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Empowering Electricity Consumers through Demand Response: Why and How

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Inter-American Development Bank
Energy Division

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March 2022

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Abstract

Massive digitalization advances have made demand response (DR) programs feasible in the residential sector; however, most households in Latin America and the Caribbean (LAC) region do not know about these types of programs. In this report, the authors explore experiments about the willingness of residential consumers to adopt demand responses (DR) to reduce their bills. The authors analyze the likelihood of lower- and middle-income households across 11 LAC countries, adopting a DR plan. The questionaries counted on explanations about the purposes and benefits of the DR programs. The authors also analyzed the type of communication technology to which consumers are more likely to be responsive. Most interviewees understood that it would be fair to have peak and off-peak tariffs to cover supply costs. In three of the five cases analyzed, more than 50% of interviewees chose to move to a DR plan. Those were the case of the DR programs with a peak saving goal and pre-agreed discount, and heater or AC control by the utility during peak times. The results suggest that policymakers should start to consider demand response programs as a tool to increase the affordability of electricity services for residential consumers. It is important to consider the learning curve that will be required of users, services providers, and regulators.

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Introduction

Affordability is one of the pillars required for citizens and companies to benefit from energy services. The authors of this paper define affordability as the financial ability to pay for these services. The Inter-American Development Bank (Cavallo et al. 2020), highlights that the affordability of electricity services is a challenge for many low-income families in Latin American and Caribbean (LAC) countries.

The challenge for the sector and stakeholders alike is how to make energy services more affordable while ensuring quality and long-term financial viability for service providers. Digitalization opens new opportunities to overcome this challenge, increasing affordability and expanding the number of services households can afford. Digitalization measuring electricity consumption in households allows consumers to respond to cost, price, and rate variability. Consequently, it can be more affordable to adapt consumer behavior to periods of lower costs. Demand response is also a key mechanism for energy transition. According to IEA (2021), 55% of emissions reductions require a mixture of deployment of low-carbon technologies and active involvement or engagement of citizens and consumers. Demand response is one of these mechanisms, mixing new technologies with consumer/citizen engagement. Briefly, demand response programs depend on electricity sector digitalization to increase system efficiency and competitiveness and decrease sector emissions.

This document aims to explore demand response as a mechanism that can improve affordability by improving the system's efficiency through strategies that prompt consumers to act. Demand response (DR) can have a broader and universal impact, as affordability is driven by increasing efficiency in the power system.

The main idea of demand response is to smooth the electricity demand curves and, as a consequence, decrease costs. This is not a new idea. The difference is that digitalization makes achieving this goal more feasible, including in the residential sector. Electricity demand responses need to be fast; digitalization fulfills the required speed, disseminating information and completing transactions fast enough to facilitate demand response mechanisms (Cavallo et al., 2020). Demand response solutions have become even more valuable given the urgent need to address climate change. DR is an efficient and low-cost tool to decrease emissions and increase system flexibility, which is the key element for higher penetration of renewables.

However, an accurate estimate of DR programs' benefits for the residential sector is impossible. Historical data does not permit such an estimate. A massive demand response program will require transformations that empower consumers' decisions. Such a DR program should include market design, regulation, investment in digitalization, knowledge dissemination, and more participation of new players in the sector. In addition, policymakers, regulators, and stakeholders need to be convinced about the potential benefits that this kind of program can bring. Regulators should conduct regulatory impact assessments before any significant change. However, the lack of reliable data is still a common obstacle in the case of transformative innovations (such as demand response), though essential to calculate potential benefits.

An additional challenge exists in LAC countries. Residential electricity consumers are not accustomed to choosing their electricity providers, services, or consumption levels, considering the time of consumption. Furthermore, residential consumers often do not fully understand the tariff schemes to which they and their electricity bills are subject. In this context, it isn't easy to estimate the potential of adoption based solely on previous experiences and elasticities. Therefore, the present study acts as a point of departure for arriving at a better understanding of demand response potential in Latin America and the Caribbean. More precisely, its main objective is to understand consumers' willingness to participate in DR programs. Specifically, are consumers willing to change the way they use electricity to increase affordability of electricity services? That question is a first step in developing DR programs. Knowing consumers' willingness to engage in a demand response program is essential to calculate a program's potential benefits and to address digitalization solutions to enable it.

This study also aims to break the vicious cycle in which a lack of information delays innovation, and lower levels of adoption of innovative approaches delay gathering enough information. Reviewing available literature and conducting experiments with residential consumers about their willingness to adopt a demand response program are initial steps in breaking that cycle. The promising results of the experiment conducted suggest that pilots and regulatory sandboxes should be implemented as next steps in order to generate a better understanding of how to develop effective demand response programs.

