Prepaid electricity and in-home displays: an alternative for the most vulnerable households in Colombia

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Prepaid electricity and in-home displays: an alternative for the most vulnerable households in Colombia.*

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Abstract

Exploiting the implementation of a Prepaid Electricity Program in the region of Antioquia (Colombia), we estimate the impact that switching to a prepaid program has on users' energy consumption behavior. In particular, we focus the analysis on those that are more vulnerable from a socio-economic perspective. The results show that the new metering scheme and the information provision is associated with a decline in electricity consumption.This scheme allow users to improve their consumption paths, while their access to public electricity services is guaranteed, minimizing disconnection risks and the associated costs.

1 Introduction

There is a growing awareness of the need to expand infrastructure and improve technology to provide energy, mainly in developing countries, given the increasingly rapid evolution of electricity consumption. Since the beginning of the 21st century, global electricity consumption has experienced faster growth, evidenced by an average annual increase of 3.4% (Liu, 2016). Moreover, electricity use increases the most in the buildings sector, particularly residential, as personal incomes rise and urban migration continues in emerging economies, according to the International Energy Outlook 2019. Regarding the Colombian context, the country doubled its electricity consumption of 1998 in 20 years, reaching 69 TWh.[1]

Modern energy services are a prerequisite for the economic and social development of populations in developing countries (Tenezakis and Tritah, 2019), in particular for low-income households with difficulties in guaranteeing their connection to electric power services (Jack and Smith, 2015). Therefore, there is a need to develop and implement new approaches,

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[1]One TeraWatt hour is equivalent to 1 billion Watts hour or one thousand million kilowatts hour.

regulations and technologies that allow a better understanding of households' energy consumption and encourage its responsible and efficient use. Its also necessary guaranteeing the access to those segments of the population that do not have a stable income flow and that have some uncertainty when paying their obligations.

Smart metering and diverse consumption-feedback systems figure as applicable technologies to encourage energy efficiency in the residential sector (Podgornik et al., 2016). In addition, numerous studies have documented the influence of electricity prepayment schemes on household energy consumption behavior and its possible use as a solution to the non-payment problem among low-income households (Tewaria and Shah, 2003; OSullivan et al., 2013; Jack and Smith, 2015; Azila-Gbettor et al., 2015; Qiu et al., 2016; Nugrohoa et al., 2017). These types of programs have been used in more than seventeen countries (see Telles-Esteves et al. (2016) for an overview of electricity prepayment experiences). In general, they consist of four components: the electricity meter, vending points, a communication unit, and a central server (Telles-Esteves et al., 2016). In most cases, an in-home display accompanies the prepaid meter (Qiu et al., 2016), providing direct feedback as real-time information on energy consumption and credit availability.

In this paper, we aim to show some evidences to better understand the effects of prepaid electricity programs and advanced metering infrastructure (AMI) on electricity consumption, billing and payment in developing countries. These types of prepaid electricity schemes have been implemented throughout the world during several years and there is some evidence about its effects on energy consumption. However, the effect of AMI and the consumption feedback it's unclear. (Darby, 2010) rises that demand reductions will not necessarily flow naturally from an improvement in information, but there is a potential to use AMI for demand reduction. A crucial issue since prepaid metering is becoming the standard technology for residential connections for both on-grid and off-grid electricity(Jack and Smith, 2020).

We analyze the potential impacts of a prepaid electricity program implemented in some regions of Colombia since 2005 by *Empresas Públicas de Medellín* (EPM henceforth, by its acronym in Spanish), one of the most recognized utilities in South America. In particular, we estimate the causal impact of being part of the program on electricity consumption and the potential improvements in energy use derived from the implementation of this scheme. This research gives evidence on possible efficiency gains for households that are part of the prepaid scheme, with special emphasis on vulnerable population. Our results suggest that low-income users, due to the information provided in the new scheme, reduce their over-consumption by tracking their energy use.

EPM's prepaid electricity program is a social innovation initiative in the Colombian and Latin American context that seeks that the provision of electric service adapts to the dynamics of household income. In order to do so, this program offers the provision of electricity service under a prepaid scheme to those families who, due to adverse conditions, are liquidity constrained and have limited electricity access. Moreover, using double-part meters with in-home displays providing real-time feedback, the consumer receives much more information. This additional information could help the consumer to manage better his electricity usage (Jack and Smith, 2015; Podgornik et al., 2016) and generate energy savings that benefit him (Faruqui et al., 2009), while the utility reduces the overdue portfolio.

This initiative is particularly relevant in the Colombian context. At the end of 90's Colombia developed a re-distributive transfer schemes that seek, in a certain way, to guarantee access to essential public services by vulnerable households. The Colombian utilities pricing system uses a cross-subsidy scheme between households. It rests on an identification instrument based on the dwelling quality to classify household by strata. It allows to identify families with higher capacity payment that economically might assist the most vulnerable population, aiming to achieve universal coverage (Bonilla et al., 2014). However, this stratification instrument nowadays shows rigidities in responding to an increasingly dynamic and complex national environment, and is subject to severe problems of miss classification. Moreover, the tariff subsidies offered to low-income households do not guarantee that they can pay their obligations with the utilities every month. Thus, the EPM's prepaid electricity program could sort out some of the problems of the cross-subsidy scheme and achieve more progress in the scope of universal coverage.

In order to assess for the causal impact of the program on household consumption, we implement a Difference-In-Differences (DiD) setting with staggered adoption, exploiting the differences when users decided to switch and adopt the prepaid scheme. We use a database from the prepaid electricity program provided by EPM, which has information on monthly electricity consumption, billing, and certain variables that allow us to characterize the dwellings in geographical and socio-economic terms between January 1, 2010, and December 31, 2017. Our proposed methodology sort out some challenges on the identification of reliable causal estimates: the application to the program is entirely voluntary, and households wishing to have prepaid electricity must file a format requesting the service, which generates a self-selection problem. Furthermore, due to data constraints, we do not have access to either those who were eligible for the program but never accessed it, neither those non-eligible households. In other words, we do won't have any untreated units in our research design. Given this setting, our methodology exploits the variation in the adoption timing to create treatment and control groups at different points in time, based on the changing in the treatment status. We tackle the self-selection issue exploiting the fact that users must meet some socio-economic requirements and have had some suspension problems to be eligible for the program. The latter makes it plausible to assume that the early-adopters and the later-adopters are not very different in their characteristics. Finally, given the dynamics of program implementation, it is plausible to assume that the prepaid scheme adoption occurred randomly within different municipalities at different points of time.

Our semi-parametric approach allows us to retrieve a decrease around 12% in monthly electricity consumption. Compared to the average user consumption in the sample before the switch, this drop represents a reduction of 17,99 kWh/month. This result is maintained over time even twelve months following the switch. Dwellings of strata 1, 2 and 3, that exhibited over-consumption before the switch, reduced their consumption outside the subsidized range but dwellings of those strata that did not exhibit over-consumption before the switch, increased their electricity consumption.

This paper relates to a large body of literature that studies household energy consumption behaviour (e.g., Faruqui et al. (2009); Lopes et al. (2012); OSullivan et al. (2013); Gans et al. (2013); Jack and Smith (2015); Azila-Gbettor et al. (2015); Nugrohoa et al. (2017)), energy affordability (e.g. Casas et al. (2005); Santa-María et al. (2009); Bonilla et al. (2014); Piai-Paiva et al. (2019)), energy efficiency and its policy implications (e.g. Tewaria and Shah (2003); Telles-Esteves et al. (2016)). Our findings echoes the conclusions in the small body of literature on the impact of prepaid metering on energy use in devloped (e.g.Qiu et al. (2016),) and developing countries. For example, Jack and Smith (2020), found that costumers in Cape-Town reduce their electricity use when switched from postpaid monthly billing to prepaid electricity metering by 1.9 kWh per costumer per day, or around 14%. Nevertheless, our results offer the first evidence on the effects of this type of programs and technologies on vulnerable low-income populations.

The rest of the paper is organized as follows. In the next Section, we provide some context about Colombian electricity market, the program and its implementation, and the main source of data. In Section 3, we present the identification strategy and the methodology. Section 4 presents the paper's key results on the impact of being part of the program on electricity consumption, while Section 5 test one alternative explanation for the results. Section 6 concludes. Additional results and robustness checks are provided in a separate appendix.

