_l) - E(YD_l|z_k', Z_l)}{E(D_l|z_k, Z_l) - E(D_l|z_k', Z_l)}, \end{aligned}$$

which denotes the counterfactual of choosing option l for compliers along the $l-k$ margin, for all $l \in \mathcal{K}\backslash k$. Given that the counterfactual for option k is only identified for the combination of compliers, rather than for one complier alone, only the effect of k vs. the next-best can be identified as a weighted average of margin specific treatment effects. Direct identification of this parameter also follows from Corollary C-5 in Heckman and Pinto (2018).

A similar logic follows for the identification of group shares and averages of baseline variables for always-takers and compliers.

Conditional response-types defined by X=x lead to bias: Suppose that the researcher wants to assume that at a given value of a covariate in X, some next-best states might disappear. For example, suppose that the researcher observes that low-income families would only choose an option l in the absence of option k, or when k is too costly. If low-income families choose l due to exogenous constraints, then the logic conditional response-types identifies pairwise LATEs since income level would effectively work as an instrumental variable. However, if families choose l over all other alternatives based on unobserved preferences or unobserved gains, conditional response-types would lead to biased estimates of pairwise LATEs. Note that in the latter, the set of next-best alternatives is endogenously determined, shifting the utility of the options as well as the potential gains of choosing them. To see this, I impose some additional structure on the potential outcomes.

Assume that potential outcomes can be decomposed into $Y_k = \gamma_k(X) + \epsilon_k$ for each $k \in \mathcal{K}$. Start with the case of 3 options, $\{l, m, k\}$. Suppose Z_k is a binary IV which induces agents towards option k and away from m and l. Following the latent utility framework in Section 2, and explicitly controlling for X, the following conditions should hold:

- $\mu_k - V_k(1, X) \geq \mu_l - V_l(X)$ and $\mu_k - V_k(1, X) \geq \mu_m - V_m(X)$.
- $\mu_l - V_l(X) \geq \mu_k - V_k(0, X)$ and $\mu_m - V_m(X) \geq \mu_k - V_k(0, X)$.

The first set of inequalities states that at $Z_k = 1$ option k is preferred, while at $Z_k = 0$ other options are preferred. Note that there is no restriction on the preferences of l over m (or viceversa). Under these conditions, the Wald estimator identifies the effect of k vs. the next-best.

Now suppose that at $X = x$ agents endogenously choose l over m, such that $\mu_l - V_l(x) > \mu_m - V_m(x)$. Then, the conditional Wald estimator,

$$\frac{E[Y|Z_k = 1, X = x] - E[Y|Z_k = 0, X = x]}{E[D_{\mathcal{K},k}|Z_k = 1, X = x] - E[D_{\mathcal{K},k}|Z_k = 0, X = x]},$$

would not identify the pairwise LATE of k versus l. To see this, take the decomposition in equation (10) conditional on $\mu_l - V_l(x) > \mu_m - V_m(x)$ such that:

$$\Pr(D_{\mathcal{K},m}(0) = 1, D_{\mathcal{K},m}(1) = 0|\mu_l - V_l(x) > \mu_m - V_m(x), X = x) = 0,$$

which means that at $X = x$, m would not belong to the next-best states. Replacing in equation (10) conditional on $\mu_l - V_l(x) > \mu_m - V_m(x)$ and given that,

$$\Pr(D_{\mathcal{K},k}(0) = 0, D_{\mathcal{K},k}(1) = 1) = \sum_{l \in \mathcal{K} \setminus k} \Pr(D_{\mathcal{K},l}(0) = 1, D_{\mathcal{K},l}(1) = 0),$$

the right hand side in equation (10), conditional on $\mu_l - V_l(x) > \mu_m - V_m(x)$, results in:

$$E[Y_k - Y_l|D_{\mathcal{K},l}(0) = 1, D_{\mathcal{K},l}(1) = 0, \mu_l - V_l(x) > \mu_m - V_m(x)].$$

This latter expression will generally differ from $E[Y_k - Y_l|D_{\mathcal{K},l}(0) = 1, D_{\mathcal{K},l}(1) = 0]$ leading to a biased estimate of the pairwise LATE of k versus l because potential outcomes are not independent of unobserved preferences, μ_l, μ_m (*i.e.*, μ_l, μ_m are correlated with the unobserved components, ϵ_l, ϵ_m, in the potential outcomes' equations). In summary, although changes in the propensity to choose k are exogenous, choosing l over m is endogenously determined leading to bias. This result generalizes to the case of multiple next-best states that are endogenously chosen at different values of X. A similar argument follows for the case of identification of pairwise MTEs, which is based on the notion that changes in Z_l shift the cost function without shifting unobserved gains, which is trivially not satisfied for variables in X which affect both potential choices and potential outcomes.

A.5 Example for $K = 3$: Panel (b) in Figure 1

This section follows the Example in Section 2.2, specifically for the case displayed in Panel (b) of Figure 1 and the combination of potential choices summarized in Table 1. In this case, the Wald estimator identifies:

$$\frac{E[Y|Z_1 = 1] - E[Y|Z_1 = 0]}{E[D_{\mathcal{K},1}|Z_1 = 1] - E[D_{\mathcal{K},1}|Z_1 = 0]} = \sum_{l=2}^{3} \frac{\Pr(D_{\mathcal{K},l}(0) = 1, D_{\mathcal{K},l}(1) = 0)}{\Pr(D_{\mathcal{K},1}(0) = 0, D_{\mathcal{K},1}(1) = 1)} \times E[Y_1 - Y_l|D_{\mathcal{K},l}(0) = 1, D_{\mathcal{K},l}(1) = 0],$$

and the MTE can be decomposed into:

$$\begin{aligned}
E[Y_1 - Y_{\mathcal{K}\backslash 1}|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z)]& \\
&= E[D_{\mathcal{K}\backslash 1,2}(Y_1 - Y_2) + D_{\mathcal{K}\backslash 1,3}(Y_1 - Y_3)|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z)] \\
&= \Pr(D_{\mathcal{K}\backslash 1,2} = 1|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z))E[Y_1 - Y_2|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z)] \\
&+ \Pr(D_{\mathcal{K}\backslash 1,3} = 1|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z))E[Y_1 - Y_3|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z)].
\end{aligned}$$