The next section introduces available DR policies. Section 3 discusses the benefits of DR programs in general. Then, section 4 identifies the challenges and the results obtained from pilot DR projects in the residential sector. Section 5 is dedicated to detailing the experiment's methodology to evaluate households' willingness to adopt a DR package in 11 LAC countries. In section 6, the experiment results are presented. Finally, section 7 presents the study's conclusions and offers some policy recommendations for improving the adhesion and success of DR programs in the residential sector.

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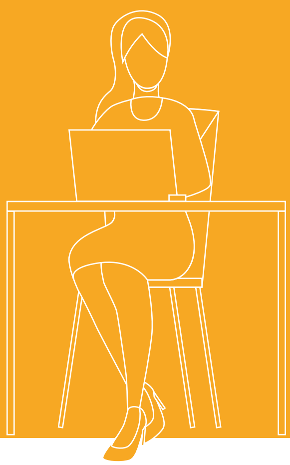


What are the demand response policies available?

Demand Response (DR) has a long history in the electricity sector and has been implemented using different approaches. DR was initially used to plan and implement mechanisms to produce large changes in electricity load curves in pursuit of improving the system's resource efficiency. The DR concept was adopted in the power sector at the end of the 1960s to optimize infrastructure investments and sustain demand during peak periods of operation. DR gained traction due to increases in oil prices, which in turn led to increased generation costs (Gellings, 1985).

Since then, DR policy options have increased in tandem with new technological advances. Historically, DR programs have usually targeted large (industrial or commercial) consumers. However, with the increased availability of advanced meters and other complementary utility technologies, these incentive programs can now be offered to residential or aggregated consumers.

The world is experiencing a digital revolution from which the energy sector is not exempt. New technologies have immersed the sector in a deeper digital environment, with massive data usage focused on increasing efficiency and reducing costs. In the demand sector, smart meters have empowered consumers, detailing their consumption by time of use and, sometimes, providing information on variation in electricity prices. Smart metering technology decreases considerably the transaction costs associated with demand response and increases the capability of timely responses (Cavallo et al. 2020)

It is important to highlight that significant investment in digitalization is essential for any DR program. These investments will certainly need to be made in telecommunications and smart metering technology. Investment may also include remote monitoring to control the use of equipment such as heat and air conditioning (HVAC) systems.

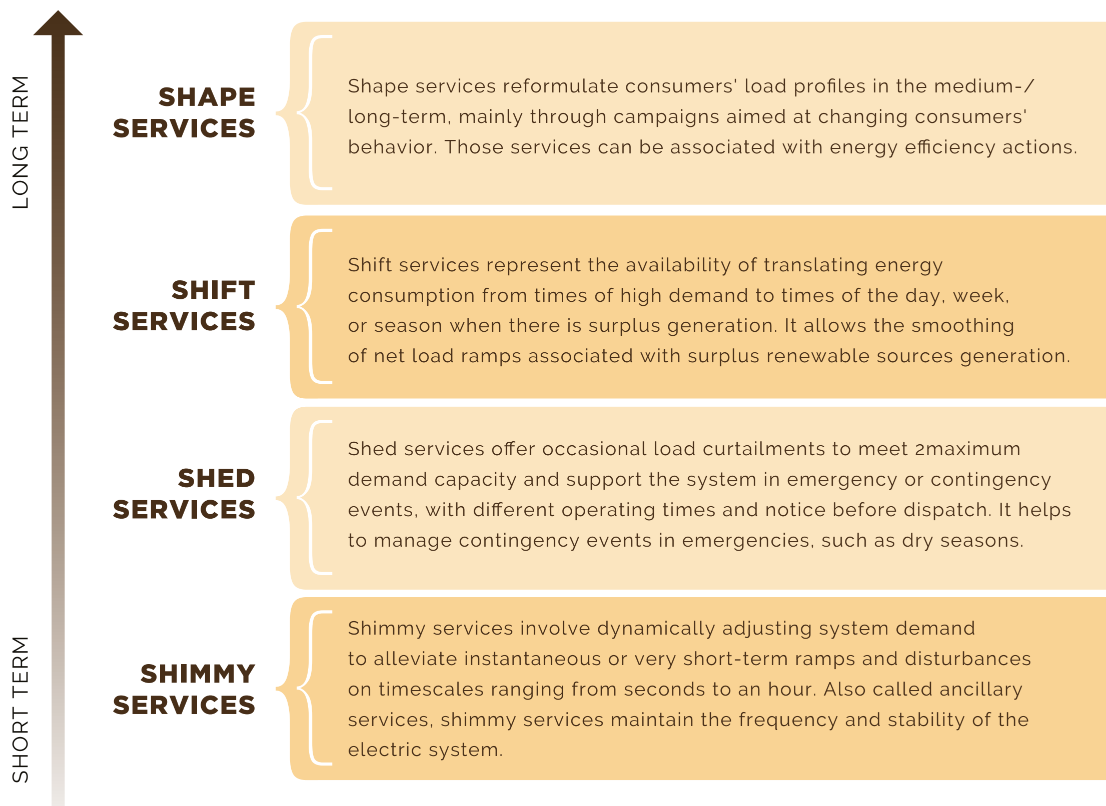
DR can be defined as a set of actions to reduce, increase, shift, or actively modulate energy demand for a limited time, compared to a baseline (or usual profile) of consumption, in response to a price signal or a command incentive, resulting in a lower service level (Satchwell et al., 2013)[2]. In other words, DR initiatives promote tools that empower consumers based on voluntary actions or decisions in response to economic incentives that operate in concert with electric system restrictions and market design.
Demand response always aims to impact or change load curves. However, there are different

