ABSTRACT

Title of Dissertation: SUBSIDIES FOR DOMESTIC TECHNOLOGY
ADOPTION UNDER HETEROGENEOUS
TREATMENT EFFECTS

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Governments and NGOs in developing countries offer subsidies to encourage the adoption of beneficial domestic technologies to generate positive externalities and improve access for poorer households. However, these subsidies may be mistargeted if the benefits come from the continued use of the technology, which is not guaranteed by its initial take-up. This dissertation examines the impact of a subsidy to promote the adoption of a rainwater harvesting (RWH) technology on the water restrictions residents of poor neighborhoods in Mexico City face. I explore this topic theoretically and empirically in three main chapters.

In the first chapter, I outline a simple economic model of technology adoption and treatment effects. The model shows how exogenous changes to the subsidy can identify the treatment effects for different types of households, characterized by their willingness to pay (WTP) for the technology. To overcome the challenge of rare exogenous variation in subsidy rates and unobservable WTP, I propose the use of contingent valuation (CV) methods. These methods can exogenously generate variation in hypothetical subsidies and provide insights into the distribution of WTP in the relevant sample. The model is then completed by incorporating the CV information for empirical analysis. This approach may be valuable when randomized interventions are unfeasible due to institutional or budget constraints.

In the second chapter, I empirically estimate the effects of the RWH Program in Mexico City on the time households spend obtaining water and the likelihood of postponing daily activities due to the lack of water. I employ the framework developed in the first chapter and local instrumental variable methods for the estimation. The data for this analysis was collected among all program participants in 2021 in partnership with the implementing agency. I find that the usage and causal effects of the RWH technology improve with the households' WTP. High-WTP households save 5 hours per week in water procurement time and reduce postponement of daily activities due to water scarcity by 25 percentage points. Conversely, low-WTP households are less likely to use the technology, yielding negligible benefits.

The empirical analysis has significant policy implications. In the third chapter, I simulate counterfactual policies and show that adjusting the subsidy structure could enhance the average benefits of the RWH Program. Specifically, introducing enrollment fees that are a fraction of the total cost of the technology could consistently improve the average impact on recipients. These fees do not seem to disproportionately affect poorer households or those facing more stringent water restrictions, suggesting a potential avenue for policy refinement.

SUBSIDIES FOR DOMESTIC TECHNOLOGY ADOPTION UNDER HETEROGENEOUS TREATMENT EFFECTS

by

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Dedication

Para Andrea, Isabel, Jimena y Nacho.

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Chapter 1: Introduction

Across developing countries, governments and NGOs heavily subsidize beneficial domestic technologies and products like clean cooking stoves, solar panels, and water purification systems. The rationale for these high subsidies is often rooted in generating externalities in the form of social benefits arising from the private use of these products and the existence of market failures, such as liquidity and credit constraints, that lead to a rapid decline in demand as prices rise. Early research on pricing essential health goods (e.g., Cohen and Dupas, 2010) established that high subsidies and free distribution are crucial for expanding coverage among low-income populations (Bates et al., 2012; Dupas, 2014a).[1] However, when the benefits derived from a product are heterogeneous, some subsidy takers may not generate additional gains because they do not need the subsidized product or do not use it.[2]

To address the trade-off between coverage and allocative efficiency, health, environment, and poverty alleviation programs with limited budgets often use targeting strategies to select recipients more likely to benefit from the subsidy. One common approach is to allocate subsidies based on the observable characteristics of potential recipients. However, this strategy may mistarget subsidies when the program's costs or benefits to potential recipients are private information.

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[1] Implementing organizations may also opt to relax adoption constraints by increasing access to credit (see Berkouwer and Dean, 2022).

[2] For instance, landholders unlikely to deforest are more likely to enroll in subsidized conservation programs, thereby undermining the program's environmental benefits (Robalino and Pfaff, 2013; Jack and Jayachandran, 2019).

For instance, individuals may benefit from the program depending on their risk preferences or opportunity costs that policymakers cannot directly observe. Empirical research analyzing the effectiveness of different targeting strategies has found that ignoring the influence of these "unobservable" factors when selecting program participants diminishes the net benefits of subsidies (Jack, 2013; Alatas et al., 2016).

An alternative approach is selecting beneficiaries based on their unobserved preferences and behavior through screening mechanisms revealing some private information. For example, individuals with a stronger demand can be identified by asking potential participants to pay a given take-up price (Berry et al., 2020) or to redeem a voucher instead of directly providing them with the product (Ashraf et al., 2010). Likewise, potential participants can be screened based on their opportunity cost of time by requiring them to travel to enroll or provide manual labor as part of the program (Dupas et al., 2016; Alatas et al., 2016).[3]

Unobserved factors become particularly relevant for targeting subsidies in the specific context of technology adoption because benefits often result from usage or continued investments rather than the initial purchase of the technology. Since subsidies are typically linked to the purchase price, recipients may take up a heavily subsidized to decide whether to use it only once they have learned about their idiosyncratic costs and benefits to it (Oliva et al., 2020).[4] The more uncertain the technology's profitability is at the time of take-up, the more likely households will stop using it later on (Oliva et al., 2020).

These challenges for subsidizing the adoption of beneficial domestic technologies to max-

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[3] Unless targeting low-income individuals, for which economic theory suggests how being poor affects enrollment, targeting through non-price screening mechanisms may be complicated if the unobserved dimension driving self-selection is less predictable (Jack and Jayachandran, 2019).

[4] For example, across contexts, more than half of households who adopted subsidized efficient lightbulbs, clean cookstoves, and antimalarial bed nets subsequently stopped using them (Alpizar et al., 2024).

imize their benefits are central to this dissertation. Specifically, I focus on a setting characterized by the following general circumstances: (a) a voluntary participation program with limited resources offers high take-up subsidies, (b) potential adopters are liquidity- and credit-constrained, (c) some household characteristics influencing take-up decisions are unobservable and are also determinants of the returns to the technology, and (d) the benefits of the technology are only realized if it is used continuously.

In anticipation of the empirical analysis, it is convenient to think of this setting in connection with the Rainwater Harvesting (RWH) Program implemented in Mexico City. This program offers households a 1,000 USD system to capture rainwater for all domestic purposes except drinking. The distribution of rainwater harvesting systems is limited to 10,000 per year, and the government provides them for free on a first-come, first-served basis. The program aims to reduce water insecurity in low-income neighborhoods with poor municipal water service. The amount and quality of the rainwater harvested by the system depends on the households' dwelling characteristics and, more importantly, the proper use and maintenance of the system. Lastly, operating the RWH system involves several recurrent steps that can constitute a nontrivial time cost and a mental load for households, dissuading some recipients from using the RWH system continuously.[5] These characteristics make the RWH Program a valuable setting for studying the use of take-up subsidies for allocative efficiency.

This dissertation aims to answer whether a lower take-up subsidy can meaningfully increase the total benefits of the RWH Program. By reducing the subsidy rate (i.e., introducing

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[5] The 2021 internal evaluation of the RWH Program, monitoring a few dozen households, indicates that the average volume of rainwater collected was about 11 thousand liters, which amounts to 50 to 60 percent of the average system's potential. See also "Abandonan, e incluso, venden colectores de programa" (Households abandon and sell the rainwater collectors received). Reforma, August 24, 2023. Available at `https://www.reforma.com/abandonan-e-incluso-venden-colectores-de-programa/ar2662961`.

a participation fee), policymakers can influence which households self-select into the program. Those who value the technology less may refrain from participating if asked to contribute part of the cost. However, this price mechanism will yield higher program benefits only if the unobservable factors favoring take-up are consistently and positively correlated with the individual net benefits resulting from its continuous use.[6] Specifically, suppose that households possess private information about their expected private benefits from the RWH system, and their willingness to pay (WTP) for it reflects those expectations. In that case, a participation fee can screen out those who expect lower benefits and are relatively less likely to use the technology after take-up. Therefore, a measure of the households' WTP serves as a central input for understanding whether the price mechanism allocates the RWH systems where their benefits are most significant or simply reduces access to the poorer.

My analysis relies on a novel empirical strategy that connects stated preference data with a heterogeneous treatment effects model. This combination allows me to identify how the causal effects of the RWH Program vary with the households' WTP and use the estimated effects to assess the potential of different targeting approaches to maximize the program's impact. Stated preferences were elicited through a contingent valuation (CV) survey designed to experimentally collect information on the household's potential treatment status in a predefined hypothetical situation. In particular, before any exposure to the RWH system, households were asked whether they would be willing to pay a hypothetical amount to participate in the RWH Program (and thus receive the RWH technology). The amount (or bid) assigned to each household in the CV survey was randomly selected from a large set of values, and the contingent stated participation was

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[6] For example, screening through take-up prices may not be desirable when individuals learn about their private benefits from the technology as they use it (Jack, 2022; Oliva et al., 2020; Dupas, 2014b; Fischer et al., 2019).

elicited in a binary format.

The stated preference information serves a dual purpose. First, in my main empirical exercise, I use the bids presented to households in the CV survey as instruments for program participation to estimate the distribution of treatment effects across quantiles of the households' WTP for the RWH technology. More concretely, the random assignment of bids generates exogenous variation in hypothetical treatment status. In principle, stated take-up rates decrease in the hypothetical amounts used in the CV survey. In this setting, compliers are households that would take up the technology only because they were presented with a bid below their (latent) WTP; that is, households with a WTP between these the bid presented to them and a smaller one. Thus, using a local instrumental variable approach, I leverage the variation in stated take-up rates between a pair of bids to statistically identify compliers and estimate the treatment effect of the RWH Program for households with a WTP within the range implied by those bids. Following the heterogeneous treatment effects model, each instrumental variable, defined as a pair of bids, identifies a causal parameter specific to the group of compliers for that instrument. Therefore, I exploit the semi-continuous nature of the bid variable to recover the distribution of treatment effects across the household's latent WTP.

Second, the stated preference data also serves as a direct link between treatment effects and subsidy policy. The heterogeneous effect model implies that households take up the technology if their WTP is greater than the cost faced. Thus, the latent dimension driving take-up decisions embedded in the CV data can be employed to statistically identify groups of households that would not enroll in the program under alternative subsidy rates. This feature allows me to simulate counterfactual policy scenarios. In particular, I recover the treatment effects of the RWH Program for households that would be screened out by introducing lower subsidy rates. Alternative subsidy rates can thus be compared based on their ability to prevent take-up by households that would attain lower benefits than the average. I further compare the impact of counterfactual subsidies with those resulting from using selection criteria based on sociodemographic characteristics and from combining the two approaches. Lastly, I characterize compliers along the WTP distribution to examine which households would be primarily affected by each targeting design.

I formalize this conceptual framework in Chapter 2. I outline a simple economic model of technology adoption and treatment effects where households take up the technology if their expected benefits exceed the costs. The model implies that the household's WTP summarizes this expectation and thus drives their enrollment decisions. Accordingly, a cost increase due to a subsidy reduction affects only the take-up decision of households with a WTP between the original and the new cost.

Next, in Chapter 3, I take these ideas to the data to estimate the benefits of the RWH Program and analyze how they vary across the WTP distribution. In the program context, most households have limited access to tap water. My analysis focuses on two primary outcomes: the amount of time spent collecting water from all sources and the postponement of daily activities due to a lack of water. I partnered with the Secretariat of the Environment of Mexico City, the program implementing agency, to survey households enrolled in the RWH Program in 2021. Households were interviewed twice, first when applying to the program (baseline) and a few months after receiving the RWH system (follow-up). Data on the relevant outcomes were collected in both rounds. In the initial survey, households completed the CV exercise and provided sociodemographic information.

For the estimation, I use the follow-up observation of the outcome for households that stated they would be willing to pay the bid asked in the CV task (hypothetical treatment group) and the baseline observation for those who stated they would not be willing to pay (hypothetical control). In addition, I use the staggered administration of the RWH Program to account for seasonality in water availability. Households received the RWH system in the order they applied to the program, and I define cohorts of participants depending on the month they enrolled. Treatment effects are estimated by comparing the outcomes of cohorts who had already received the system to those yet to receive it, conditional on the month of their interview. These contemporaneous comparisons account for the possibility of capturing rainwater and the volume of water allocated to the water utility, both of which depend on precipitation.

My results show that the benefits of the RWH system are non-negative across the WTP distribution and increasing in WTP. High-WTP households benefit from a reduction of up to 5 hours per week in the time required to obtain water. Similarly, the share of high-WTP households unable to complete a daily cleaning activity due to insufficient water decreases by 25 percentage points. In contrast, low-WTP households experience no time savings or reductions in activities postponed due to lack of water. Reassuringly, heterogeneity in treatment effects aligns closely with the usage rates observed across different WTP levels. The proportion of households using the RWH system after take-up increases with their WTP, from less than 20 to 92 percent. This pattern suggests that the WTP for the RWH technology captures the households' propensity to use it, thereby predicting the extent of their potential gains from adopting it.

My findings also suggest that the RWH system could effectively reduce both water access inequality across households and intrahousehold gender disparities. In relative terms, high-WTP households without the technology spend more time obtaining water and are more likely to postpone daily activities due to insufficient water. By contrast, among households with the RHW system, neither time spent on water-related activities nor the likelihood of postponing daily activities due to water restrictions exhibit significant differences across WTP levels. As a result, the RWH technology mainly benefits households facing more severe water restrictions in the baseline. Similarly, at the baseline, it is observed that women are primarily responsible for obtaining water when tap water is limited. However, there are no notable differences in the amount of time spent on these activities by men and women among households equipped with the RHW system. Thus, the RHW system significantly reduces the time spent on these activities for women more than for men.

Lastly, Chapter 4 provides evidence on the relative performance of strategies targeting program participants using demographic characteristics and counterfactual participation fees. I find that, across outcomes, participation fees representing between 3% and 15% of the total cost of the technology consistently reduce the probability of enrollment for households experiencing low benefits from the RWH system. By contrast, a targeting design based on observable characteristics produces qualitatively different results across outcomes for almost all characteristics. For example, selecting participants with a more limited water supply in the baseline decreases the impact of the RWH Program in terms of the time households spend collecting water but increases the usage rate. Yet, the most effective design consists of reducing the subsidy offered to potential participants with observable characteristics negatively correlated with the households' WTP. Moreover, in my setting, subsidy rate reductions do not disproportionally affect households with more limited water access or lower income-related characteristics.

My dissertation makes four main contributions. First, it adds to a developing body of research to identify the heterogeneity in treatment effects across values of an unobserved dimension, including WTP (Berry et al., 2020; Giustinelli and Shapiro, forthcoming; Jeuland et al., 2020; Bruhn et al., 2023). I complement this literature by showing how to incorporate contingent valuation methods into a program evaluation framework. My work is close in spirit to the study by Bruhn et al. (2023), who elicit preferences for various school attributes through discrete choice experiments. This strategy allows them to identify heterogeneous treatment effects of remote learning with respect to the families' propensity to choose the remote option. Different from their approach, my CV experiment to elicit preferences is directly related to (can be interpreted as) a policy instrument. By making this connection, my research strategy allows researchers to use standard methods (Heckman and Vytlacil, 2007a,b) to estimate counterfactual parameters for policy design.

Second, my dissertation aligns with the existing literature investigating mechanisms to improve the allocative efficiency of voluntary programs. Cohen and Dupas (2010); Bhattacharya and Dupas (2012); Alatas et al. (2016); Dupas et al. (2016); Jack (2013); Jack and Jayachandran (2019); Oliva et al. (2020), among others, have discussed and documented the consequences of using price instruments to change the composition of program participants under different circumstances. I add to the evidence of this body of research by comparing the relative performance of price mechanisms and selection criteria by themselves and in combination. My results create an avenue for future work on the conditions favoring each of these targeting approaches.

Third, I build on a large literature studying the conditions for stated preferences methods to generate useful information (see Manski, 1990; Arrow et al., 1993; Carson et al., 2001; Whitehead and Cherry, 2007; Johnston et al., 2017, and many others). In particular, experimental evidence has shown that CV surveys are not incentive-compatible and, thus, are prone to overestimate WTP values, a situation known as hypothetical bias (Cummings et al., 1997; List, 2001). I highlight that hypothetical bias is less concerning when CV data is used for causal inference. The identification of treatment effects exploits the *differences* in WTP revealed by assigning random bids to households, and thus, it is independent of the magnitude of elicited values.

Lastly, to the best of my knowledge, this is the first study exploring the causal effects of rainwater harvesting in urban settings[7]. Its findings have policy implications, as one-third of the global population suffers from water insecurity and water crises are predicted to take place across cities in developed countries, such as London, Tokyo, or Moscow, and developing countries, such as Sao Paulo, Bangalore, Cape Town, or Jakarta (He et al., 2021). Moreover, the RWH Program in Mexico City is planning to double its scale in the following six years, and two other governments are testing programs with the same structure in the Guadalajara and Monterrey Metropolitan Areas.

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[7] Jack et al. (2015) study the effects of easing access to credit to purchase rainwater harvesting tanks and the impacts of these tanks for farmers.

Chapter 2: Conceptual Framework

2.1 Introduction

In this chapter, I present a stylized economic model of how people take up new technologies and the effects of using them. I base this model on the generalized Roy model (Heckman and Vytlacil, 2007a; Eisenhauer et al., 2015) and focus on the households' unobserved willingness to pay (WTP) for the technology to define and identify the parameter of interest. This parameter is the average effect of participating in a program at different WTP levels. In this model, the household's take-up decisions depend on their WTP, and thus, every subsidy rate induces take-up by households with a different WTP. Households' returns to the technology may also depend on WTP. In that case, every subsidy rate results in a different treatment effect. The proposed identification approach uses contingent valuation (CV) methods to generate exogenous variation in the households' stated technology take-up rate across prices.