2 Context and Data

2.1 Colombian context

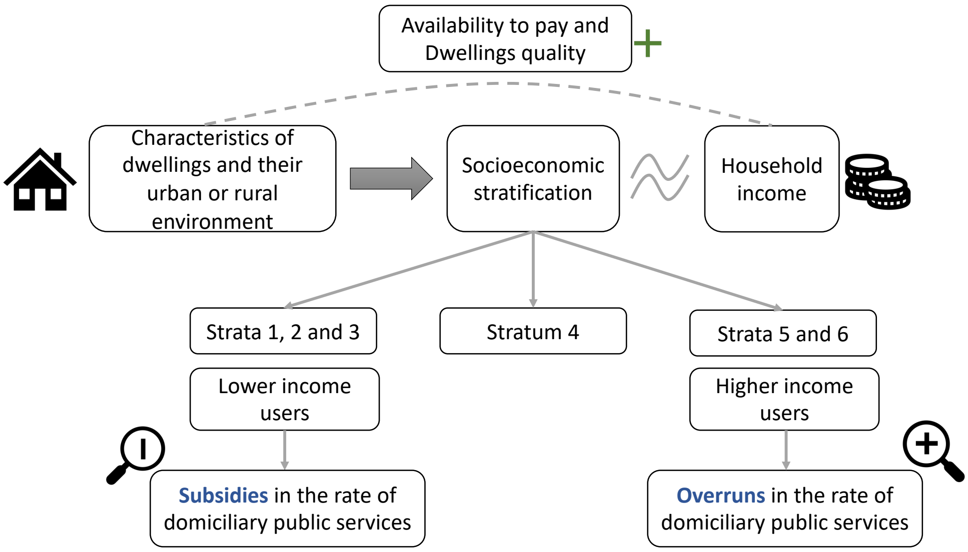
Since 1990 Colombia has increased its annual electricity demand in more than 42TWh. Moreover, the projections of Colombia's electricity demand to 2032 could be 58.5% higher than the current one, and, between 2023 and 2032, it would be necessary to incorporate new electricity generation projects, since the supply would be insufficient in 2026 Consejo Privado de Competitividad (2019).

The Colombian generation market is highly dependent on hydrology, therefore, it is characterized by being very volatile to weather conditions. Since, Colombia's annual average temperature is projected to increase between 1.3°C and 1.8°C until 2050, water resources would be significantly affected, reducing runoff from water stored in dams. Therefore, electricity production would be reduced due to the impact of climate change in the Magdalena River Basin, which provides 70% of Colombia's hydro-power USAID (2017).

From the point of view of residential electricity demand, it has passive participation because end users know the prices and quantities demanded on utility bills one month after their consumption, which implies that they don't have enough information and incentives to adjust their prevailing energy consumption patterns. Therefore, the implementation of prepaid electricity consumption schemes, supported by advanced metering infrastructure, can be established as an alternative demand response mechanism that can help mitigate the effects of the imbalance between an increasing demand and an insufficient supply.

Customers of domiciliary public services in Colombia are charged with fees that depend on a socio-economic classification based on a measure of observable dwelling quality, called stratification. The stratification system groups residential properties up to six groups or strata that reflect the condition of belonging to a specific social segment Bonilla et al. (2014). These strata groups allow entities of different levels of governance to characterize households socio-economic conditions and target social public policy. One relevant example of the application of this system is the cross-subsidy scheme applied to the utility pricing system established in 1994. Figure 1 displays a simplified scheme of this tariff system based on strata. Over time, stratification has been assimilated in the collective imagery as an element of social, economic, cultural and ideological differentiation of the population.

Figure 1: Stratification and Domiciliary Public Services



Notes: Own elaboration.

Between these stratification groups, dwellings of strata 1, 2, or 3 are those that live in residences with below-par infrastructure conditions and can be considered as vulnerable population. Households living in dwellings belonging to these strata receive subsidies in their utility bills, in order to guarantee the provision of the public services. On average, between 2010 and 2017, one user of stratum 1 had the benefit of a subsidy equivalent to 58.61% of the fee per kWh. Users of stratum 2 had a subsidy of 48.26% and users of stratum three at a subsidy rate of 15%. These subsidies apply over a specific range of consumption. For municipalities located at a height not exceeding 1000 meters above sea level, this range goes from 0 to 130 kWh/month. For municipalities located at a height greater than 1000 meters above sea level, this range goes from 0 to 170 kWh/month. The kWh consumed outside these ranges are charged at the full rate.

However, the cross subsidy scheme has not achieved its objective of guarantee the access of the vulnerable population to domiciliary public services. This may be due to the fact that over the years, the stratification scheme stopped reflecting the differentiation of groups based on their socioeconomic capacity. Moreover, this scheme has significant inclusion errors that lead to inadequate targeting of public resources Bonilla et al. (2014). According to Núnez et al. (2011), in 2008, within the group of dwellings of strata 1, 2 and 3 in Medellín, 4.16%, 3.03% and 1.9% of them, respectively, had a suspension[2] in at least one of the domiciliary public services.

In this context, prepaid electricity metering is attractive to the electricity utility and to the low-income costumer. This scheme cuts down on nonpayment or late payment of

[2]Temporary loss of service keeping the contract of uniform conditions with the utility, generated by a delay in the payment of invoices between 2 and 7 months.

electricity bills Jack and Smith (2020), since it gives the most vulnerable households a chance to self-manage their consumption and demand electricity according to their income flow. In a country like Colombia, where the prevalence of labor informality is 66.3%, many of the workers belonging to low-income households depend on what they can receive in a work-day.

2.2 EPM's Prepaid Electricity Program

The patterns presented in the previous section, prevailing even before 2008, motivated EPM to extend to vulnerable dwellings a pilot initiative of prepaid electricity metering. This initiative, developed in alliance with the government of Medellín, sought to improve the relationship between EPM and electricity users of the commercial sector in the center of Medellín, mainly informal sellers. After a feasibility study developed between 2005 and 2006, with the participation of 94 residential dwellings, EPM decided to roll out in 2007 the *Prepaid Electricity program* with defined coverage (the program henceforth). This program sought that end users self-manage their consumption and enable them to consume according to their payment possibilities without affecting their budget. This program was designed to fulfill the need of the low-income and disconnected population to have access to energy services.

To achieve this goal, the program was designed in its first stage for residential users of strata 1, 2, or 3 that were located only in the municipality of Medellín that, until June 13th, 2007, had the service suspended or cut due to outstanding bills. Besides, residential users that were paying debts that include electricity consumption, through some financing programs offered by EPM, could request the switch to the program, like those users who participated in the pilot. The objectives of the program were provide users with more significant benefits and, at the same time, improve the management of non-technical losses of the utility due to nonpayment, late payment or illegal connection.

Although this program was initially conceived as a program that would last only one year, in November of 2007, the coverage was extended to all the municipalities of Antioquia that belonged to the EPM coverage area[3]. In September of 2008, the EPM Board of Directors authorizes the enlargement of the program[4], in order to include 195,000 new costumers until December 31, 2011. Furthermore, since July 26, 2010, until December 31, 2011, the target market changed and users who, on the first calendar day of each month, had more than two suspensions or four consecutive months of suspension during the last twelve months, could access the program.

To date, four additional modifications have been made to the program regimentation, as can be seen in Figure A.2. In 2011, the affiliation of new users was extended until December 31, 2012, and the target users were redefined to users who, at the time of requesting the service, presented at least five months, consecutive or not, of suspension or cut. In 2013, the coverage of the program expanded until the end of the *Antioquia Iluminada* program and, among the characteristics of the target market, was included a SISBEN[5] score of less than 33 and a high-risk rating in the payment behavior with the utility. In 2014, all the

[3] In 2018, EPM reached a coverage of 97.3% of the residences in the department of Antioquia, for the urban and rural sectors.

[4] This extension is authorized by linking the prepaid energy program to the *Antioquia Iluminada* program, which had a financing of 96,000 million pesos.

[5] Identification System of Potential Beneficiaries of Social Programs.

prerequisites for being part of the target market were maintained, and the condition that the dwelling must be of stratum 1 and 2 is included. Finally, in 2018, the goal of covering 18,550 vulnerable or in extreme poverty households was fulfilled. Therefore, the additional conditions to be part of the target market included in the preceding periods were removed .

The affiliation to the program is subject to economic and technical feasibility[6] defined by EPM, and the users had to request the switch to the prepaid metering by themselves. When some user requests the switch to the prepaid scheme and is eligible to be part of it, he receives a prepaid double-part meter with an in-home display in bailment. This prepaid meters are located outside the dwelling and the in-home displays are located within the house in a visible and easy-to-reach place. The placement of the new meter and the disassembly of the postpaid meter is entirely free.

The in-home display allows the user to visualize the total electricity accumulated to date, the available credit, and more. It is attached to a keypad meter in which users types an alphanumeric pin code, generated every time the user makes a recharge at a certified point of sale (see Figure A.1). In 2016, approximately 34.135 recharging points were available to costumers in Antioquia, and, since 2015, EPM implemented a program called *Pre-carga*, which allowed users to make purchases through text messages.

