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RESEARCH ARTICLE

Assessing the impact of electricity subsides on electricity consumption: The case of selected Latin American countries

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Abstract

This document evaluates the impact of electricity subsidies on electricity consumption in Brazil, Argentina, Colombia, and Peru. To do this, this paper uses a Regression Discontinuity Design (RDD) to estimate the impact of the social tariff coverage policy on household electricity expenditure. The main results show mixed evidence of the effect of electricity subsidies on electricity expenditure. For instance, eligible households in Brazil experience a decrease in average electricity expenditure compared to non-eligible households. Results for Argentina point to a null effect of the electricity subsidy on household electricity expenditure. In contrast, in Colombia, the subsidy would be related to an increase in average electricity expenditure, which suggests that there might be overconsumption in the eligible group. Finally, in Peru, the subsidy does not show evidence of any impact on electricity expenditure. Understanding the differential impacts in various countries of the Latin American region can help tailor more effective subsidy programs that better target the most vulnerable populations and improve the optimization of resources. This analysis is one of the very first documents that evaluate social tariff programs in the Latin American region using an impact evaluation method.

Keywords: Electricity subsidy; Regression discontinuity design; LAC.
JEL codes: H23, O13, Q48, Q58.

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1. Introduction

Designing an efficient electricity subsidy and social tariff program is complex (Khalid and Salman, 2020). First, it is essential to recognize that electricity service affordability can be a challenge for many households in Latin American countries (LAC). It is especially challenging in low-income families and ultimately fences electricity access, which could reduce household welfare or trigger electricity thefts and lower consumption levels revenue for the utility (see, for example, Pacudan and Hamdan, 2019; Khalid and Salman, 2020). Nevertheless, subsidies can generate inefficiencies, distortions, and deficits if ill-designed. It can even impact economic competitiveness and the electric sector's sustainability. In part, this complexity is due to the targeting strategy. For instance, implementing poorly targeted subsidies for the entire residential sector in the form of discounts for electricity can substantially increase its fiscal burden, and environmental distortions and even deteriorate the protection of the most vulnerable groups (Oré et al., 2017).

Furthermore, the main problem that governments face when implementing a subsidy or targeting is who should be the beneficiaries and under which criteria to select them. Vagliasindi (2012) mentions that targeting mechanisms and methods for identifying those eligible for the subsidy program can vary, depending on the degree of coverage and the extent to which different programs benefit low-income households determining trade-offs between other solutions. Moreover, subsidies are intended to help specific groups of beneficiaries. Still, the extent they do frequently depends on how the subsidy is provided and its objective (Schwartz and Clements, 1999).

In this vein, to measure the performance of a subsidy scheme in reaching the poor, policymakers may find it helpful to define the probability that the targeted group (in this case, the low-income households) will receive the subsidy (Vagliasindi, 2012). There is a great variety of types of subsidies with different beneficiaries. In this document, we focus on subsidies for electricity for selected LAC countries with a social tariff program: Brazil, Argentina, Colombia, and Peru. Latin American countries have different electricity subsidy policies to benefit households classified within a socioeconomic profile of social vulnerability. Despite some exceptions (such as Brazil, Colombia, and the Dominican Republic), most LAC countries have electricity subsidy programs that consider only the level of domestic electricity consumption as a requirement for selecting their beneficiaries. This happens because cross-referencing energy consumption data and other household socioeconomic characteristics would require closer inter-institutional collaboration between statistical institutes and the ministry or energy regulator to harmonize consumers' and households' databases (Mori and Yepez-Garcia, 2020).

The literature on this topic highlights that universal electricity subsidies disproportionately help the middle and upper classes with higher consumption and access to clean fuels.[1] Moreover, it also suggests that using a single criterion for selecting the beneficiaries may lead to errors in including and excluding beneficiaries in electricity subsidy programs (Whitley and van der Burg, 2015; Gangopadhyay et al., 2005).

This document measures the impact of electricity subsidies on electricity expenditure in Brazil, Argentina, Colombia, and Peru. In other words, we evaluate whether subsidies generate changes in consumption behavior. For this, the paper implements an econometric model, Regression Discontinuity Design (RDD), using household income as the criteria to select eligible households, and electricity expenditure in local currency as the outcome variable.

The main results show mixed evidence of the effect of electricity subsidies on electricity expenditure. For instance, eligible households in Brazil experience a decrease in average electricity expenditure compared to non-eligible households. Results for Argentina point to a null effect of the electricity subsidy on household electricity expenditure. In contrast, in Colombia, the results show an increase in

[1] Oré et al. (2017) mention that although these subsidies make electricity more affordable for some low-income households, most benefits go to higher-income households in Central America.

average electricity expenditure, which suggests there might be overconsumption in the eligible group. This would be related to the targeting scheme; however, further investigation is required. Finally, in Peru, the subsidy scheme does not show evidence of any impact on electricity expenditure.

Research on evaluating the effects of electricity subsidies is mostly focused on distributional effects. For instance, Hancevic et al. (2016) found that electricity subsidies in Argentina were pro-rich since the non-poor sectors were receiving the largest shares. In addition, most of the papers use evaluation techniques such as the traditional benefit-incidence analysis (Giuliano et al., 2020). Others employ qualitative and decomposition techniques to assess distributional effects (Komives et al., 2005, 2007). This document distinguishes from current research on electricity subsidies in that it employs an impact evaluation method to assess whether electricity subsidies affect household electricity expenditure. This analysis is one of the very first documents that evaluates social tariff programs in the Latin American region using a Regression Discontinuity Design.

The document is organized as follows. Section 2 presents an overview of the electricity subsidies. Section 3 explains a suitable methodology to capture the impact of subsidy. Section 4 describes the data sets used. Section 5 explains the RDD methodology along with a description of the subsidy programs in each of the countries. Section 7 discusses the main results and offers a set of robustness checks to validate the identification strategy. Finally, Section 8 presents the main conclusions.

2. Electricity Subsidy: An Overview

Selecting beneficiaries for an electricity subsidy may not be straightforward since it can have multiple objectives. Moreover, beneficiaries can be, either the final consumers, companies, or both. In many cases, governments have insufficient information to subsidize efficiently. Several authors mention that non-monetary subsidies are more efficient than monetary ones (Frederiks et al., 2015; Sanin, 2019), while others argue that subsidies with cash transfers are more efficient when the objective is about a social policy (Hanna and Oliva, 2015). In short, there is no consensus on this matter, and, again, we could say that the effectiveness of the subsidy will depend on its objective and the selection of the beneficiaries.

One critical point about energy subsidies is their impact on energy poverty, which in the context of developed countries refers to the ability to afford the energy one needs; for developing countries, most often this refers to the lack of access to energy services (Pacudan and Hamdan, 2019). González-Eguino (2015) argues that specific policies and programs are required to deal with energy poverty, particularly programs designed to prevent its worst effects on health. This is because most of the electricity subsidies do not benefit the poorest, but a large part (indirectly) benefits the richest, both in developed and developing economies (see, for example, Coady et al., 2017; Oré et al., 2017; Clements et al., 2013). This is why many countries seek strategies to reform universal subsidies to target the poorest population better.

Targeting mechanisms and methods to identify those eligible for subsidy programs can vary depending on the degree of coverage and the extent to which different programs benefit the poor, determining trade-offs between different solutions (Vagliasindi, 2012). Good targeting requires that a high proportion of benefits accrue to lower-income households. If a substantial proportion of benefits leak to higher-income households, more effective approaches to social protection are likely possible (Del Granado et al., 2012). Directly targeted cash transfers represent an alternative to help low-income households cope with high electricity prices and can be included as part of an integrated, comprehensive poverty alleviation program (Troncoso and da Silva, 2017). Another mechanism might be to provide connection instead of consumption subsidies, this could substantially improve targeting, but providing such connection subsidies supposes also that recovery cost is adequate in order not to increase sector deficits further (Vagliasindi, 2012). Increasing the relative depth of subsidies for households that consume less electricity can be effective in increasing targeting efficiency (Oré et al., 2017). Therefore, the progressivity of electricity subsidies should be sought since this could represent higher revenues for governments or less spending that could be reinvested in broader social protection programs or in improving the energy supply network for citizens.

A policy that targets electricity subsidies should focus on at least four reforms: pricing, institutional, informational, and complementary (Inchauste and Victor, 2017). Table 1 shows the benefits and caveats of each of the four possible reforms for a targeting policy of electricity subsidies. It also shows how they would be associated with the four factors mentioned by Oré et al. (2017): i) access to the electricity grid; ii) coverage of subsidy mechanisms; iii) subsidy depth (subsidy amount per unit of electricity consumed), and iv) of the amount of subsidized electricity consumed.

Table 1: *Benefits and caveats of targeting policy reforms for electricity subsidies*

Policy reform	Method	Benefits	Caveats	Oré et al. (2017) factors
Pricing reform	- Direct cash transfers to beneficiaries (consumers). - Subsidy for inputs used in the production process (producers).	- Subsidize price fuel types differently so that there are lower prices for fuels that tend to be consumed by low-income and politically well-connected groups (e.g., LPG). - Reduction of smuggling and corruption.	- Subsidize fuels used by the richest and least sensitive to price changes (e.g., electricity, diesel, gasoline).	- Subsidy depth. - The amount of subsidized electricity consumed.
Institutional reform	- Removal of ad hoc government control over prices and a shift to pricing mechanisms that are more automatic or even full reliance on markets for pricing. - Reorganization of how subsidies are paid. - Having a specialized regulatory agency that administers licenses, manages regulations, keeps the public informed about prices, and reviews the proper functioning of the market. - A complete removal of the government's role in establishing prices (price deregulation), taken in an environment of falling oil prices.	- Facilitate the transition process and make it easier for firms and politicians to focus on long-term investments and policy strategies. - Reduction of smuggling and corruption.	- A profound reform is needed that could be slow due to the political processes of creating norms, laws, etc. So, there may be interference from politicians.	- Access to the electricity grid. - Coverage of subsidy mechanisms.
Informational reform	- Field campaigns with potential beneficiaries. - Communication campaigns with traditional media and social networks.	- Information can make interest groups aware of benefits that might flow to them if they were better organized politically. - Informational reforms can also play important roles in convincing stakeholders to consent to give up a benefit they have in hand (a subsidy) in exchange for some better outcome (lower tax burdens and better-functioning energy markets) in the future.	- Without adequate information, individuals do not know how subsidies are targeted. Thus, they can think that the poorest are being harmed when it is not.	- The amount of subsidized electricity consumed. - Coverage of subsidy mechanisms.
Complementary reform	- Direct cash transfers to beneficiaries (consumers). - Subsidy for inputs used in the production process (producers).	- It complements or substitutes for subsidies in ways that help reformers reduce the size of subsidies and improve their allocation.	- Political costs. - These actions can lead to greater social legitimacy of the reform process, which is critical for its political sustainability.	- Coverage of subsidy mechanisms.

Notes : Based on Oré et al. (2017), Inchauste and Victor (2017), and Vagliasindi (2012).

3. What Might Be a Good Methodology to Capture the Impact of a Subsidy?

The below-poverty line (BPL) methodology is one of the most used to select the households that will receive a subsidy. Under this approach, the authority in charge establishes a value in monetary units (electricity consumption), with which it classifies households above or below this line (threshold). Households that are below the threshold, categorized as ”below the poverty line”, become beneficiaries of the subsidy. This approach can lead to poor design in the selection of beneficiaries. Oré et al. (2017) argue that a critical key challenge is that the different mechanisms to identify beneficiaries are based on the household's level of consumption, but consumption is not a perfect proxy of income. Moreover, using consumption as a proxy of income leads to errors of inclusion, in which high-income households receive subsidies, and errors of exclusion, in which low-income households do not receive subsidies.

One of the main methodologies to reduce the errors of inclusion and errors of exclusion is the so-called Targeting Performance Indicators (TPI). These indicators facilitate the assessment of the subsidy's effectiveness by calculating (i) the proportion of poor households that benefit from the subsidy, and (ii) the degree to which the subsidy instrument accurately targets the poor in comparison to other households (Camino-Mogro and Arias, 2024). Another methodology consists of simulating changes in the estimated BPL (see, for example, Oré et al., 2017; Vagliasindi, 2012; Komives et al., 2005; 2007); nevertheless, the simulation of the BPL in many cases is discretionary, which may bias the results. An additional way to analyze whether a subsidy (electricity or LPG) has a positive impact or not on the beneficiaries is to use econometric methods. In this way, it is possible to identify if there are errors in the inclusion or exclusion of the beneficiaries. However, many of these methods (for example, Ordinary Least Squares (OLS), Instrumental Variables) may have simultaneity problems. For instance, electricity consumption (quantity) is a function of price (of electricity), but economic theory also demonstrates that quantity may have an impact on the price of electricity. Since price and quantity are jointly determined, the OLS regression would lead to biased and inconsistent estimation.

To overcome these problems, one can carry out an impact evaluation, for which there are several methods such as differences-in-differences (DID), matching techniques, synthetic control, and regression discontinuity design (RDD), among others. These methods need a control group and a treatment group to evaluate the impact of the subsidy on the different outcomes of interest. The important thing here is that the event (application of the subsidy) would need to have been entirely exogenous and that the treatment and control group would not have the possibility of transferring themselves into the other group. If this happens, then individuals have the motivation to change their behavior to be beneficiaries of the subsidy.

The literature proposes an RDD approach to evaluate social protection programs because the RDD removes selection bias by making use of the discontinuity in the eligibility criteria around the eligibility threshold of the program (Iqbal and Nawaz, 2021; Nawaz and Iqbal, 2020; Bergolo and Galván, 2018; Thistlethwaite and Campbell, 1960).

Authors like Bergolo and Galván (2018), and Firpo et al. (2014) argue that because only those applicant households with an income score above a determined threshold are eligible for the program, this rule generates a strong discontinuity in the probability of being assigned to the program that might be a source to exploit for identification. In this sense, individuals could manipulate their eligibility status by changing their income through labor, and behavioral decisions. There are two main conditions to apply RDD including i) a continuous eligibility measure on which population is ranked and ii) a clearly defined cutoff point to determine eligibility for the program (Hahn et al., 2001). Thus, the RDD is a good methodology candidate to evaluate the causal impact of a targeting performance indicator of subsidy and a subsidy because the RDD allows comparing households above and below the cutoff point to find the impact of the program on the outcome variable. RDD relies on two assumptions: i) the eligibility index should be continuous around the cutoff point and there should be no jumps in the eligibility index at the cutoff point or any chances of manipulation of score to increase their chances to become eligible; ii) households close to the cutoff point should have on average, similar observed and unobserved characteristics (Nawaz and Iqbal, 2020).

4. Data

This document uses household surveyed data conducted in each of the four countries selected for the analysis (Brazil, Argentina, Colombia, and Peru). Table 2 shows the (original) names and years of the surveys per country.

Table 2: *Data sources*

Country	Survey name	Year
Brazil	Encuesta Nacional de Gastos de Hogares	2017/2018
Argentina	Encuesta Nacional de Gastos de los Hogares	2017/2018
Colombia	Encuesta Nacional de Calidad de Vida	2019
Peru	Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza	2019

Source: Official household survey on income and expenditures of the selected countries.

The surveys are household surveys on income and expenditures, they are nationally representative and collected by the official competing institution of each country. The sample selection is random of complex design.[2] The unit of observation is at the individual/household level. Data are collected using face-to-face interviews with one or more respondents per household, who are also asked to provide information on the other household members.

The surveys have information about the domestic composition budget, characteristics of households and families, living conditions, and some sociodemographic variables. Tables A1 to A4 in the Appendix show the mean and standard deviation of selected socioeconomic variables such as household expenditure, income, gender of the head of the household, and appliance ownership, among others that are of interest for the analysis.

Descriptive statistics show a similar pattern across countries in some variables. For instance, regarding the proportion of households in which the head is a woman, in all countries it is mostly concentrated in the poorest households. Instead, Peru is an interesting case as there does not seem to be large differences across income deciles. In addition, less advantaged groups such as black, Indigenous, and the elderly are disproportionately concentrated in the lowest-income deciles in Argentina, Colombia, Brazil, and Peru. Concerning the education level of the head of household, Colombia, Brazil, Argentina, and Peru show a similar pattern. Individuals with less than elementary school are mostly concentrated in the lowest decile of the income distribution.

Regarding appliances in households, all countries show similar behavior across income deciles. For example, home appliances that are used for vital activities such as cooking (stoves), food storage (refrigerators), and televisions have similar shares across deciles, which are in most cases larger than 80%. Instead of appliances such as computers, washing machines, air conditioners, and electric ovens, better-off households have a higher participation compared to poorer ones. Overall, the descriptive statistics show that characteristics that are considered indicators of vulnerability and poverty are mostly concentrated in worse-off households.

[2]For more information about the sample selection design, please visit the official websites of the Statistics department of each country.

4.1. Brazil

Regarding the total expenditure of households, on average, they spend around 3,202.13 in local currency per month. Concerning energy, gas expenditure increases when moving from the first decile to the seventh decile, and then decreases from decile eight onwards. For electricity expenditure, it increases as income increases.

For sociodemographic characteristics, 46% of households in the first income decile are led by a woman, whereas for households in the top decile, this percentage decreases to 33%. Likewise, black individuals have the largest representation in worse-off households (77% in the first decile, and 34% in the top-income decile). The 43% of families in the lowest decile are beneficiaries of social assistance and the 41% of this group is eligible for electricity subsidy. Details of descriptive statistics are presented in Table A1 of the Appendix.