When a program's outcome is measured in monetary amounts, households make enrollment decisions based on the expected monetary gain from participation, and the program's treatment effect can be interpreted as the average willingness to pay (WTP) for participation. However, the treatment effect of technology adoption cannot always be measured in monetary units. Therefore, I extend the generalized Roy model to express enrollment decisions in terms of the expected utilities that would be attained with and without the technology. Then, following standard welfare economics theory, the household's WTP for the technology equals the difference between those utilities.[1]

Within this framework, changes in the subsidy rate impact the take-up decisions of households with different WTP levels differently. Those with a WTP between the baseline and the new subsidy rate switch their take-up decision. In contrast, the take-up status of the rest remains unchanged. If the effect of taking up the technology varies across households with different WTPs, then changes to the subsidy rate affect the average impact of the subsidy program. Take-up decisions at different prices are not observed. Thus, the chapter introduces the CV approach to elicit the households' reactions to hypothetical technology prices and shows how to incorporate them into the economic model. Lastly, the chapter discusses the assumptions necessary to identify the conditional treatment effect on the WTP level, particularly those implied by using elicited information.

2.2 A Model of Technology Take-up and Treatment Effects

Consider a program to subsidize a beneficial domestic technology for eligible households. Participating in the program is voluntary. Thus, households choose whether to enroll at the subsidy level set by the program designer. I simplify the household's problem to consist of a single decision: whether to enroll in the program or not. For convenience, consider the decision of potential participants in the RWH Program of Mexico City. Households that do not enroll rely on conventional water sources, such as municipal water supply, while program participation gives households access to RWH technology.

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[1] A Roy model based on utility maximization was first developed by Dahl (2002). Berry et al. (2020) also connect technology choices with expected WTP. However, these authors do not present the Roy model that underlies their application, as they were able to observe the WTP for each household individually.

Let D be an indicator variable, taking value one if the household enrolls. Thus, the household's enrollment decision determines its outcome as follows:

$$Y = (1 - D)Y_0 + DY_1, \tag{2.1}$$

where Y_1 and Y_0 are the potential outcomes with and without the RWH system, and Y is the realized outcome. This outcome variable can be, for example, time spent obtaining water. The return to the technology, or treatment effect, is given by $Y_1 - Y_0$.

The decision to take up the RWH system by enrolling in the program depends on the household's expectations about the utility drawn from each alternative. Let V_1 and V_0 be the household's utilities with and without the technology. Choices are made under imperfect information. By letting $\mathcal{I}$ represent the information set available to households at the time of choosing, the decision can be formalized as:

$$D = \mathbb{1}\{E(V_1 - V_0|\mathcal{I}) \geq 0\},$$

meaning that households enroll in the program if, ex-ante, they expect the net benefit from doing so to be positive.

Each alternative has an associated cost. These can be monetary or subjective costs. In my setting, costs in the absence of the technology, denoted by C_0, may arise from expenditures on water bills, water purchases from tanker trucks, and the discomfort caused by the unreliability of the municipal water network, among others. Similarly, the costs associated with the RWH system, C_1, can include chlorine tablets, the mental and physical effort of performing the RWH system maintenance tasks, the emotional reward of using an environmentally friendly technology, or co-benefits from home adaptations required to install the technology. Implicitly, any subjective benefits are modeled as negative costs and thus are captured by these terms.

Let Z be the cost of acquiring and installing the RWH system and M be the household's disposable income. I assume that the utilities V_0 and V_1 are defined as:

$$\begin{aligned} V_0 &= Y_0 - C_0 + M, \\ V_1 &= Y_1 - C_1 + M - Z. \end{aligned} \tag{2.2}$$

This model assumes that Z is an observed cost shifter variable affecting utility monotonically.[2] One can interpret Z as the cost of obtaining and installing the RWH system after the program designer chooses a subsidy rate exogenously; in this case, the higher the subsidy, the lower the cost incurred. Combining this model with a contingent valuation survey allows for the possibility of this cost to be a degenerate variable, in which case the hypothetical cost presented in the survey replaces Z (see section 2.5).

A household's maximum WTP for the technology is given by the difference in their utilities under each scenario.[3] It follows that the decision rule for enrolling in the RWH Program can be rewritten in terms of the household's WTP as:

$$D = \mathbb{1}\left[WTP \geq Z\right],$$

where the WTP is the household's valuation of the RWH system benefits, that is, its valuation of

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[2] To simplify the exposition, I suppose that Z shifts utility in a linear manner. The use of any other non-decreasing, non-degenerate function of the disposable income $M - Z$ does not change the main insights of the model.

[3] More generally, this relationship can be expressed as $V(Y_1, M - \theta, C_1) = V(Y_0, M, C_0)$, where θ stands for the compensating variation. Thus, $D = \mathbb{1}[\theta \geq Z]$.

$(Y_1 - C_1) - (Y_0 - C_0)$. Thus, households enroll in the program if this valuation exceeds the cost Z. Note that the household's expected benefit from taking up the RWH technology, captured by their WTP, is a latent index summarizing their propensity or desire to enroll in the RWH Program.

My analysis centers around the average treatment effect (ATE) across values of WTP. Specifically, I consider the following parameter:

$$ATE(w) = E(Y_1 - Y_0 | WTP = w), \tag{2.3}$$

which represents the average treatment effect conditional on a latent index and is known as marginal treatment effect (MTE) in the program evaluation literature (Heckman and Vytlacil, 1999, 2005, 2007b). Plotting the MTEs shows how the average return to the technology varies with the households' WTP for the technology. As such, the MTE curve reveals a specific type of treatment effect heterogeneity that policymakers can leverage to implement targeting strategies that consider more than observable characteristics.

2.3 Take-up under Changes to the Subsidy Policy

In the setting just described, exogenous changes to cost Z affect the enrollment decisions of some households by reducing or increasing their expected net benefits. Thus, changes to the subsidy level create different latent types of technology takers. These types are defined by indexing enrollment, D_z, to $Z = z$, for any pair of z values.

Consider, for example, the subsidy rates s_L and s_H resulting in the exogenous costs $z_L = (1 - s_L) \times r$ and $z_H = (1 - s_H) \times r$, where $z_L < z_H$ and r represents the technology's market price. The pair (D_{z_L}, D_{z_H}) defines the four mutually exclusive groups shown in Table 2.1. Never-takers

Table 2.1. Compliance types

	$D_{z_H} = 0$	$D_{z_H} = 1$
$D_{z_L} = 0$	Never	Noncomplying
$D_{z_L} = 1$	Complying	Always

Notes: This table defines the four compliance types implied by two different exogenous costs for the technology, z_L and z_H, where $z_L < z_H$. Types refer to households' take-up behavior.

are households unwilling to pay either of the two costs for the technology. Conversely, always-takers are willing to pay even the highest of these costs. Complying takers are those who, given their expected benefits, are willing to pay an amount between z_L and z_H. And noncomplying takers are willing to pay the higher cost z_H but not the lower one z_L. The existence of the latter group is ruled out if the marginal utility of money is non-negative.

Therefore, a cost increase from z_L to z_H will only affect the take-up decisions of complying households because their WTP is within the (z_L, z_H) range. Since latent types are defined locally, different pairs of costs define different sets of complying takers, characterized by their WTP. Thus, in principle, every household is a complier at some cost range. On this basis, one can use different pairs of costs to identify the treatment effects in equation (2.3) across WTP values, as discussed in the next section.[4]

2.4 Heterogeneous Treatment Effect Identification

The identification of the average treatment effects across levels of the WTP relies on exogenous changes to the price of the technology. As discussed above, an exogenous cost reduction,

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[4] Moreover, a household's classification into one of the latent types may change at different values of Z. For instance, a complying taker defined by the pair (z_L, z_H) is also an always taker at all costs less than z_L and a never taker at costs sufficiently larger than z_H. Figure B.1 in Appendix B illustrates the transition of latent types as the subsidy rate increases —–i.e., how the share of never-takers shrinks at higher subsidy rates because some of them become compliers and, eventually, always takers.

for example, from z_H to z_L, induces complying households to enroll in the program.

It is well established that such shock to prices allows one to identify the ATE for compliers by using local instrumental variables (Imbens and Angrist (1994)). The LATE parameter associated with the change from z_H to z_L identifies the ATE for households with a WTP between z_L and z_H and is defined as $LATE(z_L, z_H) = E(Y_1 - Y_0 | D_{z_L} > D_{z_H})$. Intuitively, the idea behind the ATE at *specific* WTP levels, or MTE, is that one could pick z_L arbitrarily close to z_H to identify treatment effects for households with $WTP = z_L$. In this case, the MTE is the limit of a LATE (Heckman and Vytlacil, 2007b). Then, the same exercise can be repeated over different cost ranges to identify the entire pattern of treatment effects across WTP values.

To fix ideas, consider a subpopulation of households with identical observable characteristics, denoted by X. For a complete derivation of the following exposition, see Appendix A. Thus, conditional on $X = x$, the only source of heterogeneity across households comes from their preferences for the technology, captured by their WTP. Let W_D represent quantiles of the distribution of the households' idiosyncratic WTP —that is, after accounting for the correlation between WTP and X. The average treatment effect for households with a given WTP level can now be expressed as:

$$MTE(x, w) \equiv E(Y_1 - Y_0 | X = x, W_D = w).$$

For mathematical convenience, the idiosyncratic WTP is often expressed in negative terms, so the higher W_D, the lower the idiosyncratic WTP.[5] Hence, the MTE is the expected treatment effect for households with sociodemographics $X = x$ who are at the $(1 - w)$-th quantile of the

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[5] The unobserved component of the latent index, which I call idiosyncratic WTP, is typically referred to in the literature as essential heterogeneity, unobserved resistance to treatment, or distaste for treatment.

distribution of the idiosyncratic WTP.

Given their idiosyncratic WTP, the enrollment decisions of households with $X = x$ are entirely determined by Z. Let $P(Z)$ be the probability of taking up the technology given Z: $P(Z) \equiv \textit{Pr}(D = 1|Z)$. In what follows, I refer to the latter quantity as propensity score. Under this normalization, the identification of the MTEs comes from marginal changes in the take-up rates, $P(Z)$. For the example above, complying households have a WTP such that they do not enroll in the program when faced with a propensity score of $P(z_H)$, but they do so when faced with the higher value $P(z_L)$, and the MTE at $W_D = P(z_1)$ identifies their expected treatment effect as $P(z_H) \rightarrow P(z_L)$.

Accordingly, the MTE is identified by the derivative of the outcome with respect to the propensity score (see Appendix A):

$$\frac{\partial E(Y|P(Z) = w)}{\partial w} = MTE(w). \tag{2.4}$$

Note that the left-hand side of this expression can be estimated from the data. By repeating this procedure at different values of the propensity score, treatment effects can be identified at all quantiles W_D within the empirical distribution of $P(Z)$. Therefore, one can determine which households (identified by the quantile of their WTP) are induced to take up the technology by each marginal increase in the subsidy rate affecting $P(Z)$.

Lastly, an alternative to working directly with $E(Y|P(Z) = w)$ to obtain the expectation of the difference, $E(Y_1 - Y_0|W_D = w)$, is to identify each expectation separately and then compute their difference (Heckman and Vytlacil, 2007b). These expectation functions are defined as:

$$E[Y_0|W_D = w, D = 0] \quad \text{and} \quad E[Y_1|W_D = w, D = 1], \tag{2.5}$$

and are known as marginal untreated outcome (MUO) and marginal treated outcome (MTO) or jointly as marginal treatment responses (MTR). Estimating the MTRs using this separate approach allows the researcher to investigate if treatment effect heterogeneity along the WTP distribution comes from heterogeneity in Y_1, Y_0, or a combination of both. In particular, any heterogeneity in the MUO across WTP levels is exclusively the result of selection (Kowalski, 2016). In other words, the MUO function informs whether households self-select into the program based on their outcome in the absence of the technology. The MTRs can be identified by estimating $E(Y_j|D = j, P(Z) = w)$ and their derivatives from sample data, as shown in Appendix A.

2.5 Willingness to Pay Elicitation

As this chapter details, identifying the benefits of technology across WTP levels requires the existence of an ideally large collection of exogenous costs. This is rarely the case in the context of programs subsidizing technologies in developing settings. In the absence of observable demand behavior to obtain D, researchers draw on randomized trials in which technology prices are randomized across potential program participants. However, this approach is not always feasible due to institutional or budget constraints.

An alternative for learning about households' reactions to prices for policy analysis is to conduct a contingent valuation (CV) survey. Contingent valuation (CV) is a stated preference method that presents individuals with carefully constructed hypothetical situations and uses their stated behavior to estimate preference functions, such as demand or WTP. So, in contrast to revealed preference methods, there is no need to observe actual behavior.

Within the framework described in this chapter, CV can be specifically used to elicit households *stated* take-up decisions using different *hypothetical* prices for the technology. For this purpose, a CV survey should present respondents with a clearly described technology, a payment required to access the technology, and a payment vehicle. Here, I abstract from the specifics of designing CV surveys but underscore that the way that a survey asks the WTP question is particularly important. For a comprehensive review of this method and best practices, see Phaneuf and Requate (2016) and Johnston et al. (2017).

Among the various strategies for soliciting respondents' valuation of technology, the single binary question format stands out for its simplicity and ease of understanding. By presenting survey takers with a single price for the technology and asking for a straightforward yes or no response, this format minimizes the cognitive burden of answering, thereby increasing the precision of the information elicited. An example of this type of question is, "Would you be willing to pay Z for the technology?" where Z is the presented bid amount that varies across individuals.

Unlike strategies that directly ask respondents to state their WTP (using, for example, open-ended formats or multiple price lists), the single binary choice question format offers the possibility of presenting respondents with a cost exogenously selected at random. This feature enables incorporating the information elicited into the heterogeneous treatment effects framework. In other words, the WTP question in the CV survey mirrors the enrollment decision of the technology adoption model: Households take up the technology if their WTP is at least equal to the cost faced. By interpreting the bid from the CV question as resulting from an exogenous subsidy rate and the household's answer as their potential treatment status at that subsidy level, the CV survey returns the Z and D variables needed to identify heterogeneous treatment effects across WTP values.[6]

Notwithstanding the connection between CV and the model outlined, the elicited hypothetical take-up should not be interpreted as potential demand for the technology. CV surveys are not incentive-compatible and are prone to overestimate real WTP values —i.e., when actual payment is involved (Cummings et al., 1997; List, 2001). The difference between hypothetical and actual WTP is known as hypothetical bias.

Hypothetical bias is a significant concern when using a CV survey to estimate the average WTP for a good or service. However, in my framework, CV is used to create exogenous variation in the stated take-up rates to identify the impact of public programs on outcomes observed ex-post. In this context, the relevant part of the information obtained through CV is the households' relative valuation within the sample, not its magnitude. Specifically, the CV survey is used to generate variation in the take-up function, $P(Z)$. Changes in this function across values of Z are captured by its slope parameters, which are invariant to the intercept capturing the take-up magnitude. Accordingly, the identification of MTEs depends on the occurrence of stated take-up rates that decline monotonically as the hypothetical cost increases. However, further research is necessary to generalize the use of CV within the potential outcome framework and better identify the assumptions involved and possible improvements.

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[6] It is worth noting that the MTEs are identified only within the support of the propensity score, $P(Z)$. So, the randomized bids employed in the CV exercise should ideally vary by small amounts and cover a range such that the propensity score variation is the full unit interval.

2.6 Assumptions

Identifying the MTE parameters under the model specified requires a set of standard assumptions in the instrumental variable literature. To formally present those assumptions, let $e \equiv -E\left\{(\varepsilon_1 - \eta_1) - (\varepsilon_0 - \eta_0)|\mathcal{I}\right\}$ be the residualized version of the expected benefit from the technology, $E\left\{(Y_1 - C_1) - (Y_0 - C_0)|\mathcal{I}\right\}$, conditional on X. The household's enrollment decision can now be expressed as:

$$D = \mathbb{1}\left[P(Z) \geq W_D\right], \tag{2.6}$$

where $W_D \equiv F_e(e)$ and $F_e(\cdot)$ denotes the distribution of e (see Appendix A).

The generalized Roy model specified in equations (2.1), (2.2), and (2.6) is completed by maintaining the following assumptions:

(i) Z is independent of $(\varepsilon_1, \varepsilon_0, \eta_1, \eta_0)$;

(ii) $V_1(Z)$ is non-degenerate, given (X, M);

(iii) the distribution of e is continuous.

Assumption (i) is implied by random assignment of costs Z to households in the elicitation exercise. Assumption (ii) states that the subsidy rate effectively changes households' adoption decisions by shifting the utility they derive from the RWH technology through Z. In combination with the additive separability between $P(Z)$ and W_D in equation (2.6), this assumption rules out the presence of noncomplying takers. When actual payment is involved, assumption (ii) is satisfied if the marginal utility of money is non-negative. This assumption is satisfied in my setting if the costs assigned in the CV exercise affect the stated take-up rates monotonically. Assumption (iii) is a regularity condition that is satisfied if either $(\varepsilon_1 - \varepsilon_0)$ or $(\eta_1 - \eta_0)$ vary conditional on X, implying that the households' idiosyncratic WTP is a determinant of technology take-up. These three assumptions of the latent index model are equivalent to the standard assumptions in Imbens and Angrist (1994) necessary for the LATE approach (see Vytlacil, 2002).