Prepaid users[7] could recharge from 2000 pesos on wards, between 2007 and 2012, or 3000 pesos on wards, from 2013 and later, if they are of stratum 1, 2, or 3. Ten percent of each recharge goes to pay outstanding bills with EPM, if they have any. The fee per kWh that users pay is the same as in the postpaid scheme, and the subsidies apply according to the CREG[8] regulation.

Users who made the switch to the prepaid scheme had some support by EPM staff about the use of the new scheme, the new meter and about efficient energy consumption strategies. According to EMP staff, these apprehension processes have been a fundamental part of the program's success. In December 2017, there were 230,917 users linked to the EPM prepaid energy program, distributed in 128 municipalities of Antioquia and the south of Córdoba, the area of influence of this utility. Currently, the program has also been implemented in the Santander and Norte de Santander Departments, whose electrification utilities are part of the EPM business group.

2.3 Data

In this paper we use monthly information provided by EPM on the time of switching to the prepaid scheme, dwelling's energy consumption before and after the switch and several socio-economic characteristics at the household level. We restrict our sample to those users who made the switch to prepaid scheme in the observation period 2010-2017.

This study covers 142,998 dwellings of all strata groups in 128 different municipalities of the region of Antioquia (including the metropolitan area of Medellín). The dynamic of

[6]For example, EMP takes some precautions when approving the prepaid scheme to a new user such as verifying that there is no persons with a particular medical condition that requires energy permanently, due to dependence on some medical equipment.

[7]The average nominal minimum wage between 2010 and 2017 was 611,790 Colombian pesos.

[8]CREG resolutions 096 of 2004 and 042 of 2012. CREG, by its acronym in Spanish, means Energy and Gas Regulation Commission

the monthly switching is displayed in Figure 2. Of these dwellings, 72,800 are of stratum 1, 57,017 of stratum 2 and 12,354 of stratum 3. 827 dwellings, 0.58% of our sample, belong to stratum 4, 5, and 6[9]. The green vertical lines represent the limits of the regulatory periods implemented during the program execution, in which some requirements to participate were modified. The period between June 2010 and December 2011 covers the largest number of switching to the program: 56,147 dwellings adopted the prepaid scheme in this period of time. This can be explained due to the funding obtained from the *"Antioquia Iluminada"* program, allowing EPM to purchase new meters. When we observe the raw data in Figure A.3 we can see that there is a higher accumulation of users who consume a lower level of kWh/month in the prepaid scheme than in the postpaid scheme. This gives us suggestive evidence that the change in the scheme generates reductions in consumption patterns.

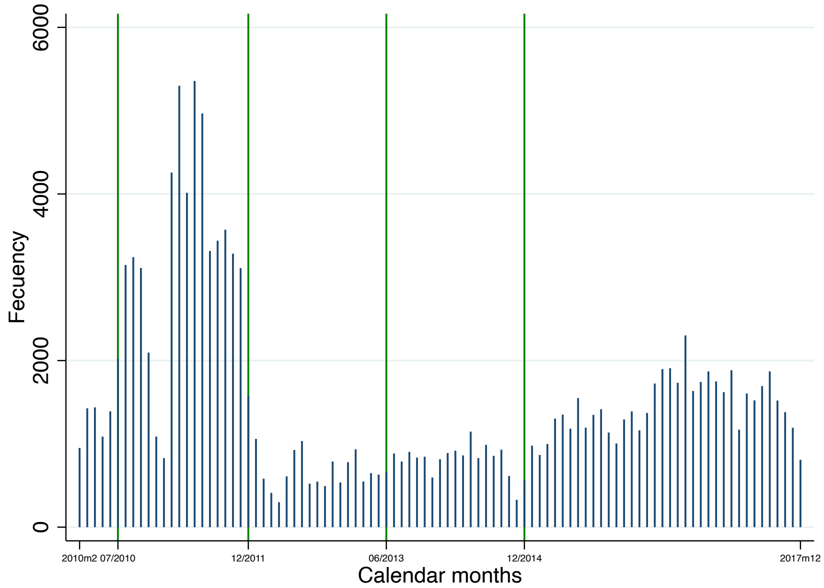


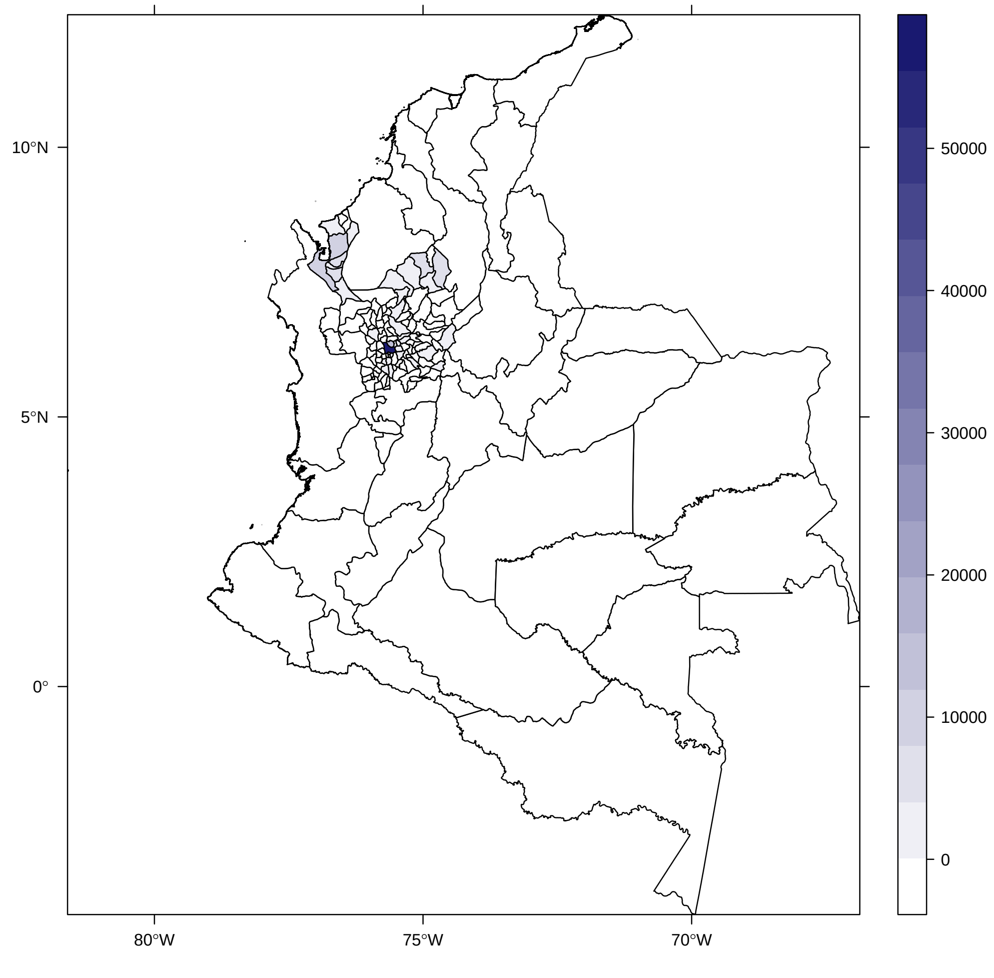
Figure 2: This Figure represents the number of swithings per month in all municipalities. The green lines represent the months in which new regulations were issued by EPM. Time period: 01/2010 - 12/2017.

Figure 3 illustrates a heat map for all the municipalities of Antioquia. As can be seen, Medellín concentrates the most significant number of switchings and users in the prepaid scheme: to 2017, a total of 55,514 new users switched to the prepaid scheme. Moreover, the municipalities located in the north of the region exhibit the second largest concentration of switched users for the period of analysis. This is partly explained by the fact that they have larger populations (*i.e.*, most of them are among the 20th most populated municipalities of the region). Once controlled by the population size, the coverage of the program has been relatively homogeneous throughout the department.

In addition, we use information on certain weather characteristics, which is available to the public in the web page of the Colombian Institute of Hydrology, Meteorology and Environmental Studies (IDEAM by its acronym in Spanish).We use the monthly average

[9]According to EPM, the inclusion of dwellings of strata 4, 5, or 6 was due to difficulties in the programs' implementation, since these are not classified as vulnerable population.

Figure 3: This Figure represents the number of switched dwellings between 2010-2017.



rainfall, measured in millimeters, between 1981 and 2010 for 89 of the 128 municipalities of Antioquia. May and October are, on average, the rainiest months for these 89 municipalities. In May the rains reached 332 millimeters on average.

3 Methodology

In this study, we aim to estimate the causal impact on the electricity consumption of switching to the prepaid electricity program. However, the application to the program is entirely voluntary, and users wishing to have prepaid electricity must file a format requesting the service, which generates a self-selection problem. In order to address this problem, we use the fact that households must meet some requirements, described in Section 2, to be part of the program's target market. The main assumption of our identification strategy is that the timing of the switch is not correlated with levels or trends in household consumption, electricity infrastructure or other observables (conditional on being eligible for being part of the target market). However, the eligibility criteria are correlated with household's socio-economic characteristics. Therefore, we restrict all estimates to the set of households that are part of the program and that are available in the data.

