Between Theory and the Bill: Quasi-Experimental Evidence on Household Response to Marginal Prices*

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Abstract

A central prediction of economic theory is that households adjust consumption to the *marginal* price they face. Yet in energy markets, growing evidence suggests that consumers often respond instead to average bills, raising doubts about the effectiveness of Increasing Block Pricing (IBP) as a conservation tool. This paper exploits a natural experiment from a subsidy reform that introduced a 350 kWh/month cap for low-income households: usage below the cap remained subsidized, while usage above it was billed at the full tariff. Using administrative billing data and a difference-in-differences design with household fixed effects and weather controls, we find that historically high-use households reduced December consumption by about 75 kWh. However, when unsubsidized households are added as an additional comparison group in a triple-difference framework, the apparent reductions disappear—suggesting that earlier RD/DiD evidence, such as Nataraj et al., may conflate marginal-price responses with broader demand dynamics. Overall, households closest to the threshold—the group directly exposed to the marginal price jump—show little adjustment. The results provide new quasi-experimental evidence that electricity consumers respond more to average than to marginal prices, with important implications for the design and evaluation of IBP schemes.

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1 Introduction

In the economic analysis of public services, tariff structure is central to allocating resources efficiently and expanding equitable access. Public utilities—such as water and electricity—often deploy non-linear pricing. A common example is the Increasing Block Pricing (IBP) scheme, designed to balance equity and efficiency objectives: safeguarding affordable basic consumption while promoting conservation at higher usage levels and stabilizing utility revenues (Borenstein, 2012).

Standard theory predicts that consumers adjust usage with respect to the *marginal* price they face at their current block. In practice, however, users may not fully understand complex tariffs or even their current block, and may instead respond to the average or expected price—or fail to react if changes are not salient (Ito, 2014). This gap between theory and observed behavior raises a central question: *do households adjust consumption in response to sharp, targeted increases in the marginal price?*

We study a natural experiment in Argentina. On June 19, 2024, the national government introduced a 350 kWh/month subsidized cap for residential users in the Social Tariff segment (RASE, N2). Prior to this change, N2 households received, on average, a 76% subsidy on the variable charge. As of June 19, 2024, consumption up to 350 kWh received a reduced subsidy (about 50%), while any usage above the cap received no subsidy, aligning the marginal price with that faced by non-subsidized users. This reform effectively introduced an IBP structure for N2 households, with a discrete jump in the marginal price at 350 kWh. We exploit this change to estimate whether households respond to marginal or average price signals. Importantly, we also take advantage of the fact that we observe households in the N1 segment, who did not experience any modification in the variable charge; this group serves as an additional comparison and enables a triple-difference (DDD) model, which reveals that the initial DiD estimates are not robust and casts doubt on the validity of those results.

The objective of this study is to identify the impact of a change in the marginal price of electricity on residential consumption, taking advantage of a natural experiment. In Argentina, during 2024, a modification was introduced to the Variable Charge for a specific group of residential users: beneficiaries of the National Social Tariff registered in the Registro de Acceso

a los Subsidios a la Energía (RASE), segment N2. Since September 7, 2022, this group had been receiving, on average, a 76% subsidy on the Variable Charge. However, as June 19, 2024, a subsidized consumption cap of 350 kWh per month was established. At or below this threshold, the average subsidy was 50% on de Variable Charge; above it, the subsidy dropped to 0%, equating the charge to that faced by users without the Social Tariff. This reform effectively introduces an Increasing Block Pricing (IBP) structure for this group, by imposing a discrete jump in the marginal price faced by households exceeding the limit. This change provides an opportunity to implement a quasi-experimental evaluation to estimate the extent to which households respond to an IBP structure and, more broadly, to determine whether consumers adjust their consumption based on the effective marginal price or, instead, if their behavior is driven by alternative perceived prices, such as the average price.

This study finds that households with persistently high consumption reduced usage by about –75 kWh in December 2024, while the effect diminishes when restricting the sample to those closer to the cutoff. Using an alternative classification based on 12-month averages, the adjustment among marginal households becomes stronger (–52.4 kWh), suggesting that consumption smoothing matters for identification. In turn, triple-difference estimates produce a positive effect in the full sample (+30.4 kWh), but this disappears once the sample is narrowed, indicating that it is driven by households far from the threshold. Overall, the evidence shows that reductions concentrate among high-use households, whereas those just above the cap display weaker responses, consistent with consumers reacting more to average rather than marginal prices.

To our knowledge, this is the first paper in Latin America to analyze a quasi-experimental change in marginal electricity prices under an IBP structure using regression-based causal designs. While meta-analytic evidence documents average demand elasticities in the region (Zabaloy & Viego, 2022), we are not aware of studies that identify the *marginal-price* response under residential IBPs using RD/DiD hybrids.

Closest to our approach, Nataraj and Hanemann (2011) examine a large marginal-price increase in a third water block in Santa Cruz, California, combining regression discontinuity (RD) and difference-in-differences (DiD). They define treatment by historical consumption relative to the new cutoff, restrict to households near the threshold, and estimate a local treatment effect; they

find a ≈12% reduction among treated households. In electricity, Zhang et al. (2017) implement a fuzzy RD with DiD in China and find households respond primarily to substantial marginal-price increases. Complementarily, Zou et al. (2020) use DiD across provinces transitioning from uniform to IBP and report a short-run average reduction of 2.9%, with heterogeneity by block design and evidence that behavior often aligns with average rather than marginal prices. Likewise, Wichman (2014) show for water in North Carolina that consumers respond to average prices when billing features reveal the perceived price.