4.2. Argentina

Like other countries, average monthly household electricity consumption increases as income per capita increases. In this country, the largest share of households led by women is seen in the poorest decile with 57 percent. 22% of households in the lowest income decile are beneficiaries of social assistance, a number that decreases as income increases. Likewise, families that are eligible to receive an electricity subsidy represent 10% of the wealthiest group, while in the poorest group, this number is 45%. Table A2 of the Appendix presents details of descriptive statistics.

4.3. Colombia

Average electricity expenditure per month, per household increases as income per capita increases. The proportion of households in which the head is a woman is the largest for the lowest deciles of the income distribution. For instance, in decile 1 the proportion is 0.43, whereas in decile 10 it is 0.31. Likewise, black individuals show the largest share in poorer households (14% in decile one, and 0.06 in decile 10). The same pattern is seen for Indigenous people. With respect to eligibility for a subsidy, there do not seem to be huge differences across income deciles. For example, 81% of households in the second decile are eligible as are 83% of households in the ninth decile. Table A2 of the Appendix presents details of descriptive statistics.

4.4. Peru

Peru shows that average monthly household electricity consumption increases as income per capita increases. Moreover, there is not much difference with respect to the gender of the head of the household across income deciles. For example, the 32% in the first decile, and the 25% in the richest group. With respect to the ethnicity of the head of household, black individuals do not have a large representation across any of the income deciles. A different situation happens for households led by indigenous, in the first decile this percentage is 40% while in the wealthiest families is 18%. Finally, 17% of the poorest households are beneficiaries of the LPG subsidy. Table A4 of the Appendix presents details of descriptive statistics.

5. Methodology

This section provides information regarding the methodological approach used to evaluate the effect of the social tariff on household electricity expenditure in the selected group of countries.[3] It starts with a description of the subsidy programs implemented in each of the countries, which includes the eligibility criteria.[4] Then, this section presents the empirical strategy, a Regression Discontinuity Approach. Finally, it provides details on the construction of the eligibility and the running variables per country, as well as the sample definition.

5.1. Description of the subsidy programs

5.1.1 Argentina

The social electricity tariff program in Brazil was created under Law nº 10.438 of 2002 and is currently regulated by de law nº 12.212 of 2013 and decree 7.583 of 2011 (Brasil, 2002, 2011, and 2013). To access this program, the following criteria are necessary: i) family registered in the Single Registry of Social Programs of the Federal Government, with monthly per capita family income less than or equal to half the national minimum wage (R$ 477 in 2018); or ii) elderly people aged 65 (sixty-five) years or older, or iii) people with disabilities, who receive the Continuous Social Assistance Benefit - BPC, under the terms of arts. 20 and 21 of Law No. 8,742, of December 7, 1993; or iv) family registered in the Single Registry with a monthly income of up to 3 (three) minimum wages, suffering from any illness or disability (physical, motor, auditory, visual, intellectual, and multiple) whose treatment, medical or therapeutic procedure requires the continued use of apparatus, equipment or instruments that, for their operation, require electricity consumption. In addition, the Brazilian social tariff provides a volume-differentiated discount for these groups.

The policy grants cumulative discounts depending on the level of consumption: a household that consumes 30 kWh per month or less will receive a 65 percent discount; consumes between 31 to 100 kWh per month receive a 40 percent discount and consumes between 101 to 220 kWh per month receive a 10 percent discount. Above 220 kWh, there is no discount on the household electricity bill. In addition, the program provides exemptions from the Energy Development Account ("Conta de Desenvolvimento Energético" - CDE) cost and the cost of the Incentive Program for Alternative Sources of Electric Energy ("Programa de Incentivo às Fontes Alternativas de Energia Elétrica" - PROINFA) (ANEEL, 2020). [5]

5.1.2 Argentina

Argentina in 2018 changed the target mechanism to include income and other socioeconomic variables (including georeferentiation) as the primary way to select lower-income households as the social tariff beneficiaries (Sanin, 2019). Moreover, the social tariff subsidy covered part of the generation cost of electricity. Specifically, the social tariff was set to cover 100% of the generation of the first 150 kWh and 50% of the following 150 kWh consumed per user per month. Beneficiaries would pay the distribution company the reduced cost of electricity, the full cost of transmission, distribution, and taxes, and the same variable cost as non-beneficiaries for kilowatts over 150 kWh. Similarly, in the case of natural gas, the social tariff subsidized 100% of the cost of the first 500 m3 in the year, with a preestablished maximum per month that varies by season. The eligibility criteria for the social tariff were categorical.

[3] It is important to mention that this document only considers the effect on the social tariff program. In this sense, it does not consider other subsidies.

[4] In this document we refer to beneficiaries of the social tariff as those households that are entitled to be beneficiaries of the program under the income condition.

[5] See, Marcoje et al. (2022) for details.

Beneficiaries who qualified for these reduced tariffs were linked to social programs, had incomes from pensions or salaries below two minimum wages (P$ 19,000 in 2018), or had specific health conditions, among others (see, for details, Giuliano et al., 2020).

5.1.3 Colombia

In Colombia, the selection method goes through a stratification system that estimates the value of the dwelling and classifies them in a category from 1 to 6, with being 1 the stratum assigned to properties with lower value and 6 to the highest (Velez Tamayo, 2019). Residents of the lower strata are eligible for electricity subsidies. Households in Stratum 1 benefit from a subsidy of approximately 55% of the base tariff; Stratum 2 has a subsidy of 45%, and Stratum 3 has a subsidy of 15%. Households in Strata 4 pay the whole bill, and Strata 5 and 6 pay an additional contribution of 20% of their bill (Marcoje et al., 2022; Vélez Tamayo, 2019).[6]

One of the main problems with the current system of transferences is that the value of the dwelling is not an accurate income proxy (Meléndez, 2008). Vélez Tamayo (2019) shows that around 17% of households in Colombia that are under the stratum 1 classification are in the 2 highest quintiles of the distribution of income in the country, and the number rises to 41.5% of the households under stratum 2 category. This is critical because people who do not need the electricity subsidy are benefiting from it. To benefit from the subsidy, households have to rank in the first, second, or third stratum, and report a maximum monthly consumption of 200 kWh.

5.1.4 Peru

Peru has a cross-subsidy scheme created to favor households with low levels of electricity consumption. The criteria used to identify the consumers benefiting from the subsidy and the consumers who finance the fund is a consumption threshold, defined as 100 kWh/month. However, recently to ensure that the subsidy only benefits low-income users, users who receive this benefit must meet the following criteria: a) residential users of the public electricity service whose monthly consumption is less than or equal to 140 kWh/ month included in the low voltage tariff options for residential use. b) residential users of collective block sale supplies with average unit consumption less than or equal to 140 kWh/month, including low voltage electrical supplies, measured through a medium voltage connected meter.

The users mentioned in the previous paragraph will be excluded from the subsidy in the event that: i) the user's delivery point is located in the blocks classified as high and medium-high strata, according to the map stratified by blocks of the National Institute of Statistics and Informatics; ii) the average consumption is greater than 140 kWh/month during the months of the summer season (January, February and March); iii) with this criterion, dwellings that are only occupied in summer will be excluded from the subsidy; iv) the user requests their exclusion.

6. Empirical strategy

6.1. Regression Discontinuity Design (RDD)

In social protection programs, it is very common that the eligibility criteria are defined based on whether households lie below or above a certain threshold. In these settings, the literature proposes a RDD approach to evaluate social protection programs, as the RDD removes selection bias by making use

[6]The law 142 of 1994 stablished in its chapter of tariffs of public service companies the current rules for stratification in the system.

of the discontinuity in the eligibility criteria around the eligibility threshold of the program (Iqbal and Nawaz, 2021; Nawaz and Iqbal, 2020; Bruhn and McKenzie, 2019; Bergolo and Galván, 2018; Firpo et al., 2014; Thistlethwaite and Campbell, 1960). RDD allows comparing households above and below the cutoff point to find the impact of the program on the outcome variable (Nawaz and Iqbal, 2020).

This document estimates the impact of the social tariff coverage policy on household's electricity expenditure, the outcome variable of interest. This variable has advantages over other (potential) outcomes; for instance, it is easier for individuals to remember how much they spent on electricity in the previous month compared to how many (new) electrical appliances they have or distinguish between low and high consumption hours and appliances. Using electricity expenditure, therefore, reduces reporting errors.

Based on the institutional setup described in the previous subsections, this paper uses a RDD using the household's income per capita as the continuous running variable (eligibility criteria). An individual is eligible for the social tariff program in each country if the individual lives under poor conditions (socioeconomic characteristics, electricity consumption, income, etc.), which is measured at the household level. This is the first challenge of this document, since the eligibility criteria to be a beneficiary of the social tariff program in each country are different and, in most cases, it is determined by electricity consumption in kWh accompanied by an income criteria and socioeconomic characteristics. As it is known, in most household surveys, electricity consumption measured in kWh is not available. In addition, if asked about this variable, the identification of consumption is difficult to remember, unless it is observed by the interviewer (as is the case in Colombia to build the index that determines in which stratum the household is).

However, household income is a variable that is found in all household surveys, and it is also a good proxy for measuring poverty and extreme poverty. In addition, it is one of the main variables for constructing poverty indices in each country. Thus, like Bernal et al. (2017), provided that the condition on electricity expenditure holds, we have a sharp RDD. A sharp RDD assumes that actual treatment status should perfectly match the eligibility of a household, implying that eligible households become beneficiaries and ineligible ones do not (Nawaz and Iqbal, 2020).

Therefore, and like Bernal et al. (2017), this document will impose linearity around the eligibility threshold and estimate the effects using the standard ordinary least squares (OLS) estimator with estimation equations of the form:

$$Y_i = \beta_0 + \beta_1 Z_i + \beta_2 \text{Eligible}_i + \beta_3 Z_i \times \text{Eligible}_i + \beta_4 X_i + \varepsilon_i \tag{1}$$

where Y is the electricity expenditure in each household i, Z is the income (per capita) centered at the threshold (which is different by each country of analysis), Eligible is an indicator for eligibility ($\text{Eligible}_i \in \{0,1\}$ is equal to 1 if the household is below the social tariff eligibility cutoff, and 0 otherwise) based on the (per capita) income (that is, an indicator for $Z_i \leq 0$). X is a vector of control variables such as the number of household residents, geographic area, whether the household has an elderly resident, whether the household has a child (¡ 19 years old) as a resident, and a set of high-electricity appliances. The parameter of interest is β_2, which is the effect of social tariff coverage for individuals who become covered because their (per capita) income crosses from above to just below the eligibility threshold. This parameter is policy-relevant because it is directly related to the question of what the effects of expanding the social tariff coverage through increasing the threshold value would be for the individuals who would then receive coverage (Bernal et al., 2017).

The first assumption we need to make for this analysis is that if no discount would be assigned to anybody around the threshold, then the respective distribution of the outcome conditional on the (per capita) income would be smooth in the income per capita (Z) around zero. Then, β_2 is indeed the effect of coverage. Like Bernal et al. (2017), this assumption cannot be tested directly and is therefore the main assumption this document will make. As argued before, the institutional rules suggest that it holds, as no other programs or rules are based on this eligibility threshold. Moreover, this assumption is supported by further evidence that this paper presents in the robustness section below.

The second assumption is that the social tariff program status is monotone in eligibility. This holds by construction, as we are facing a sharp RDD and therefore, changing from a value of the income per capita slightly higher than the threshold to a value lower than the threshold will directly make an individual eligible for the social tariff coverage. Finally, the third assumption is an exclusion restriction. It is that in a small neighborhood around the eligibility threshold, the value of the index, Z, is independent of the outcomes, and in particular ε_i. It would be violated if households were to manipulate their answers to the government official to influence the income per capita.[7] However, this document will show a test for manipulation that supports the validity of the method (Bernal et al., 2017).

Equation (1) does not involve a "first stage," as is usually the case in similar studies exploiting an RDD. If individuals are anyway not eligible and hence not covered by the program because of their income per capita, then we will control for this. Consequently, β_2 is the effect of becoming eligible due to crossing the income per capita eligibility threshold for all other individuals.

To address the concern that linearity might be too strong of an assumption even in smaller subsamples, this document also conducts a nonparametric analysis (RDD). For this, we follow Calonico et al. (2014). The main difference in terms of implementation is that we drop individuals for whom income per capita is too high to be eligible for the social tariff program. Thus, we consider the following impact model:

$$Y_i = \alpha_0 + \alpha_1 \text{Eligible}_i + f(\text{income\_percapita}_i) + \delta' X_i + \mu_i \tag{2}$$

where α_1 measures the impact of the social tariff program, $f(\text{income\_percapita}_i)$ is the running variable, the income per capita, μ_i is the error term. Equation (2) is estimated using a triangular kernel weighting scheme (default) and polynomial fit of order 1 (default). This document hypothesizes that the social tariff program assignment is based on the income per capita for each country of analysis. In this sense, the social tariff program eligibility cutoff is different for each country.[8]

6.2. Definition and construction of the eligibility criteria

This section provides details on the construction of the eligibility and the running variables per country. In addition, it also explains the sample definition and any additional criteria used to build the sample per country.

Starting with Brazil, the eligibility criteria are based on income per capita. Thus, households with a monthly per capita family income less than or equal to half the national minimum wage (R$ 477 in 2018) are considered beneficiaries. Those whose income per capita is above the threshold are considered non-eligible. Therefore, the variable Eligible_i takes the value of one for those above R$ 477, and zero otherwise (ANEEL, 2020).

For Argentina, this document also uses income per capita as the eligibility criteria. According to the Ministry of Energy of Argentina, one of the inclusion criteria to benefit from the social tariff is an income per capita below two minimum wages. For the year 2018, the minimum wage was P$ 9,500 (Argentine pesos), therefore households with an income per capita below P$ 19,000 are eligible, and

[7] This is unrealistic, because in most cases the individuals do not know which the threshold is to be a beneficiary of social programs.

[8] Equation (2) compares households just below the eligibility cutoff (treatment group) with the households just above the eligibility cutoff (control group). By comparing the observations on both sides of the cutoff level, it is possible to estimate an intervention's average treatment effect (Iqbal and Nawaz, 2021).

those above are non-eligible. To have an idea about the purchasing power of a minimum wage in 2018, a good option is to compare it with the poverty line. The poverty line for this year was between P$ 6,618 and P$ 9,638 depending on the geographical region (INDEC, 2019).

In Colombia, the official eligibility criteria are based on a strata classification that is built from an index that uses several individual indicators. Households classified under the first, second, and third strata may be beneficiaries of the electricity subsidy, whereas strata 4, 5, and 6 are not. As there is no available (for external use) information on the index construction, this document uses the official poverty line to classify households into treated and control units, which is a good indicator of low-income households. The poverty line in 2019 is COP$ 137,350 (DANE, 2019). Therefore, households with an income per capita below the poverty line are considered eligible, whereas those above are set as non-eligible. Regarding the sample definition, this document excludes households classified in strata 0, 8, and 9, which correspond to illegal electric connection, power plant, and missing information on strata. In addition, strata 4, 5, and 6 are also excluded. This means that the sample used corresponds to households that might be eligible according to the strata criteria.

Finally, Peru uses electricity consumption in kWh as the official eligibility criteria. However, due to data availability restrictions in household surveys, the information on kWh is not available. To overcome this limitation, this document relies on the official inclusion criteria of the Energy Social Inclusion Fund (FISE, in Spanish), whose primary objective is to provide the most vulnerable populations with access to cleaner energy, targeting households living in poverty or extreme poverty (Pollard et al., 2018). To be eligible for the FISE, household income in 2019 should be less than S/. 19,900 per year, which is equivalent to S/. 1,658 per month. Households with a monthly income below S/. 1,658 are considered as eligible (treated units), whereas households above this threshold are considered non-eligible. With respect to the sample definition, the analysis excludes observations with missing data on household income.

7. Results

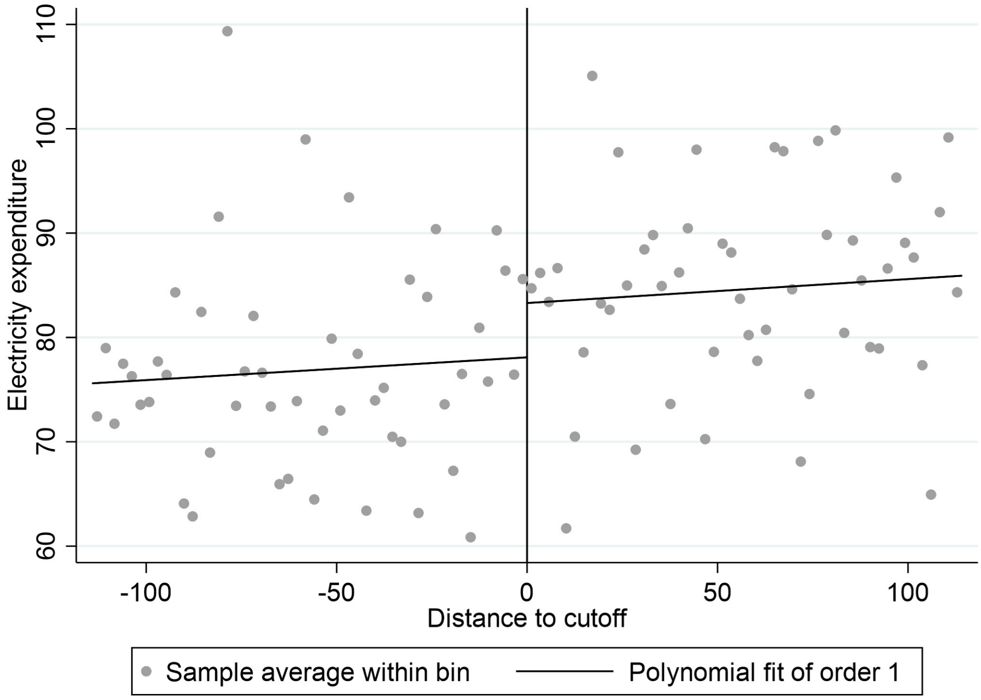
This section presents the results of the OLS and RDD estimates for each country of analysis. In all cases, this section starts by showing the relationship between receiving the social tariff program and the eligibility criteria (income per capita). Then, the results of the estimation of Equations (1) and (2) with and without controls are presented. Finally, a set of robustness (sensitivity analysis) checks are performed, such as: manipulation test; jumps in the expectations of covariates at the eligibility threshold; an assessment of whether there are discontinuities at other values of the running variable; and other polynomial orders. The results are separated by country.