The role of conditional response vectors: The following matrix summarizes conditional response vectors as $Z_3 \to z_3^{\min}$,

$$R_1(Z_3 \to z_3^{\min}) = \begin{vmatrix} 1 & 2 & 3 & 3 \\ 1 & 2 & 3 & 1 \end{vmatrix},$$

which implies that $\Pr(D_{\mathcal{K},2}(0) = 1, D_{\mathcal{K},2}(1) = 0) = 0$. That is, following the cost structure in Panel (b) of Figure 1, the likelihood of option 2 being the next-best alternative approaches zero as $Z_3 \to z_3^{\min}$. Hence, equation (10) evaluated as $Z_3 \to z_3^{\min}$ reduces to:

$$\frac{E[Y|Z_1 = 1, z_3^{\min}] - E[Y|Z_1 = 0, z_3^{\min}]}{E[D_{\mathcal{K},1}|Z_1 = 1, z_3^{\min}] - E[D_{\mathcal{K},1}|Z_1 = 0, z_3^{\min}]} = E[Y_1 - Y_3|D_{\mathcal{K},3}(0, z_3^{\min}) = 1, D_{\mathcal{K},3}(1, z_3^{\min}) = 0].$$

Invoking a limit argument as in Heckman and Vytlacil (2007) and Heckman et al. (2008, 2006), equation (11) evaluated as $Z_3 \to z_3^{\min}$ reduces to:

$$\begin{aligned}
\lim_{Z_3 \to z_3^{\min}} & E[Y_1 - Y_{\mathcal{K}\backslash 1}|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z)] \\
&= \lim_{Z_3 \to z_3^{\min}} \Pr(D_{\mathcal{K}\backslash 1,2} = 1|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z))E[Y_1 - Y_2|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z)] \\
&+ \lim_{Z_3 \to z_3^{\min}} \Pr(D_{\mathcal{K}\backslash 1,3} = 1|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z))E[Y_1 - Y_3|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z)] \\
&= E[Y_1 - Y_3|Z = z, U_1(z) = U_3(z)],
\end{aligned}$$

which is the marginal treatment effect of option 1 vs. 3 for those at the margin of indifference between option 1 and 3.

By a similar argument, as $Z_3 \to z_3^{\max}$,

$$R_1(Z_3 \to z_3^{\max}) = \begin{vmatrix} 1 & 2 & 3 & 2 \\ 1 & 2 & 3 & 1 \end{vmatrix}$$

which implies that $\Pr(D_{\mathcal{K},3}(0) = 1, D_{\mathcal{K},3}(1) = 0) = 0$, and equation (10) evaluated as $Z_3 \to z_3^{\max}$ reduces to:

$$\frac{E[Y|Z_1 = 1, z_3^{\max}] - E[Y|Z_1 = 0, z_3^{\max}]}{E[D_{\mathcal{K},1}|Z_1 = 1, z_3^{\max}] - E[D_{\mathcal{K},1}|Z_1 = 0, z_3^{\max}]} = E[Y_1 - Y_2|D_{\mathcal{K},2}(0, z_3^{\max}) = 1, D_{\mathcal{K},2}(1, z_3^{\max}) = 0],$$

and,

$$\lim_{Z_3 \to z_3^{\max}} E[Y_1 - Y_{\mathcal{K}\backslash 1}|Z = z, U_1(z) = U_{\mathcal{K}\backslash 1}(z)] = E[Y_1 - Y_2|Z = z, U_1(z) = U_2(z)],$$

the marginal treatment effect of option 1 vs. 2 for those at the margin of indifference between option 1 and 2.