In addition, I assume that

(iv) the outcome Y_1 a household would experience if it were to pay the bid faced in the CV survey is the same as the outcome Y_1 observed.

Formally, let $Y_1(z)$ represent the household's potential outcome with the technology it had paid the price $Z = z$ to acquire it. From the household's participation in the program, one can observe $Y_1(z')$, where z' is the price paid (possibly zero). I assume that $Y_1(z) = Y_1(z')$ for all z used in the CV survey.

This assumption is violated in the presence of income effects; that is if the reduction in the household's disposable income after paying for the technology affects their outcome Y_1. Similarly, assumption (iv) may not hold if, ceteris paribus, the price paid for the technology influences how much households value and use it (through loss aversion, or "sunk cost" effect). I rule out this channel based on the conclusions of Ashraf et al. (2010), Berry et al. (2020), and Cohen and Dupas (2010), who find no consistent evidence for this hypothesis in three independent field experiments related to the purchase of chlorine, water filters, and insecticide-treated bed nets, respectively.

2.7 Conclusion

The economic framework presented in this chapter uses contingent valuation methods in a novel way to instrument for program participation and identify treatment effects as a function of the households' WTP. In the presence of treatment effect heterogeneity, this CV application enables one to analyze how different subsidy rates affect the impact of a program. In particular, eliciting hypothetical behavior to recover treatment effect heterogeneity associated with WTP offers an alternative to randomized interventions charging different prices for the products or services the program seeks to offer.

Certain limitations exist when using stated preference methods to value goods or services due to hypothetical bias. This chapter suggests that using CV for causal inference does not require eliciting actual WTP values. Instead, the framework presented relies on the households' relative valuation within the sample. Nonetheless, further research is crucial to generalize the use of CV within the potential outcome framework, better identify the assumptions involved, and explore possible improvements.

Chapter 3: Empirical Estimation of the Heterogeneous Treatment Effects of a Rainwater Harvesting Technology

3.1 Introduction

In this chapter, I utilize the conceptual framework from Chapter 2 to empirically estimate the heterogeneous treatment effects of a subsidy program across the participants' willingness to pay (WTP) for a rainwater harvesting (RWH) technology. The RWH Program, implemented by the government of Mexico City, aims to alleviate water insecurity in low-income neighborhoods with inadequate water municipal service. The program provides eligible households with a 1,000 USD device to capture rainwater for all domestic, non-drinking purposes at no cost. The number of RWH systems distributed is limited to 10,000 per year, and the government processes applications on a first-come, first-served basis. Operating the RWH system involves several recurrent steps that can constitute a nontrivial time cost and a mental load for households, dissuading some recipients from using the RWH system continuously. The combination of a self-selection design, a 100 percent subsidy, and a technology whose returns depend on active usage makes this a valuable setting to study the calibration of take-up subsidies.

I consider two primary outcomes: the postponement of daily activities due to a lack of water and time spent collecting water. The data for this empirical analysis was collected through in-person surveys among all households participating in the RWH Program in 2021 in partnership with the Secretariat of the Environment of Mexico City (Sedema, the program implementing agency). Since all households in the sample received the technology, I use the staggered administration of the RWH Program to define treatment and control groups. Households received RWH systems in the order they applied to the program, and I define cohorts of participants depending on the month they enrolled. Treatment effects are given by the comparison of the outcomes of cohorts who had already received the system and those yet to receive it, conditional on the month of their interview. Because the technology was distributed for free, the identification strategy uses the variation in hypothetical take-up rates generated exogenously by randomly assigning hypothetical costs to households in a contingent valuation (CV) exercise.

I find that the benefits of the RWH system are non-negative and increasing across the WTP distribution for the technology. High-WTP households benefit from a reduction of up to 5 hours per week in the time required to collect water from any source. Similarly, the share of high-WTP households unable to carry out daily cleaning activities due to insufficient water decreases by 25 percentage points. In contrast, low-WTP households experience no time savings or reductions in the likelihood of postponing activities due to lack of water.

Moreover, the heterogeneity in treatment effects aligns closely with the usage rates observed across different WTP levels. The proportion of households using the RWH system increases with their WTP, from less than 20 to 92 percent. This pattern suggests that the WTP for the RWH technology captures the households' propensity to use it, thereby predicting the extent of their potential gains. Under these circumstances, reducing the subsidy rate offered to households could allocate the technology to households with higher returns, ultimately increasing the program's benefits per participant.

The rest of the chapter proceeds as follows. Section 3.2 presents the social context of water scarcity in Mexico City, overviews the RWH Program rules, and introduces the RWH technology. Section 3.3 describes the data collection process and explains the specifics of the CV survey. Section 3.4 presents the empirical strategy based on the framework developed in Chapter 2 and offers details on the estimation of all parameters. Section 3.5 presents the heterogeneous treatment effects on the use of time to obtain water, the postponement of daily activities due to the lack of water, and the pattern of the RWH system's usage rates. Section 3.6 concludes.

3.2 Background and Institutional Context

3.2.1 Mexico City's Water Crisis

The primary sources of fresh water in Mexico City, groundwater from its underlying aquifer and surface water imported from surrounding basins, are under severe strain. The former, representing roughly 60 percent of the total supply (Conagua, 2019), is being exploited at 1.2 times its natural recharge rate (Semarnat, 2016). As for surface water, the prolonged dry seasons associated with climate change have recently caused repeated temporal reductions in the water volume allocated to the city. In addition to the city's limited access to cost-effective water sources, 35 percent of water is estimated to be lost in the distribution network due to pipe leaks caused by seismic activity and continuous land subsidence resulting from the aquifer's depletion (Sacmex, 2012).

The over-exploitation of the Mexico City Aquifer was evident from continuous land subsidence in downtown Mexico City as early as 1930 (NRC and ANIC, 1995). In the next five decades, the federal government developed enormous infrastructure projects to transfer water from surrounding basins to the metropolitan area. The resulting Lerma-Cutzamala system transfers water from 150km away, using as much electricity as a 3-million-person city to pump water to a high altitude (Sacmex, 2012). Over time, this volume became insufficient, and a new construction stage to increase the system's capacity by 25% was to be initiated in 1997. Due to strong opposition from local communities upstream, the project has yet to be started (Tortajada, 2006).

Even at their maximum capacity, the combined volumes from all sources are insufficient to meet the city's water demand. As a result, water is rationed. While nearly all households own a connection to the network[1], a third receive piped water only during limited hours and experience persistent supply interruptions (Sacmex, 2016). Moreover, about 11% of residents typically receive water less than twice weekly.[2] In practice, rationing is done by water utility employees who manually turn the valves on and off to alternate water flow across neighborhoods (Baisa et al., 2010). Most service interruptions are unannounced and do not follow a regular pattern.

The provision of water services varies across neighborhoods and is substantially worse for marginalized areas. While the per capita piped water use is about 350 liters per day at the city level (NRC and ANIC, 1995), it ranges from 20 liters in the poorest neighborhoods to 600 liters in the wealthiest (Tortajada, 2006).[3] These inequalities in access to water are reflected in a clear geographical pattern since both underground water and deliveries from Lerma-Cutzamala are concentrated in the northwest part of the city (PDHCDMX, 2016, Chapter 6).[4] Thus, the water supply is especially short and unreliable for people on the south and east sides. In these

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[1] 2020 National Census.

[2] 2016 Consumer Expenditure Survey.

[3] As a reference, per capita water consumption in the USA is 310 liters a day (Dieter et al., 2018).

[4] A beltway started in 1982 to increase water supply in southeast Mexico City has never been completed. According to the authorities, the reason is that *there is no water to transport* (Sacmex, 2016).

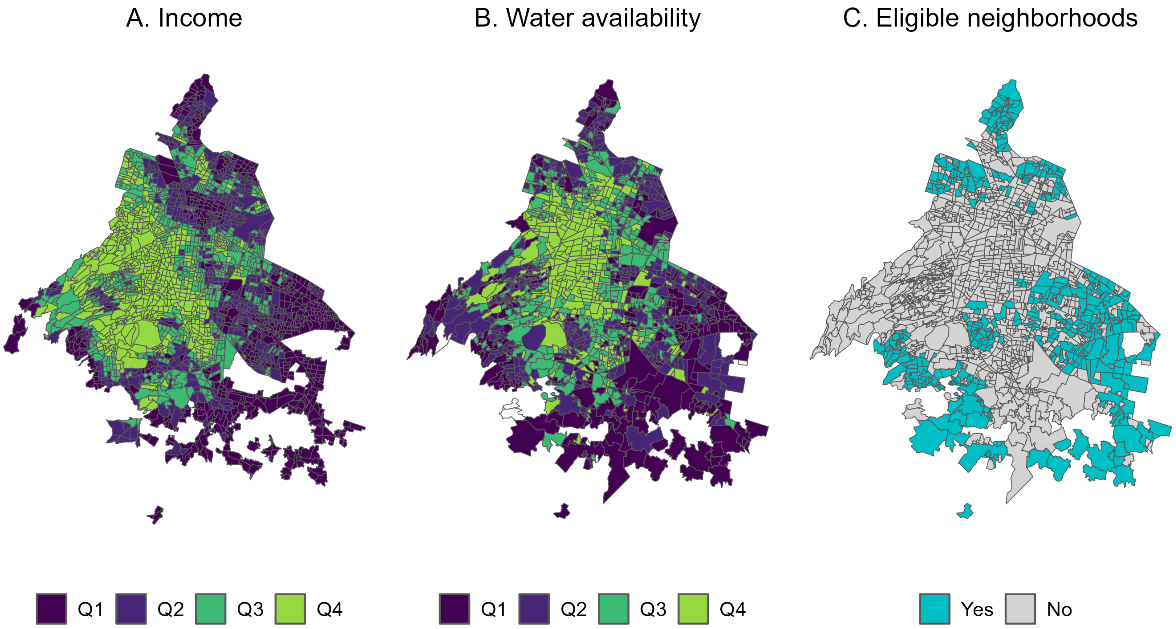

Figure 3.1. Income, piped water availability, and participation
in the RWH Program by area in Mexico City

Notes: This figure shows income and piped water availability across areas in Mexico City and the neighborhoods participating in the RWH Program in 2021. Panel A shows quartiles of income per capita in 2014 by basic statistical area (AGEB). Panel B presents quartiles of piped water supply per capita in 2016 at the neighborhood level. Panel C shows the neighborhoods selected for the RWH Program in 2021. *Sources:* Panel A: 2014 Consumer Expenditure Survey (ENIGH); Panel B: Instituto de Planeación Democrática y Prospectiva with data from Sacmex; Panel C: Gaceta Oficial de la Ciudad de México, December 30, 2020.

areas, neighborhoods under the rationing scheme receive water from the network for as little as 14 hours a week (Soto Montes de Oca, 2008). Panels A and B in Figure 3.1 show income and water availability distributions in per capita terms across geographic areas.

Families facing water scarcity are compelled to store water, limit their consumption, postpone daily activities, and rely on more expensive water sources. Some households receive water from municipal governments through tanker trucks at no cost, but the supply is limited, often leading to several-week waiting periods. These trucks usually distribute water at the street level, and families carry it home. Because of these constraints, households spend significant time fetching, storing, and cleaning water. In most cases, female household members take care of these tasks.

For instance, in Iztapalapa, the most populated city borough, 41% of women spend between 1 and 4 hours a week carrying out these activities, while only 25% of men do so (Salazar et al., 2012). In addition, water is being withdrawn from deeper wells to increase supply, in which the water mineral contents exceed the official standards (Semarnat, 2016). Consequently, even poorer households rely on bottled water for drinking, cooking, washing dishes, and even bathing children despite being expensive. Moreover, high turbidity at the source and further contamination in the tanker trucks sometimes make water unsuitable for cleaning.

3.2.2 The *Cosecha de Lluvia* Program

In 2019, Mexico City's government created a program to increase water access through rainwater harvesting at the household level as an alternative to substantial investments in centralized water infrastructure. The RWH Program, or *Cosecha de Lluvia*, offers a rainwater capture system free of charge to 10,000 households per year on a first-come, first-served basis. This technology is designed to provide safe water during the rainy season for all non-drinking domestic uses, such as flushing toilets, washing clothes and dishes, bathing, or cooking.

Cosecha de Lluvia targets neighborhoods with a medium to very high poverty index and high water insecurity levels. All residents of designated neighborhoods can apply to the program, regardless of their poverty or water insecurity condition. The 441 neighborhoods participating in Cosecha de Lluvia in 2021 are shown in Panel C of Figure 3.1. These neighborhoods are among those with the lowest income and water supply levels in Mexico City.[5]

Although all residents of participating neighborhoods can apply to Cosecha de Lluvia,

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[5] Informal settlements are excluded from the program. Participating neighborhoods may change over time, depending on the collaboration agreements between the city boroughs and the city government. This paper uses data only on households participating in the program in 2021.

some dwellings are not suitable for installing the RWH system provided by the program. Thus, after submitting the required documentation, all applicants receive the visit of a program technician to inspect their dwelling conditions. Households whose dwellings definitely do not qualify are rejected. Typically, these are families living in apartment buildings or those with limited space to fit a storage tank. In other cases, applicants are encouraged to complete home adaptations to make the installation feasible. Upon meeting all technical requirements, applicants receive a second visit during which the RWH system is installed while the supply lasts.[6]

The RWH system provided by Cosecha de Lluvia is a residential technology that harvests rainfall from the roof of the house, carries it through a set of gutters, pipes, and filters, and stores it in a tank.[7] Figure 3.2 shows a picture of the system and its components. Depending on the preexisting infrastructure of a house, water from the storage tank can be pumped to the rooftop tank to feed the house piping system and then used as regular tap water. The RWH system has a lifespan of up to 30 years. It costs 900 USD for the equipment plus 100 USD for the installation, a total amount that represents three months of minimum wage in Mexico City.[8]

In the context of the RWH Program, rainwater capture does not represent a substitute for conventional water supply. During the rainy season in Mexico City (May through October), the RWH system has the potential to provide the median household participating in Cosecha de Lluvia with 150 liters of water per day on average.[9] For a family of four, this amount is below the

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[6] Other exclusion channels are likely to be minimal. For example, renters can participate if the owners express their agreement in writing, program staff members assist households in obtaining all documents needed for application, and applications are received in person in different municipal buildings, online, and through text messages.

[7] This RWH system was originally developed in 2009 by industrial designers from Isla Urbana, a well-known local NGO promoting RWH since then. The system was designed specifically for the needs and conditions of Mexico City.

[8] All US$ figures in the paper are converted from Mexican pesos at a rate of 20 pesos per dollar.

[9] Based on a roof surface of 40m^2, the average precipitation during May through October in Mexico City in 1981-2010, and a capture coefficient of 0.85 suggested by Sedema, IU, and IRRI (2020).

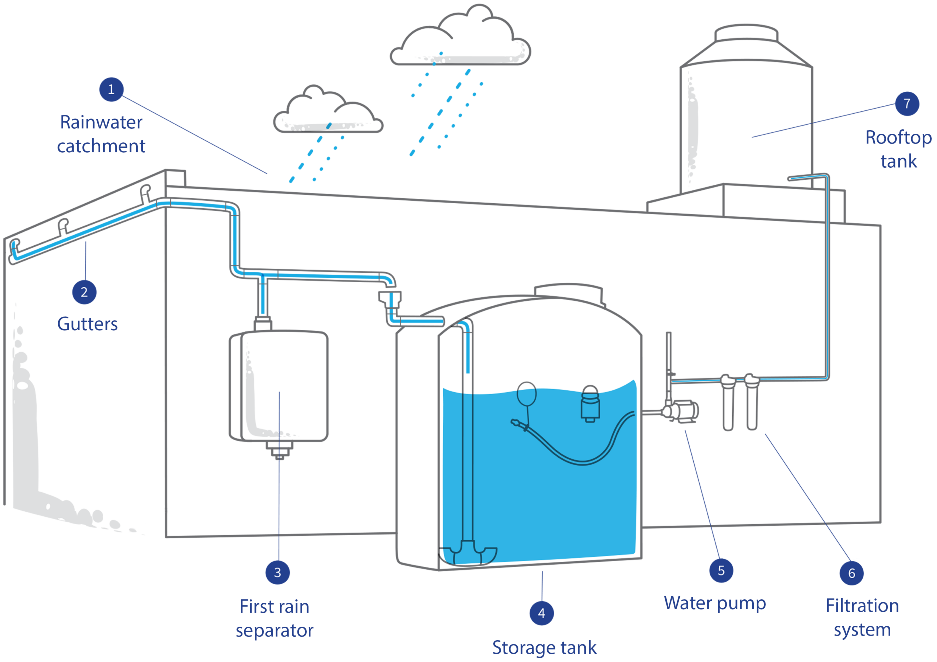

Figure 3.2. The Rainwater Harvesting System

Notes: This figure shows the design of the rainwater collecting system provided and installed by the RWH Program. Its main components are labeled in the image. *Source:* Adapted from Sedema, IU, and IRRI (2020).

minimum WHO recommendation of 50 liters per day for a person to meet their most basic needs. If used properly, the filters and mechanisms of the system remove solid particles, pathogenic microorganisms, and organic compounds, delivering safe water for all domestic activities except drinking. For that reason, rainwater collected with the system can often be of better quality than tap or truck-delivered water.