7.1. Brazil

Figure 1 presents evidence that income per capita is positively associated with electricity expenditure. Furthermore, households situated to the left of the cut-off (zero of the x-axis), eligible for the social tariff program, have less electricity expenditure than households situated on the right, which are non-eligible for the program. There is a jump in the level of expenditure around the cut-off. This graphic evidence supports a discontinuity in the consumption of electricity around the cut-off. Therefore, we can continue with the estimations of Equations (1) and (2).

Table 3 shows the estimates of Equations (1) and (2) with and without controls, respectively. Columns 1 and 2 show estimates for Equation (1). Here, the coefficient of interest β_2, which represents the effect of social tariff coverage for individuals who become covered because their income per capita crosses from above to just below the eligibility threshold, is negative and statistically significant. This evidence

Figure 1: *Receives the social tariff program*



Notes: Y axis is the average electricity expenditure. 100 bins to both sides of the cutoff using the optimal bandwidth obtained from the rdrobust estimation. The eligibility threshold is R$ 477 incomes per capita of the local currency. Source: Authors' elaboration based on IBGE, Family Budget Survey 2017-2018.

suggests that households reduce their electricity expenditure because of the electricity subsidy. The reduction in electricity expenditure estimated is around R$ 15.13 (without control variables) and R$ 15.47 (with control variables). A reduction in electricity expenditure is associated with a reduction in electricity consumption in kWh. Marcoje et al. (2022) found similar results for Brazil.

Recall from previous sections that households below the threshold are those with a monthly per capita family income lower than half the minimum wage. A reduction in electricity expenditure in this group compared to those above the threshold might suggest that Brazilian households are adjusting their consumption to benefit from or maintain the subsidy. This could imply two things: households are restricting energy consumption, or they are making a more efficient use of electricity. Further analysis would be ideal to explore these potential explanations that are beyond the scope of this document.

Table 3: *Effect of social tariff on electricity expenditure.*

	OLS estimates		Non-parametric estimates (RDD)	
	(1)	(2)	(3)	(4)
Outcome:	Bandwidth 100		Optimal bw	
Electricity expenditure	No controls	Controls	No controls	Controls
Z1	-0.0876	-0.0817		
	(0.0734)	(0.0657)		
Eligibility dummy	**-15.1280****	**-15.4663*****		
	(6.0236)	**(5.5093)**		
interaccion_EZ1	0.0692	0.0254		

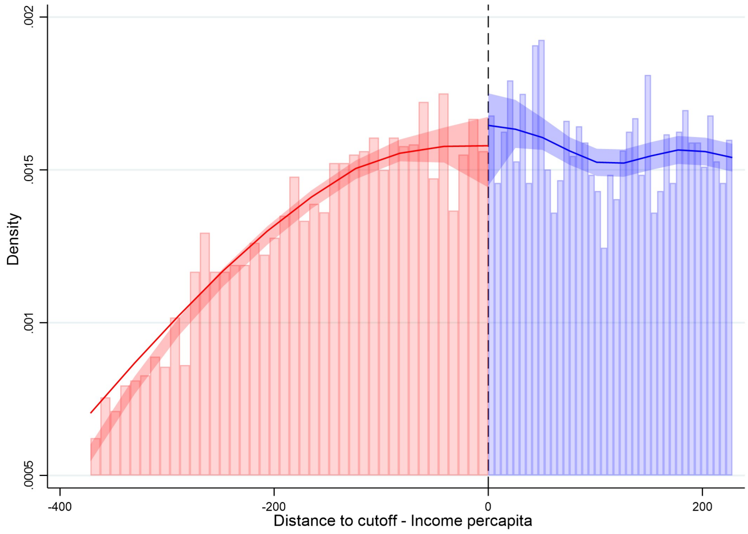
	(0.0951)	(0.0879)		
Income per capita $\leq$ cutoff			**-17.01****	**-18.03****
			(7.2484)	(7.3884)
Optimal bandwidth			114.042	108.71
Optimal bias bandwidth			196.733	190.81
Controls				
Number of residents	no	yes	no	yes
Geographic Area	no	yes	no	yes
Elderly as resident	no	yes	no	yes
Child as resident	no	yes	no	yes
High-electricity appliances	no	yes	no	yes
Observations	6,188	6,188	6,979	6,686
R-squared	0.0047	0.1132	-	-

Notes: Columns (1) and (2) show results from Equation (1). Robust standard errors in parentheses. Columns (3) and (4) show results from Equation (2). Probability weights are included to consider the survey design across all specifications.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Columns 3 and 4 present the estimates of Equation (2) by using a RDD approach with and without covariates. The coefficient of interest α_1 is negative and statistically significant at the 5% level. This evidence suggests that the treatment group has an electricity expenditure between R$ 17 and R$ 18 less than the control group. This result is in concordance with those obtained in columns 1 and 2 and shows the consistency of the identification strategy.

A common threat to studies based on RDD is the incentive to manipulate the running variable; in this sense, it is important to test that households cannot manipulate the running variable around the cutoff in the RDD methodology (Marcoje et al., 2022; Bernal et al., 2017). For households to manipulate the running variable, they need information on the income per capita threshold, which is easy to know. In addition, they need to use this knowledge to manipulate their income per capita itself. This is unlikely to be the case for two reasons. First, even though the information of how much the income per capita threshold is to access the social tariff program is known, it is not rational for individuals to decide to lower their income to access the program because a higher income allows them to have a better social status. Second, to access the social tariff, households need to also fulfill the consumption (in kWh) criteria, which is observed by the government and is challenging to manipulate.

Figure 2: *Manipulation Test for Discontinuity of the Density of the Income per Capita at the Threshold*



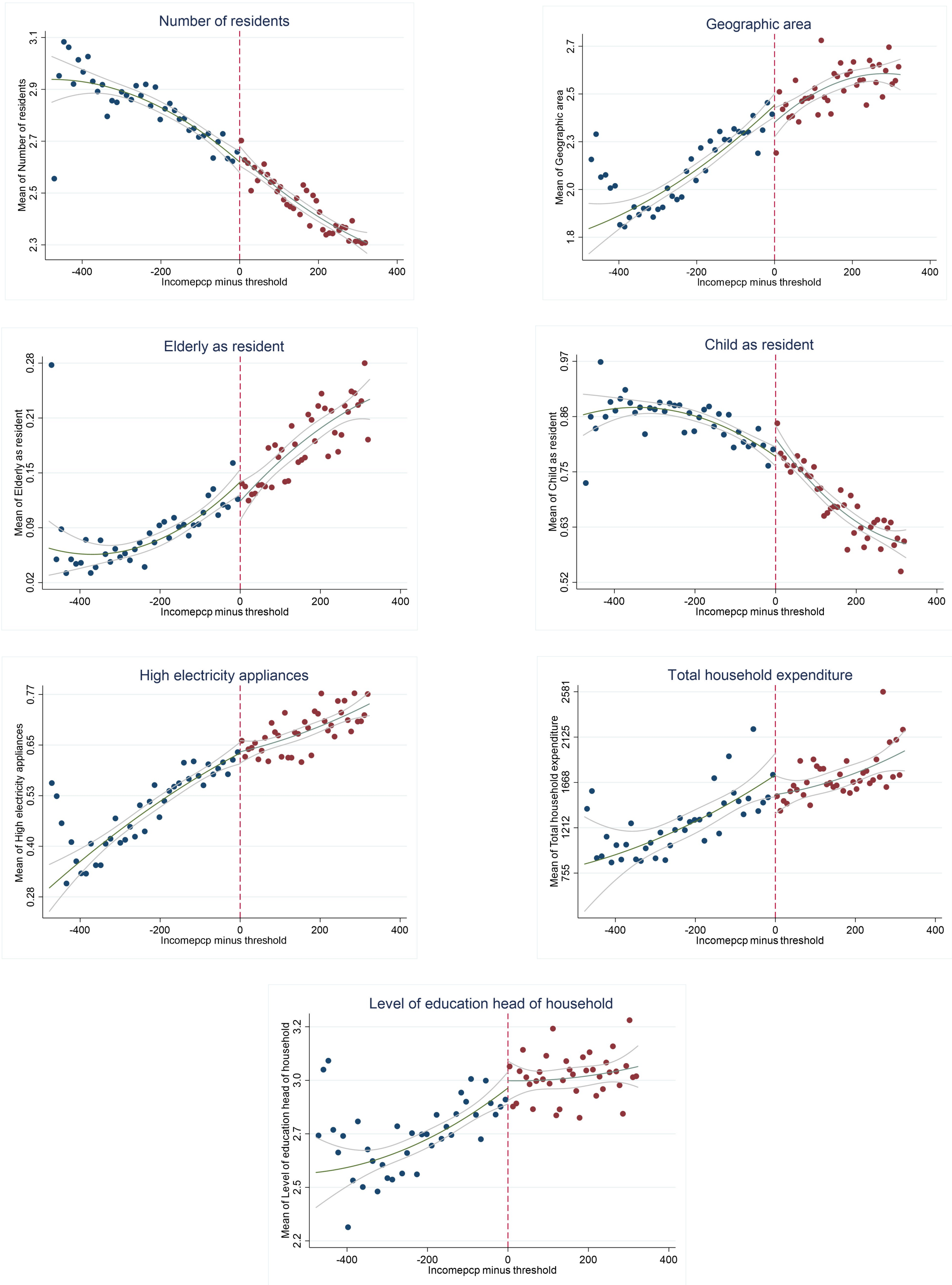
Note: The histogram of the running variable is the difference between the household income per capita and the half minimum wages per capita in 2018 (R$ 477.00). Source: Authors' elaboration based on IBGE, Family Budget Survey 2017-2018.

Figure 11 shows the Cattaneo et al. (2020) test, which checks the idea that if manipulation takes place, then the density of the running variable will be discontinuous at the cutoff. Thus, in this test, the null hypothesis states that there are no discontinuities at the cutoff. The t-statistic of this test is 0.4161, with a p-value of 0.6773. Therefore, we cannot reject the null hypothesis, which adds evidence supporting no manipulation around the cutoff.

For the identification strategy to be valid, it is necessary that the treated and non-treated households who have an income per capita close to the eligibility threshold are like one another. Bernal et al. (2017) argue that it is standard practice to test whether the expectation of covariates is a continuous function in the income per capita around the eligibility threshold. When it is found not to be, one may be concerned that the assumptions underlying the analysis do not hold and one may want to analyze without controlling for covariates.

Figure 3 shows the graphical analysis in which the dependent income variable is replaced by the observed covariates such as number of residents, geographic area, elderly as a resident, child as a resident, and high-electricity appliances of the household. These are the variables that we use as controls in Equations (1) and (2). We also test for discontinuities in total household expenditure and the level of education of the head of the household. The figure suggests that there is no evidence of discontinuities in any of the covariates. In addition, Table 4 presents estimates of the effect of the social tariff program on these variables, conducted at the household level. Again, it does not find any evidence supporting discontinuities. These evidence suggest that the covariates analyzed are not statistically different for treated and control groups.

Figure 3: *Testing for Discontinuities in Household Characteristics*



Notes: The dots denote averages. Their size represents the number of observations. The regression lines with corresponding 95 percent confidence intervals stem from separate RDD regressions to the left and to the right of the threshold using the household-level data.

The identification strategy for Brazil assumes that the only discontinuity occurs at the eligibility threshold (income per capita = 477) as it has specified conditional expectations to be linear in the forcing variable, separately to the left and to the right of this threshold. In this sense, we test for a discontinuity at values of the income per capita other than the actual threshold. Thus, now a sample of households with an income per capita that is between 100 points lower (R$ 377) than the threshold and the threshold is used, and another sample of households for whom the income per capita lies between the eligibility threshold and 100 points (R$ 577) above that. In the Appendix, Table A5 shows no significant effects on electricity expenditure when those hypothetical thresholds are analyzed.

Table 4: *Impact of social tariff on selected covariates: RDD estimates.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	# of Residents	Geographic Area	Elderly as resident	Child as resident	High-electr appliances	Total hh expenditure	Level of educ Head of hh
Income per capita $\leq$ cutoff	0.0467	-0.0317	-0.0414	0.0258	0.0250	72.4677	-0.1082
	(0.0668)	(0.1073)	(0.0435)	(0.0448)	(0.0434)	(284.4519)	(0.1206)
Optimal bandwidth	166.9	130.8	103.2	142.5	104.7	101.3	137.9
Optimal bias bandwidth	245.3	188.7	153.5	216.4	175.2	160.9	221
Observations	10,071	7,979	6,182	8,696	6,449	6,257	8,371

Notes: Standard errors are in brackets. We report the Robust RDD coefficient. Weights are included to take into consideration the survey design.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

As a final set of robustness checks, in Table A6 of the Appendix, this document shows estimates of Equations (1) and (2) changing the original bandwidth, showing that the results are not sensible to bandwidth selection. In addition, Equation (2) is re-estimated using a quadratic local polynomial to construct the point estimator. Results from these exercises are very consistent with baseline results of Table 3.

Overall, the results presented for Brazil show that there is an increase of around R$ 18 on electricity expenditure for households that are beneficiaries of the social tariff program compared with non-eligible households. The robustness checks validate the identifications strategy and the use of the RDD approach.

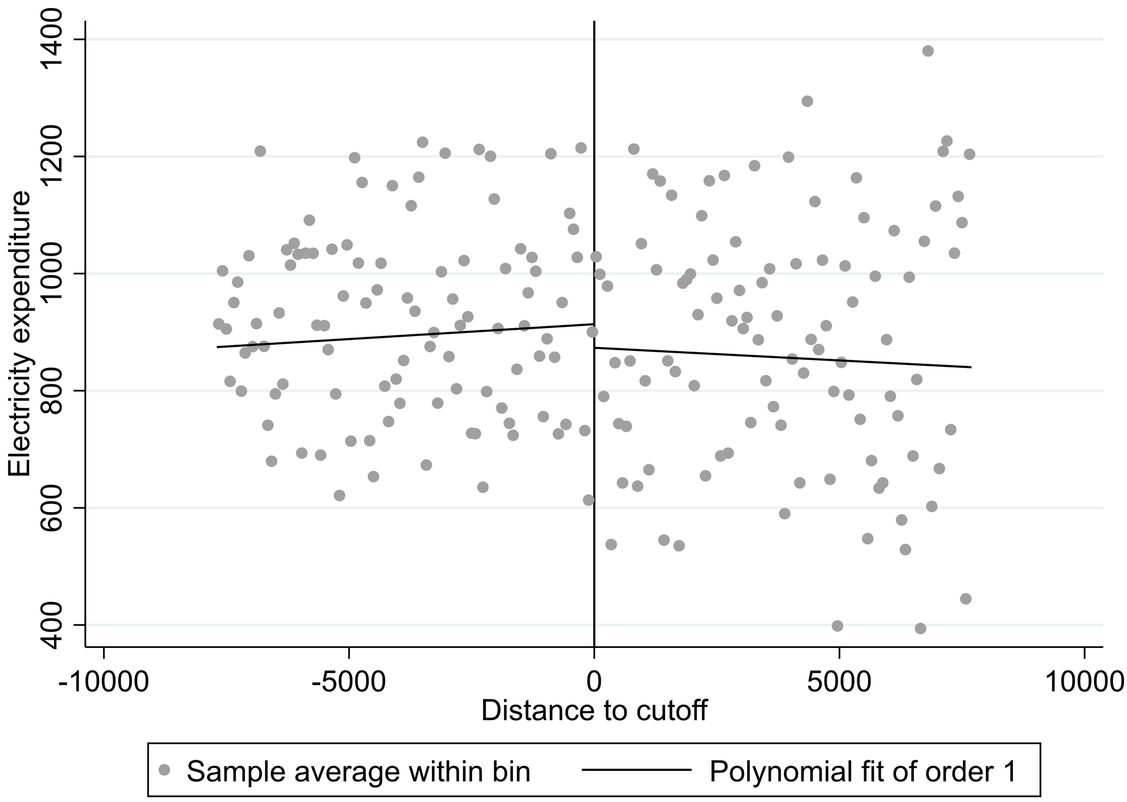
7.2. Argentina

In Argentina, the eligibility criteria for accessing the electricity subsidy are also based on income. Recall from previous sections that the threshold is set to two minimum wages (P$ 19,000 in 2018). In this sense, one can distinguish between eligible and non-eligible households in a way such that households with an income per capita below P$ 19,000 are potential beneficiaries and those above are not. Figure 4 shows average electricity expenditure for households below and above the income threshold. Here, households just below the cutoff seem to spend more on electricity compared to households just above the cutoff.