Since households request the switching at different points in time, our main estimation equation is the Difference-In-Differences with staggered adoption design (McCrary, 2007; Borusyak and Jaravel, aper; Abraham and Sun, 2018; Higgins, 2019), as specified in equation 1, which accommodates the varying of treatment and dynamic treatment effects over time.

$$c_{dt} = \alpha_d + \alpha_t + \beta log(\bar{p_{st}}) + \sum_{j=-10}^{j=-2} \delta_j + \sum_{j=0}^{j=12} \delta_j + \varepsilon_{dt} \tag{1}$$

The main outcome of interest is the logarithm of the electricity consumption measured in kWh c_{dt}, where d and t stand for dwelling and month, respectively. The parameter δ_j, in equation 1 captures the relative event time indicators. That is, δ_j is an indicator variable taking value one if it is the month j relative to the switching month, either before or after. The estimation equation includes dwelling fixed effects α_d to capture arbitrary time-invariant heterogeneity across dwellings within and between municipalities that could affect the electricity demand, and time fixed effects α_t to capture overall time trends. We also include the logarithm of the average price $log(\bar{p_{st}})$, where s and t stand for stratum and month, respectively. Given the cross subsidy scheme described in section 2, dwellings of strata 1, 2 and 3 pay an effective fee lower than the fee paid by dwellings of strata 4, 5 and 6. These last two strata groups pay an overrun of 20%. The average price variable takes into account those effective fees and averages them by stratum and month. The disturbance term ε_{dt} represents standard errors clustered at the dwelling's level (Bertrand et al., 2004).

In order to understand if the impact on consumption are sustainable along time, we create a set of treated and never treated residencies at different points in time by period. Then, within the same calendar months, we compare the electricity consumption of residencies that switched in a month t to those who decided to switch in a month $t + \delta$. This fully dynamic specification allows us to capture the dynamics of the electricity consumption relative to the month of the switching. We include ten months before switching and 12 months after switching. Furthermore, taking into account what was raised in Borusyak and Jaravel (aper) about the identification of the linear component of the path of pre-trends and dynamic treatment effects in the presence of unit and time fixed effects and, as in most event study specifications (*e.g.* (McCrary, 2007; Higgins, 2019)), we do not drop observations that are further than 10 months before or 12 months after the shock, but rather bin these by setting $\delta_{-10} = 1$ if $j \leq -10$ and $\delta_{12} = 1$ if $j \geq 12$.

Equation 1 can be seen as a demand equation in reduced form. The electricity prices, which varies across strata due to the cross-subsidy scheme, may be endogenous because there are unobserved factors that can affect at the same time the consumption patterns and the definition of the fee per kWh. Using the average price directly could bias the estimates. To account for this potential bias, we instrument the average price with the monthly average rainfall by municipality between 1981 and 2010, which is completely exogenous. This strategy ensures that we capture movements in electricity consumption driven by the switching to prepaid scheme. Therefore, in all our specifications we use 2SLS estimation method.

In addition, we estimate a parametric specification with the objective to analyze the statistical significance and magnitude of the estimates. We estimate the following specification in two stages:

$$c_{dt} = \alpha_d + \alpha_t + \beta_1 log(\bar{p_{st}}) + \beta_2 \text{PostPrepaid}_{dt} + \varepsilon_{dt} \tag{2}$$

where d and t stand for dwelling and month, respectively, and **PostPrepaid** is an indicator variable taking the value 1 for all months after the switching and 0 for all the observed months in which the user was in prepaid scheme. The parameter β_2 measures the changes in electricity consumption of the switched dwellings compared to the yet-to-be switched dwellings, conditional on the set of dwelling and month fixed effects, and the average price by stratum and month.

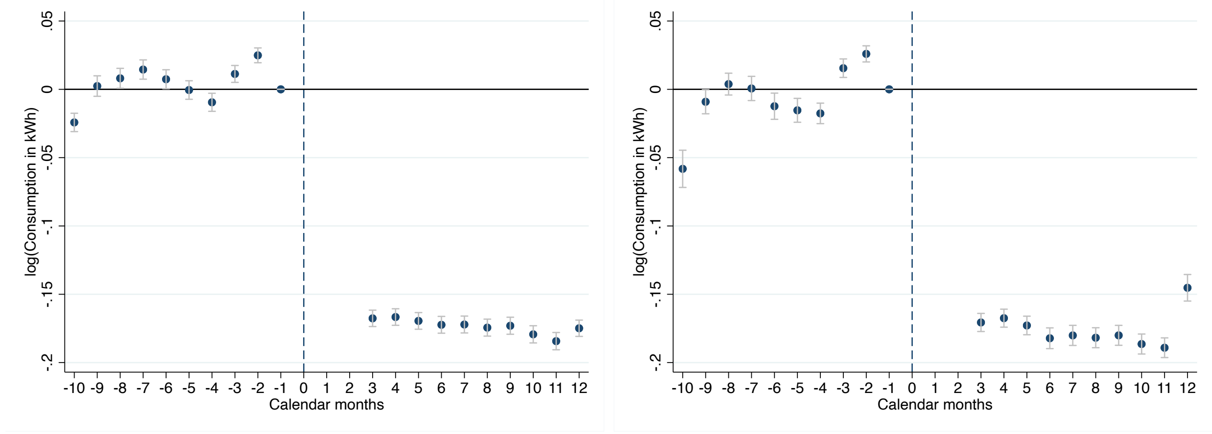
4 Results

4.1 Electricity consumption

We begin by studying the impact of switching to the prepaid scheme on electricity consumption. We first explore the dynamics of the effects around the month of switching by estimating equation 1. We estimate this specification for our complete sample. Figure 4 displays the point estimates of the non-parametric difference-in-differences with staggered adoption specification over the window of 10 months before and 12 months after the switch. Figures 4a and 4b show results form OLS and 2SLS results and illustrates the impact of the switch on the electricity consumption behavior. After the switch, we see a decrease in monthly electricity consumption ans this effect takes place the month following the switch and is persistent over time. Table 1 shows the regression coefficients from estimating 1.

It should be clarified that, in the case of those dwellings that presented disconnection or cut before the switching month, we imputed the average consumption in the months before the change in which the residences had a positive consumption for the estimation exercises. These results are robust to leave unaltered these observations and perform the exercises with

Figure 4: Effect of switching to the prepaid scheme on user's electricity consumption



(a) OLS event study estimates.

(b) 2SLS event study estimates.

This Figure shows the coefficients from equation 1, where the outcome variable is the electricity consumption of dwelling j.

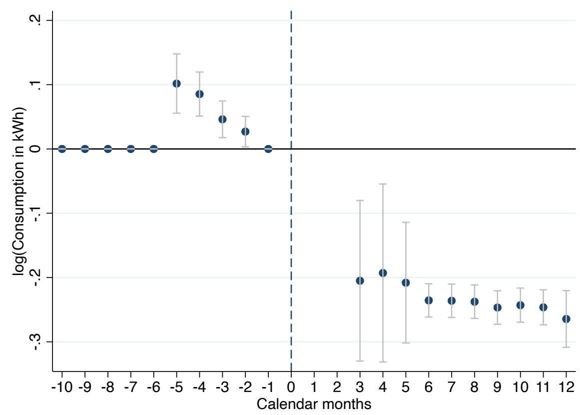
zero consumption in the months before the switch. Moreover, we exclude the switching month and the following two months due to some double register problems in the data.

We interpret the magnitude of our findings by estimating equation 2, by reporting the results of the parametric specification in Table 1. We find that switching to the prepaid scheme has a strongly and significant impact on electricity consumption. Column (2) shows a reduction in electricity consumption of 12,98% which, compared to the average user consumption in the sample before the change, represents a reduction of 17,99 kWh/month. This result is in line with those presented by Qiu et al. (2016); Nugrohoa et al. (2017); Jack and Smith (2015); OSullivan et al. (2013); Tewaria and Shah (2003); Ayres et al. (2012); Jack and Smith (2020), among others. For example, Qiu et al. (2016) find that the prepaid program is associated with a 12% reduction in electricity usage and Jack and Smith (2020) points out that the prepaid metering is associated with a reduction in consumption around 14%. The OLS and the instrumental variables specification results are similar, however, it is possible to show that the OLS results are biased upwards.