Notwithstanding the system's design, the amount and quality of harvested water largely depend on adequate use and maintenance by the users. Maintenance tasks are time-consuming and include placing chlorine tablets in the tank every two weeks, periodically washing the roof, brushing off debris from filters, and draining the first rain separator after every rain to filter out the first minutes of rainfall, which carries most contaminants.

Accordingly, the program's benefits for households are likely to depend on water scarcity and more subjective factors such as the opportunity cost of time, the household's taste, or the ability to recall the required maintenance steps. In fact, it is observed that despite providing training to all participants on the RWH system, its usage varies significantly. Evidence from the 2021 internal evaluation of the RWH Program, monitoring a few dozen households, suggests that the average amount of rainwater collected was 50 to 60 percent of the system's potential.

3.3 Data

3.3.1 Data Collection

I partnered with Sedema, the Secretariat of the Environment of Mexico City responsible for implementing Cosecha de Lluvia, to survey households applying to the program in 2021. We designed a baseline and a follow-up survey questionnaire, and Sedema administered all interviews. Baseline interviews were conducted among all interested households shortly after receiving their application.[10] The follow-up interview was administered only to the participants a few months after they received the RWH system. The questionnaires consisted of questions aimed at collecting data on:

(i) The households' hypothetical enrollment decision if they were required to pay a cost to receive the RWH system. This exercise was completed at baseline, through a contingent valuation survey module, before any exposure to the RWH system. More details on the CV module can be found in Section 3.3.3.

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[10] Applications by residents from non-participating neighborhoods were not processed, and thus, these households were not surveyed.

(ii) Outcomes at baseline and follow-up. We obtained self-reported information about the daily cleaning activities postponed by the household due to the lack of water and the time allocated to water procurement by household members.

(iii) Households' baseline socio-demographic characteristics, including geographic location, applicant's gender, asset ownership, household size, dwelling characteristics, and typical water use from different sources.

The outcomes referred to in (ii) were selected based on Sedema's expectations about the areas Cosecha de Lluvia may impact. In particular, health impacts were not believed to be relevant a priori because most households rely on bottled water for drinking, and Sedema explicitly instructs them not to use the rainwater collected for drinking. Nevertheless, the survey asked about diarrhea and vomiting episodes in children under 7, but less than 4% of the respondents reported their occurrence.

I focus on the subset of eligible households who received an RWH system.[11] This selection is motivated by my interest in examining the impacts of Cosecha de Lluvia and the potential implications of changes in the program's subsidy for households that are eligible and willing to enroll.

Sedema monitors visited all applicants in person for the baseline survey. The follow-up survey was conducted by an external provider. 60% of the follow-up interviews were conducted in person during a planned visit, and the remaining 40% were conducted by phone. Sedema selected the households to be interviewed in person in each neighborhood to avoid a disproportionate number of telephone interviews among households living in remote areas. Most enumerators, both

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[11] Non-participant households excluded from the sample either chose not to continue their application after the baseline interview or their dwelling was unsuitable for installing the RWH system. After considering the identification strategy in Section 3.4, the number of observations excluded was 134.

from Sedema and the external provider, had previous experience conducting a similar survey the year before. They all attended training sessions to familiarize themselves with the questionnaires and the mobile app developed to record answers. They were also trained in the operation of the RWH system, ensuring their understanding of the technology and its maintenance requirements.

Attrition in survey responses was negligible. Households consented to participate in both interviews by signing a written agreement during the application process. Because of that, all participants answered the initial questionnaire, and all but 44 completed the follow-up. Therefore, we obtained data even among participating households who did not use the RWH system received. Despite the high response rate, we lost answers from 1,626 out of 9,985 baseline questionnaires due to a technical error in the protocol to save the data in Sedema's server.[12] In addition, I drop observations from 1,659 households with missing values in any of the variables entering the main estimation. After trimming these observations, the sample includes 6,700 households. I refer to this sample as the sample of all participants. Lastly, as discussed in Section 3.4, my identification strategy implies using a subset of the data. The sample size for the subset of observations entering the analysis is 3,660. I refer to this sample as the analysis sample, and all results presented throughout use only these observations.

Table 3.1 provides descriptive statistics for all participating households with available data and those in the analysis sample. As seen in the table, the person applying to the program was a woman in most cases. On average, surveyed households only have access to running water three days a week. Neighborhood-level administrative data indicates that the water supply in the participants' neighborhoods is around 130 liters per person per day, roughly equivalent to the 20th

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[12] Our mobile app worked offline to store data temporarily in the mobile devices used to record survey responses and erase them after synchronization with the server. The synchronization protocol was incompatible with some devices, and the data stored in them was permanently lost.

Table 3.1. Descriptive Statistics

	All participants		Analysis sample	
Baseline characteristics				
Female applicant	0.651	[0.477]	0.645	[0.479]
Household size	4.527	[1.993]	4.576	[1.990]
Car ownership	0.482	[0.500]	0.479	[0.500]
Computer ownership	0.617	[0.486]	0.628	[0.483]
Water storage capacity (1,000L)	3.925	[4.657]	3.945	[5.011]
Days a week with access to tap water	3.196	[2.453]	3.231	[2.443]
Consumes water from tanker trucks	0.276	[0.447]	0.275	[0.447]
Is not charged for municipal water*	0.627	[0.484]	0.617	[0.486]
Pays fixed amount for municipal water*	0.251	[0.434]	0.256	[0.436]
Pays for tanker trucks*	0.119	[0.323]	0.113	[0.317]
Ex-post RWH system specifications				
Storage tank size (1=big)	0.740	[0.439]	0.744	[0.436]
Roof surface for catching rainfall (sq m)	42.767	[20.578]	42.619	[20.518]
Administrative data at the neighborhood level				
Municipal water supply per capita	132.658	[24.593]	132.618	[23.754]
Social development index	0.793	[0.040]	0.794	[0.039]
Month of interview for estimation				
August			0.169	[0.375]
September			0.536	[0.499]
October			0.296	[0.456]
Observations	6,700		3,660	
F-stat (Prob $>$ F)			19.76	(0.1378)

Notes: This table reports sample means of baseline characteristics collected in the survey, the technical specifications of the RWH systems installed, and neighborhood-level administrative data. Standard deviations are shown in brackets. Statistics for the whole set of participants with available data and those used in the analysis are presented in different columns (see Section 3.4 for details on the definition of the analysis sample). A joint F-test of equal means across variables between households in the analysis sample and the rest is included. 348 observations in the analysis sample and 316 among the rest contain missing values for at least one of the characteristics marked with a star *. For the F-test, missing values are replaced with variable means obtained separately for the analysis sample and the rest of the observations.

percentile in Mexico City. Thus, households maintain a water storage capacity of four thousand liters, and 28 percent of them consume water from tanker trucks. Car and computer ownership in the sample are very similar to their averages in Mexico City. Yet, the neighborhoods where participant households live fall in the lowest quintile of the social development index.

Based on these descriptives, the sample selection implied by the identification strategy does not introduce significant differences relative to the observations not considered. The only characteristic that differs (at the 10% level) between the analysis sample and the rest of the participants with available data is household size. The joint F-test reported in Table 3.1 indicates that the set of all characteristics considered is not statistically different between these groups.[13]

3.3.2 Research Design

My research design uses the staggered administration of the RWH Program in Table 3.2 to define comparison groups and account for seasonal variation in water availability. The baseline survey was conducted over several months, from April to October, as households applied to the program and staff capacity allowed. The follow-up survey started in August; once most applications had been processed, households had received and familiarized themselves with the RWH system, and staff could assist.

This survey schedule allows me to compare households with and without the RWH system during the rainy season. I split the sample into cohorts based on when households were first interviewed. For instance, households that completed the baseline survey in April are part of cohort A, those who completed it in May are in cohort B, et cetera. Between August and October, cohorts A, B, C, and D completed the follow-up survey once they had had access to the RWH system for three months or more. In those same months, cohorts E, F, and G completed the baseline survey and were yet to receive the system. Accordingly, I use households from cohorts E to G as a control group for households in cohorts A to D.

---

[13] The F-test is obtained by fitting a seemingly unrelated regression model. Each characteristic is regressed on cohort fixed effects and an indicator variable equal to one for households in the analysis sample. The null hypothesis that the coefficients on this indicator from all regressions are jointly zero is rejected only at the 0.14 significance level. Missing values in variables marked with a star in Table 3.1 are replaced with group-specific means for the test.

Table 3.2. Staggered Implementation of the RWH Program

	Cohort						
Month	A (Apr)	B (May)	C (Jun)	D (Jul)	E (Aug)	F (Sep)	G (Oct)
Apr	baseline						
May		baseline					
Jun			baseline				
Jul				baseline			
Aug	follow-up				baseline		
Sep	follow-up	follow-up	follow-up			baseline	
Oct		follow-up	follow-up	follow-up			baseline
Nov				follow-up	follow-up	follow-up	
Dec						follow-up	follow-up

Notes: This table presents the classification of households for the estimation of treatment effects, based on the month each cohort was interviewed for the baseline and follow-up surveys. Letters denote cohorts, indexed by the month they entered the program. Across-cohort comparisons are done within the same month. The treatment group consists of cohorts A to D, who answered the follow-up survey during the rainy season, while the control group is composed of cohorts E to G, who completed the baseline survey during the same period. Months of the rainy season are shaded in blue, and the red rectangle encloses the observations used for the estimation.

Comparisons between cohorts are made within the same month to account for seasonality in household water availability. As the rainy season advances, from May to October, more water is available in dams, and thus, water restrictions are less severe in Mexico City. Similarly, higher precipitation levels improve water access for households who have received the RWH system. Given these within-month comparisons, the analysis only considers data from interviews administered between August and October since the rest did not overlap with a comparison cohort in the same month. The proportion of observations surveyed in each of these months is shown in Table 3.1.[14]

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[14] Baseline interviews were not randomly scheduled, and their sequence is correlated with the application order of households. While cohorts are used to define the treatment and control groups for contemporaneous comparisons, the identification strategy does not rely on the households' staggered adoption of the technology.

3.3.3 Willingness to Pay Elicitation

In the context of the RWH Program, where all households are provided with the technology at no cost, demand behavior is not observed. To gain insights into households' response to prices and thereby estimate the implications of different subsidy rates, I elicited hypothetical demand for the RHW system at various cost levels using a contingent valuation approach, as detailed in Chapter 2. I implemented this approach by asking respondents about their willingness to participate in the program if they were required to pay a specific amount.

As mentioned in Section 3.2, all applicants receive a visit from a program technician to determine if their dwelling qualifies for installing the RWH system. In most cases, households need to make home adaptations to qualify.[15] This program feature is used to elicit the applicants' hypothetical decision to enroll in Cosecha de Lluvia if they were required to pay for it. During the baseline interview, households were presented with a scenario before knowing their dwelling's eligibility.[16] Specifically, households were presented with the following situation:

> *At this moment, the technician is inspecting your dwelling to determine if it meets all the requirements for installing the RWH system.*
>
> *Participants often need to make some home adaptations before we can proceed with the installation.*
>
> *If you were required to make modifications to your home to qualify for the installation of the RWH system, and the cost of those modifications amounted to Z pesos, would you be willing to pay for them?*

---

[15] Examples of minimal conditions to install the system are: a roof surface larger than 30m2 with a 5% or steeper inclination; the roof must be free of polluting objects, pets, and toxic materials (such as corrugated asphalt panels); space to install a 1,100 liter or larger storage tank on a firm surface, a power outlet located outdoors, and access to drainage or sewage, among others.

[16] Due to staff limitations, not all baseline interviews were conducted during the technician's inspection. Households were randomly assigned with a 50% probability of being surveyed during the technician's inspection or a subsequent visit. In the latter case, respondents knew they would receive the RWH system with certainty. The CV module was included in their questionnaire to increase the sample size, and the contingent scenario was adapted accordingly. 47% of baseline interviews in the analysis sample were conducted during the technician's inspection. Throughout the analysis, I control for the visit at which respondents completed the baseline survey.

The question about willingness to pay for home modifications was designed with four key considerations. First, it aimed to place respondents in a familiar decision context, responding to a posted price, to minimize the cognitive burden. Second, it directly asked about hypothetical participation status, not a purchase decision in a different context, such as acquiring the RHW system on the market. Third, it asked about paying for necessary modifications, not the technology itself, to reduce negative responses due to the perception that the government should not charge for services. Fourth, the payment vehicle was credible and did not involve giving money to the government.

The mobile app used to record survey responses automatically incorporated the respondent's assigned cost Z into the question. Costs were randomized using a uniform distribution in the range of 100 MXN to 9,000 MXN (5 USD to 450 USD) or 0.5% to 45% the total cost of the RWH system in increments of 100 MXN (5 USD). According to program staff members and technicians, these amounts were within the range of possible modification costs.[17]

Figure 3.3 plots the share of households in the analysis sample stating being willing to enroll in the RWH program as a function of the cost assigned to them in the contingent scenario. The dots in the figure correspond to the stated take-up rate at each cost level, and the line represents the quadratic fit on all responses from a least squares regression.[18] This result suggests that the CV exercise effectively recovered a hypothetical take-up pattern consistent with a conventional demand function as the fitted take-up monotonically decreases with the cost presented to households. Assuming a linear relationship, a 10 USD increase in the hypothetical cost reduces the stated take-up by 1.9 percentage points (see Table B.1 in Appendix B).

---

[17] The upper limit of the cost range was initially set at 6,000 MXN and increased to 9,000 MXN after the first month of interviews, given the variation in stated take-up rates observed at costs above 5,000 MXN.

[18] Figure B.2 in Appendix B plots hypothetical take-up separately for households interviewed during the technician's inspection or the subsequent visit without imposing parametric assumptions.

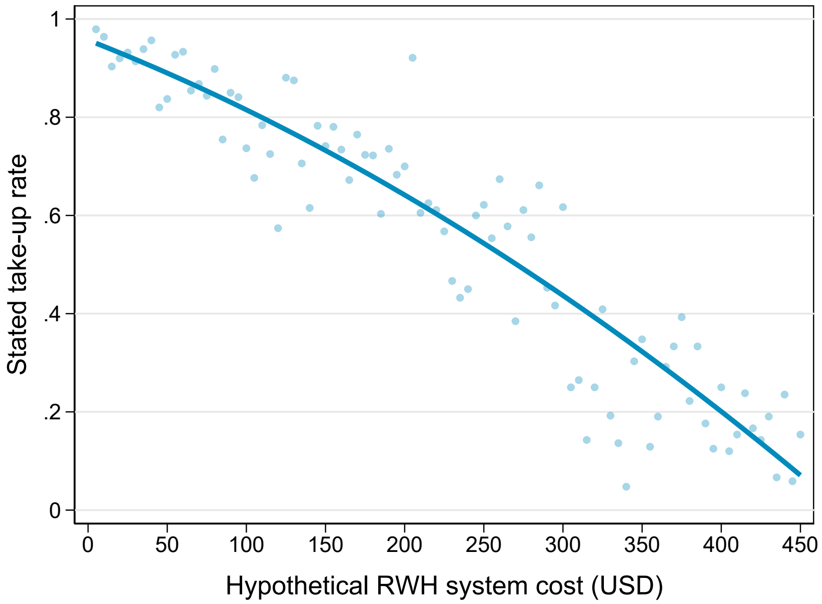

Figure 3.3. Hypothetical take-up rates

Notes: This figure shows the share of households stating being willing to enroll in the RWH program as a function of the cost presented to them in the contingent scenario. Dots correspond to the stated take-up rate at each cost level. The line is obtained by fitting a linear regression of answers from the WTP question (1 = yes) on the hypothetical cost and its squared value using the individual data.

As suggested by Whitehead and Cherry (2007), additional elements were incorporated into the CV survey to mitigate biases in the information elicited. To add consequentiality, we told respondents that the program was interested in their answers to define the installation schedule, which was contingent on completing all adaptations. The question also asked households to carefully consider their response, considering their ability to pay and the benefits they expected from receiving the RWH system. Likewise, households were asked follow-up questions about their level of certainty regarding their answer and the reasons for their response to identify any inconsistencies retrospectively.

In contrast with the typical use of CV surveys, my empirical strategy uses the exogenous variation in the stated take-up rates across hypothetical costs to identify the impact of the RWH Program on outcomes observed ex-post. Therefore, the relevant part of the information recovered through CV is given by the slope parameters of the take-up function plotted in Figure 3.3 and not its cardinal values. Given the households' unobserved WTP, their stated take-up is determined by the cost assigned to them exogenously, in the same spirit as the first stage generated by an instrumental variable. For this reason, hypothetical bias is less of a concern in my application since it only affects the magnitude of the stated take-up rates and not their relative changes as the hypothetical cost increases.[19]

3.4 Empirical Strategy and Estimation

The framework presented in Chapter 2 implies that the take-up decision, D, is contingent on the households' WTP. Therefore, a comparison between (hypothetical) takers and non-takers is prone to selection bias. My empirical strategy solves the selection problem arising from unobserved heterogeneity by comparing the outcomes Y_1 and Y_0 between groups of households with the same WTP (and the same sociodemographic characteristics).