To formally test whether the average increase in electricity expenditure seen in Figure 4 is statistically significant, Equations (1) and (2) are estimated. Column 1 of Table 5 shows that there is an increase in the average electricity expenditure for households just below versus households just above the eligibility threshold using a bandwidth of 7,700 points, though this difference is not statistically significant. Similar results are found when including covariates (controls). Possible explanations behind these results might be that households below the threshold are owners of less efficient appliances which can make spending increase, or, on the other hand, that households are now using more electricity, which makes expenditure rise. In any case, the change is not statistically significant, which means that there are no differences between households just below and just above the threshold.

To assess the strong assumption of linearity imposed in Equation (1), one can also perform a non-parametric analysis (RDD approach). Thus, columns 3 and 4 show the results of estimating Equation (2) using the methodology proposed by Calonico et al. (2014). Results without including control variables, as well as including them, show very similar results in terms of direction and statistical significance as OLS estimation, supporting that the relation between the subsidy and electricity consumption is positive though not statistically significant.

Figure 4: *Receives the social tariff program*



Notes: Y axis is the average electricity expenditure. 100 bins to both sides of the cutoff using the optimal bandwidth obtained from the rdrobust estimation. The eligibility threshold is P$ 19,000 income per capita of the local currency.

Table 5: *Effect of social tariff on electricity expenditure.*

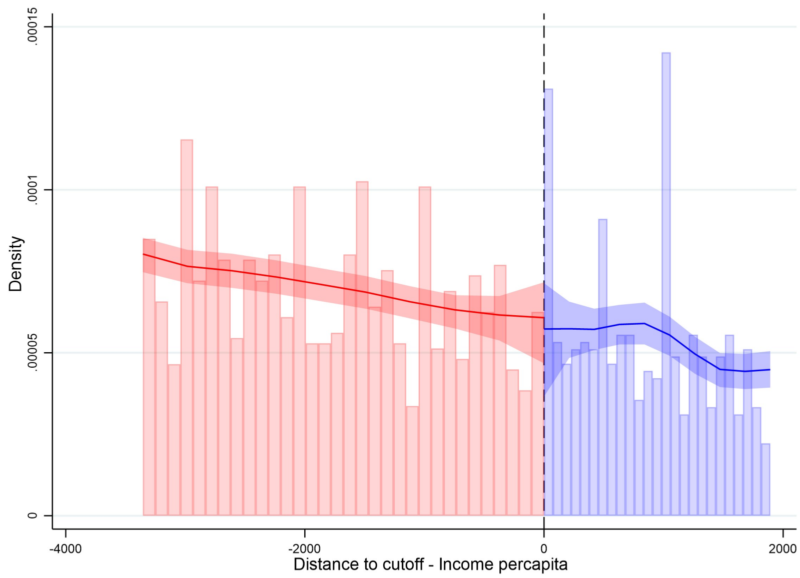
	OLS estimates		Non-parametric estimates (RDD)	
	(1)	(2)	(3)	(4)
Outcome:	Bandwidth 7,700		Optimal bw	
Electricity expenditure	No controls	Controls	No controls	Controls
Z1	-0.0073	-0.0046		
	(0.0122)	(0.0115)		
Eligibility dummy	**16.0337**	**35.8439**		
	(75.7968)	**(73.7734)**		
interaccion_EZ1	0.0105	0.0206		
	(0.0162)	(0.0156)		
Income per capita $\leq$ cutoff			**145.62**	**108.76**
			(106.39)	(98.257)
Optimal bandwidth			6673.469	7697.952

Optimal bias bandwidth			11203.781	11967.492
Controls				
Number of residents	no	yes	no	yes
Geographic Area	no	yes	no	yes
Elderly as resident	no	yes	no	yes
Child as resident	no	yes	no	yes
High-electricity appliances	no	yes	no	yes
Observations	5,950	5,950	4,988	5,950
R-squared	0.0003	0.0695	-	-

Notes: Columns (1) and (2) show results from Equation (1). Robust standard errors in parentheses. Columns (3) and (4) show results from Equation (2). Probability weights are included to consider the survey design across all specifications.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

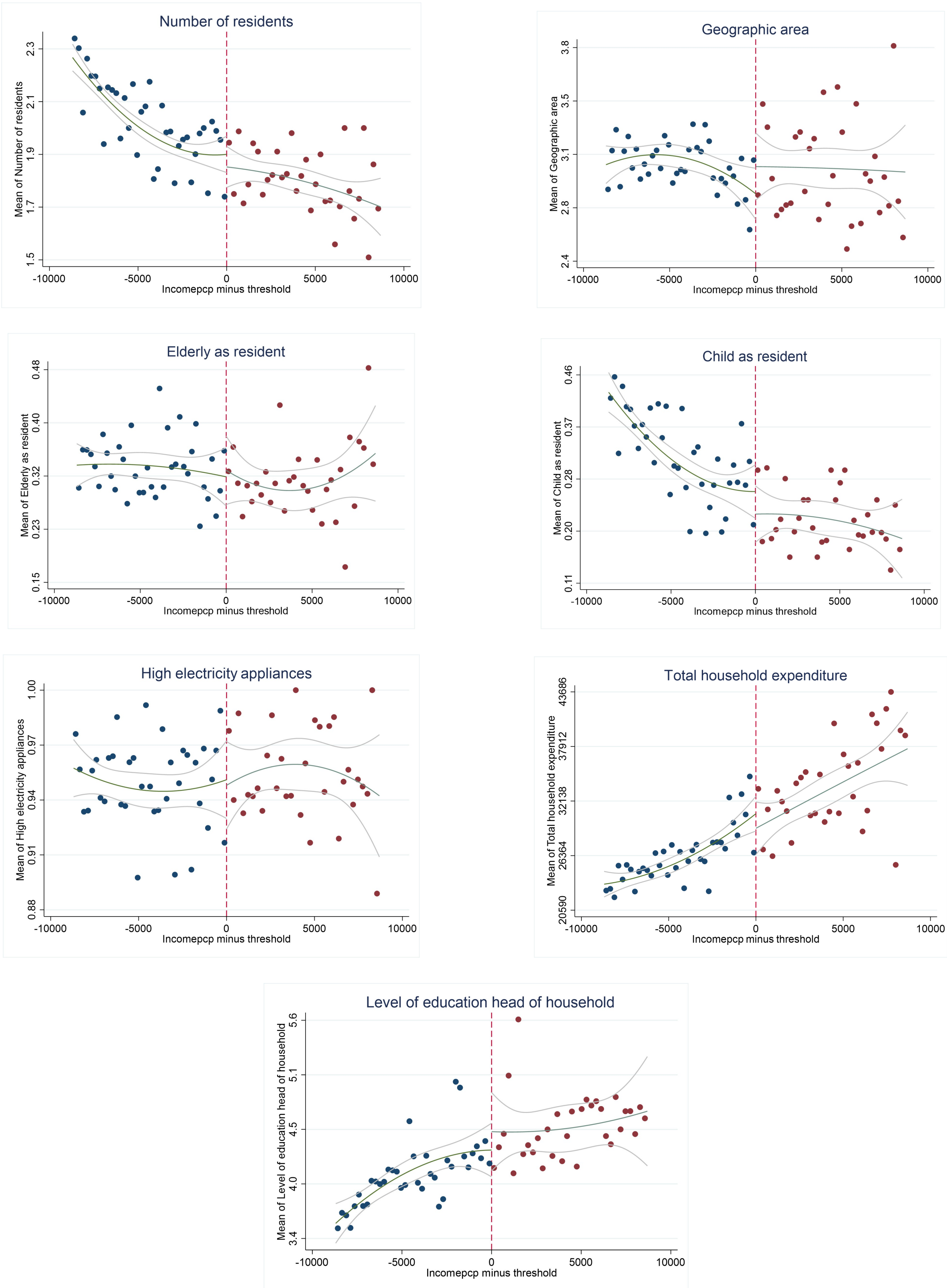
As mentioned in the results for Brazil, there are several potential threats to the identification strategy when an RDD is applied. First, one needs to show that manipulation of the eligibility criteria is very unlikely. In this setting, it means that households would not underreport income just to become eligible. To formally test this, this document implements the Cattaneo et al. (2020) manipulation test. The t-statistic of 0.3949 (p-value: 0.6929) shows that one cannot reject the null hypothesis of no discontinuities at the cutoff, which supports the empirical strategy. In addition, Figure 8 shows the density of income per capita below and above the threshold.

Figure 5: *Manipulation Test for Discontinuity of the Density of the income per capita at the Threshold*



Note: The histogram of the running variable is the difference between the household income per capita and two minimum wages per capita in 2018 (P$ 19,000). Source: Authors' elaboration based on ENGHO, National Survey of Household Expenses 2018.

Figure 6: *Testing for Discontinuities in Household Characteristics*



Notes: The dots denote averages. Their size represents the number of observations. The regression lines with corresponding 95 percent confidence intervals stem from separate RDD regressions to the left and to the right of the threshold using the household-level data.

An additional assumption for the RDD to be valid is that households below and above the threshold are statistically equal in terms of covariates that may affect the outcome (electricity expenditure), otherwise the change seen in the outcome might be due to differences in observable characteristics and not due to the subsidy. Figure 6 shows graphical evidence that most of the selected covariates are continuous around the cutoff. In addition, Table 6 presents the estimate of Equation (2) where the outcomes are the covariates. Again, most of the coefficients of interest are statistically equal to zero, except the ones for the indicator of whether an elderly/child lives in the household, though significant at 10% and of a small size. The coefficient corresponding to column 5 is statistically significant at 5%. This suggests that households just below the cutoff, on average, have a lower probability of having high-electricity consumption appliances at home compared with households just above the cutoff. Though significant, the magnitude of the coefficient is somehow of small size compared to the mean for the treated group, which is 0.911. Thus, on average, the difference is around 4 percent with respect to the mean of the households just below the cutoff. Overall, these estimates add validity to the main results, supporting the idea that there are no other observable factors affecting electricity expenditure.

Table 6: *Impact of social tariff on selected covariates: RDD estimates.*

	(1) # of Residents	(2) Geographic Area	(3) Elderly as resident	(4) Child as resident	(5) High-electr appliances	(6) Total hh expenditure	(7) Level of educ Head of hh
Income per capita $\leq$ cutoff	0.1266	-0.1483	-0.0805*	0.0770*	-0.0437**	2,626.1320	-0.4643
	(0.0775)	(0.1937)	(0.0457)	(0.0453)	(0.0209)	(2,671.6758)	(0.6024)
Optimal bandwidth	4140	6257	7098	5774	8071	5538	7634
Optimal bias bandwidth	8061	10085	12237	10755	12828	9810	14558
Observations	2,984	4,604	5,404	4,174	6,310	3,994	5,881

Notes: Standard errors are in brackets. We report the Robust RDD coefficient. Weights are included to take into consideration the survey design.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Moreover, one may also be concerned about discontinuities at other points different from the official cutoff, which would challenge the results. To show that this does not seem to be the case, the actual cutoff (P$ 19,000 in 2018) is replaced by 9,500 points below and above the original cutoff. Therefore, a placebo eligibility criterion is estimated using Equation (2), for which one should not find any significant effect in the coefficient of interest. In the Appendix, Table A5 shows consistent results from this exercise as none of the coefficients measuring the effect on electricity expenditure are statistically significant, which supports the validity of the main results.

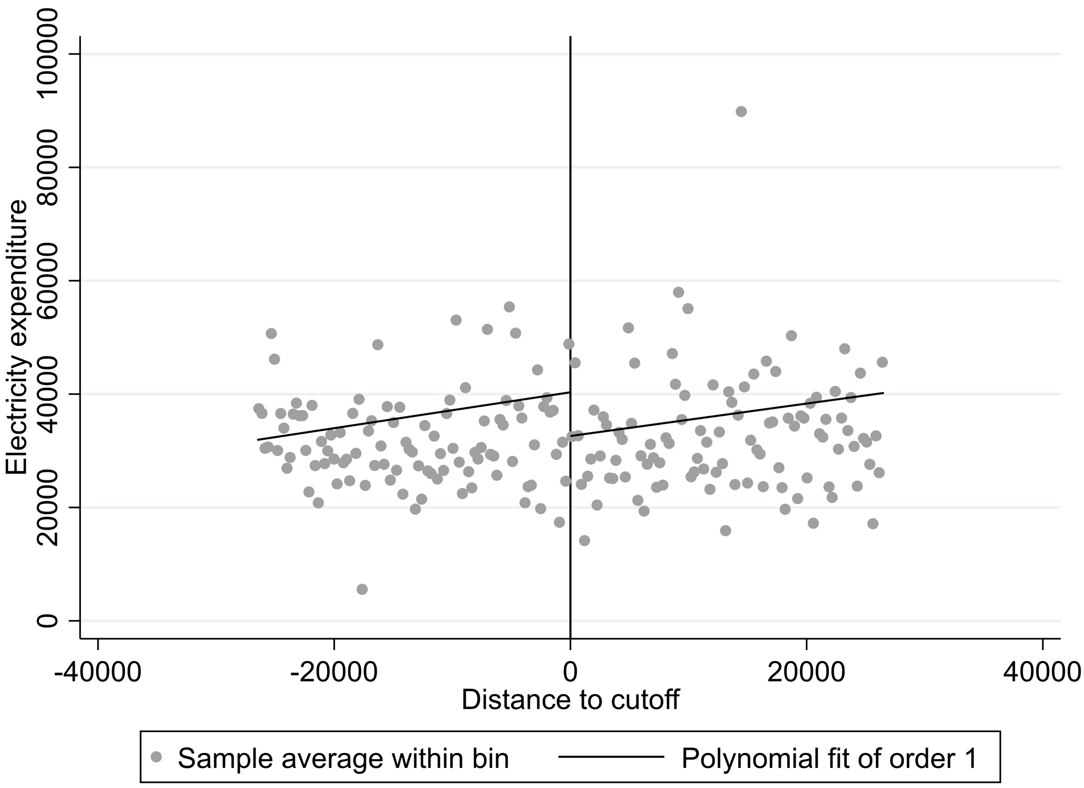
Finally, Table A7 of the Appendix presents estimates of Equations (1) and (2) changing the original bandwidth, showing that the results are like those of Table 6. In addition, Equation (2) is re-estimated using a quadratic local polynomial to construct the point estimator. Results from these exercises are very consistent with baseline results of Table 6. Results for Argentina show zero-effect evidence between electricity subsidy and electricity expenditure (in the local currency) for households just below the eligibility income compared to those just above. However, the estimated coefficient is positive, which suggests an increase in average electricity expenditure. In this line, Giuliano et al. (2020), using data from 2016 to 2019 for the city of Buenos Aires, find that there are some exclusion errors in the low-income deciles and large inclusion errors in the medium- and high-income decile, where the latter means that households that are not considered "vulnerable" are benefiting from the subsidy.

7.3. Colombia

In Colombia, the eligibility criteria for accessing the electricity subsidy are more complex than in other countries like Brazil and Argentina. Recall from previous sections that the selection of households that are beneficiaries of the electricity subsidy relies on a stratification system, which estimates the value of the dwellings and classifies them in a category from 1 to 6, with 1 being the stratum assigned to worse-off units and 6 to the richest (Vélez Tamayo, 2019). Residents of the lower strata are eligible for electricity subsidies. In this sense, households in Stratum 1 benefit from a subsidy of approximately 55% of the base tariff; Stratum 2 has a subsidy of 45%, and Stratum 3 has a subsidy of 15%. The main issue here, for this analysis, is that the score of the index to classify a household in each stratum is unknown. Thus, it is not possible to use the (official) government index to identify the eligible and ineligible households of the social tariff program. However, this document approximates the score of the government index by using the poverty line in the country defined at COP$ 137,350 incomes per capita of the local currency. The motivation to do this is that the poverty line matches with the government index score at the cutoff to be eligible for the social tariff (Vélez Tamayo, 2019).

Although this assumption may be arbitrary, we show that the identification strategy is valid for several reasons. In addition, the objective of the social tariff is to help the poorest, so the cutoff at the poverty line allows us to observe the true effect of the subsidy on households that are poor and benefit from the subsidy versus households that are not poor and do not benefit from it. Figure 7 shows average electricity expenditure for households below and above the income threshold. Here, households just below the cutoff seem to spend more on electricity compared to households just above the cutoff.

Figure 7: *Receives the social tariff program*



Notes: Y axis is the average electricity expenditure. 100 bins to both sides of the cutoff using the optimal bandwidth obtained from the rdrobust estimation. The eligibility threshold is COP$ 137,350 incomes per capita of the local currency.

To formally test whether the average increase in electricity expenditure seen in Figure 7 is statistically significant, we estimate Equations (1) and (2). Columns 1 and 2 of Table 7 present the OLS results with and without covariates. The preferred specification is the one from column 2, which includes the set of covariates. Both specifications show that there is an increase in average electricity expenditure for households just below versus households just above the eligibility income threshold, a result that is statistically significant at the 10% level.