Unlike these settings, our context provides the additional advantage of observing households in the N1 segment, who did not experience any modification in the variable charge. This unaffected group enables us to extend the standard difference-in-differences framework and implement a triple-difference (DDD) model. By contrasting N2 households exposed to the reform with N1 households entirely unaffected, we can critically assess the robustness of the estimated effects and highlight potential discrepancies relative to the DiD results. This feature distinguishes our study from prior work, where identification relies exclusively on variation around a single threshold or across treated and untreated units within the same tariff segment.

The remainder of the paper is organized as follows. Section 2 provides the background on the institutional setting and tariff design. Section 3 describes the data and sample construction. Section 4 outlines the methodology. Section 5 presents the main results. Section 6 discusses robustness checks. The final section concludes.

2 Background

In the province of Tucumán, EDET S.A. is the company in charge of distributing and marketing electricity, supplying more than 530,000 users—equivalent to approximately 1.6 million inhabitants—with an annual supply of nearly 2,700 GWh. Its infrastructure comprises more than 15,600 kilometers of power lines and over 8,600 transformer substations. The company's activity is regulated by the Ente Único de Control y Regulación de los Servicios Públicos Provinciales de Tucumán (ERSEPT), an autonomous provincial body responsible for protecting users' rights and ensuring compliance with the current regulatory frameworks. Until September 2022, the electricity tariff was structured under a scheme introduced in January 2021 that combined

a fixed charge and a variable charge. Users were classified into four categories (C1 to C4) according to their twelve-month moving average consumption (MAC) for months with consumption greater than zero, which determined the monthly value of the fixed charge—this value increased with the consumption level. The variable charge had a single price throughout the year, with only one price increase step when consumption exceeded 750 kWh/month, at which point the marginal price rose due to the application of the so-called efficiency charge. In addition, there was a provincial-level subsidy, granted by ERSEPT and called the Tarifa Social Eléctrica (TSE), which provided a discount of approximately 55% on the fixed charge for low-income households.

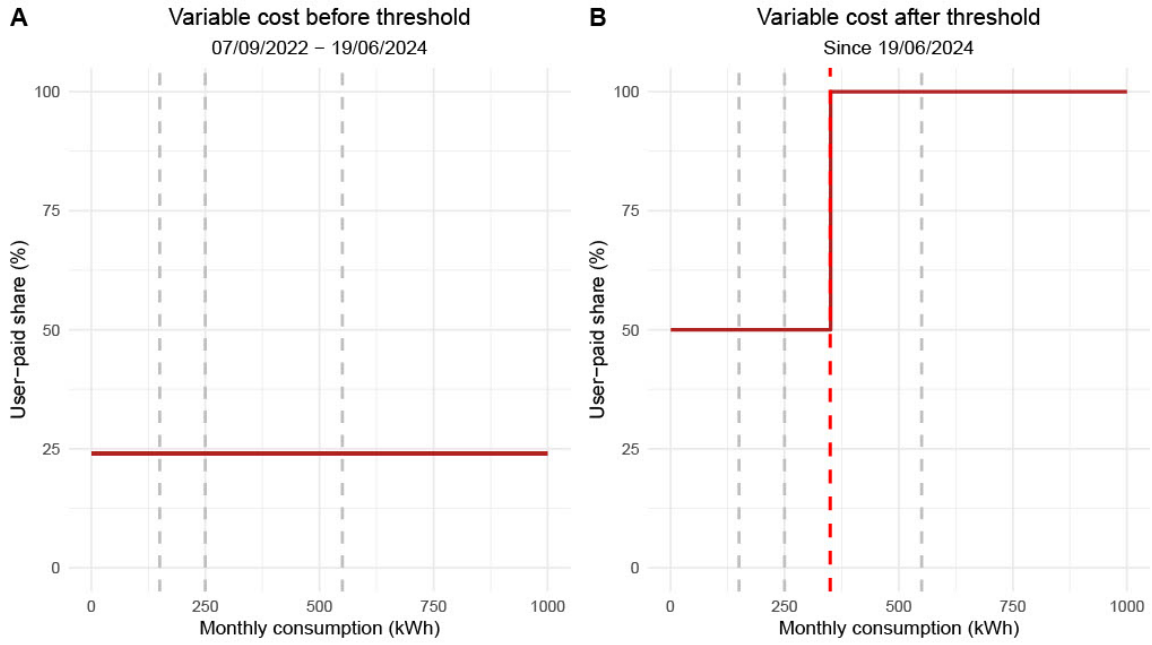
With the implementation of the Régimen de Segmentación de Subsidios al Consumo de Energía Eléctrica (RASE) on September 7, 2022 (Res. 552/22), the C1–C4 category system was maintained for the fixed charge, but the variable charge came to depend on the socioeconomic segment defined by the Secretariat of Energy:

- N1 (high-income): Households with incomes equal to or greater than 3.5 Canastas Básicas Totales (CBT, total basic consumption baskets) for a type-2 household according to INDEC, or those with high-value assets (three or more real estate properties, three or more recent vehicles, luxury boats or aircraft, among others).
- N2 (low-income): Households with incomes below 1 CBT (or 1.5 CBT in cases with a Certificado Único de Discapacidad—CUD), without recent vehicles and with at most one real estate property. This category also automatically includes those holding a ReNaBaP certificate, a lifetime pension for former combatants, or a CUD, as well as addresses with community kitchens registered in RENACOM, provided they do not exceed certain asset and income limits.
- N3 (middle-income): Households not included in N1 or N2, with incomes between 1 and 3.5 CBT (or between 1.5 and 3.5 CBT with a CUD), up to two real estate properties, and up to one recent vehicle.