2. The U.S Department of Energy (2006) describes demand response as a tariff or program established to motivate changes in electric consumption by end-users in response to changes in the price of electricity over time.

ways that DR can impact demand curves. While time-of-use (henceforth, ToU) tariffs are indeed the most common use of DR, it is not the only option for implementing it. DR is composed of various strategies that touch upon different parts of the electricity sector.

As presented in the first 80s studies, the impacts of the DR programs on the load behavior can be listed as: peak cut, valley filling, load-displacement, strategic conservation, strategic load growth, and flexible load format (Gellings, 1985). Alstone et al. (2016) created a didactic taxonomy for DR services that groups these services into the main categories: Shape, Shift, Shed, and Shimmy. Figure 1 details those DR services.

Figure 1. Demand Response Services



Source: Authors' design, based on Alstone et al. (2016)

The above DR services show the different objectives that the utility or policymaker can pursue to change the current shape of the daily load curve, which can be classified as either short- or long-term load curve changes. The question is, how can consumer behavioral change be incentivized to achieve the desired daily demand curve format?

DR programs must offer conditions perceived as beneficial for their adopters in order to incentivize consumers to take intentional actions. The principles of intentional actions and proper incentives are among DR programs' main characteristics.

DR programs can be grouped into two categories depending on the incentive rationale: (i) price-based programs and (ii) contract incentive-based programs.

2.1 Price-based DR programs

In price-based DR programs, electricity tariffs reflect better the actual electricity costs to fulfill consumption through different periods. Thus, the electricity tariff tends to increase when electricity generation presents higher costs to meet demand. Some examples of increased electricity generation costs are the usual challenge of attending to fast-increasing demand ramps and peak demand during the weekdays, or more critical situations, such as droughts or dry seasons, increased oil prices, network interconnection constraints, or misalignment of market design[3]. The schedule for price setting depends on each system.

As Muller (2016) and Satchwell et al. (2013) show, electricity tariff design can lead consumers to adapt their energy use. Suppose the tariff design relies on price differentiation to reflect generation costs. In that case, it may lead consumers to adapt their electricity consumption behavior and reduce the energy demand in critical periods when the cost to meet the demand is significantly increased. Thus, price-based DR programs are expected to enable consumers to respond to price signals, achieving an average tariff below the competitive flat tariff's conditions. The adoption of price-based DR programs is normally not mandatory, but optional.

DR programs with price differentiation are attached to induce change in the consumers by leading their consumption away from the expensive periods. Price-based DR programs come in various forms: static and dynamic time-varying prices. The first type is generally preset for pre-determined hours and days. It is less costly to implement since they only require monitoring the time consumption and depending on the prices in those consumption segments. The second type counts on electricity rates that change on short notice, often a day or less. It requires higher-costly metering (Albadi et al., 2008; Hale, 2018).

Therefore, price-based DR programs present diverse tariff designs with different objectives. The most famous ones are:

- **Time-of-Use (ToU):** Time-of-use (ToU) consists of predetermined blocks of time. The day is divided into periods with varying rates, or a seasonal rate, where the year is divided into multiple seasons and different rates are provided for different seasons. The simplest ToU has two blocks of time: peak and off-peak. Rates are pre-determined, and their design attempts to reflect average generation and transmission costs during these periods. In this way, the consumer shifts energy use to moments when the price is lower, reducing consumption when the price is higher (SEDC, 2017; Faruqui & Sergici, 2013). ToU has become a more viable rate option, thanks to the increasing prevalence of smart meters. Although the ToU tariff is largely used by higher-demand consumers (e.g., industries), those tariffs are also available for smaller-demand consumers in many countries.