My identification strategy uses the exogenous variation in hypothetical take-up rates generated by the random assignment of costs to households in the CV survey. Intuitively, stated take-up rates at two similar cost levels differ because some households (the complying-takers) are willing to pay the lower amount but not the higher one. That is, compliers are households whose WTP lies in between those costs. Compliers in the group assigned with the lower cost will receive the technology (because they are willing to pay that cost) and will experience the Y_1 outcome. Conversely, compliers assigned with the higher cost will not receive the technology and will experience the Y_0 outcome. One can then compare the average outcome across those similar

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[19] Embedding and scope problems (Carson and Mitchell, 1995) are not likely to affect the quality of the CV data in this paper. From the households' perspective, the RWH system is a private good, and non-use values are not involved.

costs. By randomization, potential outcomes are the same, in expectation, across assigned costs. Thus, any difference in the average outcome across costs identifies the difference $E(Y_1 - Y_0)$ for compliers —households with the same WTP whose take-up decision was determined randomly by the cost assigned to them.

To estimate the parameter $E(Y_1{-}Y_0|WTP = w)$ in equation (2.3), I use the Y_1 outcome for the group of takers ($D = 1$) and the Y_0 outcome for non-takers ($D = 0$). Recall that households completed the baseline survey before obtaining the RWH system and the follow-up survey a few months after receiving it. Thus, I use the Y_1 outcome measured in the follow-up survey for households that stated being willing to pay the cost presented to them in the CV exercise and the outcome Y_0 measured in the baseline for those that stated not being willing to pay. Besides, I compare cohorts of takers and non-takers interviewed in the same month. This design prevents me from using all available observations since, between April and July, I only observe Y_0 from the baseline survey, and, in November and December, I only observe Y_1 from the follow-up (see Table 3.2).

3.4.1 Assumptions

As discussed in Chapter 2, using information from a CV survey to identify the treatment effect parameter entails an additional assumption. Specifically, it implies assuming that the outcome Y_1 a household would experience if it were to pay the hypothetical cost from the CV survey is the same as the outcome Y_1 observed in the follow-up survey. In other words, assuming that the price paid for the technology does not influence the outcome.

This assumption is violated in the presence of income effects, that is if paying for the

RWH system limits the household's ability to meet its water needs. I argue that this assumption is reasonable in the context being analyzed and for the outcomes being considered since most households receive free municipal water service or pay a flat fee for it, do not buy water from private tanker trucks, and do not hire labor to collect water (see Table 3.1).

3.4.2 Estimation

In principle, it is possible to estimate the MTE curve for different samples defined by $X = x$ to account for heterogeneity in observed characteristics. However, identifying the MTEs requires the propensity score, $P(Z)$, to vary substantially over the unit interval for both treated and untreated groups. This range of variation in $P(Z)$ is rarely feasible within all unique combinations of the values in X. A commonly used alternative is to constrain the shape of the MTE function to be the same across values of X. Adopting this approach allows me to control for covariates parametrically. Then, using $p = P(Z)$, the conditional expectations of Y_1 and Y_0 in the sample of treated and untreated households can be specified as:

$$\begin{aligned} E(Y_1|X=x, D=1) &= x\beta_1 + E(\varepsilon_1|W_D \leq p) = x\beta_1 + K_1(p) \\ E(Y_0|X=x, D=0) &= x\beta_0 + E(\varepsilon_0|W_D > p) = x\beta_0 + K_0(p), \end{aligned} \tag{3.1}$$

where I use the fact that households enroll in the program if $W_D \leq P(Z)$. Once the $K_j(p)$ terms have been estimated, it is possible to construct the $k_j(w)$ functions to obtain the MTE as:

$$MTE(x, w) = E(Y_1|X=x, W_D=w) - E(Y_0|X=x, W_D=w)$$

$$= x(\beta_1 - \beta_0) + k_1(w) - k_0(w),$$

where $k_j(w) = E(\varepsilon_j | W_D = w)$ as shown in Appendix A. Note that the $k_1(w)$ and $k_0(w)$ terms defining the shape of the MTE curve over values of the WTP are independent of X. Instead, the intercept of the MTE curve, $X(\beta_1 - \beta_0)$, will necessarily vary across samples with different covariates.

Following Heckman and Vytlacil (2007b), I use local instrumental variable methods (Heckman and Vytlacil, 1999) to estimate the expectations in (3.1) separately. My estimation consists of the following basic steps (see the estimation Appendix of Heckman et al., 2006, for a detailed description):

1. Obtain the predicted propensity score $\hat{p}$ using a logit regression of D on Z and X and repeat the following three steps separately for treated and untreated observations.
2. Partial out $P(Z)$ from Y and X by regressing each of them on $\hat{p}$ using local polynomial regressions and predicting the residuals.
3. Estimate the β_j parameter vector by a linear regression of the outcome on the covariates using their residualized versions obtained in the previous step. Obtain $\hat{Y} = Y - X\hat{\beta}_j$.
4. Model the residualized outcome $\hat{Y}$ non-parametrically as a flexible function of $\hat{p}$ to estimate the corresponding $K_j(p)$ function by a local polynomial regression.
5. Use the estimates from the previous step to construct the $k_j(w)$ functions as $\hat{k}_1(w) = \hat{K}_1(p) + \hat{p}\hat{K}_1'(p)$ and $\hat{k}_0(w) = \hat{K}_0(p) - (1 - \hat{p})\hat{K}_0'(p)$, where primes denote derivatives.

To implement these steps, I leverage functions from the `mtefe` package for Stata (Andresen, 2018, version 2019/05/13).

In addition, I trim off 1% of the treated and untreated observations from the thinnest tails of the distribution of their propensity scores. This helps to reduce noise in the MTE and MTR curves at the extreme ends of the latent WTP. The common support of the propensity scores between the treated and untreated samples over which the MTE can be identified ranges from 0.12 to 0.95. Figure B.3 in Appendix B plots the distribution of the propensity score for treated and untreated households and indicates the limits of the common support after trimming observations. Table B.2 presents the coefficients on all variables entering the logistic regression for predictions.

All estimations use survey data on program participants interviewed during the rainy season. The analysis sample comprises 3,660 households, of which 1,356 are in the control group and 2,304 in the treatment group. The control variables include car and computer ownership, number of days per week with access to water from the municipal network, a dummy for consuming water from tanker trucks, water storage capacity, the size of the roof used to collect rainwater, and a dummy for having a bigger RWH system storage tank. I also include fixed effects by month and an indicator variable for completing the CV survey before knowing the eligibility status of the dwelling.

To present the estimation results in the next section, the intercepts of the MTE and MTR curves are evaluated at the sample means of X. For an easier interpretation, I plot all curves against $1 - W_D$ so the horizontal axis shows the percentiles of the WTP. Standard errors to construct confidence intervals are obtained by bootstrapping the estimation of the MTEs — including predicting the propensity score and defining the common support— with 300 samples taken independently within treatment groups and months.

To facilitate comparing the results for different outcomes, I estimate the propensity score once and keep the same predicted values in all estimations. This step is required because some observations are missing for specific outcomes, which could lead to different propensity scores for the same observation if predicted in each estimation. In the same way, I use the same mean values of X for all estimations so that the intercept of the MTE is evaluated to represent the average household in the sample, regardless of any missing values in the outcome variable.[20]

Lastly, I test whether the treatment effect differs across WTP values. The MTEs can be thought of as the sum of the ATE (a constant) and the unobserved heterogeneity over the WTP distribution. Therefore, I follow Heckman et al. (2010) to examine the degree of unobserved heterogeneity captured by the WTP. Specifically, I test whether the averages of the MTE over different segments of the WTP are equal, meaning that the slope of the MTE curve is zero along those segments. To implement this test, I construct groups of four percentiles of the WTP and obtain the average of the MTE within these groups —that is, 1^{st} to 4^{th}, 5^{th} to 8^{th}, and so on until covering the support of the WTP. Then, I compare the average MTE across non-adjacent groups —e.g., (9^{th}, 12^{th}) versus (17^{th}, 20^{th})— and test whether the difference is equal to zero. Given that I bootstrap the nonparametric MTE, I compute the difference in the MTE averages between pairs of non-adjacent segments, Δ, and the b^{th} bootstrap replication of this difference, Δ_b. The p-value of the test is the proportion of bootstrap replications for which $|\Delta_b - \Delta| > |\Delta|$, where bars denote absolute values.

3.5 Results

3.5.1 Effects on Water Restrictions and Time Use

This subsection presents the treatment effects of receiving the RWH system on the two outcomes considered. First, I examine the restrictions imposed by water shortages. Rather than measuring water consumption, which is unfeasible in my context, I indirectly evaluate the impact

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[20] In particular, 1,193 observations have missing data on time spent obtaining water.

of the RWH technology on water availability through the likelihood of postponing daily activities due to a lack of water.[21] Measuring water access in this manner reflects the extent to which the RWH system can reduce water insecurity by providing additional water to meet the most basic needs. Figure 3.4 plots the results for three activities —showering, flushing toilets, and washing dishes— and an index that aggregates the three activities by standardizing each variable and taking their average by household. For each activity, I construct an indicator variable equal to one if the household postponed the activity at least once a week over the previous 30 days. Thus, the treatment effects reflect the reduction in the likelihood of postponing these activities caused by having the RWH technology. Figure 3.5 shows the impact of the RWH system on the time households spend obtaining water from all sources. This measure encompasses time used in fetching, storing, and cleaning water, and, in the follow-up survey, it also accounts for the time spent using and maintaining the RWH system.

The results show the difference in benefits experienced by households with varying levels of WTP. Households with a high WTP benefit the most from the RWH system, while those with a low WTP are not expected to obtain significant gains. In all cases, benefits are concentrated in households with a WTP above the median, and the magnitude of the heterogeneity in returns originating from the households' WTP is substantial. For example, the share of households in the 90th percentile of the WTP that did not wash dishes because of insufficient water decreased by 25 percentage points. In other words, 25 percent of households in that WTP percentile would have postponed washing dishes in the absence of the RWH technology. Similarly, during the rainy season, the technology saves up to 5 hours per week in water procurement time for high-

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[21] In the context where households use water from multiple sources, it is difficult to measure consumption. Some of these sources are untractable (e.g., water fetched from a neighbor's house), and many households do not own a water meter in their connection to the network. Similarly, measuring rainwater passing through the RWH system requires costly meters to measure low-pressure flows.

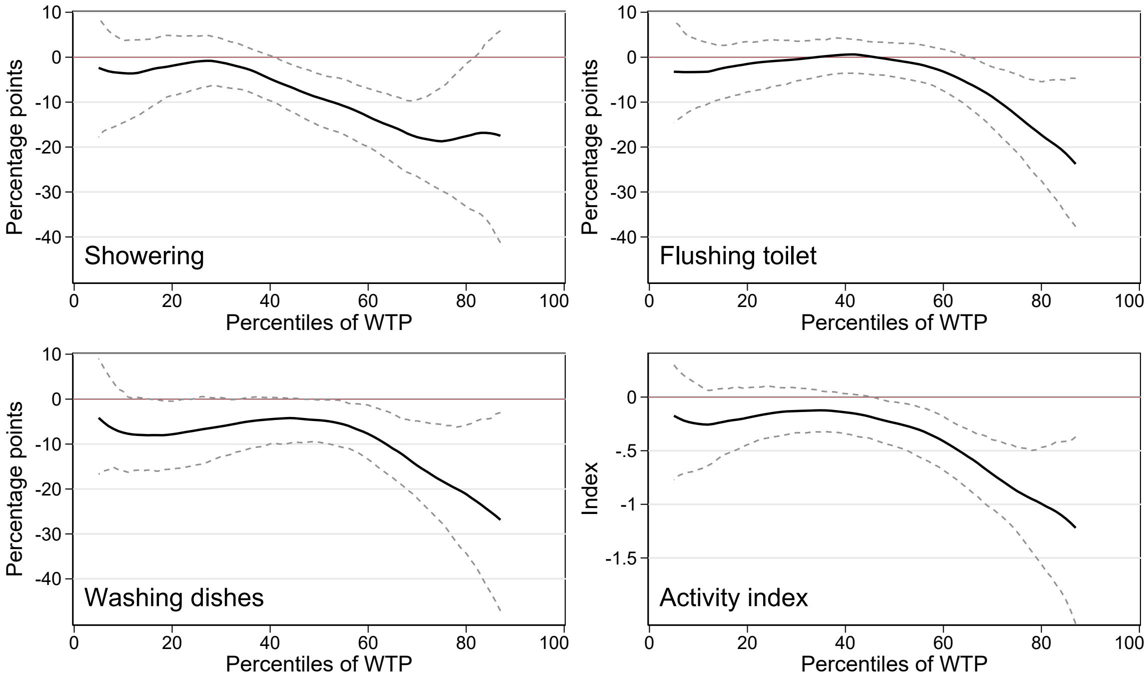

Figure 3.4. Effects on the likelihood of postponing daily activities due to insufficient water

Notes: This figure shows the average effects of the RWH program on the likelihood of postponing daily activities due to lack of water over WTP percentiles, including showering, flushing toilets, and washing dishes. Indicator variables for each activity are equal to one if the household postponed the activity at least once a week over the last 30 days. The last panel aggregates all activities in a single index by standardizing each variable and taking their average by household. Gray dashed lines represent the bootstrapped 90 percent confidence interval. The number of observations is 3,622 after trimming 1% of the observations from the thinnest tails of the propensity score distribution for the treated and untreated groups. Treatment effects in all panels are evaluated at the mean of the covariates for the analysis sample.

WTP households, equivalent to roughly two workdays per month. In contrast, reductions in water restrictions and time savings are negligible for households with a WTP below the median. Overall, these results suggest that the households' ex-ante WTP for the technology is a good predictor of its benefits.

Although the semiparametric estimates of the MTE have large standard errors, in all cases I reject the hypothesis that the MTE is constant along percentiles of the WTP at the 10 percent level of significance (see section 3.4.2 for details). Table 3.3 presents the comparisons of the average MTE over different sections of the WTP for each outcome variable. For example, the fifth column reports that the absolute difference between the average MTE on time spent collecting

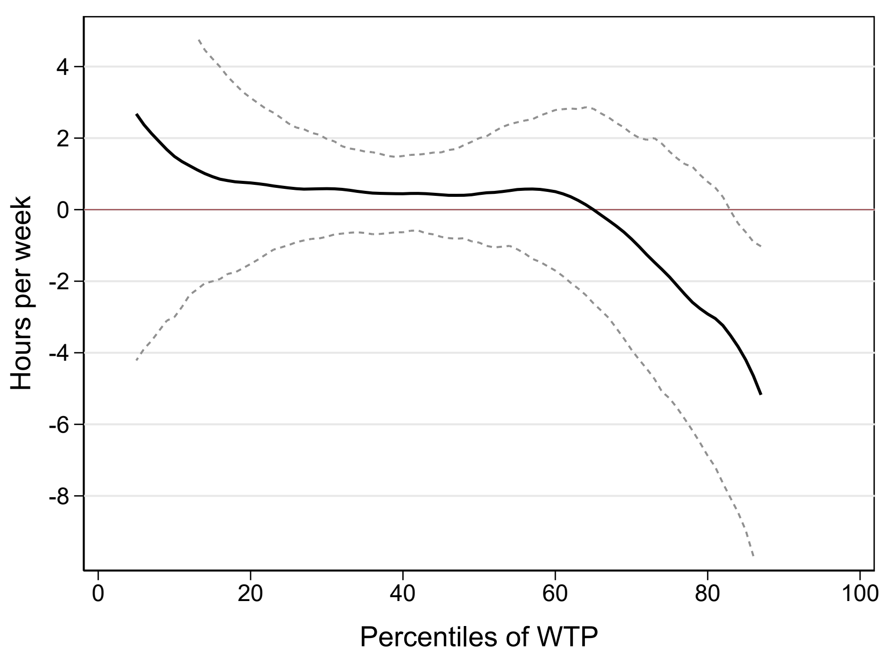

Figure 3.5. Effects on time spent procuring water

Notes: This figure shows the average effects of the RWH program on time spent obtaining water from any source across percentiles of the WTP. Gray dashed lines represent the bootstrapped 90 percent confidence interval. Confidence interval bounds greater than 5 or less than 10 are omitted for readability. The number of observations is 2,442 after dropping missing values in the outcome variable and trimming 1% of the observations from the thinnest tails of the propensity score distribution for the treated and untreated groups. To ease comparing results across outcome variables, the propensity scores and the mean of the covariates are estimated using all observations in the analysis sample.

water at the 65^{th} to 68^{th} interval of the WTP percentiles and the average MTE over the 73^{th} to 76^{th} interval is 1.56hr per week. The p-value of the test of the hypothesis that this difference is equal to zero is reported in parentheses and is 0.0433. The tests indicate that the slope of the MTE on time spent obtaining water is negative and statistically significant between the 65^{th} and 76^{th} percentiles of the WTP and that it remains negative but statistically insignificant after that. Similarly, the slope of the MTE on the likelihood of postponing showering is negative and statistically significant (at the 10 percent confidence level) between the 33^{th} and 60^{th} percentiles of the WTP. For each of the variables presented, certain segments of the treatment effects increase with the WTP and this relationship is statistically significant at the 10 percent level. This is further

Table 3.3. Test of equality of average MTE over segments of the WTP

WTP segments (percentiles)	Postponed showering	Postponed flushing toilets	Postponed washing dishes	Postponed activity index	Time spent collecting water	Usage rate
(1, 4) vs. (9, 12)						0.38
						(0.1233)
(9, 12) vs. (17, 20)	1.38	1.49	0.42	0.05	0.66	0.19
	(0.7333)	(0.6367)	(0.9233)	(0.7500)	(0.6733)	(0.0833)
(17, 20) vs. (25, 28)	1.31	1.01	1.30	0.06	0.19	0.07
	(0.6167)	(0.5767)	(0.5333)	(0.4933)	(0.8300)	(0.2533)
(25, 28) vs. (33, 36)	1.51	0.82	1.49	0.02	0.09	0.01
	(0.4400)	(0.5767)	(0.4467)	(0.8567)	(0.8933)	(0.7833)
(33, 36) vs. (41, 44)	3.55	0.46	0.88	0.03	0.05	0.00
	(0.0600)	(0.7133)	(0.6333)	(0.5767)	(0.9333)	(0.9233)
(41, 44) vs. (49, 52)	3.30	1.26	0.46	0.09	0.01	0.02
	(0.0667)	(0.3467)	(0.8067)	(0.1500)	(0.9867)	(0.5733)
(49, 52) vs. (57, 60)	3.20	1.90	2.29	0.13	0.09	0.00
	(0.0800)	(0.1867)	(0.2667)	(0.0633)	(0.8500)	(0.9800)
(57, 60) vs. (65, 68)	3.78	3.95	4.95	0.23	0.77	0.03
	(0.1233)	(0.0433)	(0.0400)	(0.0067)	(0.1967)	(0.3333)
(65, 68) vs. (73, 76)	2.39	5.93	5.83	0.26	1.56	0.00
	(0.5700)	(0.0200)	(0.0700)	(0.0633)	(0.0433)	(0.8633)
(73, 76) vs. (81, 84)	1.59	6.75	5.24	0.20	1.62	0.03
	(0.7900)	(0.0600)	(0.2967)	(0.3233)	(0.1467)	(0.4867)

Notes: To obtain the numbers in this table, I create groups of four percentiles of the WTP and average the MTE within these groups. Then, I compare the average MTE across non-adjacent groups and test whether the difference is equal to zero using 300 bootstrap replications. For example, the first row compares the average MTE defined over the 1^{st} to 4^{th} percentiles of the WTP with that over the 9^{th} to 12^{th} percentiles. p-values for each test are shown in parentheses.

evidence that households' stated WTP for the technology depends on heterogeneous returns in realized outcomes; that is, they behave in the CV survey as if they possess some knowledge of their idiosyncratic returns, although the rejection of these tests is only strong in the right half of the estimated MTEs.