During the period following the resolution, in early 2024, the N2 segment received on average a 76% subsidy on the variable charge. Resolution 486/24 established a subsidized consumption cap of 350 kWh per month and reduced the subsidy coverage in that initial block to 52%.

Once this threshold was exceeded, additional consumption began to be billed without subsidy, that is, paying 100% of the prevailing variable charge. With this modification, a traditional Increasing Block Pricing (IBP) scheme was established, in which the marginal price rises upon moving to the second consumption block. Figure 1 depicts the evolution of the marginal price structure for the N2 segment before and after the introduction of the 350 kWh subsidized cap, illustrating the shift from a flat price scheme with a high subsidy level to a block tariff with a reduced subsidy in the first tier and no subsidy in the second.

Figure 1: Evolution of variable cost for the N2 segment before and after the 350 kWh subsidized cap.



Source: Own elaboration

3 Data

The database used corresponds to a residential billing panel provided by the Ente Único de Control y Regulación de los Servicios Públicos de Tucumán (ERSEPT). The panel covers the period from September 2022 to February 2025 and contains more than 9 million bills, corresponding to 543,291 households. Of these households, 153,178 are billed on a monthly cycle, while the rest correspond to users with a bi-monthly billing cycle. Each observation represents an issued bill and includes detailed information such as the service number, energy consumption, reading dates, total billed amount, social tariff status, as well as georeferenced information (latitude and longitude) and complementary variables such as the RASE national

electricity subsidy segment and billing characteristics.

Before conducting the analysis, a series of restrictions were applied to the data. First, we focused only on users with monthly billing, excluding bi-monthly users due to differences in reading periods, which affect the timing of when households receive their bills and, consequently, their exposure to tariff changes. Second, we considered only households in the N2 segment with monthly billing and available information for three billing periods corresponding to December 2022, 2023, and 2024. Third, users were classified into treatment and control groups based on their historical consumption in December 2022 and December 2023. Users were defined as treated if in both periods they recorded consumption above 350 kWh, and as control if in both periods they consumed less than 350 kWh. Those who did not meet the conditions in both periods were excluded from the analysis.

Additionally, observations with consumption above the 99th percentile of the monthly distribution were excluded. This decision was made to mitigate the influence of outliers that may arise from measurement errors or positive exogenous shocks. Excluding the upper extreme of the distribution reduces bias from regression to the mean and allows the analysis to focus on representative consumption patterns, without results being driven by a small number of extreme observations.

The filtering process applied to the billing panel results in a final analytical sample of 75,312 households, differentiated according to their treatment status. Table 1 presents the distribution of households between control and treated groups, reporting both absolute and relative frequencies.

Table 1: Summary of the distribution of households by treatment status.

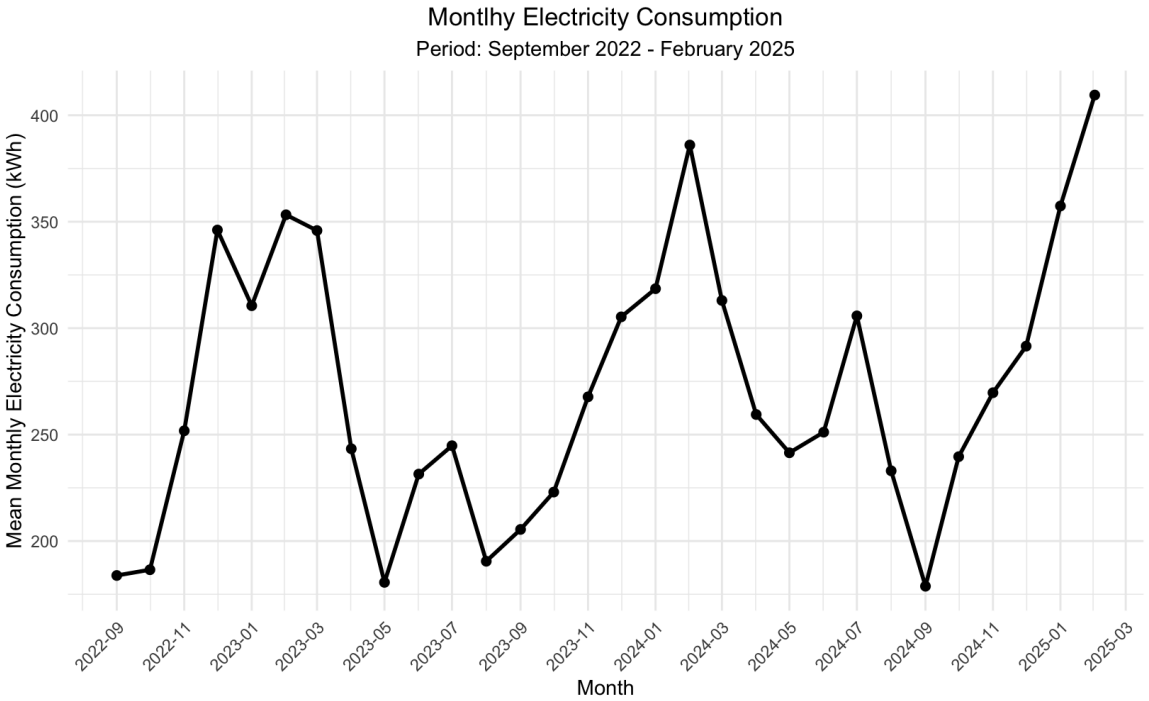
Treatment status	**Absolute frequency**	**Relative frequency**
Control	48,066	63.82%
Treated	27,246	36.18%
Total	**75,312**	**100%**