- **Critical Peak Pricing (CPP):** CPP consists of an additional time-dependent rate added to the flat rate during a contingency or high wholesale electricity price. Consumers pay higher prices during days when the cost of energy is high. In exchange, participants will have a discount on the standard tariff during other hours of the season or year (Batlle & Rodilla, 2019). Estimating consumers' response to price changes is challenging, so this mechanism introduces more complexity to the system operation. CPP tends to work with pre-determined rates.

3. In theory, all points in the grid can have the same price in a region under compatible market designs and a lack of restrictions.

• **Critical Peak Rebate (CPR):** CPR is similar to CPP, but the utility anticipates critical events. It can be challenging because it requires information about each client's consumption behavior pattern. CPR is less complex in terms of system operation than CPP, as the consumer's response is agreed upon in advance by the client and supplier. Participants are remunerated to reduce their consumption compared to a baseline offered by the utility. However, suppose the consumer decides to participate in the tariff modality, and they do not change consumption behavior. In that case, they can pay a higher electricity price. Customers who do not wish to participate, pay the current energy tariff. CPR tends to work with predetermined rates.

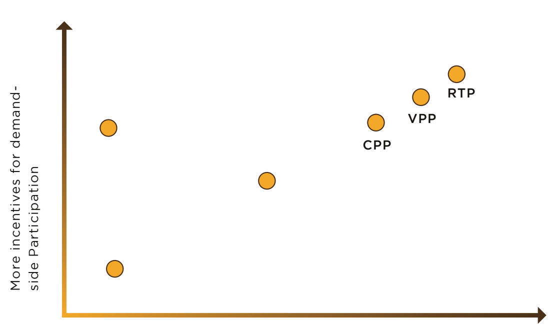
• **Variable peak pricing (VPP):** VPP is a hybrid of ToU and real-time pricing (RTP). The off-peak tariff and blocks of time are defined in advance. However, on-peak prices are more variable because they follow wholesale electricity prices. As such, this mechanism requires more accurate measures and communication equipment. VPP tends to work with dynamic time-varying rates.

• **Real-Time Pricing (RTP):** RTP reflects all variations of wholesale electricity prices. RTP is based on dynamic time-varying rates. Participants are informed about prices a day ahead or an hour ahead. In this way, they pay for prices being signaled economically for the energy market, reflecting each hour's actual generation and transmission costs. Two examples of RTP mechanisms are the Day-Ahead Real-Time Pricing (DA-RTP) and the Two-Part Real-Time Pricing (TP-RTP) (Batlle & Rodilla, 2019).

These price-based DR programs differ regarding the amount and frequency of information shared between utilities and customers. In general, ToU rates require a lower information exchange and offer more user-friendly price signals. However, those tariffs may be supplemented by other mechanisms, such as the CPP and CPR. Further, VPP and RTP are considered purer forms of dynamic pricing. They are based on actual market conditions and thus offer a more accurate price signal for electricity costs (Faruqui & Bourbonnais, 2020)[4].

All DR mechanisms present a significant trade-off between the level of incentives for demand-side participation and the complexity of the DR mechanism interpreted as a consumer risk. Figure 2 illustrates the trade-offs of different dynamic pricing programs. Default flat rates are the mechanism with lower complexity and lower incentives. Among the many options shown in Figure 2, the most risk-averse customers would likely go with a flat rate, which remains constant regardless of the volatility in their load profiles or their electricity prices.

Figure 2. Comparison of different dynamic pricing programs



Source: Prepared by the authors, adapted from Faruqui and Bourbonnais (2020)

4. Acuña et al. (2016), compared ToU schemes with Day-Ahead Real-Time Pricing (DA-RTP) and found that ToU implementation led to bigger cost savings than DA-RTP.

Price-based DR mechanisms increase in complexity as they increase their incentives to consumers' participation (Figure 2). ToU has lower incentives, complexity, and consumer risk than the presented price-based mechanism. CPR presents low complexity and high incentives to entice consumers' adoption. Low complexity can be explained probably due to adherence to flat rates. High incentive levels can be related to consumers never paying a higher price in that modality. Indeed, they receive a discount due to demand reduction during peak hours.