Like in Argentina, one possible explanation behind this increase might be that households below the threshold are owners of less efficient appliances, which can make spending increase. Another explanation could be that households are acquiring new appliances because of an initial lower expenditure on the electricity bill. Similarly, households may be using more electricity (with the same stock of appliances), which makes expenditure rise. At this point, one may wonder whether an increase in electricity expenditure is desirable, which is crucial for the sustainability of subsidies in the medium and long term.

To address the strong assumption of linearity imposed in Equation (1), one can also perform a non-parametric analysis (RDD approach). Thus, Columns 3 and 4 show the results of estimating Equation (2) using the methodology proposed by Calonico et al. (2014). We get similar results in terms of direction and statistical significance as in OLS results, supporting that the relation between the subsidy and electricity consumption is positive and statistically significant.

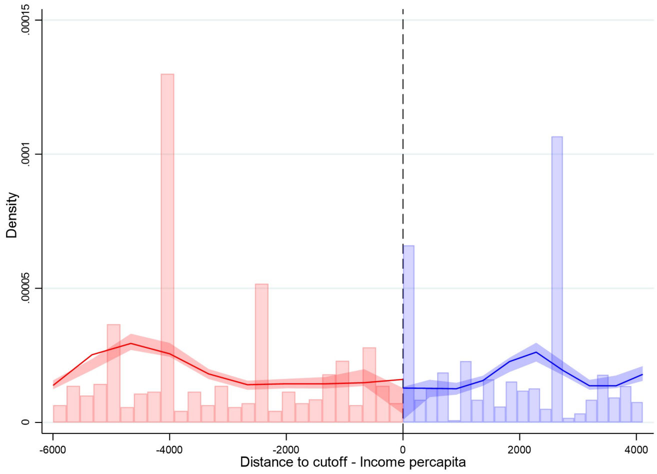
Table 7: *Effect of social tariff on electricity expenditure.*

	OLS estimates		Non-parametric estimates (RDD)	
	(1)	(2)	(3)	(4)
Outcome: Electricity expenditure	Bandwidth 26,500		Optimal bw	
	No controls	Controls	No controls	Controls
Z1	0.2862	0.2448		
	(0.2431)	(0.2264)		
Eligibility dummy	**7,847.1337***	**8,601.0964***		
	(4,552.3625)	**(4,406.8083)**		
interaccion_EZ1	0.0448	0.1382		
	(0.3226)	(0.3016)		
Income per capita $\leq$ cutoff			**11,400****	**12,428****
			(5,462.7)	(5,144.2)
Optimal bandwidth			27,428	26,572
Optimal bias bandwidth			45,601	45,942
Controls				
Number of residents	no	yes	no	yes
Geographic Area	no	yes	no	yes
Elderly as resident	no	yes	no	yes
Child as resident	no	yes	no	yes
High-electricity appliances	no	yes	no	yes
Observations	6,036	6,036	6,246	6,057
R-squared	0.0029	0.0937	-	-

Notes: Columns (1) and (2) show results from Equation (1). Robust standard errors in parentheses.
Columns (3) and (4) show results from Equation (2). Probability weights are included to consider the survey design across all specifications.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

As mentioned in the results for Brazil and Argentina, there are several potential threats to the identification strategy when a RDD is applied. First, one needs to show that manipulation of the eligibility criteria is very unlikely. In this setting, it is very difficult to occur. Like Bernal et al. (2017), we argue that the information on how the government index is computed is, technically speaking, public, however, it is not easy to obtain and compute it. Also, the set of variables included in the index construction are verified by the government officials and therefore difficult to manipulate. Finally, it means that households would not underreport income just to become eligible. To formally test this, this document implements the Cattaneo et al. (2020) manipulation test, in which the null hypothesis is that the density of the running variable is continuous at the cutoff. The t-statistic of -0.2249 (p-value: 0.8220) shows that one cannot reject the null hypothesis, which implies that there is no statistical evidence of manipulation at the cutoff, supporting the empirical strategy. Figure 8 shows the density of income per capita below and above the threshold.

Figure 8: *Manipulation Test for Discontinuity of the Density of the income per-capita at the Threshold*

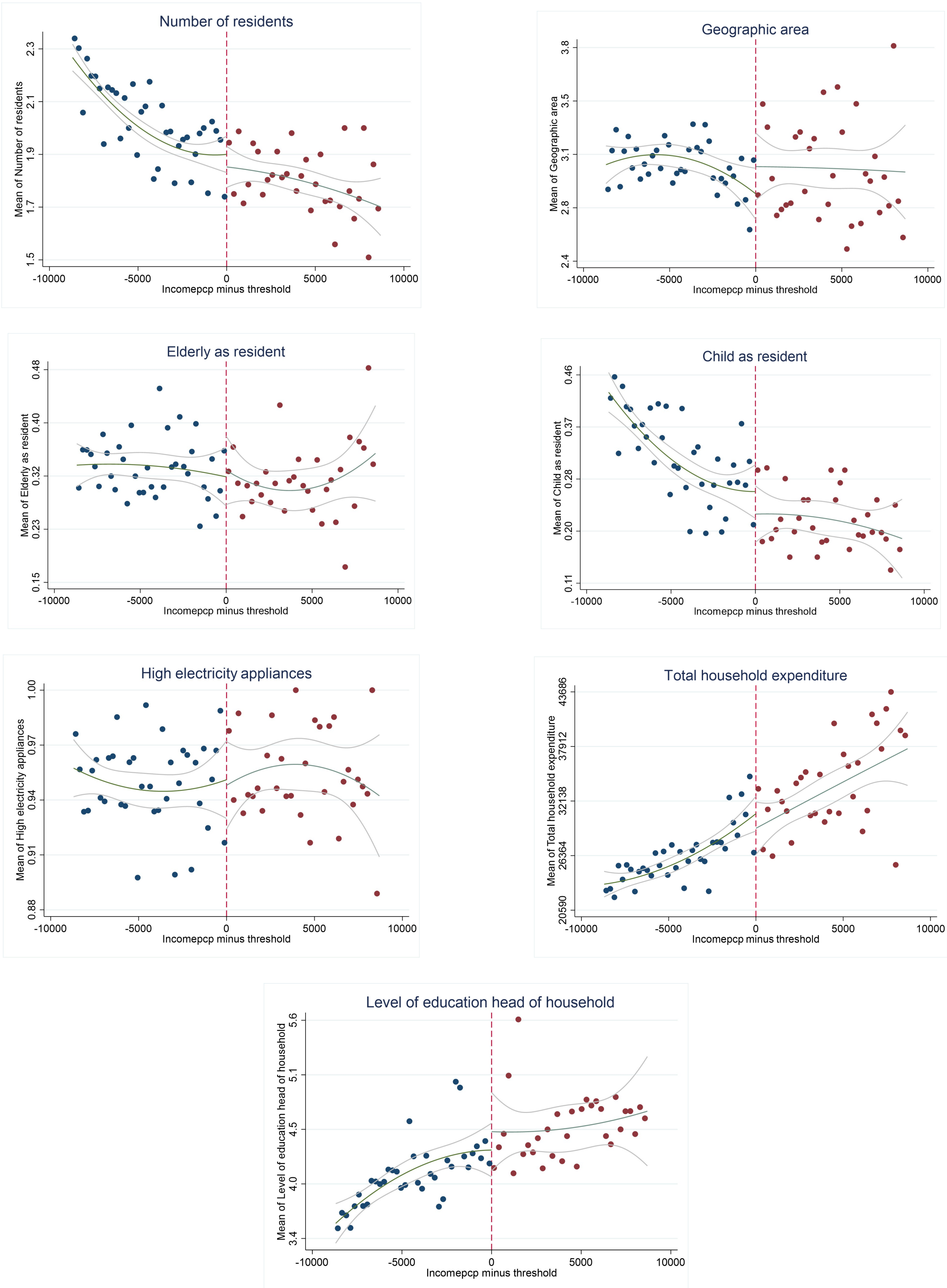


Note: The histogram of the running variable is the difference between the household income per capita and the poverty line for the year 2019 (COP$ 137,350). Source: Authors' elaboration based on ECV, Encuesta de Condiciones de Vida 2019.

An additional assumption for the RDD to be valid is that households below and above the threshold are statistically equal in terms of covariates that may affect the outcome (electricity consumption), otherwise the change seen in the outcome might be due to differences in observable characteristics and not due to the subsidy. Figure 9 shows graphical evidence that the set of selected covariates are continuous around the cutoff. In addition, Table 8 presents estimate of Equation (2) where the outcomes are the covariates. Overall, none of the coefficients of interest are statistically significant, which adds validity to the main results and supports the idea that there are no other observable factors affecting electricity expenditure.

One may also be concerned about discontinuities at other points different from the official threshold, which would challenge the results. To show that this does not seem to be the case, the actual threshold (COP$ 137,350 in 2019) is replaced by 100,000 points below and above the original cutoff. Therefore, a placebo eligibility criterion is estimated using Equation (2), for which one should not find any significant effect in the coefficient of interest. In the Appendix, Table A5 shows consistent results from this exercise as none of the coefficients measuring the effect on electricity expenditure are statistically significant, which supports the validity of the main results.

Figure 9: *Testing for discontinuities in household characteristics*



Notes: The dots denote averages. Their size represents the number of observations. The regression lines with corresponding 95 percent confidence intervals stem from separate RDD regressions to the left and to the right of the threshold using the household-level data.

Table 8: *Impact of social tariff on selected covariates: RDD estimates.*

	(1) # of Residents	(2) Geographic Area	(3) Elderly as resident	(4) Child as resident	(5) High-electr appliances	(6) Level of educ Head of hh
Income per capita $\leq$ cutoff	0.0115	-0.3955	-0.0456	0.0430	-0.0051	-0.0348
	(0.0753)	(0.2455)	(0.0391)	(0.0443)	(0.0422)	(0.1783)
Optimal bandwidth	34,821	32,885	44,201	33,553	45,081	34,484
Optimal bias bandwidth	56,163	52,809	70,389	52,252	71,513	52,479
Observations	4,173	4,009	5,355	4,070	5,423	4,083

Notes: Standard errors are in brackets. We report the Robust RDD coefficient. Weights are included to take into consideration the survey design.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Finally, Table A8 of the Appendix presents estimates of Equations (1) and (2) changing the original bandwidth; the results are similar to those of Table 7. In addition, Equation (2) is re-estimated using a quadratic local polynomial to construct the point estimator. Results from these exercises are very consistent with the baseline results in Table 7.

As mentioned in previous sections, the sample of households used in the analysis for Colombia corresponds to those in strata one, two, and three, and therefore, across eligible groups. With this sample definition, results point to an increase in average electricity expenditure for households just below the 2019 poverty line relative to households just above, which sheds light on the possibility of promoting overconsumption within eligible groups. There are some possible explanations for these findings.

First, it might be the case that low-income households that were not able to afford (and therefore consume) electricity before, now do so because of the subsidy. This aligns with the statement of Eras et al. (2022), who mention that the electricity subsidy in Colombia has achieved high access to electricity. However, one should also keep in mind that access may have also increased because of an increase in supply rather than in demand.

Second, there might be an increase in electricity expenditure because of the subsidy across beneficiaries. For example, Eras et al. (2022) find that from 2010 to 2019, the average electricity consumption per capita increased by 16%, and the increments in strata 1 to 3 (between 8 and 22%) are higher than in strata 4 to 6 (up to 5%), where strata 2 and 3 consume from 3 to 25% more electricity than stratum 1.

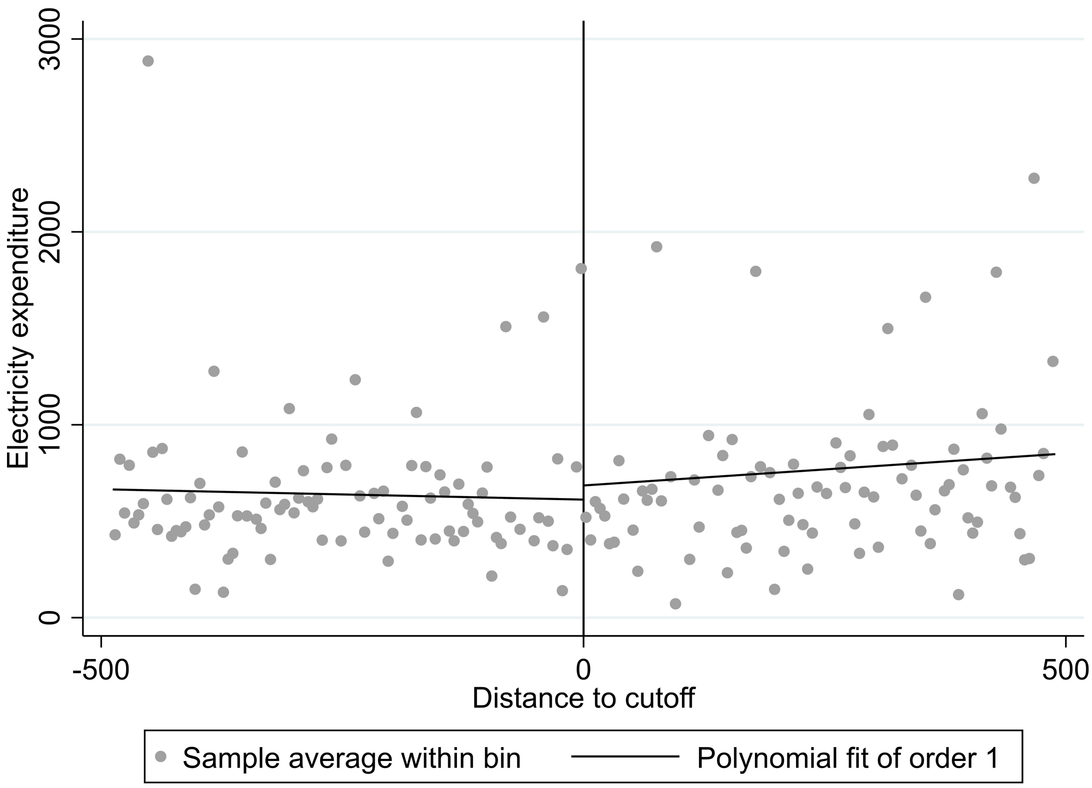
7.4. Peru

To assess the impact of the electricity subsidy on electricity expenditure in Peru, this document employs household income as the running variable. Using the official cutoff defined for the Energy Social Inclusion Fund (FISE, in Spanish), that is, yearly household income up to S/. 19,900 of the local currency, control and treatment units are classified. In this way, households with a monthly income lower than S/. 1,658 ($= \frac{19{,}900}{12}$) are considered as treatment units, whereas households above are classified as control units.

Figure 10 shows average electricity expenditure for households below and above the income threshold. Households just below the cutoff seem to spend less on electricity compared to households just above the cutoff.

To formally test whether the average decrease in electricity expenditure seen in Figure 10 is statistically significant, Equations (1) and (2) are estimated. Columns 1 and 2 of Table 9 show OLS estimates in which the coefficient of interest is negative but not statistically significant. These results suggest that

Figure 10: *Receives the social tariff program*



Notes: Y axis is the average electricity expenditure. 100 bins to both sides of the cutoff using the optimal bandwidth obtained from the rdrobust estimation. The eligibility threshold is S/. 1,658 monthly household income of the local currency.

the subsidy does not seem to be affecting electricity expenditure in households around the cutoff.

In addition, to relax the strong assumption of linearity imposed in Equation (1), one can also perform a non-parametric analysis (RDD approach). Columns 3 and 4 of Table 9 show the results of Equation (2) using the methodology proposed by Calonico et al. (2014). Results are similar in terms of direction and statistical significance to those of the OLS estimation, which supports the validity of the results.