Source: Own elaboration based on ERSEPT data.

This summary shows that approximately two-thirds of the households belong to the control group, while slightly more than one-third are classified as treated.

Figure 2 shows clear seasonal fluctuations in electricity consumption, with pronounced peaks

Figure 2: Mean Monthly Electricity Consumption for N2 Households.



Source: Own elaboration based on ERSEPT data.

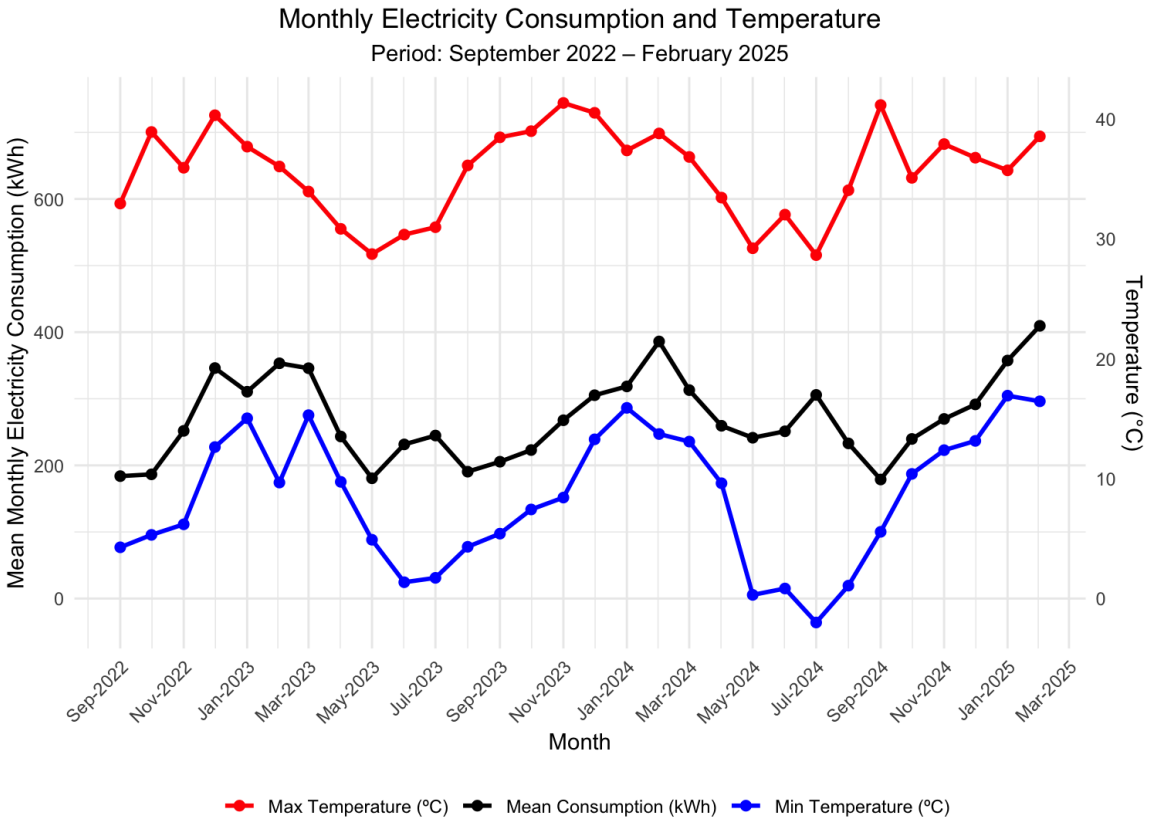
in December-February and milder increases in June-July, aligning with the austral summer and winter holiday periods, respectively.

To account for the pronounced seasonal patterns documented in Figure 2—and to avoid confounding the policy effect with weather-driven demand—we augment the billing panel with locality-level meteorological data from NASA POWER (Prediction Of Worldwide Energy Resources). NASA POWER combines satellite observations with NASA's atmospheric assimilation models to produce global, continuous climate series. Using this source, we retrieve monthly maximum and minimum temperatures for all localities in Tucumán over the study horizon and merge them to the billing panel at the service-locality and reading-month level, assigning to each observation (user–reading month) the corresponding maximum and minimum temperature (measured in ^{o}C).