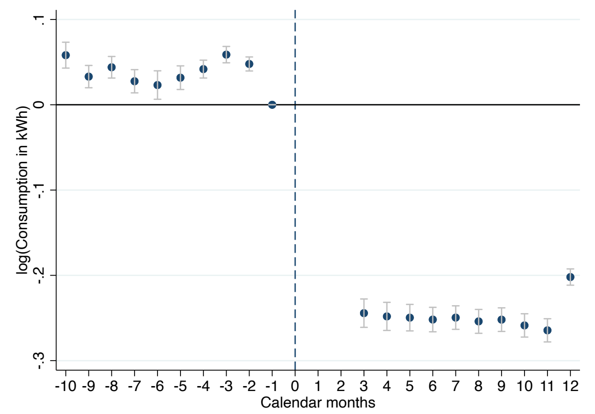
4.2 Heterogeneous effects

Regulatory period - In this section we analyse the impacts of the prepaid scheme on different types of costumers. First, we subdivided the sample by the regulation period. In other words, we create different sets of treated dwellings depending on the month in which they decided to switch and the regulation of EPM that was in force at that time. As can be seen in Figure 5, for those periods in which the number of switched dwellings was higher, between July 2010 and November 2011 and, after November 2014, it seems not to be an anticipatory behavior by users. Columns 5 to 14 of table A.2 shows the regression coefficients.

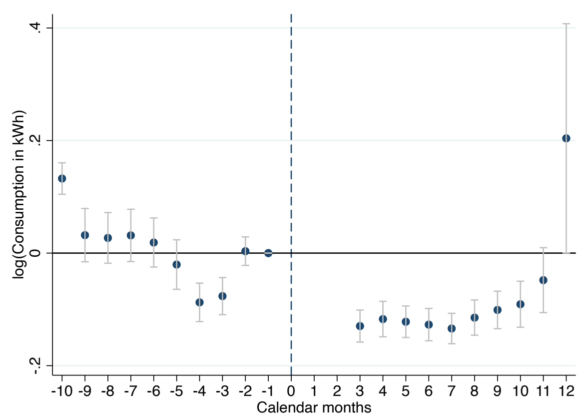
Figure 5: Effect of switching to the prepaid scheme on user's electricity consumption by regulation period.



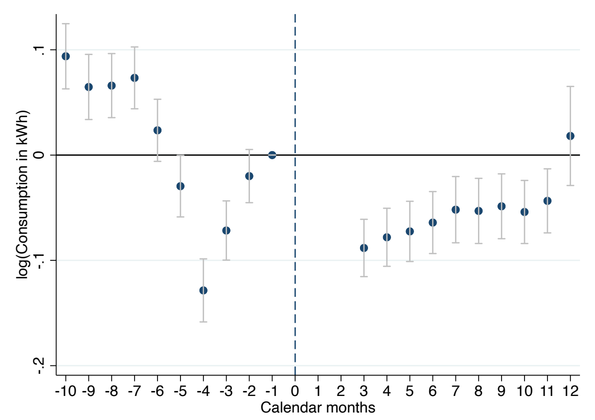
(a) First regulation period (Before July 2010).



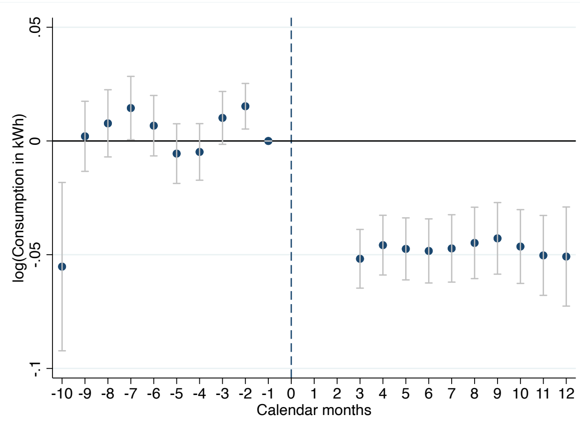
(b) Second regulation period (Between July 2010 and November 2011).



(c) Third regulation period (Between December 2011 and May 2013).



(d) Fourth regulation period (Between June 2013 and November 2014).



(e) Fifth regulation period (After November 2014).

Each regulation period includes those dwellings that decided to switch to the prepaid scheme during the term of the different decrees described in Section 2 and in the Figure A.2.

Table 1: The impact of prepaid schemes in electricity consumption

	log(consumption in kWh)	
	OLS	IV
Variable	1	2
PostPrepaid	-0.163***	-0.122***
	(0.00198)	(0.00642)
$\log(\bar{p})$	0.0136***	-0.225***
	(0.000897)	(0.0376)
Observations	9,977,684	8,956,486
Clusters	142,920	128,189
R-squared	0.457	-
Adj. R-squared	0.449	-
Dwelling FE	✓	✓
Month FE	✓	✓

Notes: Clustered standard errors in parenthesis.
Significance level: *** 1% ** 5% * 10%.
Estimation method: Difference-In-Differences.

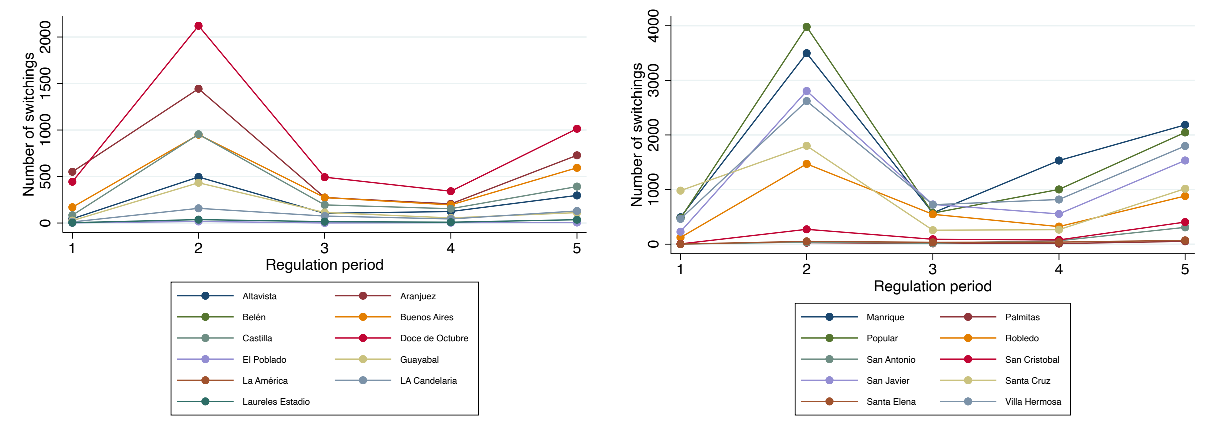
As in the full sample case, the effect takes place the month following the switch, and is persistent over time. Moreover, analyzing the behavior of the coefficients after the switch in each of the regulatory periods, it seems that the total effect is being guided mainly by the first two regulation periods and, to a lesser degree, by the last regulation period. For this last regulation period, the coefficients preceding the switch are never statistically significant, indicating that there is no anticipatory behavior from customers.

In the case of the third and fourth regulatory periods (see Figures 5c and 5d), we observe that the effect seems to disappear after the eleventh month following the switch. This consumption behaviour could be partially explained by improvements in targeting on venerable population and users with debt, due to an imbalance in the optimal composition of the market. In 2011 EPM established that the financial viability of the program was associated with the consumption of households that were linked to the prepaid scheme and that, before the switch, presented significant delays in their payments. Therefore, after December 2011, the entry of users with minimal propensity to delay their payments was limited and, in April 2013, EPM established that users who wanted to request a transfer to the prepaid scheme should have a SISBEN score less or equal to 33.

Given these regulatory changes in the program, we can expect that the population that was linked from this date obtained a significant re-connection benefit, but, given their conditions of high vulnerability, they were not able to hold their reduction in their consumption. We suspect that the consumption of these users prior to the switch was very close to their minimum level required to subsist, but they could not afford the monthly payment of the service. By linking to the program, they were reconnected to the system and could consume according to their payment possibilities without affecting their budget.

Some descriptive evidence can support this hypothesis, particularly in the case of Medellín and its metropolitan area. As can be seen in the Figures 6a and 6b, the number of users who switched to the program since the third regulatory period and who are part of the most vulnerable communes in Medellín, like Manrique, Popular or Villa Hermosa, grew.