3.5.2 Differential Impact by Gender

Given the prevalent disparity in the distribution of unpaid domestic work between men and women in Mexico (Cabrera-Hernández et al., 2023), including the distribution of chores related to obtaining water (Salazar et al., 2012), I estimate the effects on time use by gender. To that end, I employ the subsample of households with both male and female members. Time use recorded separately for each member is aggregated by gender. To capture whether the measure of WTP comes from a male or a female member, I split the subsample by the gender of the baseline survey respondent. Here, I present the results for households where the WTP was stated by a woman, representing 67 percent of this subsample.

In Figure 3.6, the left and central panels display the time spent fetching water based on gender, with and without the RWH system. Without the RWH technology, women typically spend more time obtaining water from any source compared to men within the same household. In particular, in households with women who have high WTP, women spend about twice as much time as men procuring water. By contrast, the time spent obtaining water in households with the RWH system does not differ significantly between genders. As a result, the impact of the RWH system is more pronounced for women across all WTP values. Specifically, women with higher WTP benefit more from the technology, saving between 2 to 4.5 hours per week.

The findings suggest that the RWH system has the potential to more equitably divide water-related tasks between men and women within the household. A closer examination (not included here) of the distribution of household chores related to obtaining water from traditional sources and those involved in using and maintaining the RWH system shows that men tend to focus on the latter, while women still manage the former. This may be because the activities associated with

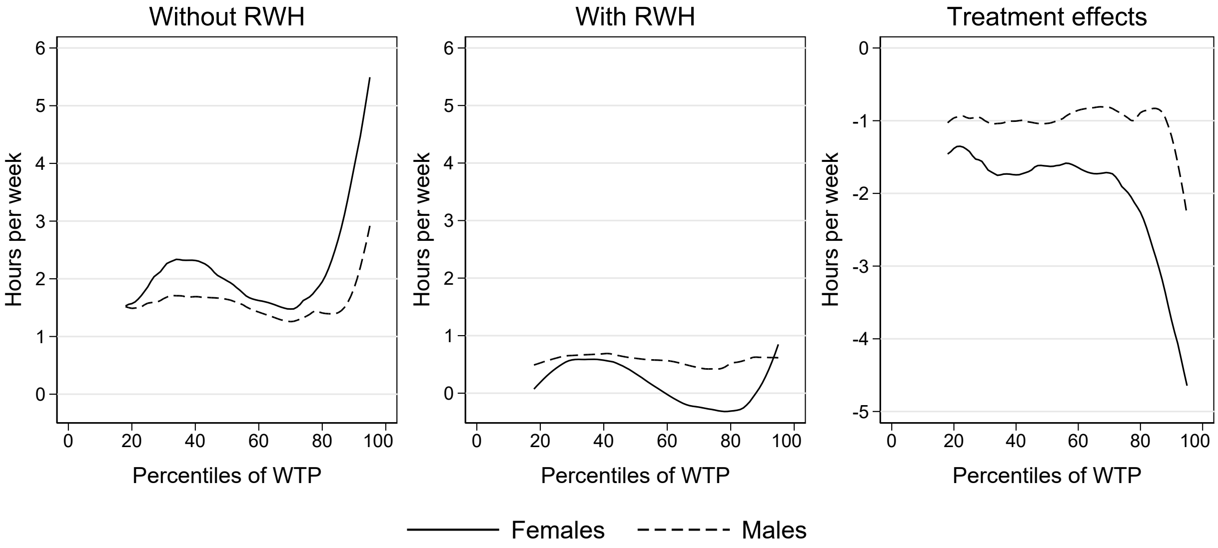

Figure 3.6. Effects on time spent procuring water by gender (females' valuation)

Notes: The left and central panels plot, respectively, the marginal untreated and treated outcome by gender. The right panel displays the average treatment effects, which are equivalent to the difference in the marginal outcomes in the other two panels. Only households where the CV survey was completed by a female member are considered. The number of observations is 925 after dropping missing values in the outcome variable and trimming 1% of the observations from the thinnest tails of the propensity score distribution for the treated and untreated groups. Propensity scores and means of covariates were obtained from the subset of households with both male and female members with available data by gender and, thus, they do not match those in subsection 3.5.1.

the RWH system are more flexible and can be carried out at any time, allowing men to handle them outside of their work hours.

3.5.3 Treatment Effect Heterogeneity and Use of the RWH System

This subsection explores the reasons behind the pattern of benefits that increase with the households' WTP. First, I examine why some households have a higher WTP for the technology before receiving it. Figure 3.7 plots the marginal untreated outcome, measured during the baseline survey, across WTP percentiles for the outcomes of interest. It is evident from the figure that households value the RWH technology more when they are more affected by water scarcity. The left panel indicates that the share of households facing water restrictions that result in the postponement of daily activities increases at higher WTP levels, from less than 10 to up to 45

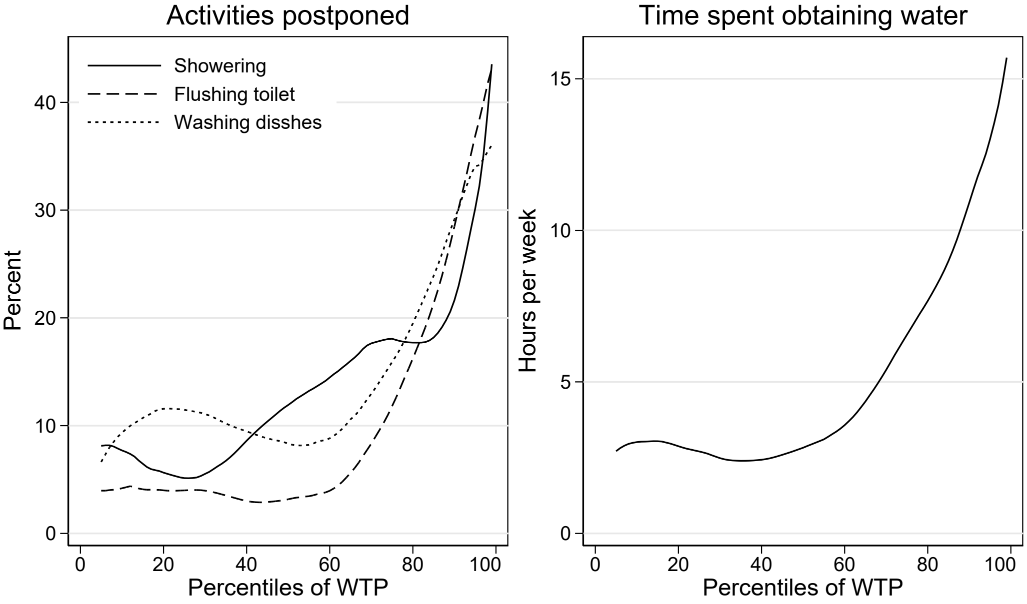

Figure 3.7. Marginal untreated outcomes

Notes: These figure shows average outcomes for households without the RWH system over WTP percentiles. The left panel corresponds to the postponement of daily activities due to a lack of water, and the right panel corresponds to time spent obtaining water from any source. The support of the WTP over which the untreated outcomes are plotted is not trimmed on the right given the high density of untreated observations in the upper percentiles. Average outcomes are evaluated at the means of the covariates using the full analysis sample of treated and untreated households.

percent. Similarly, the right panel shows that households typically spend between 3 and 16 hours per week fetching, cleaning, and storing water. In particular, the number of hours devoted to these activities increases continuously in the upper 40 percentiles of the WTP. In these circumstances, the treatment effect heterogeneity would be partly explained by the baseline outcome, indicating that households needing the RWH system most benefit the most.

Next, I show that the usage rate of the RWH system also drives the heterogeneity in treatment effects. To that end, I assume that households who reported spending no time utilizing or cleaning the RWH system in the previous week did not use it. Figure 3.8 plots the share of households using the RWH system. The average of the marginal treated outcome indicates that 14 percent of complier households in the sample did not use their system the week before the

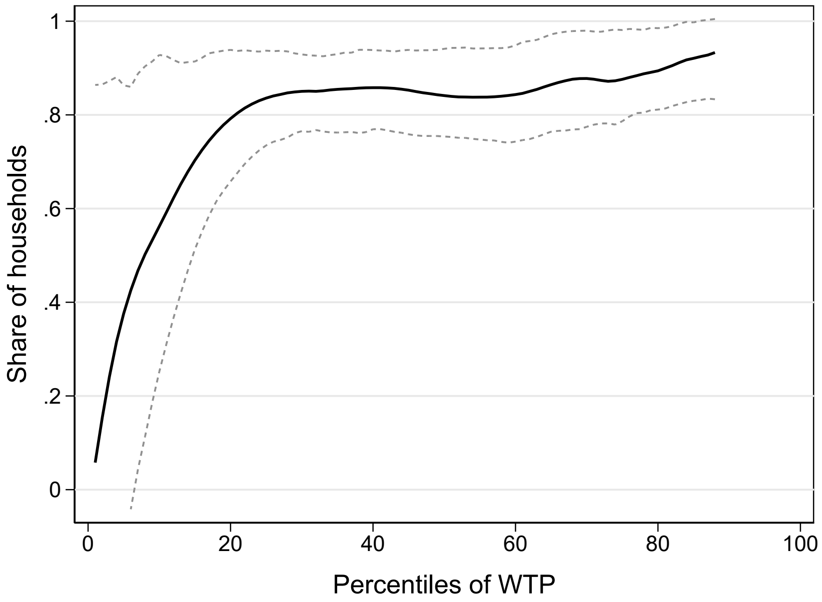

Figure 3.8. Usage of the RWH system

Notes: This figure plots the share of households that spend time using the RWH system the week before over percentiles of the WTP. Gray dashed lines represent the bootstrapped 90 percent confidence interval. The support of the WTP over which the treated outcome is plotted is not trimmed on the left given the high density of treated observations in the lower percentiles. The average outcome is evaluated at the mean of the covariates using the full analysis sample of treated and untreated households.

follow-up interview.[22]

More importantly, the proportion of households using the RWH increases with the WTP. This similarity in the usage and treatment effect patterns suggests that the benefits of the RWH system can only be achieved if the households use it continuously and that the households' ex-ante WTP is a good predictor of its usage and benefits after take-up. In addition, the similarity in usage patterns and untreated outcomes indicates that households that need the system more are more likely to put it to good use. Based on these findings, it appears that the current design of the RWH Program is subsidizing households that do not benefit from the subsidized technology, either because they do not need it or will not use it. Thus, reducing the subsidy rate may improve the program's overall benefits by screening out households who will not use the technology even

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[22] This average aligns with the estimations obtained by the program managers at Sedema, who metered the volumes of rainwater collected by a few dozen households in 2021.

if it is provided for free.

3.6 Conclusion

This chapter presents evidence of the heterogeneous causal effects of a domestic technology to harvest rainwater on households' time collecting water and their likelihood of postponing daily activities due to lack of water. I show that the ex-post benefits households derive from the RWH system vary meaningfully with their ex-ante WTP for it. This finding suggests that the benefits households expect to obtain from participating in a program (captured by their WTP) can convey valuable information for policymakers to design targeting strategies.

In my sample, the positive impact of providing the RWH system on water procurement time and the postponement of daily activities due to water scarcity increases with the households' WTP. Moreover, at higher WTP levels, fewer households abstain from using the RWH system, indicating that the system benefits are associated with continuous usage. Therefore, allocating the technology to households that are more likely to use it could improve the benefits of the RWH Program.

Chapter 4: Policy Implications

4.1 Introduction

In this chapter, I return to the motivating question of the present dissertation: whether a lower subsidy rate can meaningfully increase the average benefits of the RWH Program. For that purpose, I compare the relative performance of targeting households using counterfactual participation fees as a screening mechanism. To that end, I simulate scenarios in which households face different costs Z between 30 and 150 USD, representing between 3% and 15% of the total cost of the RWH system. Recall that households were presented in the CV survey with hypothetical values of Z ranging from 5 to 450 USD. Because the simulated scenarios intend to assess the potential impact of policies reducing the subsidy rate, they operate only on participants assigned with a cost below 150 in the CV survey and leave unchanged the hypothetical participation status of the rest of the households. To evaluate their relative effectiveness, the simulated subsidy policies are compared and combined with the more common approach of targetting program participants based on their sociodemographic characteristics.

For all simulations, I consider the average benefits of the program under alternative policies from the households' and government's perspectives. For households, I use the treatment effects on each outcome variable from the previous chapter. For the government's benefit, I assume that policymakers only care about the variable cost of supplying water and, thus, social benefits, such as reducing water withdrawals from the aquifer, are not considered.[1] In the following sections, I first present a back-of-the-envelope cost-benefit analysis for the government, then simulate the effect of alternative reductions in the subsidy rates, and finally compare those effects with targeting strategies based on observable characteristics.

4.2 Program Costs and Benefits

For the cost-benefit analysis, I adopt a budgetary approach to compare the cost of providing a family with the RWH system ($= 1,000$ dollars) with the funds the government saves from not providing them with an amount of water equal to the rainwater households harvest. For the latter quantity, I assume that the amount of rainwater harvested by households that use the RWH system is equal to the system's catching potential. Thus, the budget savings can be expressed as $\text{Savings} = \text{Cost} \times \mathbb{1}[\text{Use}] \times \text{Potential}$. The potential rainwater harvest is equal to the rainfall multiplied by a factor that is proportional to the size of the roof surface used to collect it. I assume that households reporting that they did not spend any time using or cleaning the RWH system (see Section 3.5.3) harvest zero liters. As for the cost, it corresponds to the public cost of providing a litter of water either through the municipal network or tanker truck deliveries, depending on whether the household consumes water from the latter.[2]

Figure 4.1 shows the government's cost savings associated with the RWH Program in two

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[1] The impact on the marginal cost of public funds is beyond the scope of this exercise.

[2] The household's rain harvesting potential is given by the 1981-2010 average precipitation in Mexico City from May through October multiplied by their roof size times 0.85 (a capture coefficient suggested by Sedema, IU, and IRRI (2020)). For the cost of supplying water from the network, I use the average rate charged by Sacmex, the public utility, without any subsidies, which is 52 pesos (2.6 USD) per 1,000 liters (Mexico City's Fiscal Code, art. 172). For the cost of a 10 thousand-liter tanker truck provided by a municipal government, I take the difference between the tanker truck's market price (2,000 pesos, or 100 USD) and the rate charged by Sacmex for withdrawals from the aquifer (710 pesos, 35 USD). Then, I assume that half of this difference corresponds to the markup of private firms and that the government does not charge it. As a result, the cost of supplying water by tanker trucks is 6.8 USD per 1,000 liters.