Appendix B: Empirical Applications

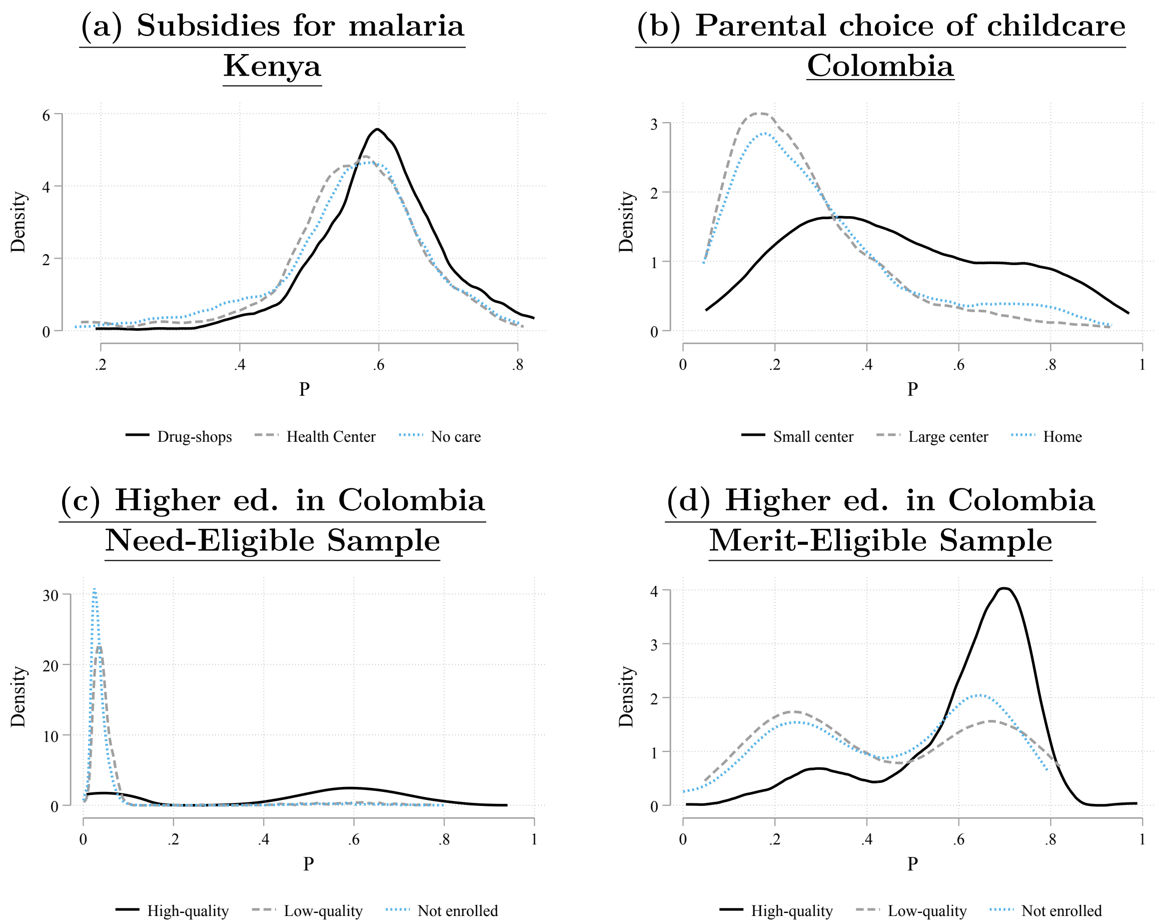
B.1 Common Support

Figure 9 plots propensity scores estimated with equation (3). Panel (a) displays the predicted probability of choosing the drug-shop for those who chose the drug-shop (in black), the health center (the dashed line in gray), and no care (the dotted line in blue). In this case, the common support is defined as the set of values $P \in [0.28, 0.8]$. Panel (b) shows the predicted probability of choosing small childcare centers and its distribution across childcare choices. The common support for this application is the interval $P \in [0.16, 0.76]$. Panels (c) and (d) show the predicted probability of enrolling in a high-quality university and its distribution across choices. The common support for this application is the interval $P \in [0.12, 0.8]$.

B.2 IV Weights

The estimation of IV Weights follows Heckman et al. (2006) and its supplemental material. Figure 10 shows estimates of the weights that IV would place on the marginal treatment effects estimated across values of the propensity score.

Figure 9: Propensity Score



Source: Panel (a) subsample from Cohen et al. (2015). Panel (b) subsample from Bernal et al. (2019). Panels (c) and (d) subsample from Londoño-Vélez et al. (2023).
Note: The figure shows the distribution of agents across values of the propensity score for each application. Panel (a) presents a density plot for the propensity score of choosing drug-shops. Panel (b) presents a density plot for the propensity score of choosing small childcare centers. Panels (c) and (d) present density plots for the propensity score of choosing high-quality universities.

B.3 Average of Baseline Variables

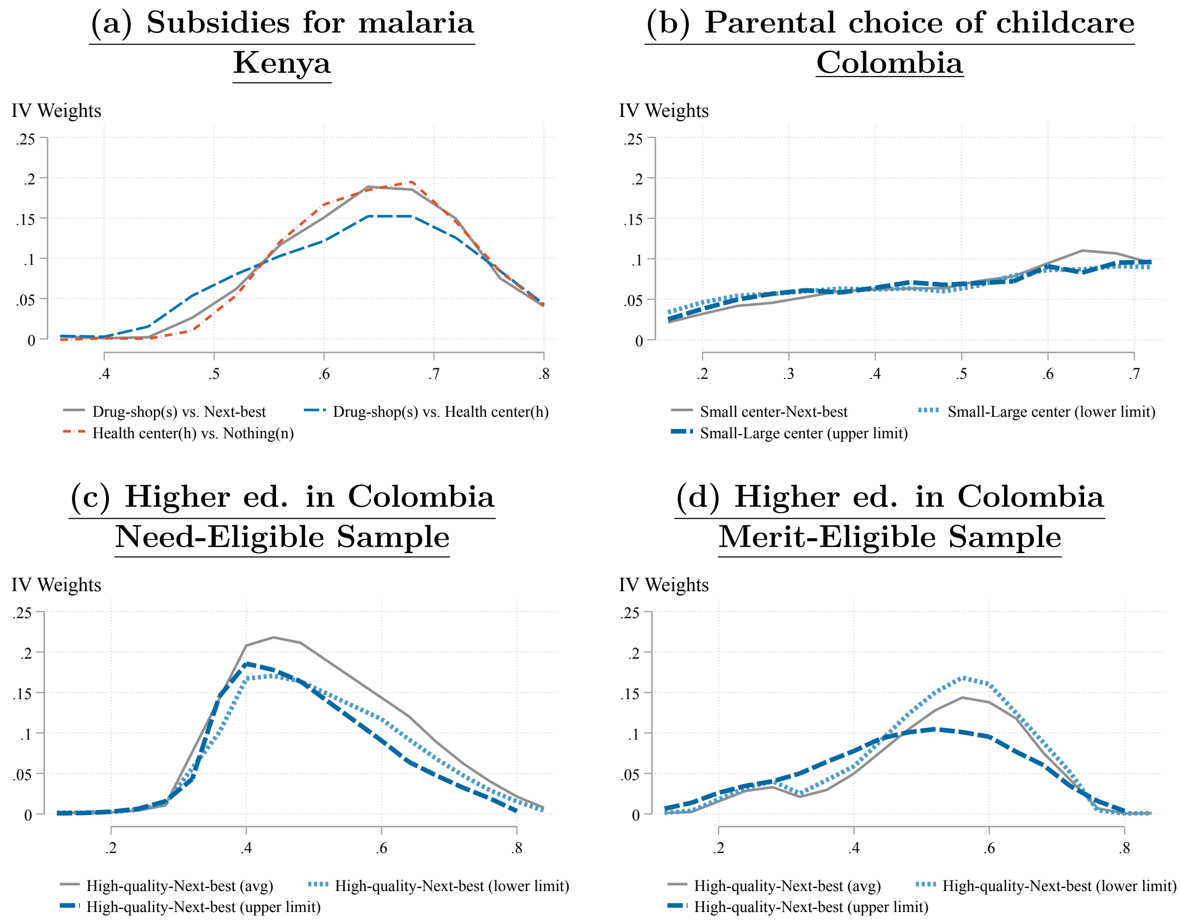
Subsidies for malaria treatment in Kenya: The following average of baseline variables can be identified (see equation (9) in Appendix A.2). For simplification, conditioning on Z_2 is left implicit.