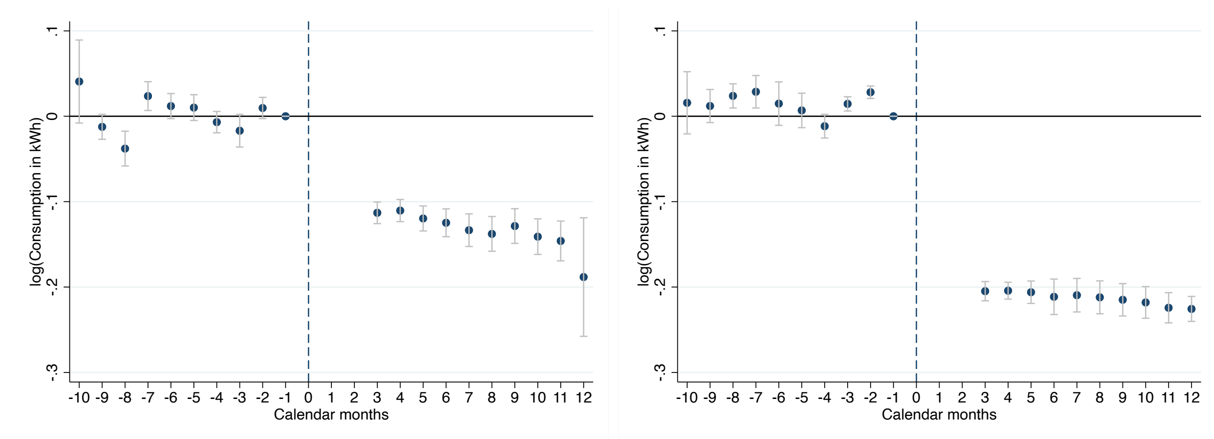
Figure 6: Number of swithings by commune and regultory period



(a) (b)

Municipality height - Since the height of the municipalities is directly related to the weather conditions faced by households and these conditions affect the demand for electrical energy, we analyse the impacts of the prepaid scheme on consumers located in lowland and highland municipalities. Following the structure of the cross subsidy scheme, we classify the municipalities located at a maximum height of 1000 meters as lowland municipalities and those located above the 1000 meters as highland municipalities.

Figure 7: Effect of switching to the prepaid scheme on user's electricity consumption by municipality height



(a) 2SLS Event study estimates-Lowland. (b) 2SLS event study estimates-Highland.

This Figure shows the coefficients from equation 1, where the outcome variable is the electricity consumption of dwelling j.

Figure 7 displays the point estimates of the non-parametric difference-in-differences with staggered adoption specification for both kind of dwellings, those located in lowland municipalities and those located in highland municipalities. As can be seen, there doesn't seem to be an anticipatory behavior from customers in both kind of municipalities and the effect seems to be more pronounced in dwellings located in highland. Columns 1 to 4 of table A.2 shows the regression coefficients. This dwellings reduce their consumption 14,45% more than those located in lowland.

5 Mechanisms

We argue that the main channel behind the effect of the switch on the electricity consumption behavior is the tracking and budgeting electricity expenditure channel based on the real-time information that the user receives in the In-Home Display, and on the fact that in the prepaid scheme the provision of the electric service adapts to the dynamics of the household income. This approach is consistent with two of the four possible channels, present in the literature, via which a prepaid plan leads to electricity consumption reduction: nudging, price effects, information provision, and costs of discontinuation (Qiu et al., 2016).

Due to the prepaid scheme, users can understand their energy consumption better than when it is provided by standard billing. Conventional electricity schemes are postpaid, involving monthly billing and collections. This system implies that users receive information about quantities consumed and fees charged one month after the consumption. This scheme can lead to a certain kind of "inattention" to energy costs (Allcott and Greenstone, 2012). This "inattention" could lead users to not recognize opportunities to save money by choosing more efficient consumption patterns and avoiding over-consumption. We hypothesize that, due to the information provision, consumers reduce their over-consumption by tracking their energy use. This hypothesis is consistent with the results presented in the previous Section and with those presented in Figure 8a.

Table 2: The impact of prepaid schemes in electricity consumption by stratum

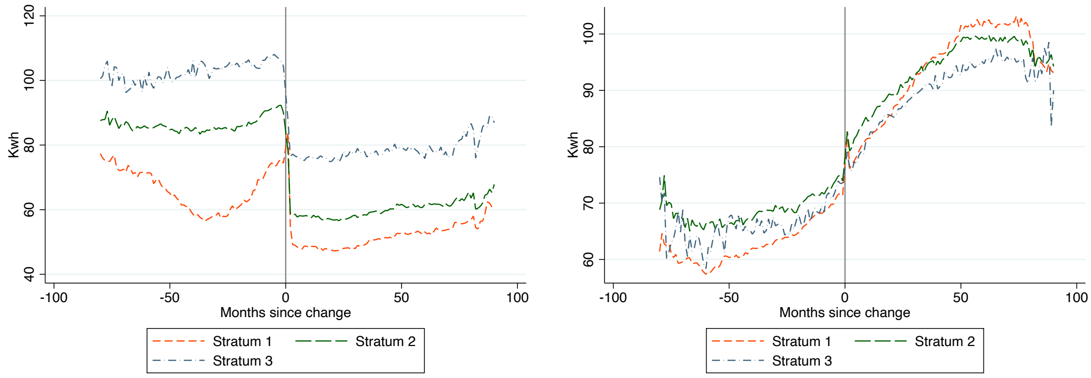
Variables	Stratum 1		Stratum 2		Stratum 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Postpaid	-0.104***	-0.0876***	-0.199***	-0.132***	-0.292***	-0.317
	(0.0028699)	(0.0050623)	(0.0029715)	(0.0145609)	(0.00739)	(0.224)
$\log(\bar{p})$	0.0213	-0.124***	0.0023	-0.3356***	-0.0575***	0.0685
	(0.0010264)	(0.0290956)	(0.0017865)	(0.0801713)	(0.0202)	(1.073)
Observations	4,722,473	4,330,692	4,265,994	3,750,577	939,261	828,371
Clusters	72,754	66227	56,993	50,267	12,348	10,928
R-squared	0.4545	-	0.4447	-	0.480	-
Adj. R-squared	0.4460	-	0.4372	-	0.473	-
Dwelling FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓

Notes: clustered standard errors by dwelling in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Estimation method: Difference-in-Differences.

Figure 8: Raw data

(a) Average consumption outside the subsidized range before and after the switch

(b) Average consumption inside the subsidized range before and after the switch



(a) This Figure represents the average consumption outside the subsidized range before and after the switch for dwellings of strata 1, 2 and 3, that exhibited overconsumption before the switch.

(b) This Figure represents the average consumption before and after the switch for dwellings of strata 1, 2 and 3, that did not exhibited overconsumption before the switch.

In Figure 8a, we represent the average consumption outside the subsidized range before and after the switch for dwellings of strata 1, 2, and 3. The computation of these averages takes into account only those dwellings that had non-zero consumption outside the subsidized range before the switch. We interpret this as a measure of over-consumption. If the prepaid plan leads to electricity consumption reduction through the information provided, we would expect that users of strata 1, 2, and 3 would be more aware of their consumption during the month and avoid exceeding the subsidized range of consumption. In contrast, Figure 8b shows the average consumption before and after the switch for dwellings of strata 1, 2 and 3, that did not exhibited over-consumption before the switch. As can be seen, these dwellings seem to be increasing their electricity consumption, without exceeding the limits of the subsidized range. We suspect that, due to the information provision, these consumers are able to expand their consumption to more optimal levels, without exceeding subsidy limits.

Table 2 report the results of the parametric specification by stratum. Columns 2, 4 and 6 presents the results of the 2SLS estimation and show that switching to the prepaid scheme has a strongly significant impact on consumption for low-income households. Furthermore, the effect is greater for stratum 3 users and follows a descending order. This finding can be explained both by the average levels of dwellings' consumption (Figure 3) and the access to home appliances by users of strata 2 and 3. Since households of strata 2 and 3 have a higher level of income than those of stratum 1, they will be able to access more easily to appliances.

6 Conclusions

In this paper, we analyze the impact that switching to a prepaid electricity program has on the behavior of users' energy consumption, mainly on those that are more vulnerable from a socio-economic point of view. The paper is guided by one central question: how is affected the energy consumption of a dwelling, which may or may not have the electric power service discounted or cut off, when it is passed to a prepaid scheme, where he can self-manage his consumption and consume according to his payment possibilities? We find that switching to the prepaid scheme has a strongly significant impact on electricity consumption. This is, a reduction of 12.98% compared to the consumption under a postpaid scheme. Analyzing the dynamics, we observe that this effect is persistent over time, even 12 months after the switch.

Besides, this kind of program introduces new flexibility in how and when low-income users purchase energy. As pointed out by (Jack and Smith, 2015), allowing households to smooth expenditures according to their income stream, much of which comes from informal labor relations. As shown in Section 4, this scheme allows users to generate consumption reductions, while their access to public electricity services is guaranteed, minimizing disconnection risks and the associated costs.

This kind of energy efficiency is relevant both for the Colombian context and its energy sufficiency in the medium and long term, and for the global context, since the European Commission has listed improved energy efficiency among its top objectives for 2020, and most countries that have ratified the recent Paris Agreement plan to improve energy efficiency in order to meet their goals (The European Commission, 2010; International Energy Agency, 2014). Furthermore, many international institutions pointed out that energy efficiency is the best tool to keep energy demand under control, as can be done with a prepaid scheme like the one analyzed in this article, while it facilitate the transition towards a low-carbon future (Ramos et al., 2015).