As shown in Figure 3, electricity consumption co-moves with temperature: demand peaks in December–February coincide with higher maximum temperatures, where as winter troughs align with lower minima. This pattern justifies controlling for maximum and minimum temperature in the estimations to avoid conflating the policy effect with weather-driven variation.

Finally, Table 2 summarizes the descriptive statistics for the climate variables used in the anal-

Figure 3: Maximum and Minimum Temperature and Mean Monthly Electricity Consumption for N2 Households.



Source: Own elaboration based on ERSEPT and NASA POWER data.

ysis. It reports the locality-level average maximum and minimum temperatures for December 2023 (pre-reform) and December 2024 (post-reform) across the province of Tucumán. The results indicate a moderate decline in maximum temperatures between the two periods, while minimum temperatures remained relatively stable.

Table 2: December Temperature Summary by Locality (2023 vs 2024)

	December 2023		**December 2024**	
Descriptive	**Max temp (°C)**	**Min temp (°C)**	**Max temp (°C)**	**Min temp (°C)**
Mean	40.52	13.28	36.77	13.15
Variance	11.35	6.42	9.22	7.55
Std. Dev.	3.37	2.53	3.04	2.75
Maximum	45.95	16.57	41.53	16.29
Minimum	27.34	3.11	25.71	0.44
N	128	128	128	128

Source: Own elaboration based on NASA POWER data.

4 Methodology

In this paper, we empirically assess whether N2 households with persistently high consumption reduce their electricity use when the marginal price rises upon crossing the 350 kWh cap. Our working hypothesis is that, during a high-demand month in the post reform regime (specifically December) households that historically lay above the threshold reduced their consumption relative to those historically below it.

4.1 Model

Following Nataraj and Hanemann (2011), we estimate a difference-in-differences (DiD) model with household fixed effects:

$$Q_{it} = \alpha + \beta_1 Post_t + \beta_2.Treat_i + \beta_3(Post_t \times Treat_i) + \gamma X_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

Where:

- Q_{it} is the monthly electricity consumption of household i in period t (measured in kWh).
- $Post_t$ is a binary indicator variable that takes the value 1 if the observation corresponds to December 2024, and 0 if it corresponds to December 2023.
- $Treat_i$ is a binary indicator variable that takes the value 1 if the household user belongs to the treatment group, and 0 otherwise.
- $(Post_t \times Treat_i)$ captures the difference-in-difference estimator, β_3, which measures the average effect of the new subsidy scheme on the consumption of treated households.
- X_{it} is a vector of control variables (maximum temperature, minimum temperature)
- μ_i represents household fixed effects that control for unobserved heterogeneity over time.
- ε_{it} is the idiosyncratic error term.

Let $Q_{it}(d)$ denote household i's potential consumption in period t under treatment status $d \in \{0, 1\}$, where $d = 1$ means "historically above the cap. The coeffiencient β_3 from the two-period DiD with household fixed effects identifies:

$$ATT = E[Q_{i,post}(1) - Q_{i,pre}(1)|Treat_i = 1] - E[Q_{i,post}(0) - Q_{i,pre}(0)|Treat_i = 1]$$

Under the following conditions. First, in the absence of the reform, treated and control households would have followed parallel trends conditional on household fixed effects and weather controls. Second, no spillovers holds: one household's treatment status does not affect another household's consumption. Third, stable classification: the historical rule used to define $Treat_i$ is fixed ex ante and cannot be influenced by post-reform outcomes. Fourth, composition stability: there is no selective entry or exit that differentially changes the treated/control mix between pre and post. With only two periods (Dec-2023 vs. Dec-2024), the household fixed-effects OLS estimator is algebraically equivalent to the simple DiD contrast. With only two periods, the household-FE OLS estimator is algebraically equivalent to a simple DiD constrast.

5 Results

5.1 Baseline Model

Table 3 presents the results of the baseline specification. In column (1), which includes only the treatment interaction, the post-period dummy, and household fixed effects, the estimated coefficient is −75.380, significant at the 1% level. This implies that treated households reduced their monthly electricity consumption by approximately 75 kWh compared to control households, who did not face increases in the marginal price.

Table 3: Baseline results: effect of the cap (DiD) with and without weather controls

	(1) Baseline	(2) Weather controls
Treated × Post	−75.380***	−74.779***
	(1.119)	(1.118)
Post period	13.511***	48.126***
	(0.451)	(4.051)
Max. temperature (°C)		8.933***
		(1.023)
Min. temperature (°C)		−19.721***
		(1.420)
Constant	305.306***	224.611***
	(0.235)	(38.701)
Observations	150,624	150,624
R^2 (within)	0.0831	0.0850
Household FE	Yes	Yes
Clustered SE (servic)	Yes	Yes

Notes: Household fixed effects (within). Robust standard errors clustered by *servic*. Treatment and post dummies omitted due to collinearity.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