First, for $h-$always-takers:

$$
\begin{aligned}
E[XD_h|Z_1 = 1] &= E[X|D_h = 1, Z_1 = 1]\Pr(D_h = 1|Z_1 = 1) \\
&= E[X|D_h(0) = 1, D_h(1) = 1]\Pr(D_h(0) = 1, D_h(1) = 1)
\end{aligned}
$$

identifies the average of baseline variables after dividing the RHS by the share of $h-$always-takers estimated using equation (7) in Appendix A.2.

Figure 10: IV Weights



Source: Panel (a) subsample from Cohen et al. (2015). Panel (b) subsample from Bernal et al. (2019). Panels (c) and (d) subsample from Londoño-Vélez et al. (2023).
Note: The figure shows estimated IV weights. Panel (a) presents IV weights for malaria treatment in Kenya. Panel (b) presents IV weights for parental choice of childcare in Colombia. Panels (c) and (d) present IV weights for higher education choices in Colombia.

For $n-$always-takers:

$$\begin{aligned} E[XD_n|Z_1 = 1] &= E[X|D_n = 1, Z_1 = 1]\Pr(D_n = 1|Z_1 = 1) \\ &= E[X|D_n(0) = 1, D_n(1) = 1]\Pr(D_n(0) = 1, D_n(1) = 1) \end{aligned}$$

identifies average of baseline variables after dividing the RHS by the share of $n-$always-takers estimated using equation (7) in Appendix A.2.

For $s-$always-takers:

$$\begin{aligned} E[XD_s|Z_1 = 0] &= E[X|D_s = 1, Z_1 = 0]\Pr(D_s = 1|Z_1 = 0) \\ &= E[X|D_s(0) = 1, D_s(1) = 1]\Pr(D_s(0) = 1, D_s(1) = 1) \end{aligned}$$

identifies the average of baseline variables after dividing the RHS by the share of $s-$always-takers estimated using equation (7) in Appendix A.2.

For $h - s$ compliers,

$$E[XD_h|Z_1 = 0] - E[XD_h|Z_1 = 1] = E[X|D_h(0) = 1, D_s(1) = 1]\Pr(D_h(0) = 1, D_s(1) = 1)$$

identifies the average of baseline variables after dividing the RHS by the share of $h - s$ compliers estimated using equation (7) in Appendix A.2. Note that

$$\begin{aligned} E[XD_h|Z_1 = 0] &= E[X|D_h = 1, Z_1 = 0]\Pr(D_h = 1|Z_1 = 0) \\ &= E[X|D_h(0) = 1, D_h(1) = 1]\Pr(D_h(0) = 1, D_h(1) = 1) \\ &+ E[X|D_h(0) = 1, D_s(1) = 1]\Pr(D_h(0) = 1, D_s(1) = 1). \end{aligned}$$

For $n - s$ compliers,

$$E[XD_n|Z_1 = 0] - E[XD_n|Z_1 = 1] = E[X|D_n(0) = 1, D_s(1) = 1]\Pr(D_n(0) = 1, D_s(1) = 1)$$

identifies the average of baseline variables after dividing the RHS by the share of $h - s$ compliers estimated using equation (7) in Appendix A.2. Note that

$$\begin{aligned} E[XD_n|Z_1 = 0] &= E[X|D_n = 1, Z_1 = 0]\Pr(D_n = 1|Z_1 = 0) \\ &= E[X|D_n(0) = 1, D_n(1) = 1]\Pr(D_n(0) = 1, D_n(1) = 1) \\ &+ E[X|D_n(0) = 1, D_s(1) = 1]\Pr(D_n(0) = 1, D_s(1) = 1). \end{aligned}$$

Figure 11 presents estimates of average baseline characteristics for compliers.

Parental choice of childcare in Colombia: The following average of baseline variables can be identified (see equation (9) in Appendix A.2). For simplification, conditioning on Z_2 is left implicit.

First, for $h-$always-takers (home care always takers):

$$\begin{aligned} E[XD_h|Z_1 = 0] &= E[X|D_h = 1, Z_1 = 0]\Pr(D_h = 1|Z_1 = 0) \\ &= E[X|D_h(0) = 1, D_h(1) = 1]\Pr(D_h(0) = 1, D_h(1) = 1) \end{aligned}$$

identifies the average of baseline variables after dividing the RHS by the share of $h-$always-takers using equation (7) in Appendix A.2.