7 Acknowledgement

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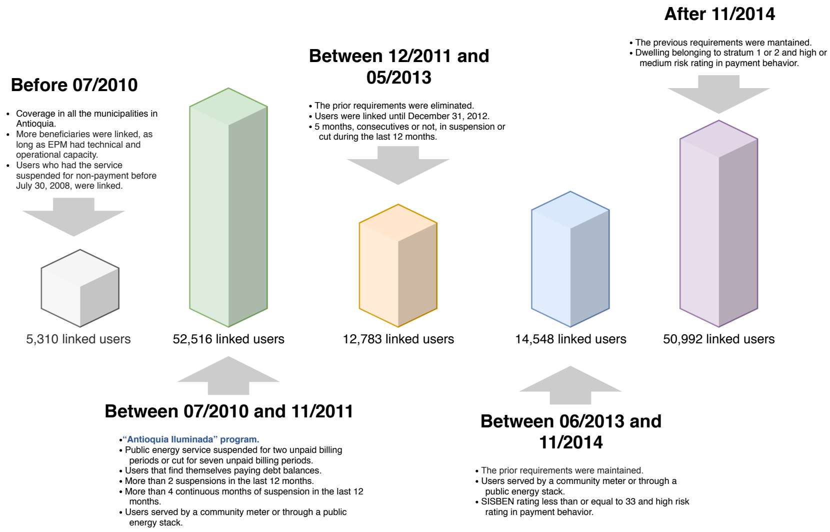
8 Appendix

Figure A.1: Installation of a prepaid meter in May of 2009

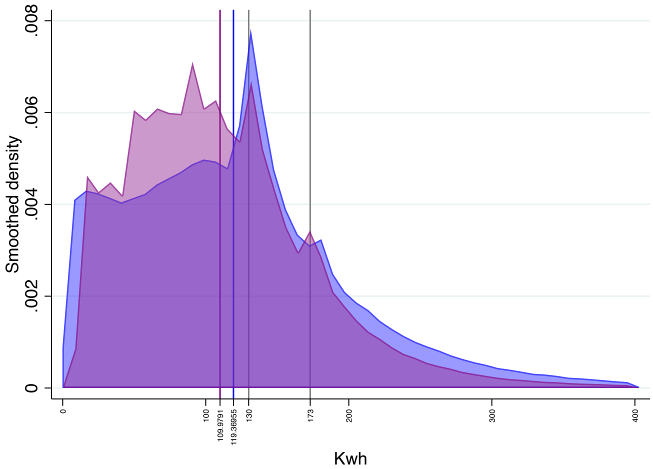
Source: EPM.

Figure A.2: Definition of the target market of the program

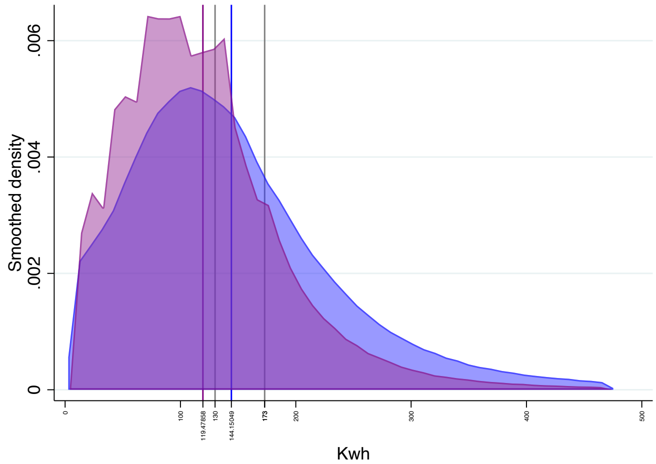


Notes: Own elaboration.

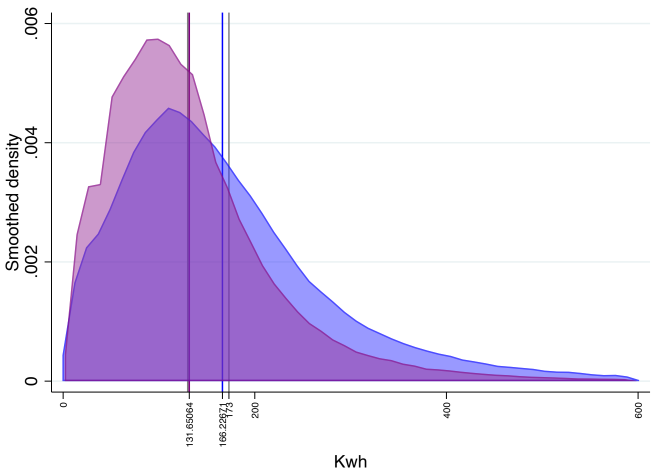
Figure A.3: Smoothed kernel density of consumption in both schemes by strata



(a) Stratum 1



(b) Stratum 2



(c) Stratum 3

A trimming of 1% was done in both tails of the consumption distribution. The kernel densities plotted in blue correspond to dwelling's consumption under the postpaid scheme and those plotted in purple correspond to dwelling's consumption under the prepaid scheme. Gray lines represent the limits of the subsidized range, subject to the height of the municipality.

Table A.1: The impact of prepaid schemes in electricity consumption

	log(consumption in kWh)	
	Full sample	
	OLS	IV
Variable	1	2
10 months before	-0.0242***	-0.0582***
	(0.00342)	(0.00695)
9 months before	0.00239	-0.00910**
	(0.00382)	(0.00449)
8 months before	0.00805**	0.00382
	(0.00372)	(0.00407)
7 months before	0.0145***	0.000631
	(0.00360)	(0.00452)
6 months before	0.00739**	-0.0124**
	(0.00354)	(0.00489)
5 months before	-0.000507	-0.0154***
	(0.00346)	(0.00446)
4 months before	-0.00949***	-0.0176***
	(0.00337)	(0.00383)
3 months before	0.0113***	0.0155***
	(0.00316)	(0.00346)
2 months before	0.0249***	0.0259***
	(0.00276)	(0.00301)
3 months after	-0.168***	-0.171***
	(0.00306)	(0.00338)
4 months after	-0.167***	-0.167***
	(0.00309)	(0.00336)
5 months after	-0.169***	-0.173***
	(0.00311)	(0.00347)
6 months after	-0.172***	-0.182***
	(0.00313)	(0.00387)
7 months after	-0.172***	-0.180***
	(0.00315)	(0.00375)
8 months after	-0.174***	-0.182***
	(0.00317)	(0.00373)
9 months after	-0.173***	-0.180***
	(0.00318)	(0.00372)
10 months after	-0.179***	-0.186***
	(0.00321)	(0.00373)
11 months after	-0.184***	-0.189***
	(0.00322)	(0.00367)
12 months after	-0.175***	-0.145***
	(0.00305)	(0.00496)
$\log(\bar{p})$	0.0120***	-0.234***
	(0.000864)	(0.0387)
Observations	9,977,684	8,956,486
Clusters	142,920	128,189
R-squared	0.457	-
Adj R-squared	0.449	-
Dwelling FE	✓	✓
Month FE	✓	✓

Notes: Clustered standard errors in parenthesis.
Significance level: *** 1% ** 5% * 10%.
Estimation method: Difference-In-Differences with staggered adoption.