Table 9: *Effect of social tariff on electricity expenditure.*

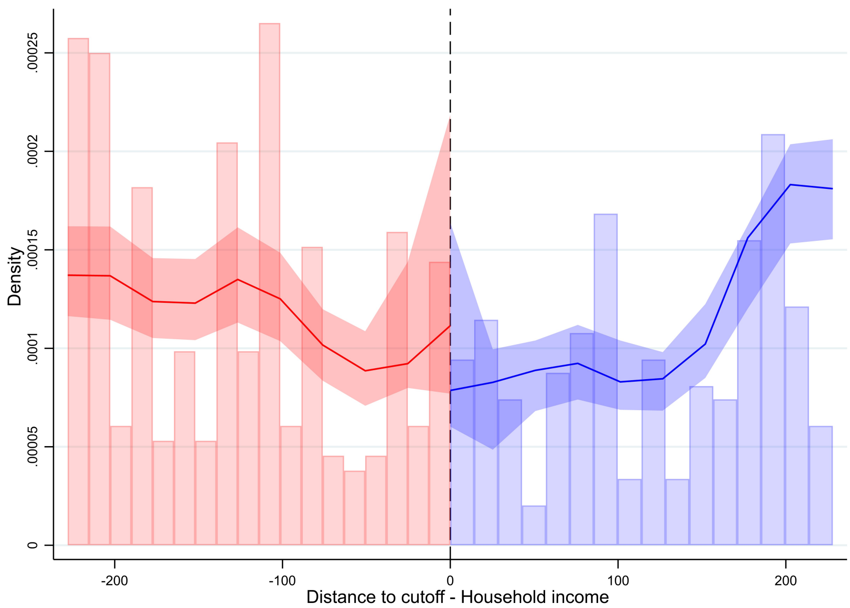
	OLS estimates		Non-parametric estimates (RDD)	
	(1)	(2)	(3)	(4)
Outcome: Electricity expenditure	Bandwidth 500		Optimal bw	
	No controls	Controls	No controls	Controls
Z1	0.2741	0.0596		
	(0.1847)	(0.1571)		
Eligibility dummy	**-85.3668**	**-100.5433**		
	(**76.6197**)	(**69.6292**)		
interaccion_EZ1	-0.3739	-0.1050		
	(0.2422)	(0.2065)		
Income per capita $\leq$ cutoff			**-29.704**	**-44.406**
			(98.924)	(85.527)
Optimal bandwidth			536	492

Optimal bias bandwidth			867	785
Controls				
Number of residents	no	yes	no	yes
Geographic Area	no	yes	no	yes
Elderly as resident	no	yes	no	yes
Child as resident	no	yes	no	yes
High-electricity appliances	no	yes	no	yes
Observations	2,276	2,276	2,391	2,236
R-squared	0.0152	0.1924	-	-

Notes: Columns (1) and (2) show results from Equation (1). Robust standard errors in parentheses.
Columns (3) and (4) show results from Equation (2). Probability weights are included to consider the survey design across all specifications.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

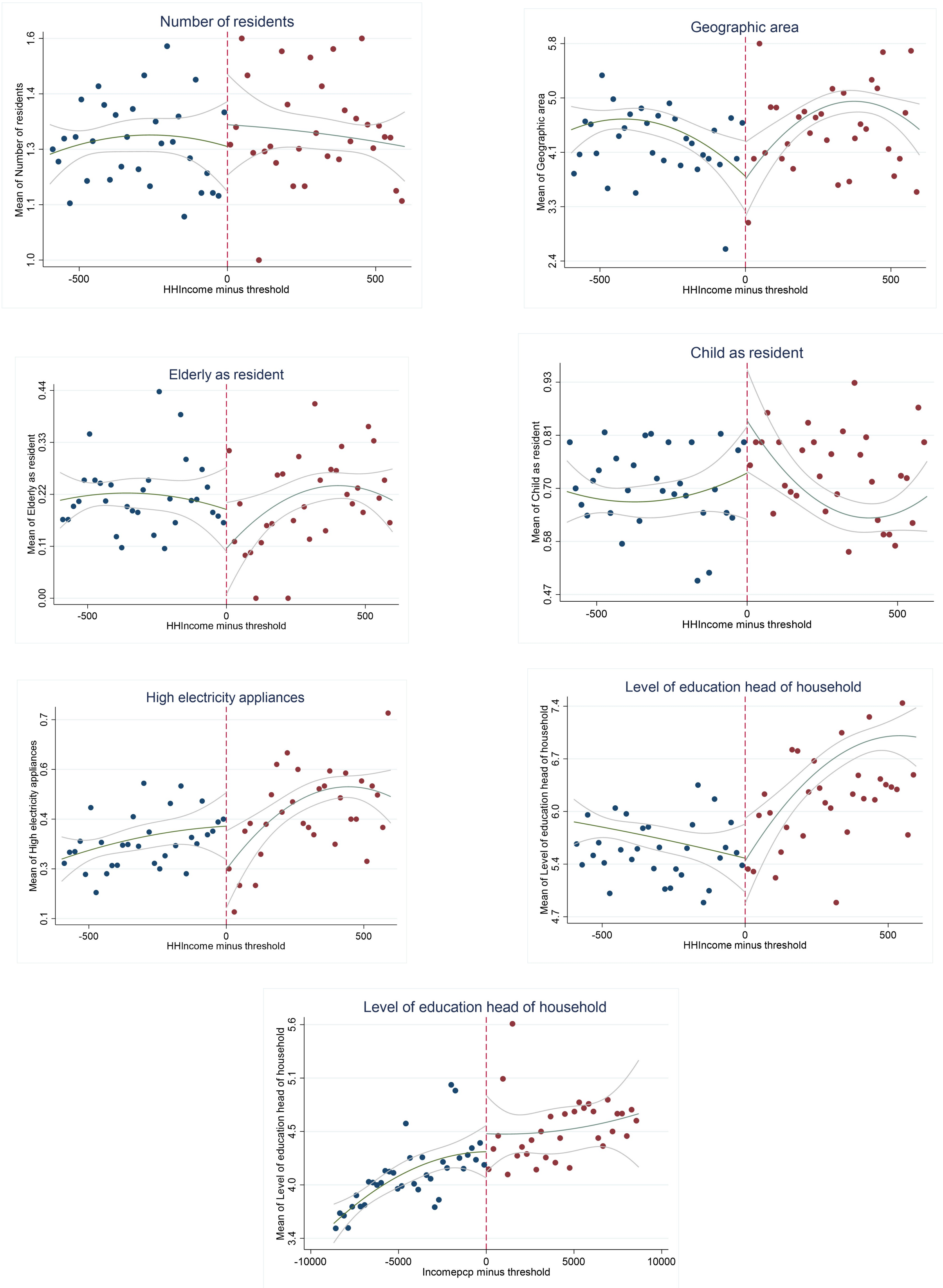
To assess the impact of the electricity subsidy on electricity expenditure in Peru, this document employs the household income as the running variable. Using the official cutoff defined for the Energy Social Inclusion Fund (FISE, in Spanish), that is yearly household income up to S/. 19,900 of the local currency, control and treatment units are classified. In this way, households with a monthly income lower than S/. 1,658 (= 19,900/12) are considered as treatment units whereas households above as control units.

Figure 11: *Manipulation Test for Discontinuity of the Density of household income at the Threshold*



Notes: The histogram of the running variable is the difference between the monthly household income and the FISE cutoff of S/. 1,658. Densities reported within 100 bins. Source: Authors' elaboration based on ENAHO, National Household Survey 2019.

Figure 12: *Testing for discontinuities in household characteristics*



Notes: The dots denote averages. Their size represents the number of observations. The regression lines with corresponding 95 percent confidence intervals stem from separate RDD regressions to the left and to the right of the threshold using the household-level data.

A common concern in RDD is the possibility of manipulation of the running variable which could bias the estimates. In this setting, manipulation would occur if households underreported their income with the objective to become eligible for the subsidy. To rule out that this is not happening in our research design, this document implements the Cattaneo et al. (2020) manipulation test, in which the null hypothesis is that the density of the running variable is continuous at the cutoff. The test shows a t-statistic of -0.8113 with a p-value of 0.4172, therefore one cannot reject the null hypothesis. In this way, the result of this test adds support to no suspicion of manipulation of the running variable. Figure 11 shows the density of household income below and above the eligibility cutoff. Robust confidence intervals are also depicted.

For the RDD to be valid, one should also show evidence supporting that treated and control units are not statistically different in terms of observed characteristics that might influence the outcome. In this setting, other characteristics such as the number of residents, geographic area of the household, presence of a child/elderly, the use of high-electricity consumption appliances, and the level of education of the head of the household should not show any significant jump around the threshold. Figure 12 depicts the mean of these variables across household income, along with 95 percent confidence intervals. For all covariates, confidence intervals overlap. In addition, Table 10 shows the estimates of Equation (2) using the mentioned covariates as outcomes. From here, none of the coefficients of interest are statistically significant different from zero, which adds validity to the assumption that treated and untreated households are similar in terms of some observable characteristics.

One may also be concerned about discontinuities at other points different from the official cutoff, which could cast doubt on the validity of the results. To show that this is not the case, the actual cutoff (S/. 1,658 in 2019) is replaced by 200 points below and above the original cutoff. Thus, a placebo eligibility criterion is estimated using Equation (2), for which one should not find any significant effect in the coefficient of interest. In the Appendix, Table A5 shows that there is not any significant difference in average electricity expenditure between treated and control households around the placebo cutoffs.

Table 10: *Impact of social tariff on selected covariates: RDD estimates.*

	(1) # of Residents	(2) Geographic Area	(3) Elderly as resident	(4) Child as resident	(5) High-electr appliances	(6) Level of educ Head of hh
Income per capita $\leq$ cutoff	-0.1127	-0.3561	0.1258	-0.1673	0.0193	-0.3135
	(0.1135)	(0.5571)	(0.0847)	(0.1151)	(0.0764)	(0.3138)
Optimal bandwidth	630	656.1	476.5	403.5	855.9	612.6
Optimal bias bandwidth	1065	1051	763.4	680.5	1345	1008
Observations	1,342	1,486	1,034	825	1,991	1,330

Notes: Standard errors are in brackets. We report the Robust RDD coefficient. Weights are included to take into consideration the survey design.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Finally, Table A9 of the Appendix presents estimates of Equations (1) and (2) with two alternative bandwidths showing that the results are like those of Table 12. In addition, Equation (2) is re-estimated using a quadratic local polynomial to construct the point estimator. Results from these exercises are very consistent with baseline results of Table 12.

Overall, results for Peru show evidence supporting a zero effect of electricity subsidy on electricity expenditure for households just below the reference income compared to those just above, though the relation is negative. That is, eligible households around the reference income, on average, consume less than non-eligible households, though the difference is not statistically significant. This suggests that the subsidy might not be generating changes in electricity consumption behavior (measured through electricity expenditure).

8. Conclusion and Policy Implications

Electricity subsidies in developing countries have been used to increase the access to electricity services for low-income households. The idea behind this subsidy is to help poor families to afford the cost of electricity, which otherwise would be impossible to consume. Access to electricity is crucial for addressing poverty and improving health, education, and productivity, which matters for human development (Mulugetta et al., 2019; Eras et al., 2022). In this sense, the design and evaluation of subsidy programs become relevant to determine whether beneficiaries are those who need the subsidy (the worse-off). In addition, evaluation also helps to understand whether the subsidy is inducing overconsumption or any other change in consumption behavior.

This document assesses the relationship between electricity subsidy and electricity expenditure for households in selected Latin-American countries. Using household survey data in a regression discontinuity framework, it is found mixed evidence on the effect of electricity subsidies on electricity expenditure. For instance, eligible households in Brazil experience a decrease in average electricity expenditure compared to non-eligible households. Results for Argentina point to a null effect of the electricity subsidy on household electricity expenditure. In contrast, in Colombia, the subsidy would be related to an increase in average electricity expenditure, which suggests that there might be overconsumption in the eligible group. Finally, in Peru, the subsidy does not show evidence of any impact on electricity expenditure. In general, it is shown that the criteria used in this document are adequate to evaluate the social tariff. However, its applicability cannot be considered since in some cases the income criteria is not part of the program in some countries.

While the results are very consistent and robust to several tests, this document has some limitations that mainly come from data availability. First, the literature has raised some concerns about the use of household income as the eligibility variable; instead, total household expenditure is proposed as a more reliable measure of economic welfare; however, this last variable is missing in some countries. Therefore, for consistency reasons, this document employs household income across all the countries. Second, it would be ideal to measure electricity consumption in kWh, but only data on expenditure is available. Despite these drawbacks, the results from this study are robust and have important policy implications.

For example, in the case of Colombia, where an increase in electricity expenditure is found, policy makers need to consider the sustainability of the subsidy and its long-term impact on both fiscal budget and environmental outcomes. It is necessary to revisit the design and targeting of the subsidy as there is room for improvement. Additionally, understanding the differential impacts in various countries of the Latin American region can help tailor more effective subsidy programs that better target the most vulnerable populations.

In this sense, having access to better information on electricity consumption is necessary. Although it is true that the results should not be so different between using consumption or spending, obtaining information on consumption in kWh could refine the results. Likewise, a central discussion in terms of electricity subsidies is whether only consumption in kWh but not income should be considered as a criterion for accessing the social tariff, or the opposite. These results are a first approach to evaluate electricity subsidies in the region, which should be of high relevance in the countries' agenda. Identifying potential inclusion or exclusion errors may help to improve the design of the subsidy, and therefore, promote access to electricity for those who cannot afford it.

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Ethical Approval

The manuscript is under review in this journal and that all or part of its content has not been published or submitted in any other journal in any language. We have not submitted this manuscript to a preprint server before submitting it to *Environmental Science and Pollution Research*. All authors have made substantial contributions and are in concurrence with the content of the manuscript.

Consent to Participate

All authors participated in the study conception and design. All authors read and approved the final manuscript.

Consent to Publish

All authors agreed with the content and all gave explicit consent to submit this paper.

Authors Contributions

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Segundo Camino-Mogro and Karla Arias. The first draft of the manuscript was written by Segundo Camino-Mogro and Karla Arias. The corresponding author agrees to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

- **Conceptualization:** Segundo Camino-Mogro and Karla Arias
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Appendix

Table A1: *Descriptive Statistics for Brazil*

	(1) Full sample	(2) Decile 1	(3) Decile 2	(4) Decile 3	(5) Decile 4	(6) Decile 5	(7) Decile 6	(8) Decile 7	(9) Decile 8	(10) Decile 9	(11) Decile 10
Types of expenditure											
TotalExpenditure	3202.13	1072.23	1363.65	1550.52	1837.6	2325.81	2566.39	3314.24	4136.51	5290.62	12456.15
	(14591.8)	(2354.7)	(4627.9)	(2038.6)	(3377.4)	(7916)	(5834.8)	(8025.9)	(11026.7)	(15387.6)	(45401.4)
TotalEnergyExpenditure	152.24	90.93	106.26	119.89	130.69	141.45	155.56	169.93	187.71	216.23	277.55
	(113)	(71.15)	(72.59)	(79.66)	(80.78)	(88.26)	(95.97)	(100)	(113)	(132.3)	(177)
GasExpenditure	109.69	89.03	101.45	108.04	113.97	114.51	116.97	119.46	116.58	115.48	109.35
	(76.24)	(66.9)	(69.51)	(70.32)	(73.61)	(74.39)	(75.82)	(80.43)	(80.53)	(81.97)	(89.9)
ElectricityExpenditure	111.6	55.76	68.13	79.68	87.8	99.21	113.02	126.83	146.71	175.56	234.96
	(109.2)	(65.68)	(67.16)	(76.31)	(76.34)	(85.18)	(92.97)	(97.03)	(111.3)	(128.6)	(172.8)
OtherfuelsExpenditure	9.44	11.95	9.7	9.77	11.43	10.33	9.48	9.65	7.24	7.03	5.36
	(42.33)	(43.87)	(37.93)	(40.58)	(48.25)	(47.67)	(41.91)	(46.81)	(37.45)	(40.66)	(31.84)
Income											
Income per cápita	1846.27	409.33	754.07	913.97	1097.75	1234.6	1413.97	1713.69	2181.75	3132.64	8119.54
	(3648)	(310.4)	(446.8)	(551.8)	(617)	(690.2)	(773.7)	(936.9)	(1199.8)	(1781.8)	(10967.7)
Gender head of household											
Female	0.42	0.46	0.48	0.46	0.43	0.42	0.39	0.39	0.35	0.37	0.33
	(0.493)	(0.498)	(0.5)	(0.498)	(0.495)	(0.494)	(0.488)	(0.489)	(0.478)	(0.484)	(0.471)
Ethnicity head of household											
Black	0.61	0.77	0.71	0.68	0.66	0.63	0.6	0.55	0.5	0.47	0.34
	(0.488)	(0.423)	(0.453)	(0.468)	(0.475)	(0.483)	(0.489)	(0.497)	(0.5)	(0.499)	(0.475)
Indigenous	0.01	0.01	0.01	0.01	0.01	0.01	0	0	0	0	0
	(0.0733)	(0.0805)	(0.0743)	(0.0846)	(0.0781)	(0.0776)	(0.063)	(0.0674)	(0.069)	(0.068)	(0.0569)
Beneficiary of social assistance											
Yes	0.17	0.43	0.27	0.25	0.17	0.15	0.11	0.09	0.06	0.02	0.01
	(0.378)	(0.495)	(0.443)	(0.43)	(0.378)	(0.356)	(0.315)	(0.279)	(0.233)	(0.154)	(0.119)
Type of Household											
House	0.91	0.96	0.96	0.95	0.95	0.93	0.93	0.91	0.89	0.84	0.71
	(0.285)	(0.203)	(0.204)	(0.22)	(0.222)	(0.248)	(0.254)	(0.286)	(0.317)	(0.37)	(0.454)
Elderly as resident (> 65)											
Yes	0.24	0.1	0.23	0.22	0.32	0.29	0.26	0.26	0.23	0.26	0.27
	(0.428)	(0.304)	(0.421)	(0.417)	(0.466)	(0.456)	(0.441)	(0.44)	(0.422)	(0.437)	(0.445)
Child as resident (< 18)											
Yes	0.5	0.56	0.48	0.51	0.45	0.49	0.51	0.52	0.51	0.49	0.44
	(0.5)	(0.496)	(0.5)	(0.5)	(0.498)	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)	(0.496)