For $s-$always-takers:

$$\begin{aligned} E[XD_s|Z_1 = 1] &= E[X|D_s = 1, Z_1 = 1]\Pr(D_s = 1|Z_1 = 1) \\ &= E[X|D_s(0) = 1, D_s(1) = 1]\Pr(D_s(0) = 1, D_s(1) = 1) \end{aligned}$$

identifies average of baseline variables after dividing the RHS by the share of $s-$always-takers using equation (7) in Appendix A.2.

For $l-$always-takers:

$$\begin{aligned}E[XD_l|Z_1=0] &= E[X|D_l=1,Z_1=0]\Pr(D_l=1|Z_1=0)\\ &= E[X|D_l(0)=1,D_l(1)=1]\Pr(D_l(0)=1,D_l(1)=1)\end{aligned}$$

identifies the average of baseline variables after dividing the RHS by the share of $l-$always-takers using equation (7) in Appendix A.2.

For $s-h$ compliers,

$$E[XD_h|Z_1=0]-E[XD_h|Z_1=1]=E[X|D_s(0)=1,D_h(1)=1]\Pr(D_s(0)=1,D_h(1)=1)$$

identifies the average of baseline variables after dividing the RHS by the share of $s-h$ compliers using equation (7) in Appendix A.2. Note that

$$\begin{aligned}E[XD_h|Z_1=1] &= E[X|D_h=1,Z_1=1]\Pr(D_h=1|Z_1=1)\\ &= E[X|D_h(0)=1,D_h(1)=1]\Pr(D_h(0)=1,D_h(1)=1)\\ &+ E[X|D_s(0)=1,D_h(1)=1]\Pr(D_s(0)=1,D_h(1)=1).\end{aligned}$$

For $s-l$ compliers,

$$E[XD_l|Z_1=1]-E[XD_l|Z_1=0]=-E[X|D_s(0)=1,D_l(1)=1]\Pr(D_s(0)=1,D_l(1)=1)$$

identifies the average of baseline variables after dividing the RHS by the share of $s-l$ compliers using equation (7) in Appendix A.2. Note that

$$\begin{aligned}E[XD_l|Z_1=1] &= E[X|D_l=1,Z_1=1]\Pr(D_l=1|Z_1=1)\\ &= E[X|D_l(0)=1,D_l(1)=1]\Pr(D_l(0)=1,D_l(1)=1)\\ &+ E[X|D_s(0)=1,D_l(1)=1]\Pr(D_s(0)=1,D_l(1)=1).\end{aligned}$$

Figure 12 presents estimates of average baseline characteristics for compliers.

Higher education choices in Colombia: The following average of baseline variables can be identified (see equation (9) in Appendix A.2). For simplification, conditioning on Z_2 is left implicit.

First, for $n-$always-takers:

$$\begin{aligned}E[XD_n|Z_1=1] &= E[X|D_n=1,Z_1=1]\Pr(D_n=1|Z_1=1)\\ &= E[X|D_n(0)=1,D_n(1)=1]\Pr(D_n(0)=1,D_n(1)=1)\end{aligned}$$

identifies the average of baseline variables after dividing the RHS by the share of $n-$always-takers using equation (7) in Appendix A.2.

For $l-$always-takers:

$$\begin{aligned}E[XD_l|Z_1=1] &= E[X|D_l=1,Z_1=1]\Pr(D_l=1|Z_1=1)\\ &= E[X|D_l(0)=1,D_l(1)=1]\Pr(D_l(0)=1,D_l(1)=1)\end{aligned}$$

identifies the average of baseline variables after dividing the RHS by the share of $l-$always-takers using equation (7) in Appendix A.2.

For $h-$always-takers:

$$\begin{aligned}E[XD_h|Z_1=0] &= E[X|D_h=1,Z_1=0]\Pr(D_h=1|Z_1=0)\\ &= E[X|D_h(0)=1,D_h(1)=1]\Pr(D_h(0)=1,D_h(1)=1)\end{aligned}$$

identifies the average of baseline variables after dividing the RHS by the share of $h-$always-takers using equation (7) in Appendix A.2.

For $n-h$ compliers,

$$E[XD_n|Z_1=0]-E[XD_n|Z_1=1]=E[X|D_n(0)=1,D_h(1)=1]\Pr(D_n(0)=1,D_h(1)=1)$$

identifies the average of baseline variables after dividing the RHS by share of $n-h$ compliers using equation (7) in Appendix A.2. Note that

$$\begin{aligned}E[XD_n|Z_1=0] &= E[X|D_n=1,Z_1=0]\Pr(D_n=1|Z_1=0)\\ &= E[X|D_n(0)=1,D_n(1)=1]\Pr(D_n(0)=1,D_n(1)=1)\\ &+ E[X|D_n(0)=1,D_h(1)=1]\Pr(D_n(0)=1,D_h(1)=1).\end{aligned}$$