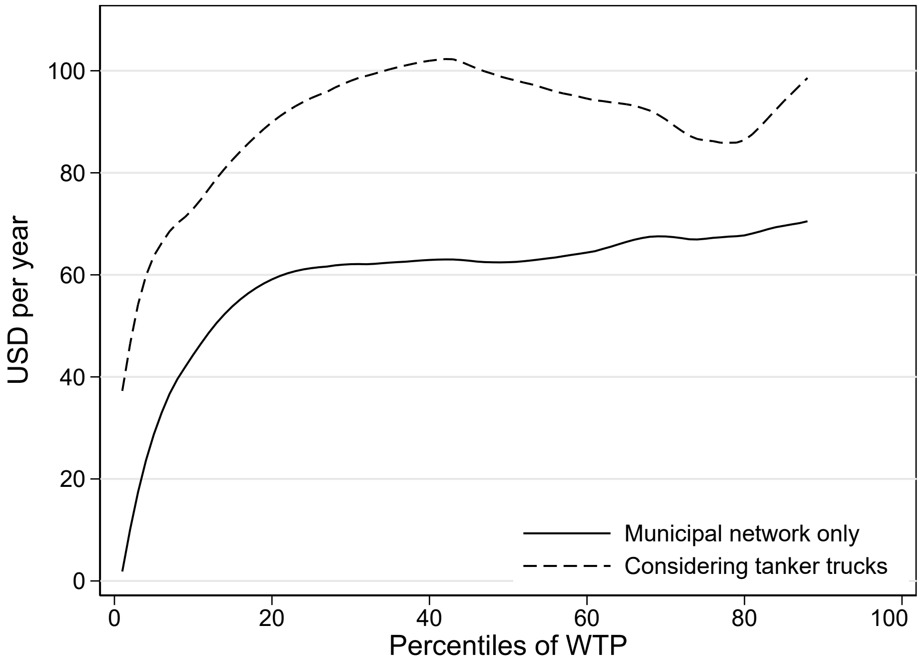

Figure 4.1. Benefit

Notes: The figure displays estimates of the government's annual average spending to provide the same amount of water as the RWH system's capacity per system used. Two scenarios are considered. The first one assumes that all water is supplied through the network by the water utility, while the second scenario factors in households' consumption of water from tanker trucks. The support of the WTP over which spending is plotted is not trimmed on the left given the high density of treated observations in the lower percentiles. The average spending over WTP percentiles is evaluated at the mean of the covariates using the full analysis sample of treated and untreated households.

scenarios, one imputing the cost of providing water through the network to all households, and the other considering the cost of supplying water by tanker trucks to households that typically consume from them.

The average cost savings in the two scenarios are 59 and 89 dollars a year per RWH system installed. Using a 3% discount factor, this range for the program effects implies that the government can recover its investment in the RWH Program in a period of 14 to 24 years, provided that households use the technology at the observed rate over that entire period. Notwithstanding, the public fund benefits are substantially lower when providing low-WTP households with an RWH system relative to giving it to households with a higher WTP. Despite low-WTP households having, on average, larger roof surfaces for catching rainfall, the lower returns to subsidizing them are mostly explained by the fact that they have a substantially lower usage rate. Based on these results —and the 30-year expected lifespan of the RWH system—, it would be financially undesirable to subsidize the technology for households respectively below the 14^{th} and 3^{rd} percentiles of the WTP, depending on the scenario.

4.3 Policy Counterfactual Simulations

From the government's and households' points of view, the low returns to the technology among low-WTP households suggest the existence of a misallocation problem. The current policy's self-selection scheme and the government's budget constraints allow households with a relatively lower WTP to receive a subsidy that does not result in significant benefits while limiting the participation of other households that could attain better outcomes.

In this context, a sensible policy design is to use the subsidy rate as a screening mechanism to allocate the technology among households who value it more and can benefit more from it. By reducing the subsidy rate or introducing a participation fee, the program can discourage low-WTP individuals, who tend to have low benefit attainment, from enrolling. On the other hand, existing literature has found that, under certain circumstances, even small fees restrict access to the poor and often do not result in efficiency gains (Dupas, 2014a).

Accordingly, I simulate counterfactual policies under two approaches: the use of participation fees and targeting based on observables. My analysis consists of comparing the average treatment effect for households who would not enroll in the program under each alternative scenario. I conduct this exercise for different outcome variables and for government cost-savings. The scenarios considered include policies that select participants based on sociodemographic characteristics, the use of alternative participation fees, and the introduction of participation fees for specific populations ——that is, the combination of the first two approaches.

A policy that selects participants based only on sociodemographics is represented by a change in the intercept of the MTE curve. Thus, I obtain the MTE curve for households that would not be eligible for participation and take the average of the MTEs over WTP percentiles. Instead, a policy based on a participation fee will affect households differently along the WTP distribution. Intuitively, it will discourage households with a WTP below the participation fee from enrolling. Therefore, the effect of introducing a fee is given by the weighted average of the MTEs across WTP percentiles, using weights that depend on the share of households who would not enroll at each percentile. Specifically, I take the following steps, separately for each variable and each participation fee, $\tilde{z}$:

1. Replace the bids, Z, presented to households in the CV survey with $\tilde{z}$ if $Z < \tilde{z}$ to obtain $\tilde{Z}$.

2. Predict the new propensity scores $P(\tilde{Z})$ using the coefficients from the first stage of the MTE estimation. Note that $P(Z) = P(\tilde{Z})$ for all $z \geq \tilde{z}$.

3. Estimate the weights ω_w for each quantile, W_D, of the WTP, which are given by: $\omega_w \equiv Pr(P(\tilde{Z}) > w) - Pr(P(Z) > w)$. These weights represent the change in the probability of being treated at $W_D = w$ induced by introducing the participation fee. Note that the weight is zero for quantiles at which no households switch from treated to untreated.

4. Construct the average MTE for the population that switches from a treated to an untreated

status as follows:

$$\frac{1}{N}\sum_{i=1}^{N}\frac{P(\tilde{Z})-P(Z)}{\bar{p}^{'}-\bar{p}}X(\beta_1-\beta_0)+\sum_{w=1}^{99}\frac{\omega_w}{\bar{p}^{'}-\bar{p}}(k_1(w)-k_0(w)),$$

where $\bar{p}$ and $\bar{p}^{'}$ represent the average propensity score in the status quo and the counterfactual scenario, respectively. This parameter is typically known as the policy-relevant treatment effect (PRTE, Heckman and Vytlacil (2001)).

4.4 Targeting on Observables and Unobservables

Figure 4.2 presents the average treatment effect of the RWH Program on households that would not participate under different targeting policies. Four outcomes are considered, namely time savings, the reduction in the likelihood of postponing washing dishes due to insufficient water, the usage rate, and the cost the government saves from not providing the water households harvest from the rain. Blue dots in the figure correspond to the average of the MTEs attained by households who would not participate in the program under each targeting strategy. For comparison, the figure also plots in orange vertical lines the average of the MTEs in the sample under the status quo, estimated in chapter 3. A dot to the left of the vertical line means that households being selected out by a given targeting policy have an expected treatment effect smaller than the average. From a program design perspective, this implies that the policy is more efficient than the status quo in allocating the technology to households that benefit relatively more.

The first four rows in Figure 4.2 show the potential consequences of different participation fees. These simulations suggest that fees may be effective in reallocating the RWH system by discouraging the enrollment of households that would benefit less than the average across all

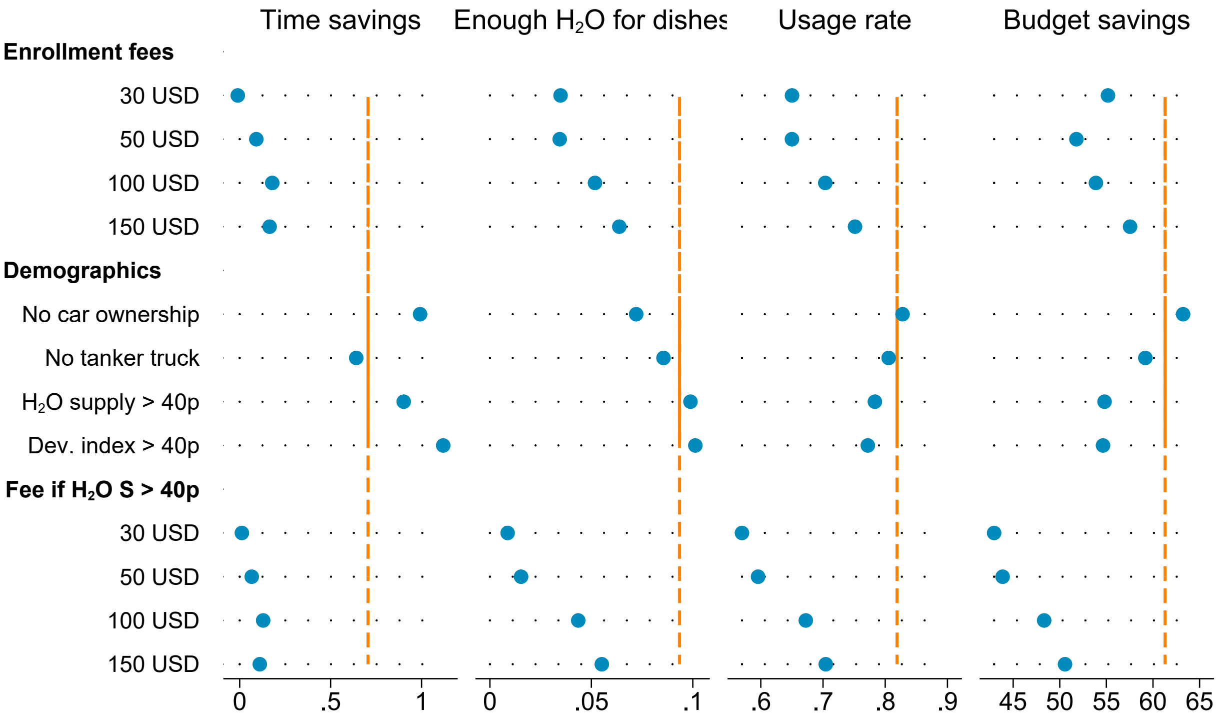

Figure 4.2. Policy counterfactuals

outcomes considered. For instance, the usage rate for households not willing to enroll in the program should a participation fee of 30 USD be introduced is about 20 percentage points less than the average household. Likewise, those households experience no time gains, compared to the average household that saves 42 minutes per week.

The interpretation of these simulations has some limitations. Firstly, it does not provide information about the number of households that would be selected under the counterfactual policies. The results suggest that small fees may be more effective than larger ones. However, this interpretation changes when one considers that higher participation fees could prevent a larger number of low-benefit households from enrolling. Secondly, the algorithm outlined above relies on the magnitude of the costs used in the CV survey, which may be affected by a hypothetical bias. For this reason, it should not be concluded that the impacts of calibrating the subsidy correspond to the specific fee values of each scenario. For instance, the data top row in Figure 4.2 shows that the households that would not take up the RWH system when facing a participation fee of 30 USD have a usage rate of .63. If this policy were to be implemented, the average usage rate among participants would then increase. However, this increase in the usage rate does not necessarily correspond to a participation fee of 30 USD. As a matter of fact, the same increase in usage is likely to be attained with a smaller participation fee, given that people usually overstate their WTP when participating in CV surveys. Thus, this analysis cannot be used to provide specific, quantitative policy recommendations about the optimal subsidy rate. Yet, the suggestive evidence of benefit improvements from small reductions to the subsidy rate holds even in the presence of hypothetical bias.

Having described the potential of participation fees for allocative efficiency in the context of the RWH Program, I turn now to examine which households would be more affected by charging positive prices for the RWH system. To contextualize the heterogeneity of treatment effects, I begin by characterizing compliers at each level of WTP in terms of the availability of water and social development index in their neighborhoods. The choice of the neighborhood-level observed characteristics is due to the fact that the RWH program managers use them to target neighborhoods. The implementation rules of social programs in Mexico City often restrict targeting based on individual characteristics, but those at the neighborhood level are easier to implement.

The relationship between these characteristics and WTP appears in Figure 4.3. The red dashed line represents the median in the sample, and the gray dashed lines correspond to the first and third quartiles. On average, households with a higher WTP live in neighborhoods with lower water supply from the municipal network. This indicates that households experiencing higher levels of water insecurity have a greater valuation for the RWH technology. Specifically, households with the highest WTP are located in neighborhoods receiving less water than the

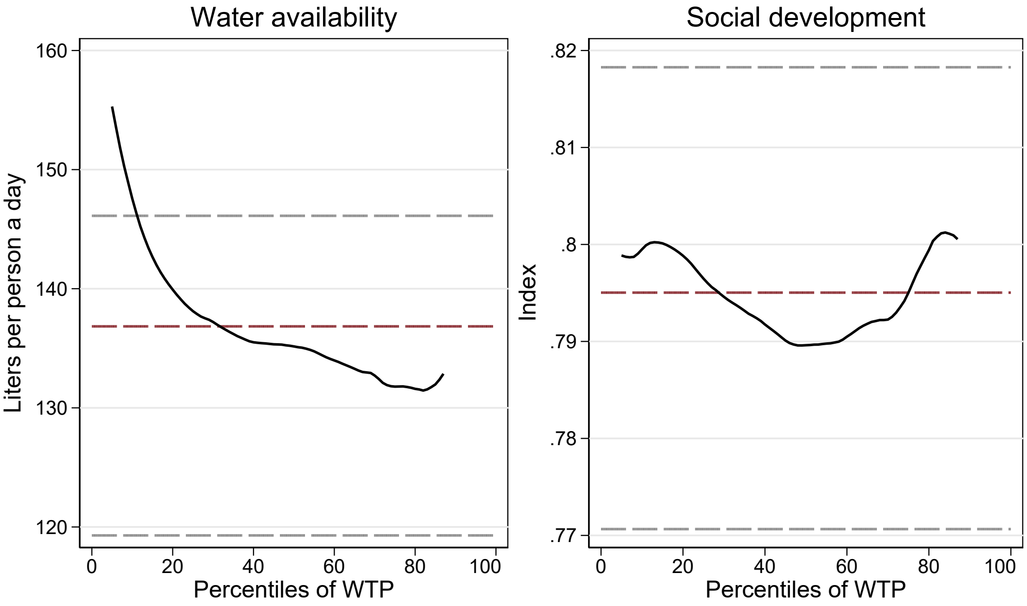

Figure 4.3. Compliers' characteristics

Notes: This figure plots the average characteristics of compliers with different WTP levels in black continuous lines. The red dashed line corresponds to the sample median and the gray dashed lines to the first and third quartiles. Estimates are obtained semiparametrically and evaluated at the average of covariates. For identification, the sample is restricted to participants in the treatment group.

median neighborhood and 19% less water than those participants with the lowest WTP. On the other hand, the WTP is not related to the overall social development of the neighborhoods. On average, participant households at all levels of WTP live in neighborhoods classified in the "low" social development stratum.[3]

Given this relationship between compliers' characteristics and WTP, program designers may choose to select participants based on a given characteristic, such as water availability in different areas of the city. The fifth to eighth rows of Figure 4.2 plot the potential consequences of targeting policies based on demographic characteristics associated with income and water insecurity, including car ownership, consuming water from tanker trucks, and water availability and social development index at the neighborhood level. The results suggest that each characteristic

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[3] The social development index is estimated by the independent evaluation council of the government of Mexico City. Its construction includes dwelling conditions, asset ownership, and access to health, education, and public services. The index classifies households into five strata: very low, low, medium, high, and very high.

produces a qualitatively different result across outcome variables. For example, an eligibility criterion based on living in a neighborhood with relatively lower water availability would leave out of the program households who attain time savings above those of average households and simultaneously have a lower usage rate. At the same time, in contrast with the use of participation fees, there is not a clear pattern suggesting that targeting on observable characteristics yields better results than those observed in the status quo.

The contrast between targeting strategies based on observables or a price mechanism can be rationalized by considering how each of them operates on household enrollment decisions. Demographics affect the intercept of the MTE function, meaning that targeting strategies based on these characteristics select households along all WTP percentiles with the characteristic in question. Instead, participation fees disproportionally discourage low-WTP households from enrolling. Figure 4.4 plots the weights used to obtain the average MTE for policy scenarios characterized by a participation fee. As expected, all fees primarily affect the probability of treatment for households at the lower end of the WTP.

Inspecting Figures 4.3 and 4.4, it is possible to infer that households more likely affected by the fees are no poorer than the average and, instead, have relatively better access to water from the municipal network. Figure 4.4 also shows that, as the fee increases, households with relatively higher WTP begin to drop out from the RWH Program. Based on this evidence, program designers may allocate the technology using a combination of a price mechanism and neighborhood characteristics. Accordingly, I repeat the same counterfactual analysis but restrict the set of households affected by the participation fee to those in the top three quintiles of the distribution of water availability. The results are presented in the last four rows in Figure 4.2. As can be observed, the use of observed characteristics and prices for targeting is more efficient. For example,

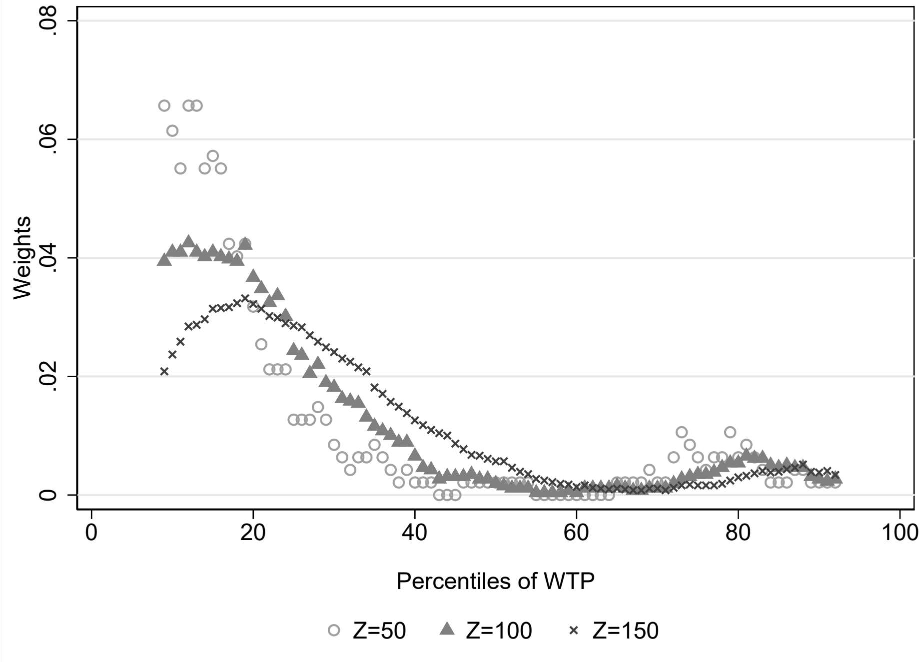

Figure 4.4. PRTE weights for alternative participation fees

about 50 percent of households deciding not to enroll at a fee of 30 USD would stop using the RWH system after take-up. Similarly, their reduction in water restrictions measured by the likelihood of postponing washing the dishes is negligible, and the cost savings for the government represent 66 percent of the average.