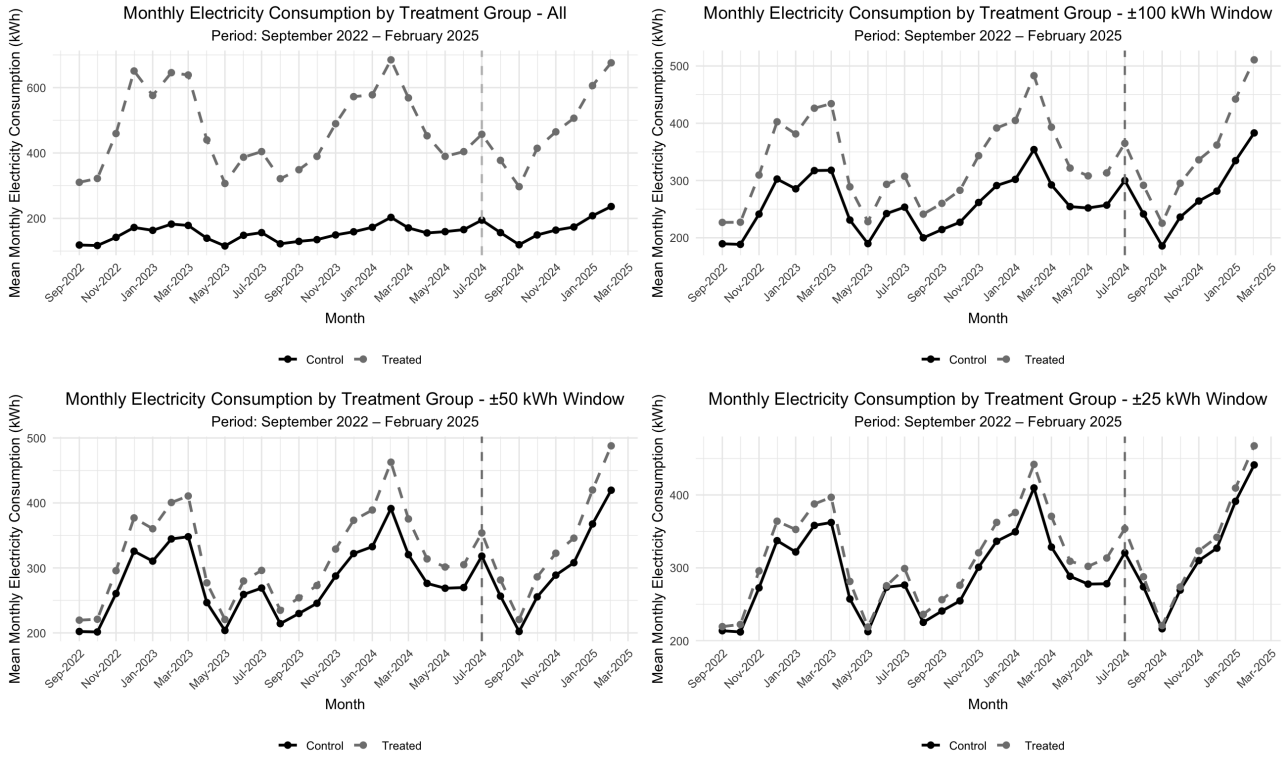
Columns (2) add controls for maximum and minimum temperature. As expected, higher maximum temperatures are associated with increased electricity use, while lower minimum temperatures reduce demand. The coefficient on the treatment dummy remains virtually unchanged (–74.8 kWh) and highly significant at the 1% level.

5.2 Regression discontinuity analysis

We now re-estimate equation (1) using households within the ±100, ±50, and ±25 kWh windows around the 350 kWh threshold. As the window narrows, the characteristics of treated and control households become more similar, making the comparison between the two groups more credible.

Figure 4 shows the average electricity consumption of treatment and control groups over time, under different window definitions around the 350 kWh threshold.

Figure 4: Average electricity consumption of treatment and control groups under different window definitions around the 350 kWh threshold.



Source: Own elaboration based on ERSEPT data.

In the unrestricted panel, treated households display a clearly higher level of consumption compared to controls. However, as we restrict the sample to windows closer to the threshold (±100, ±50, and ±25 kWh), the pre-treatment gap between the two groups progressively decreases. This occurs because, when approaching the cut-off, households share more homogeneous consumption characteristics, and the only systematic difference is their treatment status.

The figure highlights an important point. With broader windows, treated households appear structurally different from controls, which weakens their validity as a counterfactual group. By

contrast, in the ±25 kWh window, treated and control households follow much more similar pre-treatment trajectories, making the comparison more credible. This graphical evidence motivates the use of a restricted model, where the estimation is limited to households within narrower windows around the threshold, thus improving the reliability of the identification strategy.

To construct the restricted model, we applied a strict selection criterion that varies with the width of each window. Households are required to have electricity consumption in both December 2022 and December 2023 within the corresponding range: 250–450 kWh for the ±100 kWh window, 300–400 kWh for ±50 kWh, and 325–375 kWh for ±25 kWh. As the window narrows, treated and control households become increasingly similar in their pre-treatment consumption, differing essentially only in treatment status.