For $l-h$ compliers,

$$E[XD_l|Z_1=0]-E[XD_l|Z_1=1]=E[X|D_l(0)=1,D_h(1)=1]\Pr(D_l(0)=1,D_h(1)=1)$$

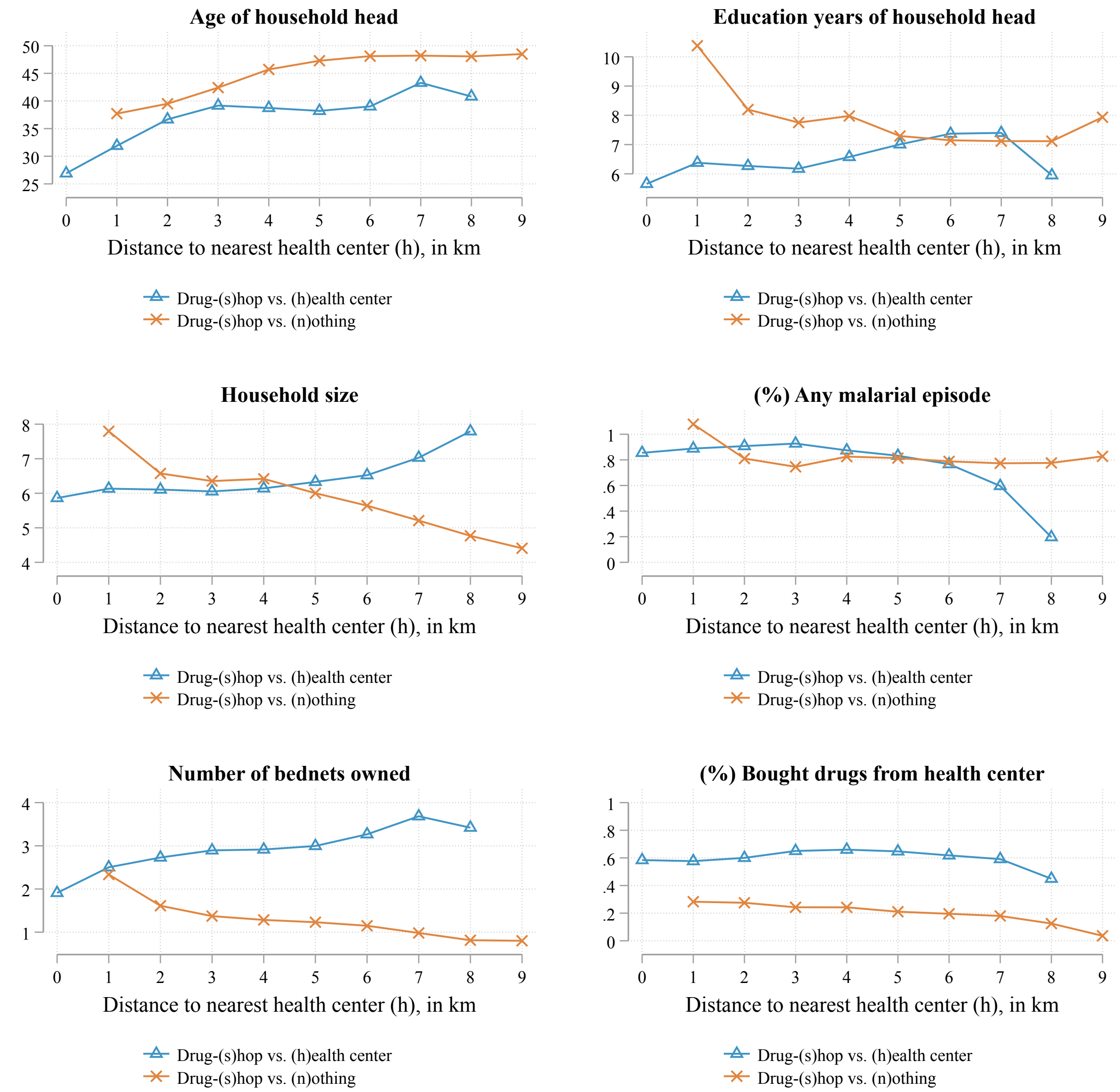
identifies the average of baseline variables after dividing the RHS by the share of $l-h$

compliers using equation (7) in Appendix A.2. Note that

$$
\begin{aligned}
E[XD_l|Z_1 = 0] &= E[X|D_l = 1, Z_1 = 0]\Pr(D_l = 1|Z_1 = 0) \\
&= E[X|D_l(0) = 1, D_l(1) = 1]\Pr(D_l(0) = 1, D_l(1) = 1) \\
&+ E[X|D_l(0) = 1, D_h(1) = 1]\Pr(D_l(0) = 1, D_h(1) = 1).
\end{aligned}
$$