4.5 Conclusion

Considering the treatment effect heterogeneity of the RWH program, characterized by the fact that households with higher WTPs benefit more than the rest, this chapter examines the potential implications of different targeting strategies that aim to prioritize the enrollment of households with high WTP. Two approaches are considered: one targets households with specific demographic characteristics, while the other requires households to contribute to the cost of the RWH system.

I find that a design in which households contribute to the cost of the RWH system (between 3% and 15%) screens out households that benefit less than the average participant across all outcomes studied. Furthermore, lower participation fees are more effective in dissuading households with very low WTP from enrolling. However, it is important to note that further research is required to determine the average benefit of the program when these fees are applied. On the other hand, targeting program participants based on their demographic characteristics yields mixed results. A particular characteristic may improve benefits for one outcome but worsen them for another.

This chapter also shows that participation fees can be introduced without disproportionately affecting vulnerable households, particularly when social needs are correlated with the households' WTP. Specifically, in my setting, participation fees reduce the likelihood of enrollment for households with greater water availability. Moreover, in these circumstances, targeting strategies that combine demographic characteristics and participation fees result in the most significant improvements in the program's impact.

Appendix A: Mathematical derivations

A.1 Identification of the Marginal Treatment Effect

The households' WTP can be decomposed into its mean and an idiosyncratic error term, given the household's socioeconomic demographics and neighborhood characteristics, denoted by X. Consider a subpopulation of households with characteristics fixed at $X = x$. The deviations of a household's potential outcomes and costs with respect to the mean in this subpopulation are

$$\varepsilon_j = Y_j - E(Y_j|X = x) \quad \text{and} \quad \eta_j = C_j - E(C_j|X = x), \quad \text{for } j = 0, 1.$$

Thus,

$$WTP = \mu_D(x) - e, \tag{A.1}$$

with the elements of the expression defined as $e \equiv -E\left\{(\varepsilon_1 - \varepsilon_0) - (\eta_1 - \eta_0)|\mathcal{I}\right\}$ and $\mu_D(x) \equiv E\left\{E(Y_1 - Y_0|X_1 = x_1) + E(C_1 - C_0|X_2 = x_2)|\mathcal{I}\right\}$.

In this expression, a single term, e, captures all unobserved heterogeneity in the WTP. Households with greater values of e have a lower WTP and are less likely to enroll in the program. This unobserved heterogeneity is typically referred to in the literature as unobserved resistance to treatment or distaste for treatment as it enters the latent index with a negative sign.

Note that costs influence utility but not outcomes. The implications are that there is no other aspect of the treatment effect than $Y_1 - Y_0$ and that subjective costs η_j's reflect the household's taste for each alternative. By definition, e stems from both heterogeneity in treatment effects (given by $\varepsilon_1 - \varepsilon_0$) and the household's idiosyncratic preferences (captured by $\eta_1 - \eta_0$). Thus, conditional on (X, Z), technology choices can differ even across households with the same potential outcomes due to discrepancies in their WTP.

To simplify the exposition, I normalize both parts of the latent index in equation (A.1). Define $W_D \equiv F_e(e)$, where $F_e(\cdot)$ denotes the distribution of e. It is a uniform variable by construction ($W_D \sim U[0,1]$), and different values of W_D correspond to different quantiles of e. Define the probability of taking up the technology given Z as:

$$P(Z) \equiv \mathbf{\mathit{Pr}}(D = 1|Z) = \mathbf{\mathit{Pr}}(e < \mu_D - Z) = F_e(\mu_D - Z).$$

The household's decision to enroll in the RWH Program becomes:

$$D = \mathbb{1}\left[P(Z) \geq W_D\right], \tag{A.2}$$

and the MTE can be expresses (the conditioning on X is now explicit):

$$MTE(x, w) \equiv E(Y_1 - Y_0|X = x, W_D = w).$$

Consider an exogenous cost reduction from z_2 to z_1. The LATE condition $D_{z_1} > D_{z_2}$ is then equivalent to $P(z_1) > W_D > P(z_2)$. In this case, the MTE for $W_D = P(z_1)$ is the limit of LATE for $P(z_2) \to P(z_1)$. In general terms, the MTE at $W_D = P(z)$ is the LATE identified from a marginal change in the propensity score induced by an exogenous change in Z.

It follows that the MTE is identified by the derivative of the outcome with respect to the propensity score:

$$\frac{\partial E(Y|P(Z)=w)}{\partial w} = MTE(w).$$

A.2 Derivation of the MTE and MTRs

To obtain equation (2.4), consider the definition of D, the orthogonal properties of Z, and the definition of the propensity score (the conditioning on X is left implicit):

$$\begin{aligned}
E\left[Y|P(Z)=w\right] &= E\left[Y_0 + D(Y_1 - Y_0)|P(Z)=w\right], \\
&= E\left[Y_0 + \mathbb{1}(W_D \leq w)(Y_1 - Y_0)|P(Z)=w\right], \\
&= E\left[Y_0 + \mathbb{1}(W_D \leq w)(Y_1 - Y_0)\right], \\
&= E[Y_0] + E\left[Y_1 - Y_0|W_D \leq w\right] \mathit{Pr}[W_D \leq w], \\
&= E[Y_0] + E\left[Y_1 - Y_0|W_D \leq w\right] w.
\end{aligned}$$

The definition of (truncated) conditional expectation implies:

$$\begin{aligned}
E\left[Y_1 - Y_0|W_D \leq w\right] &= \frac{1}{F_{W_D}(w)} \int_0^w E\left[Y_1 - Y_0|W_D = t\right] f_{W_D}(t)\, dt, \\
&= \frac{1}{w} \int_0^w E\left[Y_1 - Y_0|W_D = t\right] dt.
\end{aligned}$$

where I used the fact that W_D is uniform.

Therefore

$$\begin{aligned} E\left[Y|P(Z)=w\right] &= E[Y_0] + \int_0^w E\left[Y_1 - Y_0|W_D = t\right] dt. \\ &= E[Y_0] + \int_0^w MTE(t)\, dt. \end{aligned}$$

The left-hand side of this expression can be estimated from sample data. Differentiating with respect to w, we obtain the MTE (the reference to X is made explicit here):

$$\frac{\partial E\left[Y|P(Z)=w, X=x\right]}{\partial w} = MTE(x,w).$$

To identify the expressions in (2.5) from sample data, let $\mu_1(x) = E(Y_1|X=x)$. Implicitely conditioning on X, we have:

$$\begin{aligned} E\left[Y_1|D=1, P(Z)=w\right] &= \mu_1 + E\left[\varepsilon_1|D=1, P(Z)=w\right], \\ &= \mu_1 + E\left[\varepsilon_1|W_D \leq w, P(Z)=w\right], \\ &= \mu_1 + E\left[\varepsilon_1|W_D \leq w\right]. \end{aligned}$$

Note that

$$\begin{aligned} E\left[\varepsilon_1|W_D \leq w\right] &= \frac{1}{F_{W_D}(w)} \int_0^w E\left[\varepsilon_1|W_D = t\right] f_{W_D}(t)\, dt, \\ &= \frac{1}{w} \int_0^w E\left[\varepsilon_1|W_D = t\right] dt, \end{aligned}$$

where the last equality follows because $W_D \sim U(0,1)$.

Combining the last two equations and rearranging terms, we obtain:

$$E\left[Y_1|D=1, P(Z)=w\right] w = \mu_1 w + \int_0^w E\left[\varepsilon_1|W_D=t\right] dt.$$

Taking derivatives with respect to w on both sides, we get

$$E\left[Y_1|D=1, P(Z)=w\right] + w\frac{\partial E\left[Y_1|D=1, P(Z)=w\right]}{\partial w} = \mu_1 + E\left[\varepsilon_1|W_D=w\right],$$

since, by the fundamental theorem of calculus,

$$\frac{\partial}{\partial w}\int_0^w E\left[\varepsilon_1|W_D=t\right] dt = E\left[\varepsilon_1|W_D=w\right].$$

Finally, substitute for $E\left[Y_1|W_D=w\right] = \mu_1 + E\left[\varepsilon_1|W_D=w\right]$ to get (the reference to X is now explicit):

$$\begin{aligned} E\left[Y_1|W_D=w, X=x\right] &= E\left[Y_1|D=1, P(Z)=w, X=x\right] \\ &\quad + w\frac{\partial E\left[Y_1|D=1, P(Z)=w, X=x\right]}{\partial w} \\ &= MTR_1(x,w). \end{aligned}$$

Appendix B: Additional Figures and Tables

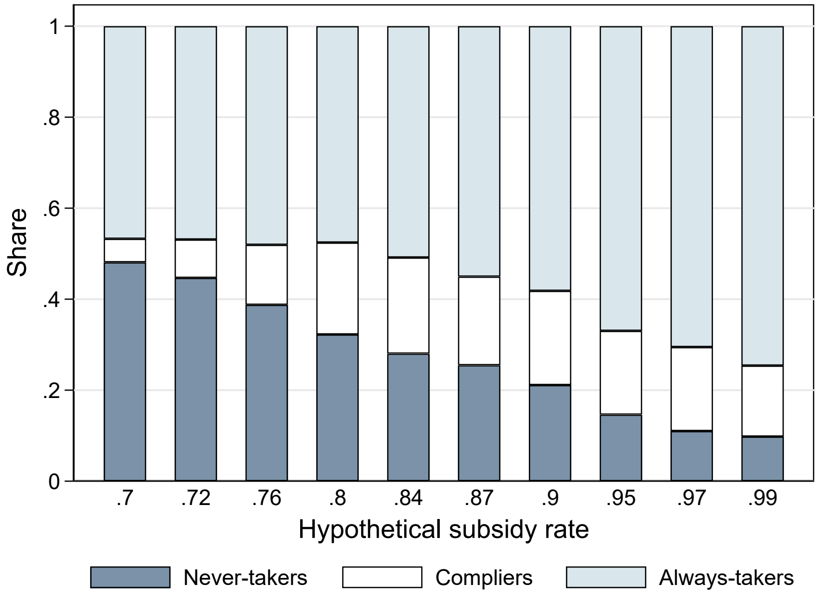

Figure B.1. Share of latent types at different subsidy levels

Notes: This figure shows the shares of latent types for a set of different subsidy rates. The data to construct the graph comes from the contingent valuation survey implemented among participants in the RWH Program in Mexico City in 2021. Subsidy rates correspond to those implied by the costs assigned to households in the CV survey. Values in each column are obtained by regressing the stated take-up variable on the subsidy and an indicator for the subsidy being greater than the value plotted. The shares of always-takers and compliers correspond to the intercept and the coefficient on the indicator, respectively. Never-takers are the remaining share. See Battistin et al. (2017) for a derivation of these parameters.

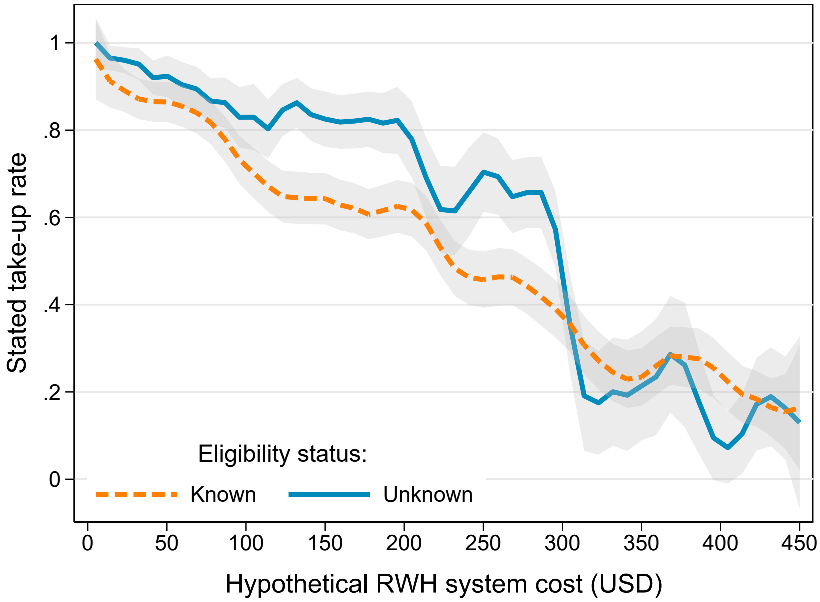

Figure B.2. Hypothetical take-up rates by timing of CV survey

Notes: This figure shows the share of households stating being willing to enroll in the RWH program as a function of the cost presented to them in the CV survey. Lines are obtained by a local polynomial regression of answers from the WTP question (1 = yes) on the assigned cost. Gray areas correspond to 95 percent confidence intervals. Data is plotted separately depending on whether households completed the CV exercise before or after learning about the eligibility of their dwelling to install the RWH system (see footnote 16 for details).

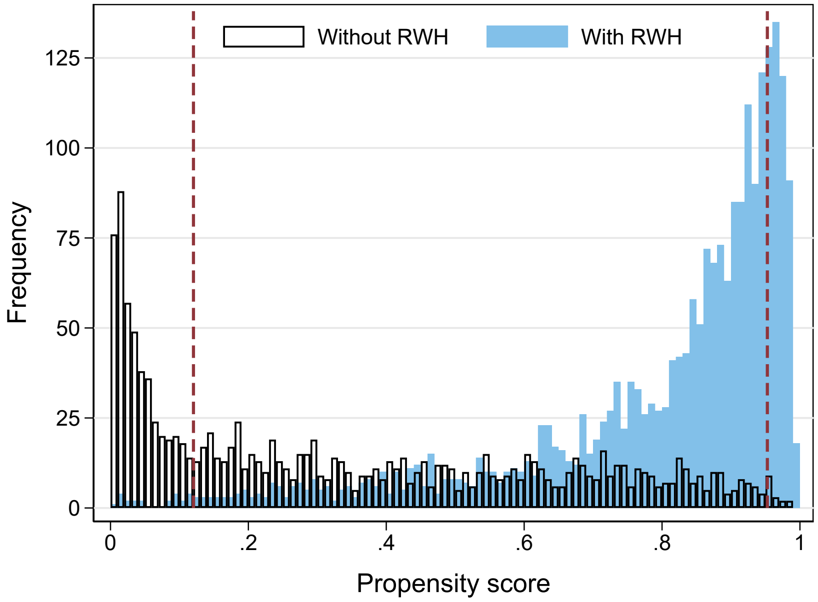

Figure B.3. Support of the propensity score

Notes: This figure plots the histograms of the propensity score for treated and untreated samples using a 1% bin width. The vertical axis corresponds to the number of observations in each bin. The scores in the horizontal axis are predictions from a logistic regression of the hypothetical take-up on the cost assigned in the CV survey and the control variables in Table B.2. Vertical dashed lines are drawn at the lowest and highest scores for observations included in the estimation to ensure common support between treated and untreated units.

Table B.1. Hypothetical take-up estimation

	Coefficient	Std. Err.
Intercept	.938093	.014559
Cost	-.001863	.000053
Unaware	.114076	.014077
Number of households	3,660	
F-stat (Prob $>$ F)	766.60	(0.0000)

Notes. This table presents coefficients from a linear regression of answers from the WTP question (1 = yes) on the assigned cost and fixed effects by the visit in which households were interviewed. Unaware refers to responses elicited during the technician's inspection when applicants did not know the eligibility of their dwellings (see footnote 16 for details). Robust standard errors are included.

Table B.2. Propensity score estimation

	Coef.	Std. err.
Cost Z	-0.0096^{***}	0.0004
Car ownership	0.4408^{***}	0.0969
Computer ownership	0.4304^{***}	0.0984
Water storage capacity (1,000L)	-0.0220^{**}	0.0105
Days a week with access to municipal water	0.2244^{***}	0.0240
Consumes water from tanker trucks	0.3720^{***}	0.1179
Unaware of participation at baseline	0.9734^{***}	0.0980
Storage tank size (1=big)	0.2188^{*}	0.1168
Roof surface for catching rainfall (sq m)	-0.0026	0.0024
Month of interview = September	3.5592^{***}	0.1673
Month of interview = October	3.3272^{***}	0.1744
Constant	-2.0397^{***}	0.2486
Wald chi2 (Prob $>$ chi2)	1912.33	(0.0000)
Observations	3660	

Notes: This table shows coefficients and standard errors from a logistic regression of stated take-up on the cost presented in the contingent scenario and household characteristics. The results are used to predict the individual propensity scores for the subsequent estimation stage. The F-test for the joint significance of the variables considered appears at the bottom of the table. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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