Table 4: Effect of the 350 kWh cap (DiD) with weather controls, by window around the threshold

	All (no window)	±100 kWh	±50 kWh	±25 kWh
Treated × Post	−74.779***	−19.718***	−11.979***	−7.937
	(1.118)	(2.438)	(4.522)	(9.949)
Post period	48.126***	50.551***	62.793**	160.712**
	(4.051)	(11.355)	(26.715)	(63.506)
Max. temperature (°C)	8.933***	15.474***	19.886***	43.237***
	(1.023)	(2.854)	(6.660)	(15.691)
Min. temperature (°C)	−19.721***	−33.269***	−42.148***	−53.541***
	(1.420)	(4.500)	(8.341)	(19.606)
Constant	224.611***	173.446	137.021	−694.073*
	(38.701)	(120.346)	(177.902)	(378.728)
Observations	150,624	17,378	4,372	1,030
R^2 (within)	0.0850	0.0415	0.0518	0.0349
Household FE	Yes	Yes	Yes	Yes
Clustered SE (servic)	Yes	Yes	Yes	Yes

Notes: Household fixed effects (within). Robust standard errors clustered by *servic*. Treatment and post dummies omitted due to collinearity. *Significance levels:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 reports the results. In the unrestricted specification, the Treated × Post effect is estimated at −74.8 kWh, highly significant at the 1% level. Within the ±100 kWh window, the effect decreases in magnitude to −19.7 kWh, and in the ±50 kWh window it further declines to −11.9 kWh, both coefficients remaining significant at the 1% level. In the narrowest ±25 kWh window, the estimated coefficient is −7.9 kWh and is no longer statistically significant. This pattern suggests that among households most homogeneous in their historical consumption, the

marginal price change does not induce an adjustment in electricity use. The loss of statistical significance may partly reflect reduced sample size, but it also indicates that households closest to the threshold do not exhibit a detectable behavioral response to the new tariff structure.

6 Robustness

6.1 Alternative window selection criterion

While applying a strict selection criterion for the inclusion of households within the windows helps to mitigate the influence of short-term shocks that could affect their classification, we also implement an alternative restriction based on average consumption over the last 12 months with positive usage. This approach further reduces potential biases associated with regression-to-the-mean dynamics and serves as a robustness check of our results.

Table 5 presents the estimates under this alternative definition. The treatment effects remain negative and statistically significant across all windows. The most relevant difference appears in the ±25 kWh window: under the strict December-based criterion (see Table 4) the estimate was not significant, whereas under the 12-month average criterion the effect is approximately −52.4 kWh and significant at the 1% level.

Table 5: Effect of the 350 kWh cap (DiD) with weather controls, by window around the threshold

	All (no window)	±100 kWh	±50 kWh	±25 kWh
Treated × Post	−74.779***	−19.718***	−11.979***	−7.937
	(1.118)	(2.438)	(4.522)	(9.949)
Post period	48.126***	50.551***	62.793**	160.712**
	(4.051)	(11.355)	(26.715)	(63.506)
Max. temperature (°C)	8.933***	15.474***	19.886***	43.237***
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Min. temperature (°C)	−19.721***	−33.269***	−42.148***	−53.541***
	(1.420)	(4.500)	(8.341)	(19.606)
Constant	224.611***	173.446	137.021	−694.073*
	(38.701)	(120.346)	(177.902)	(378.728)
Observations	150,624	17,378	4,372	1,030
R^2 (within)	0.0850	0.0415	0.0518	0.0349
Household FE	Yes	Yes	Yes	Yes
Clustered SE (servic)	Yes	Yes	Yes	Yes

Notes: Household fixed effects (within). Robust standard errors clustered by *servic*. Treatment and post dummies omitted due to collinearity. *Significance levels:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The difference found in the ±25 kWh window can be explained by the fact that the alternative criterion based on average consumption over the last 12 months corrects classification biases in a stronger and more systematic way. This approach smooths consumption and produces a more stable measure of household behavior. As a result, standard errors tend to be smaller, which makes it possible to detect a significant effect in the narrowest window. Therefore, the finding of significance in ±25 under the alternative definition should be interpreted as evidence that this criterion enhances the robustness of the results by more effectively reducing biases associated with regression to the mean.

6.2 Triple Difference Model

Unlike Nataraj and Hanemann (2011), our base allows us to incorporate an additional group (N1) from RASE segmentation. N1 households do not receive a subsidy on the variable charge, so they did not face the marginal price jump at 350 kWh that affects. This enables a triple-differences (DDD) design that compares, between pre (December 2023) and post (December 2024), the change above vs. below the threshold across segmentes N2 vs N1.

We estimate the following model:

$$\begin{aligned} Q_{it} = \alpha + \beta_1 Post_t + \beta_2(Post_t \times Treat_i) + \beta_3(Post_t \times Category_i) \\ + \beta_3(Post_t \times Category_i) + \beta_4(Post_t \times Treat_i \times Category_i) + \gamma X_{it} + \mu_i + \varepsilon_{it} \end{aligned} \tag{2}$$

Where:

- Q_{it} is the monthly electricity consumption of household i in period t (measured in kWh).
- $Post_t$ is a binary indicator variable that takes the value 1 if the observation corresponds to December 2024, and 0 if it corresponds to December 2023.
- $Category_i$ is a binary indicator equal to 1 for N2 households and 0 for N1 households.
- $Treat_i$ is a binary indicator variable that takes the value 1 if the household user belongs to the treatment group, and 0 otherwise. However, if households N1 are not "treated" by the policy, we classify them as treated/controlled using the same historical rule to keep the comparison above / below threshold symmetric between segments.
- X_{it} is a vector of control variables (maximum temperature, minimum temperature)

- μ_i represents household fixed effects that control for unobserved heterogeneity over time.
- ε_{it} is the idiosyncratic error term.