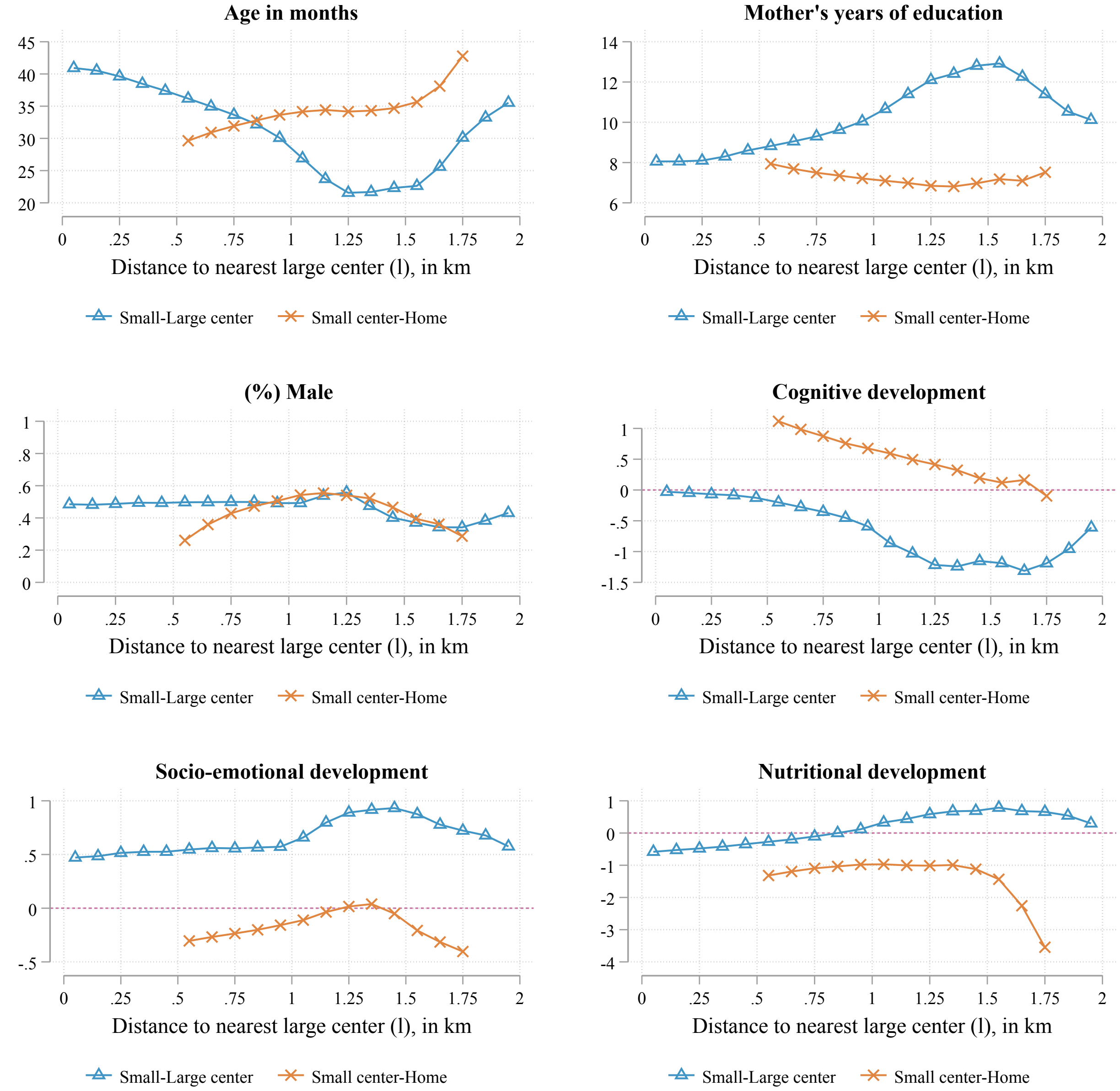
Figures 13 and 14 present estimates of average baseline characteristics for compliers for the need-eligible and merit-eligible students, respectively.

Figure 11: Average of baseline characteristics for compliers, by distance to the nearest health center (h)



Source: subsample from Cohen et al. (2015)
Note: The figure shows the average of baseline characteristics for compliers along the drug-shop vs. health centers margin (hollow triangles in blue) and compliers along the drug-shop vs. no care margin (x in red), by distance to the nearest health center.

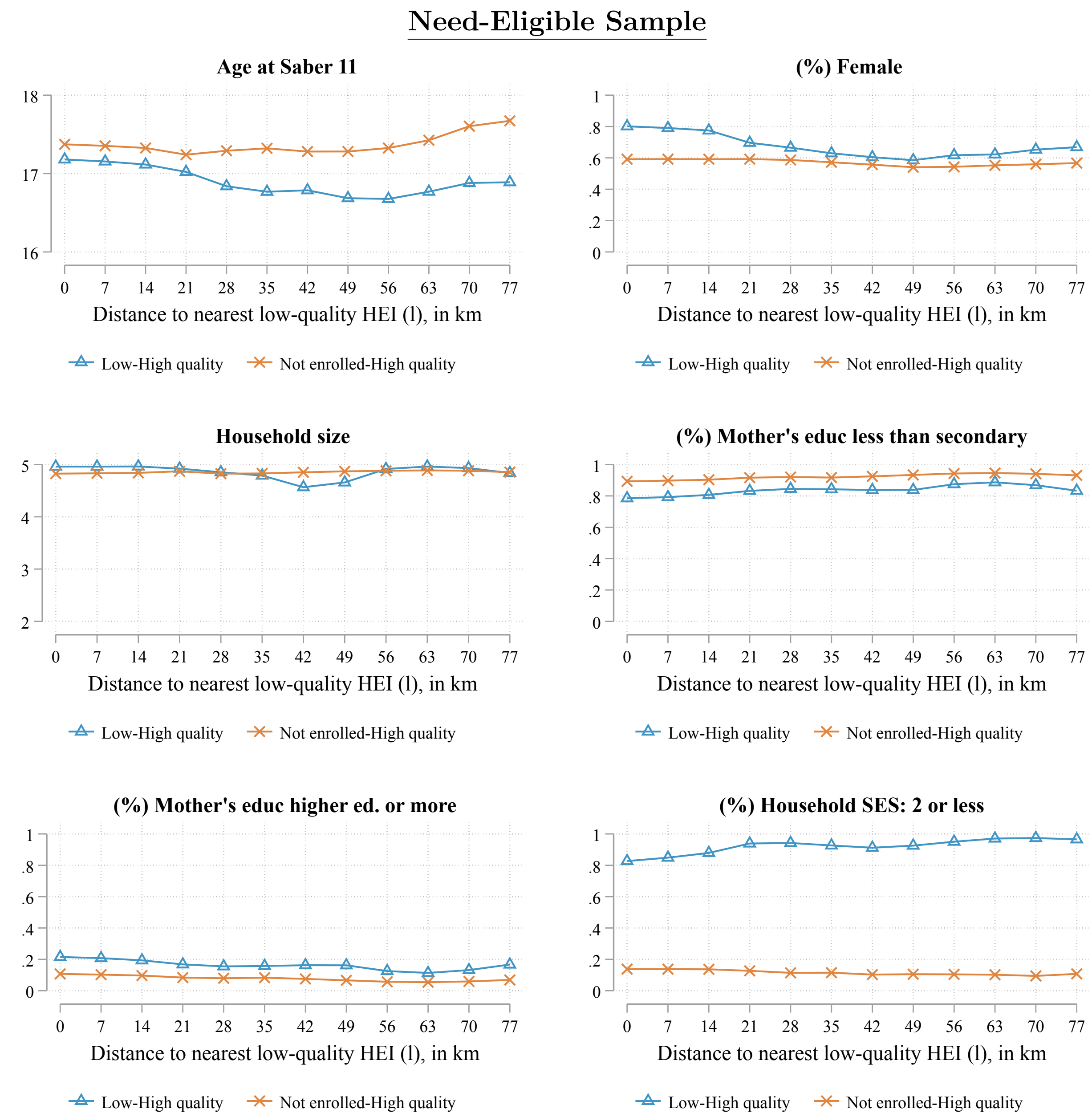
Figure 12: Average of baseline characteristics for compliers, by distance to the nearest large center (l)