Appliance ownership											
Refrigerator	0.97	0.9	0.95	0.96	0.97	0.98	0.98	0.99	0.99	0.99	0.99
	(0.179)	(0.299)	(0.22)	(0.199)	(0.167)	(0.146)	(0.13)	(0.112)	(0.104)	(0.0905)	(0.0713)
TV	0.96	0.88	0.93	0.95	0.96	0.97	0.97	0.98	0.98	0.99	0.99
	(0.207)	(0.321)	(0.255)	(0.215)	(0.204)	(0.171)	(0.175)	(0.146)	(0.153)	(0.115)	(0.102)
Washing machine	0.58	0.26	0.35	0.46	0.49	0.59	0.66	0.74	0.79	0.85	0.9
	(0.493)	(0.439)	(0.478)	(0.498)	(0.5)	(0.492)	(0.474)	(0.44)	(0.405)	(0.353)	(0.302)
Computer/notebook	0.36	0.09	0.13	0.19	0.22	0.3	0.37	0.47	0.59	0.7	0.83
	(0.479)	(0.29)	(0.332)	(0.396)	(0.413)	(0.456)	(0.484)	(0.499)	(0.492)	(0.46)	(0.378)
stove	0.99	0.96	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	(0.121)	(0.205)	(0.152)	(0.134)	(0.105)	(0.0856)	(0.0859)	(0.0762)	(0.077)	(0.0736)	(0.0713)
air conditioner	0.21	0.05	0.07	0.1	0.13	0.16	0.21	0.26	0.33	0.44	0.61
	(0.409)	(0.228)	(0.259)	(0.3)	(0.331)	(0.369)	(0.407)	(0.437)	(0.471)	(0.496)	(0.489)
fan	0.77	0.65	0.7	0.74	0.76	0.78	0.81	0.83	0.83	0.84	0.82
	(0.422)	(0.476)	(0.457)	(0.438)	(0.43)	(0.416)	(0.394)	(0.375)	(0.375)	(0.371)	(0.382)
Microwave or electric oven	0.63	0.3	0.42	0.51	0.56	0.65	0.71	0.78	0.85	0.9	0.94
	(0.482)	(0.459)	(0.493)	(0.5)	(0.496)	(0.477)	(0.453)	(0.413)	(0.361)	(0.302)	(0.243)
Eligible for subsidy											
Electricity	0.12	0.41	0.22	0.15	0.08	0.06	0.04	0.04	0.03	0.03	0.02
	(0.327)	(0.492)	(0.412)	(0.359)	(0.269)	(0.243)	(0.201)	(0.195)	(0.165)	(0.163)	(0.153)
LPG	0.12	0.41	0.22	0.15	0.08	0.06	0.04	0.04	0.03	0.03	0.02
	(0.327)	(0.492)	(0.412)	(0.359)	(0.269)	(0.243)	(0.201)	(0.195)	(0.165)	(0.163)	(0.153)
Number of residents											
One	13.95	24.76	28.58	19.37	14.4	10.64	7.72	6.9	6.25	6.47	7.12
Two or three	51.47	45.4	46.06	49.33	56.19	55.22	55.33	53.76	52.46	51.12	52.3
Four or five	28.27	23.91	22.18	25.33	23.77	27.69	30.17	31.76	33.82	35.19	35.22
Six or more	6.31	5.93	5.18	5.98	5.63	6.45	6.77	7.59	7.48	7.22	5.36
Number of rooms											
one to three	7.07	18.51	12.13	9.79	6.47	4.95	4.54	3.25	2.09	1.13	0.93
four to six	62.81	71.5	74.29	72.97	71.23	69.34	64.78	61.4	55	43.22	24.94
seven to nine	25.18	9.49	12.92	16.17	20.92	23.7	27.79	31.08	36.42	43.96	46.19
ten or more	4.94	0.49	0.66	1.07	1.39	2.01	2.89	4.27	6.48	11.69	27.94
Education head of household											
Less than elementary school	49.13	66.14	65.78	59.09	61.14	54.45	48.84	42.4	33.11	24.57	11.7
More than elementary school and incomplete high school	13.35	14,39	14.25	14.89	13.46	14.52	14.55	13.42	14.06	11.08	6.27
Complete high school and incomplete undergraduate	25.79	18.08	17.99	23.09	21.98	25.55	28.27	33.02	35.4	33.07	27.25
complete undergraduate	11.73	1.39	1.98	2.93	3.42	5.48	8.34	11.16	17.43	30.38	54.78

N	58039	7103	6685	6526	6200	5958	5787	5482	5027	4961	4310

Mean coefficients; sd in parentheses. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A2: *Descriptive Statistics for Argentina*

	(1) Full sample	(2) Decile 1	(3) Decile 2	(4) Decile 3	(5) Decile 4	(6) Decile 5	(7) Decile 6	(8) Decile 7	(9) Decile 8	(10) Decile 9	(11) Decile 10
Types of expenditure											
TotalExpenditure	22280.3	9557.98	12198.63	14521.63	16400.61	18560.28	21257.55	24250.09	28069.81	34381.64	52889.7
	(19201.6)	(6938.8)	(7307.8)	(8802.3)	(9703)	(10731.1)	(12008.3)	(14433.3)	(15583.8)	(19294.6)	(33101)
TotalEnergyExpenditure	1360.57	877.47	997.62	1091.72	1224.98	1277.89	1414.9	1513.37	1629.27	1734.7	2148.08
	(1271.1)	(860.1)	(787.4)	(892.2)	(1023.7)	(1090)	(1113.9)	(1251.3)	(1397.9)	(1486)	(2061.2)
GasExpenditure	481.29	306.22	342.26	383.72	416.23	419.08	484.93	517.83	580.92	640.58	844.23
	(641.9)	(319.2)	(347)	(385.2)	(481.4)	(467)	(596.9)	(613.8)	(712.7)	(824.1)	(1189)
ElectricityExpenditure	860.63	551.89	636.79	696.55	789.95	840.55	909.07	981.06	1022.55	1070.65	1286.95
	(903.1)	(697.2)	(628.1)	(720.2)	(801.7)	(872.7)	(815.2)	(922.8)	(997.6)	(975.8)	(1311)
Otherenergyexpenditures	18.66	19.37	18.57	11.44	18.8	18.26	20.89	14.48	25.8	23.47	16.91
	(173.6)	(200.2)	(143.9)	(91.96)	(166.1)	(197)	(164.9)	(119.4)	(228.7)	(231.2)	(152.9)
Income											
Income per cápita	12017.78	3994.6	5704.93	7182.97	8429.86	9519.46	10811.2	12884.16	15383.08	18804.52	33394.14
	(15692)	(2528.6)	(3507.9)	(4412.6)	(5351.1)	(6090.7)	(6898.6)	(8076.3)	(9673.8)	(11400.1)	(39984.9)
Gender head of household											
Female	0.44	0.57	0.53	0.47	0.46	0.45	0.4	0.42	0.4	0.36	0.3
	(0.497)	(0.495)	(0.499)	(0.499)	(0.498)	(0.498)	(0.49)	(0.493)	(0.49)	(0.481)	(0.458)
Beneficiary of social assistance											
Yes	0.13	0.15	0.22	0.17	0.15	0.15	0.12	0.09	0.07	0.07	0.03
	(0.333)	(0.357)	(0.412)	(0.379)	(0.359)	(0.353)	(0.322)	(0.293)	(0.262)	(0.254)	(0.17)
Type of Household											
House	0.81	0.82	0.82	0.84	0.82	0.82	0.81	0.8	0.77	0.78	0.77
	(0.396)	(0.388)	(0.382)	(0.369)	(0.386)	(0.385)	(0.395)	(0.402)	(0.418)	(0.414)	(0.423)
Elderly as resident (> 65)											
Yes	0.27	0.25	0.26	0.33	0.28	0.28	0.27	0.29	0.26	0.26	0.22
	(0.444)	(0.432)	(0.436)	(0.472)	(0.449)	(0.447)	(0.442)	(0.453)	(0.44)	(0.438)	(0.416)
Child as resident (< 18)											
Yes	0.48	0.37	0.48	0.44	0.5	0.51	0.52	0.49	0.51	0.53	0.5
	(0.5)	(0.483)	(0.5)	(0.497)	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)	(0.499)	(0.5)
Appliance ownership											
Refrigerator	0.98	0.93	0.95	0.97	0.97	0.99	0.99	0.99	1	0.99	1
	(0.153)	(0.256)	(0.221)	(0.165)	(0.17)	(0.114)	(0.0804)	(0.105)	(0.0692)	(0.0717)	(0.0456)

TV	0.96	0.9	0.94	0.96	0.97	0.96	0.97	0.98	0.98	0.99	0.99
	(0.194)	(0.305)	(0.242)	(0.191)	(0.183)	(0.19)	(0.158)	(0.154)	(0.136)	(0.115)	(0.111)
Washing machine	0.86	0.69	0.78	0.83	0.86	0.87	0.9	0.92	0.92	0.93	0.94
	(0.349)	(0.464)	(0.413)	(0.374)	(0.351)	(0.332)	(0.295)	(0.269)	(0.277)	(0.258)	(0.231)
Computer/notebook	0.28	0.12	0.13	0.18	0.22	0.25	0.3	0.33	0.38	0.43	0.51
	(0.447)	(0.329)	(0.339)	(0.387)	(0.412)	(0.431)	(0.459)	(0.472)	(0.486)	(0.496)	(0.5)
stove	0.86	0.87	0.88	0.87	0.86	0.87	0.85	0.85	0.85	0.86	0.84
	(0.347)	(0.337)	(0.33)	(0.341)	(0.346)	(0.339)	(0.357)	(0.353)	(0.36)	(0.349)	(0.368)
air conditioner	0.46	0.29	0.34	0.4	0.41	0.46	0.5	0.53	0.56	0.6	0.63
	(0.499)	(0.453)	(0.475)	(0.49)	(0.491)	(0.499)	(0.5)	(0.499)	(0.497)	(0.49)	(0.484)
fan	0.63	0.65	0.65	0.69	0.66	0.63	0.65	0.64	0.6	0.57	0.48
	(0.484)	(0.478)	(0.477)	(0.461)	(0.475)	(0.483)	(0.479)	(0.481)	(0.489)	(0.495)	(0.5)
Microwave or electric oven	0.51	0.27	0.34	0.38	0.44	0.47	0.55	0.58	0.65	0.71	0.83
	(0.5)	(0.446)	(0.474)	(0.486)	(0.497)	(0.499)	(0.498)	(0.493)	(0.476)	(0.454)	(0.376)
Eligible for subsidy											
Electricity	0.24	0.45	0.36	0.32	0.25	0.23	0.19	0.19	0.15	0.13	0.1
	(0.43)	(0.497)	(0.48)	(0.466)	(0.434)	(0.418)	(0.392)	(0.391)	(0.355)	(0.335)	(0.297)
LPG	0.4	0.35	0.36	0.33	0.36	0.42	0.39	0.42	0.42	0.46	0.51
	(0.489)	(0.476)	(0.479)	(0.47)	(0.48)	(0.493)	(0.488)	(0.493)	(0.494)	(0.499)	(0.5)
Number of residents											
One	18.3	45.38	27.9	20.84	18.56	14.67	12.13	10.76	9.95	7.95	6.15
Two or three	43.31	35.05	40.82	45.77	44.94	44.55	44.35	45.23	44.22	44.22	45.67
Four or five	28.72	15.65	23.58	25.01	25.89	29.07	32.45	31.64	33.96	36.95	38.43
Six or more	9.67	3.92	7.71	8.38	10.61	11.7	11.06	12.37	11.87	10.89	9.75
Number of rooms											
one to three	67.88	85.38	81.35	76.52	75.78	70.66	64.67	62.49	59.36	53.66	37.8
four to six	31.11	14.45	18.25	23.12	24.09	28.67	34.68	36.48	39.73	44.58	57.51
seven to nine	0.93	0.12	0.4	0.31	0.13	0.59	0.6	0.98	0.8	1.55	4.54
ten or more	0.07	0.04	0	0.04	0	0.09	0.05	0.05	0.11	0.21	0.16
Education head of household											
Less than elementary school	11.07	19.61	16.51	15.36	13.93	10.04	9.34	7.68	6.84	4.8	2.09
More than elementary school and incomplete high school	37.99	46.86	47.76	45.9	42.92	41.36	37.75	36.97	29.14	27.3	15.95
Complete high school and incomplete undergraduate	32.87	27.42	29.67	30.58	32.18	33.53	34.77	34.23	39.2	36.74	32.95
complete undergraduate	18.07	6.11	6.06	8.16	10.97	15.08	18.13	21.12	24.81	31.17	49.01
N	21547	2422	2477	2279	2225	2222	2151	2045	1870	1938	1918

Mean coefficients; sd in parentheses. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A3: *Descriptive Statistics for Colombia*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Types of expenditure										
GasExpenditure	26979.51	20460.81	24394.78	27376.59	28886.93	29557.08	30011.95	29844.17	30787.4	35555.02
	(28065)	(27471)	(27061.8)	(27673.4)	(27309.2)	(27596.6)	(27755.5)	(28657.9)	(28053.9)	(31966.2)
ElectricityExpenditure	46909.47	28111.88	30747.22	37889.6	41736.67	46412.06	53292.26	63229.65	81470.8	1.20E+05
	(63431.4)	(44463.7)	(39489.7)	(47883.2)	(51494.7)	(53163.7)	(60224.8)	(66276.2)	(82375.1)	(124586.6)
Income										
Incomepercapita	7.10E+05	1.00E+05	2.90E+05	4.30E+05	5.10E+05	6.00E+05	7.50E+05	9.80E+05	1.50E+06	4.20E+06
	(1509620.5)	(85618.8)	(187952.5)	(266981.7)	(323271)	(378595.9)	(481368.6)	(640178.3)	(1028282.7)	(4916751.9)
Gender head of household										
Female	0.36	0.43	0.38	0.33	0.32	0.35	0.34	0.36	0.35	0.31
	(0.481)	(0.495)	(0.486)	(0.469)	(0.468)	(0.477)	(0.474)	(0.481)	(0.478)	(0.461)
Ethnicity head of household										
Black	0.1	0.14	0.11	0.09	0.08	0.09	0.09	0.08	0.08	0.06
	(0.297)	(0.342)	(0.31)	(0.286)	(0.276)	(0.283)	(0.28)	(0.274)	(0.271)	(0.244)
Indigenous	0.09	0.22	0.1	0.07	0.07	0.07	0.06	0.05	0.05	0.03
	(0.292)	(0.416)	(0.3)	(0.259)	(0.248)	(0.249)	(0.233)	(0.223)	(0.213)	(0.179)
Beneficiary of social assistance										
Yes	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0
	(0.11)	(0.097)	(0.121)	(0.12)	(0.116)	(0.118)	(0.119)	(0.0989)	(0.0908)	(0.0466)
Type of Household										
House	0.76	0.78	0.83	0.79	0.79	0.76	0.72	0.69	0.65	0.58
	(0.426)	(0.414)	(0.377)	(0.41)	(0.405)	(0.429)	(0.451)	(0.46)	(0.477)	(0.493)
Elderly as resident (> 65)										
Yes	0.23	0.31	0.23	0.19	0.18	0.19	0.2	0.22	0.25	0.29
	(0.421)	(0.46)	(0.422)	(0.389)	(0.388)	(0.395)	(0.401)	(0.414)	(0.432)	(0.452)
Child as resident (< 18)										
Yes	0.54	0.42	0.53	0.59	0.6	0.61	0.59	0.58	0.53	0.45
	(0.498)	(0.494)	(0.499)	(0.491)	(0.49)	(0.487)	(0.492)	(0.493)	(0.499)	(0.498)
Appliance ownership										
Refrigerator	0.72	0.45	0.6	0.73	0.78	0.84	0.87	0.92	0.95	0.96
	(0.448)	(0.498)	(0.489)	(0.446)	(0.415)	(0.37)	(0.331)	(0.272)	(0.226)	(0.202)
TV	0.82	0.58	0.75	0.84	0.87	0.91	0.92	0.95	0.96	0.97
	(0.388)	(0.493)	(0.434)	(0.369)	(0.334)	(0.292)	(0.269)	(0.227)	(0.193)	(0.179)
Washing machine	0.44	0.18	0.26	0.38	0.45	0.54	0.62	0.72	0.82	0.89
	(0.497)	(0.388)	(0.441)	(0.485)	(0.497)	(0.498)	(0.484)	(0.447)	(0.384)	(0.316)
Computer/notebook	0.21	0.06	0.06	0.11	0.14	0.21	0.31	0.43	0.62	0.78
	(0.409)	(0.244)	(0.24)	(0.307)	(0.351)	(0.409)	(0.463)	(0.496)	(0.487)	(0.412)
Stove	0.78	0.57	0.69	0.79	0.84	0.87	0.9	0.93	0.95	0.96

	(0.412)	(0.495)	(0.461)	(0.409)	(0.371)	(0.332)	(0.304)	(0.258)	(0.21)	(0.2)
Air conditioner	0.04	0.01	0.01	0.01	0.02	0.03	0.04	0.06	0.13	0.23
	(0.191)	(0.103)	(0.0854)	(0.113)	(0.135)	(0.16)	(0.196)	(0.244)	(0.333)	(0.419)
Fan	0.41	0.3	0.36	0.4	0.42	0.45	0.46	0.49	0.55	0.55
	(0.492)	(0.458)	(0.48)	(0.49)	(0.494)	(0.498)	(0.499)	(0.5)	(0.497)	(0.498)
Microwave or electric oven	0.14	0.04	0.04	0.06	0.09	0.13	0.17	0.25	0.39	0.61
	(0.343)	(0.189)	(0.195)	(0.245)	(0.283)	(0.338)	(0.379)	(0.435)	(0.488)	(0.487)
Eligible for subsidy										
Yes	0.82	0.69	0.81	0.86	0.87	0.89	0.89	0.9	0.83	0.6
	(0.388)	(0.462)	(0.389)	(0.351)	(0.335)	(0.313)	(0.314)	(0.305)	(0.374)	(0.489)
Number of residents										
One	18.5	34.6	22.22	17.24	15.08	11.39	10.55	9.96	11.11	10.05
Two or three	45.74	44.88	48.1	46.16	44.33	44.38	43.52	41.85	44.16	51.39
Four or five	27.84	16.21	23.85	29.48	32.35	33.6	34.36	35.88	32.34	31.11
Six or more	7.91	4.31	5.82	7.12	8.25	10.63	11.57	12.3	12.39	7.45
Number of rooms										
One to three	66.94	83.32	78.29	73.48	68.78	63.67	57.23	48.76	39.04	28.99
Four to six	32.43	16.55	21.47	26.2	30.85	36.46	42.03	50.27	59.34	67.51
Seven to nine	0.62	0.13	0.24	0.31	0.37	0.47	0.73	0.94	1.57	3.42
Ten or more	0.01	0	0	0.01	0	0	0.01	0.03	0.05	0.08
N	93993	14010	25039	10285	9992	8792	7771	6786	6255	5063