Table A.2: The impact of prepaid schemes in electricity consumption

	log(consumption in kWh)													
	Municipality heigh				Regulatory period									
	OLS		IV		OLS					IV				
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
10 months before	-0.0568***	0.0187***	0.0407	0.0158		0.0422***	0.125***	0.135***	-0.00634		0.0582***	0.133***	0.0938***	-0.0552***
	(0.00548)	(0.00436)	(0.0248)	(0.0186)		(0.00626)	(0.0124)	(0.0127)	(0.00558)		(0.00774)	(0.0143)	(0.0158)	(0.0189)
9 months before	-0.00422	0.0144***	-0.0124*	0.0120		0.0326***	0.0948***	0.0965***	0.0149**		0.0330***	0.0319	0.0647***	0.00205
	(0.00607)	(0.00491)	(0.00747)	(0.00988)		(0.00620)	(0.0133)	(0.0140)	(0.00623)		(0.00667)	(0.0242)	(0.0158)	(0.00786)
8 months before	-0.00855	0.0251***	-0.0378***	0.0238***		0.0364***	0.0874***	0.0955***	0.0180***		0.0440***	0.0270	0.0660***	0.00775
	(0.00599)	(0.00474)	(0.0104)	(0.00723)		(0.00570)	(0.0133)	(0.0141)	(0.00617)		(0.00646)	(0.0229)	(0.0155)	(0.00753)
7 months before	0.000304	0.0290***	0.0236***	0.0287***		0.0349***	0.0949***	0.0969***	0.0211***		0.0276***	0.0315	0.0733***	0.0145**
	(0.00576)	(0.00459)	(0.00860)	(0.00970)		(0.00524)	(0.0133)	(0.0140)	(0.00610)		(0.00695)	(0.0237)	(0.0150)	(0.00710)
6 months before	-0.00207	0.0166***	0.0119	0.0148		0.0368***	0.0742***	0.0458***	0.0131**		0.0231***	0.0188	0.0235	0.00673
	(0.00569)	(0.00452)	(0.00749)	(0.0130)		(0.00499)	(0.0134)	(0.0143)	(0.00606)		(0.00851)	(0.0223)	(0.0150)	(0.00678)
5 months before	-0.00748	0.00711	0.0102	0.00684	0.108***	0.0400***	0.0300**	-0.0165	0.000764	0.102***	0.0318***	-0.0203	-0.0295**	-0.00555
	(0.00558)	(0.00441)	(0.00770)	(0.0103)	(0.0225)	(0.00475)	(0.0134)	(0.0146)	(0.00599)	(0.0235)	(0.00706)	(0.0224)	(0.0149)	(0.00669)
4 months before	-0.00489	-0.00920**	-0.00687	-0.0116	0.0852***	0.0447***	-0.0489***	-0.114***	-0.00222	0.0853***	0.0418***	-0.0875***	-0.129***	-0.00482
	(0.00539)	(0.00431)	(0.00638)	(0.00708)	(0.0170)	(0.00455)	(0.0136)	(0.0148)	(0.00586)	(0.0175)	(0.00534)	(0.0174)	(0.0153)	(0.00634)
3 months before	0.0115**	0.0132***	-0.0169*	0.0145***	0.0478***	0.0516***	-0.0452***	-0.0636***	0.0112**	0.0461***	0.0588***	-0.0764***	-0.0716***	0.0102*
	(0.00509)	(0.00402)	(0.00978)	(0.00427)	(0.0143)	(0.00427)	(0.0135)	(0.0141)	(0.00552)	(0.0145)	(0.00490)	(0.0168)	(0.0143)	(0.00593)
2 months before	0.0208***	0.0281***	0.00970	0.0281***	0.0362***	0.0442***	0.0181	-0.00919	0.0172***	0.0270**	0.0478***	0.00345	-0.0200	0.0153***
	(0.00448)	(0.00351)	(0.00634)	(0.00373)	(0.0117)	(0.00384)	(0.0115)	(0.0125)	(0.00482)	(0.0121)	(0.00419)	(0.0129)	(0.0129)	(0.00511)
3 months after	-0.101***	-0.206***	-0.113***	-0.205***	-0.239***	-0.232***	-0.144***	-0.0871***	-0.0634***	-0.205***	-0.244***	-0.130***	-0.0882***	-0.0518***
	(0.00509)	(0.00382)	(0.00645)	(0.00576)	(0.0122)	(0.00414)	(0.0122)	(0.0133)	(0.00575)	(0.0637)	(0.00849)	(0.0145)	(0.0139)	(0.00659)
4 months after	-0.0972***	-0.206***	-0.110***	-0.204***	-0.236***	-0.235***	-0.140***	-0.0773***	-0.0585***	-0.193***	-0.248***	-0.117***	-0.0781***	-0.0458***
	(0.00514)	(0.00386)	(0.00661)	(0.00503)	(0.0124)	(0.00419)	(0.0122)	(0.0134)	(0.00581)	(0.0706)	(0.00842)	(0.0161)	(0.0141)	(0.00670)
5 months after	-0.101***	-0.208***	-0.120***	-0.206***	-0.237***	-0.238***	-0.136***	-0.0771***	-0.0622***	-0.208***	-0.250***	-0.122***	-0.0725***	-0.0474***
	(0.00517)	(0.00388)	(0.00746)	(0.00669)	(0.0122)	(0.00422)	(0.0122)	(0.0134)	(0.00586)	(0.0478)	(0.00792)	(0.0143)	(0.0146)	(0.00695)
6 months after	-0.102***	-0.212***	-0.125***	-0.211***	-0.237***	-0.241***	-0.141***	-0.0714***	-0.0654***	-0.236***	-0.252***	-0.127***	-0.0641***	-0.0483***
	(0.00524)	(0.00390)	(0.00831)	(0.0106)	(0.0121)	(0.00427)	(0.0123)	(0.0134)	(0.00592)	(0.0132)	(0.00732)	(0.0146)	(0.0150)	(0.00719)
7 months after	-0.102***	-0.210***	-0.133***	-0.210***	-0.235***	-0.241***	-0.141***	-0.0660***	-0.0651***	-0.236***	-0.250***	-0.134***	-0.0518***	-0.0472***
	(0.00527)	(0.00392)	(0.00975)	(0.0100)	(0.0122)	(0.00428)	(0.0124)	(0.0135)	(0.00598)	(0.0132)	(0.00704)	(0.0138)	(0.0161)	(0.00756)
8 months after	-0.105***	-0.212***	-0.138***	-0.212***	-0.239***	-0.244***	-0.136***	-0.0649***	-0.0655***	-0.238***	-0.254***	-0.115***	-0.0530***	-0.0448***
	(0.00533)	(0.00394)	(0.0104)	(0.00983)	(0.0122)	(0.00430)	(0.0124)	(0.0135)	(0.00605)	(0.0133)	(0.00713)	(0.0160)	(0.0158)	(0.00801)
9 months after	-0.0946***	-0.216***	-0.129***	-0.215***	-0.250***	-0.242***	-0.128***	-0.0613***	-0.0624***	-0.247***	-0.252***	-0.101***	-0.0486***	-0.0428***
	(0.00536)	(0.00394)	(0.0104)	(0.00967)	(0.0122)	(0.00432)	(0.0123)	(0.0135)	(0.00611)	(0.0133)	(0.00706)	(0.0170)	(0.0157)	(0.00803)
10 months after	-0.105***	-0.219***	-0.141***	-0.218***	-0.248***	-0.248***	-0.133***	-0.0625***	-0.0673***	-0.243***	-0.259***	-0.0909***	-0.0540***	-0.0464***
	(0.00544)	(0.00397)	(0.0106)	(0.00947)	(0.0123)	(0.00436)	(0.0124)	(0.0136)	(0.00621)	(0.0135)	(0.00698)	(0.0209)	(0.0153)	(0.00827)
11 months after	-0.105***	-0.225***	-0.146***	-0.224***	-0.252***	-0.255***	-0.119***	-0.0549***	-0.0750***	-0.246***	-0.264***	-0.0480	-0.0435***	-0.0503***
	(0.00546)	(0.00399)	(0.0119)	(0.00903)	(0.0123)	(0.00436)	(0.0123)	(0.0136)	(0.00629)	(0.0139)	(0.00694)	(0.0294)	(0.0155)	(0.00896)
12 months after	-0.0509***	-0.230***	-0.188***	-0.226***	-0.275***	-0.215***	-0.0881***	-0.0337***	-0.0846***	-0.264***	-0.202***	0.204**	0.0181	-0.0508***
	(0.00524)	(0.00373)	(0.0354)	(0.00746)	(0.0113)	(0.00406)	(0.0119)	(0.0130)	(0.00616)	(0.0225)	(0.00486)	(0.104)	(0.0240)	(0.0111)
$\log(\bar{p})$	0.0232***	0.00447***	0.904***	-0.0105	-0.00373	0.00288**	0.00933***	0.0121***	0.00494***	-0.0420	-0.0902**	-1.434***	-0.357***	-0.280***
	(0.00193)	(0.000907)	(0.221)	(0.103)	(0.00266)	(0.00138)	(0.00254)	(0.00196)	(0.00150)	(0.0613)	(0.0405)	(0.505)	(0.116)	(0.0962)
Obervations	3,566,252	6,411,432	3,249,318	5,707,168	545,527	4,468,238	925,159	972,393	3,066,367	507,546	3,981,744	856,553	897,481	2,713,162
Clusters	56,074	86,846	50,468	77,721	6,293	56,137	12,924	14,687	52,879	5,864	50,236	11,996	13,558	46,535
R-squared	0.489	0.436	-0.165	0.019	0.447	0.458	0.425	0.409	0.475	0.012	0.015	-0.498	-0.019	-0.013
Adj- R-squared	0.480	0.428	-0.165	0.0191	0.441	0.451	0.417	0.400	0.466	0.0115	0.0149	-0.498	-0.0189	-0.0128
Dwelling FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Clustered standard errors in parenthesis. Significance level: *** 1% ** 5% * 10%. Estimation method: Difference-In-Differences with staggered adoption.

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