Critical Peak Pricing (CPP) has the same rates with the same level of incentives as CPR rates, but a more complex implementation and operation. Variable Peak Pricing (VPP) and Real-Time Pricing (RTP) rates are the most complex price-based DR mechanisms. Risk-taking customers would likely go with a RTP rate that, on average, would probably give them a lower average price. Each of these rate options presents a unique trade-off between the tariff savings that customers would experience and the risk they would be exposed to in the form of tariff volatility.

RTP and VPP rates require more advanced metering infrastructure for constant communication between system operators and customers. In contrast, ToU, CPP, and CPR rates are calculated and communicated ahead of time and are simpler to implement (Hale, 2018). CPR mechanisms carry much lower informational burdens that can be satisfied by installing interval electricity consumption meters and sending customers electronic messages about electricity prices through SMS, web portals, or apps.

2.2 Contract incentive-based programs

A contract incentive-based program is a more 'explicit' form of demand response (DR). Consumers, directly or through an intermediary (such as an aggregator), commit to changing the demand behavior given a specific compensation pre-set by the contract incentive-based program (European Commission, 2016). As a result, this type of DR program is easier to track.

Contract incentive-based DR programs can be set up through bilateral contracts or regulated auctions of capacity, ancillary services, or emergency response. In all cases, there is an ex-ante commitment to comply with the program and a set of penalties in case of non-compliance.

Consumers generally receive a discount to change their demand load baselines, adhering to the program's system requirements. Incentives are included in a contract and are 'explicit' in these programs. Thus, operators can better predict load impacts since the nature of the contracts often involves penalty clauses for noncompliance.

Like price-based DR programs, contract incentive-based programs also require a high level of investment in digitalization. Contract incentive-based programs can also demand investment in remote monitoring and controlling tools to control electrical appliances owned by the consumer, such as heaters and air conditioners. As such, these programs allow fast response and flexibility, as seen in the shimmy and shed load impact models described above. It also allows the operator to have deeper control over the system.

Since there is an aspect of direct control ingrained in incentive-based programs, data specificity data gains significant importance. The US Department of Energy (US DOE, 2006) and the European Commission (EC) (2016) point to response timescale as a crucial issue for system operators and policymakers. The closer the commitment of loads is to real-time, the greater avoided value and the need for accurate price signals and system operator control reliability (European Commission, 2016). Such a level of information can be obtained at different times for different areas of operation. It can be implemented over time in order to even out need for investment.

3

What are the expected benefits of demand response?

Demand response (DR) aims to reduce the operational costs that stem from the variability of the electricity load curve. The load curve comprises the total electricity used by consumers connected to a national or sub-national electricity system. This load curve is specific to the set of circumstances, customs, and traditions of every country or region, and daily behavior patterns.

Since electricity is challenging to store under current technological constraints, electricity generation must ideally match consumption instantly. Otherwise, it creates system disruptions, such as blackouts, brownouts, or losses that hinder network performance and whose costs accumulate over time.

Therefore, DR is mainly a mechanism to decrease costs associated with net demand load curve variation. Net demand curve is the difference between the demand for electricity minus the non-dispatchable electricity sources, which operators cannot control, such as wind power and solar photovoltaic (PV).

Dispatchable electricity generation needs to vary in response to variation in net electricity demand. However, the cost structure of electricity generation is discontinuous. Electricity generation is most often produced by a portfolio of power plants. These plants have different cost structures, which means they have different fixed and variable costs.

For some power plants, it is more efficient to have the power plant running most of the time. These are called base load plants. In contrast, there are also peak load plants. Peak load power plants have a faster starting-up system and higher operational cost. Therefore, they are normally dispatched only for a few hours, typically during peak hours. In other words, peak load power plants are used to cater to net demand peaks, and they are started up whenever there is a spike in demand. They stop when demand recedes.

Therefore, variation of net demand may lead to increased short-term system costs, mainly due to:

- **Additional starting-up costs:** Before a thermal plant can feed electricity to the grid, it has to be started up, i.e., ramped up, at least to the minimum generation level. That usually comes at a cost, independent of how much output is produced. It is a kind of quasi-fixed cost. The size of these quasi-fixed costs stemming from wear and tear and the fuel required to heat the steam cycle depends on the type and size of a particular plant. The higher the demand variation, the higher the costs and risks associated with starting up. The expected increase of the net demand variation has increased these costs and risks in different power systems[5].