β_4 is the triple difference coefficient and the main parameter of interest. It isolates the causal effect of the 350 kWh subsidy cap bay comparing the change in electricity use of N2-treated households against: N1-treated households; N2-control households; and N1-control households. In other words, β_4 captures the net effect of the policy on the target group (Treated N2), net of time trend, treatment differentials in N1, and category differentials in N2.

We would expect the coefficient to be negative, given that only N2 households are directly subject to the consumption cap. However, as shown in Table 6, the estimate is positive, around 30 kWh, and statistically significant at the 1% level. This result implies that, on average, treated N2 households consumed 30 kWh more than the comparison group in the post-treatment period, which runs counter to the expected hypothesis of a reduction in consumption as a consequence of the cap.

Table 6: Triple differences (DDD) with weather controls — Full sample and by bandwidths

	(1) All (no window)	(2) ±100 kWh	(3) ±50 kWh	(4) ±25 kWh
Post × Treated	−104.976***	−21.261	−42.186	−87.615
	(4.554)	(16.412)	(41.032)	(67.143)
Post × Category	−19.306***	20.713**	3.388	15.201
	(2.709)	(7.493)	(22.934)	(55.470)
Post × Treated × Category	30.364***	1.714	30.901	80.632
	(4.694)	(16.601)	(41.295)	(68.053)
Post period	67.421***	26.867**	44.523	138.354*
	(4.714)	(12.939)	(32.852)	(73.600)
Max. temperature (°C)	8.989***	14.702***	16.197**	41.432**
	(0.994)	(2.757)	(6.551)	(15.187)
Min. temperature (°C)	−18.638***	−31.335***	−35.803***	−50.100**
	(1.368)	(4.324)	(8.279)	(18.972)
Constant	208.116***	176.432	197.832	−668.762*
	(36.398)	(113.059)	(174.673)	(366.869)
Observations	158,722	17,582	4,408	1,034
R^2 (within)	0.0863	0.0432	0.0502	0.0476
Household FE	Yes	Yes	Yes	Yes
Clustered SE (servic)	Yes	Yes	Yes	Yes

Notes: Household fixed effects (within). Robust standard errors clustered by *servic* in parentheses. Bandwidths are defined based on December 2022 and 2023 consumption.
Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Nevertheless, as we narrow the bandwidths to ± 100, ± 50, and ± 25 kWh around the threshold, the coefficient loses statistical significance. This pattern suggests that the individual result is driven by households farther from the cutoff, rather than by those at the margin who are of an

affect of the measure is not robust to choice of local windows.

7 Preliminary Conclusions

This study evaluates the impact of the introduction of 350 kWh subsidy cap on residential electricity demand in Argentina. The evidence points to a heterogeneous and somewhat fragile behavioral response, with clear differences depending on the econometric specification and the definition of treatment and control groups.

1. **Baseline DiD results.** The main difference-in-differences specification (Table 3) shows that treated households —those with persistent consumption above the 350 kWh threshold in December 2022 and 2023— reduced their electricity use by about **−75 kWh** in December 2024 relative to controls (**−75.4 kWh** without climate controls; **−74.8 kWh** with climate controls; both significant at the 1% level). This provides initial evidence that the reform induced a reduction in demand among high-use households.

2. **Window restrictions and regression discontinuity logic.** When restricting the sample to households around the cutoff, the magnitude of the estimated effect declines substantially: **−19.7 kWh** within the ±100 kWh window and **−12.0 kWh** within the ±50 kWh window (both significant at the 1% level), while in the narrowest ±25 kWh window the effect shrinks to **−7.9 kWh** and becomes statistically insignificant (Table 4). This pattern suggests that the strongest reductions come from households with consistently higher baseline consumption, while those just above the cutoff —the ones most directly targeted by the policy— show little or no detectable response.

3. **Alternative classification using 12-month averages.** Robustness checks based on average consumption over the preceding 12 months alter the conclusions for the narrowest bandwidth. Under this alternative criterion, the estimated treatment effect in the ±25 kWh window is **−52.4 kWh** (significant at the 1% level), instead of being insignificant as in the December-only classification (Table 5). This finding indicates that smoothing consumption histories reduces regression-to-the-mean problems and uncovers a stronger behavioral adjustment among marginal households.

4. **Triple-difference (DDD) results.** Incorporating N1 households into a triple-difference

framework (Table 6) produces unexpected results. In the full sample (no window), the triple interaction coefficient is **+30.4 kWh** and significant at the 1% level, implying that treated N2 households consumed more —not less— than the comparison groups after the reform. However, this counterintuitive effect disappears as the sample is restricted: the coefficients drop to **+1.7 kWh** (±100), **+30.9 kWh** (±50), and **+80.6 kWh** (±25), none of which are statistically significant. This suggests that the positive result in the full sample is driven by households far from the cutoff, rather than by those at the margin who are actually subject to the policy change.

5. **Interpretation and policy implications.** Taken together, these results indicate that while high-consumption households reduce demand in response to the cap, households close to the threshold -the group that should be most sensitive to marginal price increases- do not show a robust adjustment. This aligns more closely with Ito2014, who finds that households respond primarily to *average prices* rather than *marginal prices*. From a policy perspective, relying solely on changes in marginal block prices is unlikely to generate large or widespread demand responses. Instead, tariff design should account for how reforms alter the **average bill** faced by consumers, as this appears to be the salient economic signal guiding household behavior.

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