Source: subsample from Bernal et al. (2019)

Note: The figure shows the average of baseline characteristics for compliers along the small vs. large centers margin (hollow triangles in blue) and compliers along the small center vs. home margin (x in red), by distance to the nearest large center.

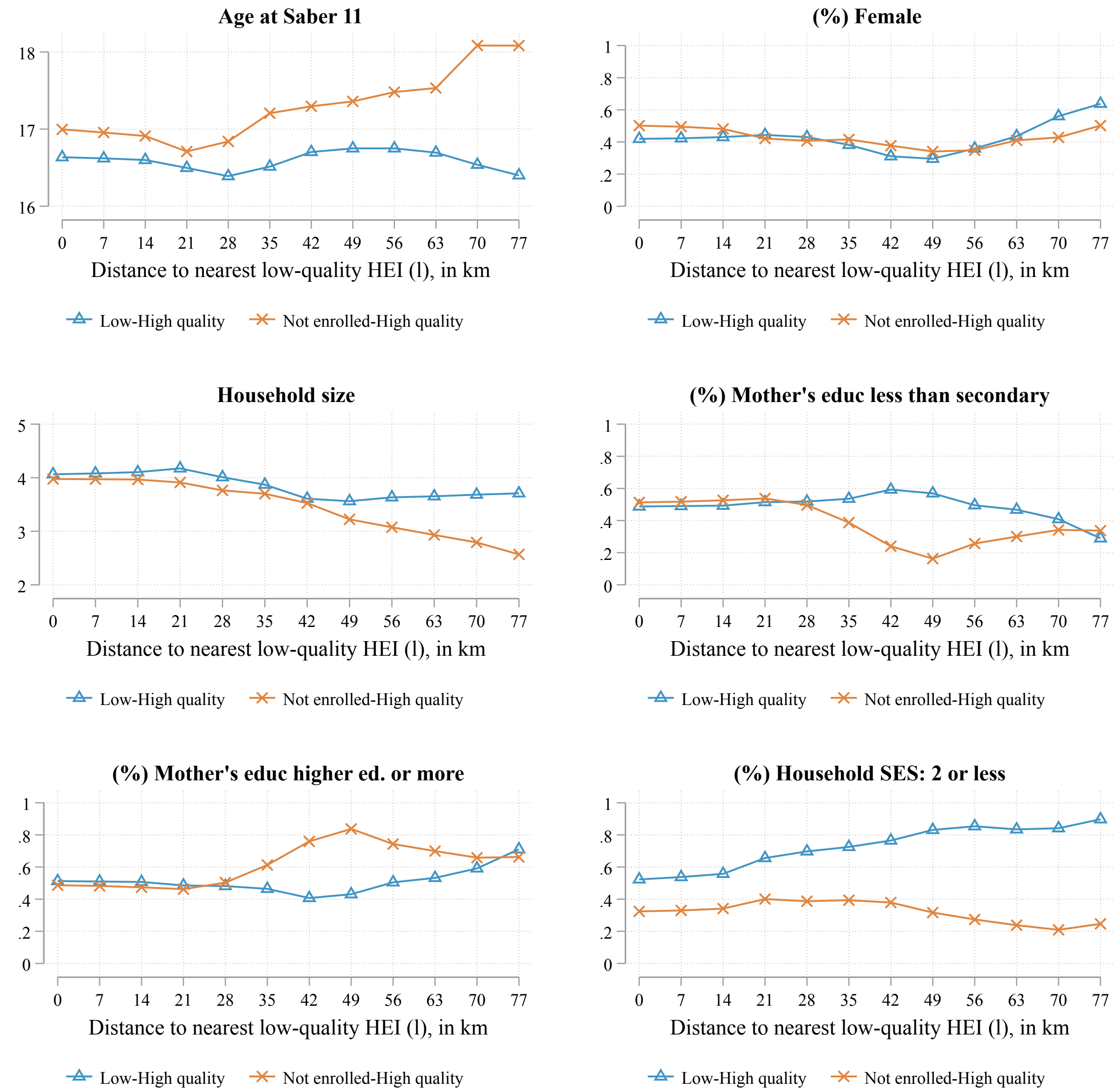
Figure 13: Average of baseline characteristics for compliers, by distance to the nearest low-quality HEI (l) in km



Source: subsample from Londoño-Vélez et al. (2023)
Note: The figure shows the average of baseline characteristics for compliers along the low vs. high-quality HEI margin (hollow triangles in blue) and compliers along the not enrolled vs. high-quality HEI (x in red), by distance to the nearest low-quality HEI.

Figure 14: Average of baseline characteristics for compliers, by distance to the nearest low-quality HEI (l) in km

Merit-Eligible Sample



Source: subsample from Londoño-Vélez et al. (2023)

Note: The figure shows the average of baseline characteristics for compliers along the low vs. high-quality HEI margin (hollow triangles in blue) and compliers along the not enrolled vs. high-quality HEI (x in red), by distance to the nearest low-quality HEI.