- **Higher marginal costs of peak load plants:** An electric system has power plants with different cost structures. The electricity dispatch process identifies which plants will be dispatched and how much electricity they should generate. This process is based on a merit order, ranking available sources based on the ascending order of marginal costs or prices[6]. In both cases, it is expected that plants with higher marginal costs are the last to be brought online[7]. Peak load implies that power generation with the highest marginal cost is dispatched, which increases the short-term system cost. Moreover, in most cases, peak plants tend to run on fossil fuels and have a lower level of energy efficiency. Consequently, they tend to have a higher level of CO2 emissions.

The expected value of net peak demand also impacts long-term costs. Both generation portfolios and network systems are built to face peak demand. Consequently, grid size and available capacity need to be reliable in response to peak demand, independently of peak demand length. Higher peaks requiring expensive infrastructure will be less used, generating a large idle capacity. It means that decreasing peaks may mean an increase of service higher than investment requirements and costs.

Decreased costs resulting from implementing DR programs will impact different players, depending on electricity market design and regulation. In ideal scenarios, decreased costs are an economic benefit of Demand Response programs[8].

Depending on the specificities of each context, DR programs can offer a range of financial and economic benefits for electricity markets: direct benefits, which are experienced by consumers who carry out demand response; and indirect (or collateral) benefits, which are enjoyed by a segment of market-wide participants. These benefits are perceived and shared depending on regulation and business models. Key benefits of demand response are described in the following five groups:

5. For more information about the impact on risks and costs associated with demand variability, see Stoft (2002), Vazquez et al. (2017), and Shill et al. (2017).

6. For the market-based systems, it is assumed that prices reflect the order of marginal costs of production.

7. Sometimes, generating units must be started out of merit order, due to transmission congestion, system reliability, or other reasons.

8. In cases in which consumers answer to price variation individually, it is not easy for market operators to estimate the impact of DR programs and their respective benefits. Consult Rodas-Gallego and Mejía-Giraldo (2020) for more context in this regard. The authors simulated the evaluation of DR program impact on electricity costs in Colombia. Their results indicate that the daily economic benefit of this DR program could range between 44 and 381 million.

1. **Participant financial benefits** are the monetary reward enjoyed by those customers who respond to the economic signal by adjusting their electricity demand.

2. **Market-wide financial benefits** result from lower use of peak-load power plants and lower network capacity requirements.

3. **Reliability benefits** are operational security and adequacy savings that result from reduced consequences of forced outages.

4. **Market performance benefits** refer to demand response's value in mitigating suppliers' ability to exercise market power, so that DR programs avoid power prices rising significantly above production costs.

5. **CO_2 emissions reduction:** Shifting demand from peak to valley avoids generation through speed-dispatchable power plants that rely upon fossil fuels. That allows more efficient use of intermittent renewable energy sources and the drop of CO_2-intensive electricity supply.

The U.S. Department of Energy (2006) groups benefits resulting from demand response programs into participant financial benefits, market-wide financial benefits, reliability benefits, market performance benefits, and market performance benefits. The authors of this paper would add environmental benefits, which are increasingly vital in the context of climate change and its impacts.

Historically, while initial DR efforts aimed to prevent generation outages and improve resource efficiency and affordability, advanced DR programs seek wider impacts beyond the electricity market. In recent years, DR programs have been a possible solution to provide a more flexible demand load compatible with variable renewable source expansion (such as solar and wind power) and CO2 emissions mitigation goals (IEA, 2021; Gagne et al., 2018; Dranka & Ferreira, 2019). The rise of variable renewable sources, which frequently have zero variable costs, is expected to increase the variability of the marginal costs of electricity. In this context, the maximum marginal electricity cost will be defined by the highest net demand peak, which combines the highest demand and lowest participation of renewable energy. In contrast, the lowest marginal costs will be defined by the lowest net demand points, lowest demand, and the highest participation of renewables generation in the mix. The interaction of both curves can substantially increase the differences of peaks and valleys, leading to the growth of economic value of demand flexibility.

Goldenberg et al. (2018) analyzed DR strategies as a path to enhance renewable integration in the ERCOT market (Texas' electricity system). The study found that demand response programs could lower peak demand net of renewables by 24% and reduce the average magnitude of multihour generation ramps by 56%. The authors concluded that demand response programs are cost-effective compared to new gas-fired generation. According to the modeled system, those programs would avoid approximately $1.9 billion of annual generator costs and 20% of total annual CO2 emissions (Goldenberg et al., 2018).