Mean coefficients; sd in parentheses. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A4: *Descriptive Statistics for Peru*

	(1) Full sample	(2) Decile 1	(3) Decile 2	(4) Decile 3	(5) Decile 4	(6) Decile 5	(7) Decile 6	(8) Decile 7	(9) Decile 8	(10) Decile 9	(11) Decile 10
Types of expenditure											
TotalEnergyExpenditure	796.95	596.23	683.52	801.99	850.91	973.55	1036.6	1136.72	1224.22	1324	1674.72
	(657.1)	(550.1)	(475.3)	(528.4)	(562.8)	(609.1)	(612.9)	(653.3)	(649.3)	(707.7)	(849.5)
GasExpenditure	308.93	255.06	301.92	337.61	350.32	371.89	389.96	408.64	425.91	425.29	434.73
	(214.5)	(208)	(196.9)	(197.1)	(203.1)	(187.9)	(193.7)	(184.7)	(193.2)	(193.7)	(218.4)
ElectricityExpenditure	459.23	311.05	346.66	430.04	471.06	576.75	616.63	701.44	772.54	878.05	1225.95
	(538.5)	(426.3)	(355.5)	(420.9)	(460.8)	(536.2)	(532.6)	(591.4)	(580.2)	(641.9)	(776.6)
OtherfuelsExpenditure	28.79	30.12	34.95	34.33	29.52	24.91	30.01	26.65	25.78	20.67	14.05
	(114.1)	(124.4)	(107.7)	(112.5)	(92.95)	(89.04)	(105.3)	(111.1)	(93.56)	(94.9)	(70.97)
Income											
Income per capita	701.35	10.2	214.87	367.67	638.35	888.76	1184.29	1586.59	2031.01	2880.04	5390.76
	(1453.6)	(33.18)	(78.73)	(130.1)	(233.9)	(311.8)	(400.2)	(521.5)	(694.1)	(1024.5)	(3052)
Gender head of household											

Female	0.32	0.32	0.31	0.31	0.34	0.36	0.32	0.33	0.31	0.28	0.25
	(0.465)	(0.466)	(0.461)	(0.464)	(0.474)	(0.479)	(0.466)	(0.47)	(0.462)	(0.447)	(0.433)
Ethnicity head of household											
Black	0.06	0.06	0.1	0.07	0.06	0.07	0.08	0.04	0.05	0.04	0.04
	(0.24)	(0.241)	(0.298)	(0.262)	(0.243)	(0.248)	(0.264)	(0.2)	(0.21)	(0.19)	(0.203)
Indigenous	0.34	0.4	0.28	0.29	0.32	0.28	0.29	0.27	0.25	0.24	0.18
	(0.474)	(0.489)	(0.449)	(0.454)	(0.466)	(0.448)	(0.454)	(0.445)	(0.433)	(0.429)	(0.385)
Beneficiary of social assistance											
Yes	0	0	0	0	0	0	0	0	0	0	0
	(0.0447)	(0.0487)	(0)	(0.036)	(0.0629)	(0.0267)	(0.0388)	(0.0378)	(0.045)	(0.0372)	(0.0272)
Type of Household											
House	0.94	0.95	0.96	0.96	0.94	0.92	0.92	0.91	0.92	0.89	0.8
	(0.245)	(0.217)	(0.194)	(0.205)	(0.229)	(0.278)	(0.276)	(0.279)	(0.276)	(0.309)	(0.396)
Elderly as resident (>65)											
Yes	0.32	0.4	0.19	0.18	0.22	0.24	0.22	0.23	0.24	0.25	0.25
	(0.468)	(0.49)	(0.392)	(0.382)	(0.416)	(0.429)	(0.412)	(0.42)	(0.429)	(0.433)	(0.43)
Child as resident (<18)											
Yes	0.57	0.49	0.71	0.73	0.7	0.66	0.65	0.66	0.66	0.64	0.62
	(0.495)	(0.5)	(0.453)	(0.442)	(0.458)	(0.472)	(0.479)	(0.475)	(0.475)	(0.48)	(0.486)
Appliance ownership											
Refrigerator	0.45	0.33	0.38	0.47	0.47	0.58	0.64	0.68	0.73	0.78	0.89
	(0.498)	(0.47)	(0.486)	(0.499)	(0.499)	(0.494)	(0.481)	(0.466)	(0.446)	(0.412)	(0.314)
TV	0.76	0.65	0.79	0.82	0.86	0.91	0.92	0.95	0.96	0.97	0.98
	(0.457)	(0.498)	(0.436)	(0.394)	(0.396)	(0.348)	(0.334)	(0.305)	(0.305)	(0.257)	(0.213)
Washing machine	0.23	0.14	0.11	0.15	0.2	0.28	0.34	0.41	0.46	0.57	0.75
	(0.421)	(0.345)	(0.311)	(0.362)	(0.404)	(0.447)	(0.473)	(0.491)	(0.498)	(0.495)	(0.434)
Computer/notebook	0.27	0.14	0.14	0.19	0.27	0.35	0.42	0.51	0.66	0.75	0.87
	(0.446)	(0.351)	(0.344)	(0.391)	(0.444)	(0.478)	(0.493)	(0.5)	(0.475)	(0.435)	(0.337)
Stove	0.84	0.78	0.85	0.89	0.89	0.93	0.93	0.96	0.95	0.95	0.93
	(0.367)	(0.414)	(0.358)	(0.317)	(0.314)	(0.263)	(0.263)	(0.196)	(0.224)	(0.209)	(0.249)
Microwave or electric oven	0.14	0.08	0.05	0.08	0.12	0.16	0.2	0.25	0.28	0.36	0.54
	(0.347)	(0.272)	(0.225)	(0.278)	(0.327)	(0.366)	(0.398)	(0.43)	(0.447)	(0.482)	(0.499)
Receives LPG subsidy											
Yes	0.12	0.17	0.11	0.11	0.09	0.06	0.05	0.03	0.02	0.01	0
	(0.329)	(0.378)	(0.315)	(0.308)	(0.29)	(0.238)	(0.216)	(0.178)	(0.15)	(0.117)	(0.0543)
Number of residents											
One	74.78	77.69	72.16	71.85	71.11	69.74	70.69	72.1	70.88	70.59	68.59
Two or three	21.53	19.52	23.33	24.06	24.35	25.64	24.42	23.46	24.39	24.36	23.87
Four or five	3.31	2.5	3.92	3.7	3.86	4.47	4.67	4.22	3.92	4.5	6.5
Six or more	0.39	0.29	0.59	0.39	0.68	0.14	0.23	0.21	0.81	0.55	1.03
Number of rooms											

one to three	12.78	15.41	16.08	12.91	12.26	11.22	9.34	8.15	6.15	3.94	1.63
four to six	82.44	81.31	80.65	83.2	82.97	83.38	85.83	84.55	86.42	86.37	82.71
seven to nine	3.33	2.41	1.7	1.95	2.44	3.2	3.24	3.24	4.93	7.2	13.08
ten or more	1.45	0.87	1.57	1.95	2.33	2.2	1.58	1.58	2.5	2.49	2.59
Education head of household											
Less than elementary school	26.02	35.36	27.52	21.47	19.3	14.2	12.81	9.51	7.09	4.5	2.07
More than elementary school and incomplete high school	28.43	32.1	36.47	36.71	30.7	25.85	24.64	19.24	15.54	13.36	5.1
Complete high school and incomplete undergraduate	36.34	28.19	34.71	39.82	44.72	52.7	53.65	53.86	53.78	53.49	40.5
complete undergraduate	9.21	4.36	1.31	2.01	5.28	7.24	8.89	17.38	23.58	28.65	52.33
N	30945	17700	1530	1542	1762	1408	1327	1398	1480	1445	1353

Mean coefficients; sd in parentheses. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A5: *Results for Subsamples of Eligibles and Ineligibles using income per capita with Hypothetical Threshold of the Actual Threshold by country*

	Brazil		Argentina		Colombia		Peru	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
	Income per capita < threshold		Income per capita < threshold		Income per capita < threshold		Income per capita < threshold	
	(-100 points)	(+100 points)	(-9500 points)	(+9500 points)	(-100000 points)	(+100000 points)	(-200 points)	(+200 points)
Effect of the electricity subsidy on:								
Electricity consumption	-0.1389	5.2361	10.843	-48.329	462.39	-12,282	-27.445	15.321
	(9.2956)	(6.5764)	(121.58)	(78.814)	(2966.5)	(8611.2)	(69.347)	(105.81)
Optimal bandwidth	64.813	89.442	11779	2852	89,501	31,764	727	382
Optimal bias bandwidth	100.082	140.803	18385	4471	1.42e+05	40,179	1119	654
Observations	3,885	5,306	3,812	6,506	21,702	3,066	3,323	1,656

Notes: Robust Standard errors are in brackets. We report the Robust RDD coefficient. Weights are included to take into consideration the survey design. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A6: Robustness checks Brazil: Bandwidths and order of polynomials

	(1) Bandwidth 200 No controls	(2) Bandwidth 200 Controls	(3) Bandwidth 400 No controls	(4) Bandwidth 400 Controls	(5) Optimal bw, 2nd order pol
Outcome: Electricity expenditure					
Panel A: OLS estimates					
Z1	0.0088	-0.0031	0.0143	0.0056	
	(0.0279)	(0.0251)	(0.0133)	(0.0123)	
Eligibility dummy	-7.1683*	-8.4173**	-4.8297	-6.4982**	
	(4.2570)	(3.9050)	(3.2526)	(3.0030)	
Interaccion_EZ1	0.0426	0.0369	0.0583***	0.0401***	
	(0.0357)	(0.0329)	(0.0166)	(0.0153)	
R-squared	0.0074	0.1085	0.0201	0.1205	-
Panel B: Non-parametric RDD estimates					
Income per capita ¡= cutoff	-16.981**	-17.706**	-11.455**	-11.639**	-15.057
	(6.9831)	(6.9729)	(5.3259)	(5.1343)	(9.9693)
Optimal bandwidth	200	200	400	400	108.710
Optimal bias bandwidth	200	200	400	400	190.810
Controls	no	yes	no	yes	yes
Number of residents	no	yes	no	yes	yes
Geographic Area	no	yes	no	yes	yes
Elderly as resident	no	yes	no	yes	yes
Child as resident	no	yes	no	yes	yes
High-electricity appliances	no	yes	no	yes	yes
Observations	11,992	11,992	19,126	19,126	6,686

Notes: Panel A shows results from Equation (1) using different bandwidths. Robust standard errors in parentheses. Panel B shows results from Equation (2) using the same bandwidths as in Panel A. Column (5) shows results from Equation (2) using a second order polynomial to construct the point estimator. All regressions include probability weights to take into consideration the survey design. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A7: Robustness checks Argentina: Bandwidths and order of polynomial

	(1) Bandwidth 8,700 No controls	(2) Bandwidth 8,700 Controls	(3) Bandwidth 9,700 No controls	(4) Bandwidth 9,700 Controls	(5) Optimal bw, 2nd order pol
Outcome: Electricity expenditure					
Panel A: OLS estimates					
Z1	-0.0046	-0.0006	0.0012	0.0053	
	(0.0103)	(0.0098)	(0.0106)	(0.0100)	
Eligibility dummy	19.5445	53.3933	46.1177	76.7139	
	(71.0234)	(69.0185)	(68.5370)	(66.2389)	
Interaccion_EZ1	0.0071	0.0190	0.0045	0.0154	
	(0.0133)	(0.0130)	(0.0126)	(0.0120)	
R-squared	0.0002	0.0689	0.0003	0.0695	-
Panel B: Non-parametric RDD estimates					
Income per capita ¡= cutoff	218.75*	192.72*	181.24	159.16	263.47**
	(117.43)	(115.7)	(110.92)	(109.21)	(133.13)
Optimal bandwidth	8,700	8,700	9,700	9,700	7697.952
Optimal bias bandwidth	8,700	8,700	9,700	9,700	11967.492
Controls	no	yes	no	yes	yes
Number of residents	no	yes	no	yes	yes
Geographic Area	no	yes	no	yes	yes
Elderly as resident	no	yes	no	yes	yes
Child as resident	no	yes	no	yes	yes
High-electricity appliances	no	yes	no	yes	yes
Observations	6,961	6,961	8,110	8,110	5,950

Notes: Panel A shows results from Equation (1) using different bandwidths. Robust standard errors in parentheses. Panel B shows results from Equation (2) using the same bandwidths as in Panel A. Column (5) shows results from Equation (2) using a second order polynomial to construct the point estimator. All regressions include probability weights to take into consideration the survey design. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A8: Robustness checks Colombia: Bandwidths and order of polynomial

	(1) Bandwidth 36,500 No controls	(2) Bandwidth 36,500 Controls	(3) Bandwidth 46,500 No controls	(4) Bandwidth 46,500 Controls	(5) Optimal bw, 2nd order pol
Outcome: Electricity expenditure					
Panel A: OLS estimates					
Z1	0.2302*	0.2139*	0.2133**	0.1947*	
	(0.1175)	(0.1091)	(0.0967)	(0.0900)	
Eligibility dummy	6,446.6042*	6,943.9524*	6,686.8117*	6,685.6629*	
	(3,698.8316)	(3,558.6248)	(3,531.5319)	(3,447.4665)	
Interaccion_EZ1	0.0034	0.0371	0.1033	0.1106	
	(0.1825)	(0.1759)	(0.1513)	(0.142)	
R-squared	0.0035	0.0811	0.0035	0.0781	-
Panel B: Non-parametric RDD estimates					
Income per capita ¡= cutoff	11,728**	12,195**	10,668**	11,803**	10,883**
	(5,298.3)	(5,234.9)	(5,278.8)	(4,992.3)	(5,537.3)
Optimal bandwidth	36,500	36,500	46,500	46,500	26,572
Optimal bias bandwidth	36,500	36,500	46,500	46,500	45,942
Controls	no	yes	no	yes	yes
Number of residents	no	yes	no	yes	yes
Geographic Area	no	yes	no	yes	yes
Elderly as resident	no	yes	no	yes	yes
Child as resident	no	yes	no	yes	yes
High-electricity appliances	no	yes	no	yes	yes
Observations	8,123	8,123	10,584	10,584	6,057

Notes: Panel A shows results from Equation (1) using different bandwidths. Robust standard errors in parentheses. Panel B shows results from Equation (2) using the same bandwidths as in Panel A. Column (5) shows results from Equation (2) using a second order polynomial to construct the point estimator. All regressions include probability weights to take into consideration the survey design. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A9: Robustness checks Peru: Bandwidths and order of polynomial

	(1) Bandwidth 600 No controls	(2) Bandwidth 600 Controls	(3) Bandwidth 700 No controls	(4) Bandwidth 700 Controls	(5) Optimal bw, 2nd order pol
Outcome: Electricity expenditure					
Panel A: OLS estimates					
Z1	0.0615	-0.0192	0.1915	0.1081	
	(0.1320)	(0.1145)	(0.1230)	(0.1119)	
Eligibility dummy	-114.1570*	-120.9547**	-81.7224*	-75.5042	
	(67.5733)	(62.0444)	(64.0836)	(59.4739)	
Interaccion_EZ1	-0.0570*	-0.0208	-0.2035	-0.1237	
	(0.1764)	(0.1571)	(0.1486)	(0.1366)	
R-squared	0.0144	0.1944	0.0188	0.0197	-
Panel B: Non-parametric RDD estimates					
Income per capita ¡= cutoff	16.737	-26.392*	-8.0558	-51.319	-26.487
	(121.31)	(96.293)	(109.26)	(88.527)	(115.56)
Optimal bandwidth	600	600	700	700	492
Optimal bias bandwidth	600	600	700	700	785
Controls	no	yes	no	yes	yes
Number of residents	no	yes	no	yes	yes
Geographic Area	no	yes	no	yes	yes
Elderly as resident	no	yes	no	yes	yes
Child as resident	no	yes	no	yes	yes
High-electricity appliances	no	yes	no	yes	yes
Observations	2,840	2,840	3,561	3,561	2,236

Notes: Panel A shows results from Equation (1) using different bandwidths. Robust standard errors in parentheses. Panel B shows results from Equation (2) using the same bandwidths as in Panel A. Column (5) shows results from Equation (2) using a second order polynomial to construct the point estimator. All regressions include probability weights to take into consideration the survey design. $***p < 0.01, **p < 0.05, *p < 0.1$.