IEA (2021) expects DR mechanisms to bring 500 GW of demand response onto the market by 2030. In a net-zero emission scenario, those mechanisms will shift up to 15% of average annual demand by 2050. However, DR's potential is far from being explored fully. At present, demand response represents less than 3% of the flexibility requirement, and most adopters are industrial or large commercial consumers. The demand-side flexibility provision should increase as adoption of batteries and electric cars grows (IEA, 2021). According to IEA (2021), introducing DR programs combined with batteries will be an important arbitrage power for consumers, especially residential ones[9].

Although demand response is estimated to grow most rapidly in advanced economies, it will be present in developing countries, too. As IEA (2021) shows, demand response mechanisms in developing economies will be responsible for around 14% of electricity system flexibility in 2030, assuming a net-zero scenario. Some developing countries in Latin America are already adopting important measures to increase demand response uptake. Chile launched a power system flexibility strategy focused on market design, regulatory frameworks, and system operation. Colombia extended tax incentives to non-conventional energy sources and energy efficiency projects, including smart metering and demand response. However, as IEA (2021b) expects AC stocks in Latin America and the Caribbean to increase more than sixfold, an AC energy efficiency strategy combined with a demand response program could be an interesting solution to the electric system's affordability and sustainability.

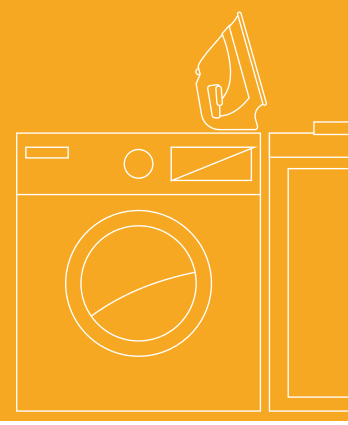
Dranka and Ferreira (2020) expect that DR potential in Brazil will double, increasing from 12.8 GW in 2017 to almost 25.6 GW by 2050. Most of that potential is in the industrial sector. Still, the authors identify a huge potential in the residential sector, especially from air conditioning systems between 10 p.m. and 6 a.m. The study estimates that the highest value for demand response potential in the residential sector to be 5.5GW at 10 p.m. for the entire power system.

The next section will discuss the application of DR programs in the residential sector and the results of pilot projects developed in that sector.

9. An example of analysis for Mexico can be found in Castro Abril (2020).

4

Demand response programs applied to the residential sector



DR policies in LAC have been implemented generally for industrial consumers with flexible electricity consumption. Factories can organize production schedules in low-cost hours to minimize electricity costs while obtaining the same outcome. Factories are easier to monitor, since they are equipped with more sophisticated meters to track consumption. However, Advanced Measuring Infrastructure (henceforth, AMI) has reduced costs in recent years, signifying its feasibility for household applications.

In most LAC countries, the consumption peak occurs after business closes, when citizens return to their dwellings (Sanchez et al., 2021). Enticing these users to adopt DR programs has enormous potential to shift the load curve, lowering structural costs of the system to make electricity a more affordable service.

The active consumer's participation is made possible by enhanced grid digitalization and continuous cost reduction of advanced metering infrastructure (AMI) and monitoring technologies. In this context, home energy management systems or building energy management systems are essential. HEMS can focus on automatic control devices for specific appliances like electrical water heaters and HVAC (heating, ventilation, and air conditioning). These systems are essential in price-based DR, automating the decision of price signal responses and connecting advanced meters of small-scale consumers to load aggregators.

More targeted DR tariffs also rely upon the remote control of certain dwelling appliances, such as heaters or air conditioners (two of the most energy-intensive dwelling appliances). However, occupants' electricity price sensitivity levels significantly impact cost-savings (Wang et al., 2018), so DR program adoption allows identification of activities that the consumer considers flexible.
Identifying flexible energy service demand, such as heating and air conditioning, is especially challenging in lower-income households with more stringent budget limitations. Lower-income households see the electricity bill as a heavy budget burden. Thus, DR programs can be an alternative for low-income families, increasing the affordability of their electricity services. With a DR program, these families may use these services during off-peak hours due to a lower rate. A

DR program can alleviate the burden of electricity bills and contribute to reducing energy poverty and deprivation of energy services. It is worth noting that families with the lowest income often do not have access to many appliances, especially the most flexible. It is vital to develop a more detailed analysis of the reaction of different households in this context[10].

Box 1. The role of AMI's in residential Demand Response programs

Residential Demand Response programs require some degree of improvement over the very metering and monitoring of electricity consumption. Although some programs require more frequency of metering and communication, not all programs stand at the exact requirements of complexity. Some programs require only the identification of the current day's consumption periods.

Residential Demand Response programs are facilitated by installing advanced metering infrastructure (AMI). AMI is especially important in the case of dynamic systems. AMI includes a smart metering system and a telecommunication system. A smart metering system is an electronic system that can measure energy consumption, providing more information than a conventional meter. Smart metering is normally associated with telecommunication systems that retrieve electricity consumption data and share it with the utility in the frequency required by the tariff. Similarly, AMI enables customers to access their electricity consumption data (Borenstein et al., 2002).

Advanced meters and telecommunication systems are essential elements of successful Real-Time Pricing - RTP and Variable peak pricing - VPP mechanisms. These systems record usage on a specific time interval, upload the data from the customer site to a central data processing center, and permit customers to access their usage data. These systems should be adaptable enough to allow differential rates of data uploading and display commensurate with the tariff for the customer.

According to the Federal Energy Regulatory Commission (FERC, 2018), 78.9 million advanced meters were operational in 2017 out of 152.1 million meters, indicating a 52% penetration rate in all USA regions and an increase of approximately 5% from 2016 to 2017. Around 200 million smart meters were expected to be installed in Europe by 2021 (Jansen et al., 2020). According to Eid et al. (2016), the installation cost of a smart meter in Europe is, on average, between 235-293 USD. Several technologies can be used to deploy smart meters, including wireless and wired solutions.

Current trends in the smart grid application for DR research are explored in numerous smart grid labs worldwide. For instance, 57 laboratories are conducting extensive research on DR, and 35 are conducting research on AMI (Jansen et al., 2020), underscoring how DR policies depend on the development of some hardware applications. In addition, AMI expands opportunities for better network management, resulting in more affordable costs to the consumer.

DR brings electricity consumers greater agency, knowledge, and management over their consumption in response to supply conditions. DR empowers consumers, centering their ability to make their consumption affordable and the system more efficient. In this way, DR mechanisms should be part of a country's energy policy because they can contribute to economic efficiency, and to improving reliability and security of electricity supply sustainably. More active participation of DR can prevent supply crises, which raise prices and operating costs. For these benefits to accrue, an adequate infrastructure with communication in real-time must be in place for DR implementation.

10. Further studies and measurements are necessary regarding the capacity of low-income groups to answer to price variations.

4.1 Examples of general residential demand response programs in LAC

The authors wish to share a few examples of pilot and commercial projects applied to the residential sector. Residential programs are mainly focused on price-based DR programs. Time-of-use (ToU) and Critical Peak Pricing (CPP) are the most common models applied in residential experiments.

LAC countries have already presented some voluntary-adoption time-of-use tariff modalities for the residential sector. Adoption has not been significant, however. Brazil, Uruguay, and Costa Rica are examples of LAC countries that have commercial DR programs for the residential sector. Adoption is limited. No publicly available comprehensive study evaluates these programs.

The Brazilian Residential ToU plan (also known as Tarifa Branca) has been available since 2018. The program had 51,138 household adopters as of September 2021. The number of adopters underscores the fact that this is only a first step, which needs to be further analyzed to understand the program's advantages and challenges. Areas of potential study include assessing information about the DR program that reached consumers; level of financial incentive (considering discount and risks); and behavior and cultural barriers. The program's peak tariff is almost double the flat tariff. The off-peak tariff represents a discount of around 20% compared to the flat tariff. By adopting the ToU plan, the consumer takes an important risk: the potential of a substantial increase in their electricity bill. This can be an important barrier to adopting a new program.

4.2 Examples of pilot projects for residential demand response programs

Pilot programs for residential demand response programs raise some interesting points, especially concerning the heterogeneity of results.

Faruqui and Sergici (2013) developed a study based on the Arcturus database of price-based DR programs containing 163 samples, which encompassing seven countries. The study found a discrepancy in results for demand response applied in the residential sector, which varies from 0 to 58% in terms of peak reduction. At first glance, there is little consistency in these results, with significant variation among pricing types. Due to their tendency to have higher energy price ratios than TOU rates, CPP and PTR rates could show a tendency to result in higher customer response. This hypothesis was justified using high price ratios for these rates.

However, Faruqui and Sergici's (2013) analysis found that much of the discrepancy in results is eliminated when DR is expressed as a function of the peak to off-peak price ratio because customers respond to rising prices by lowering their peak demand consistently in order to keep expenses affordable. This finding supports the case for the rollout of dynamic pricing wherever advanced metering infrastructure is in place. Consumers have more control of energy consumption inside their residential dwelling. Filtering by rate type and enabling technologies, it is possible to see that enabling technology appears to increase DR adoption levels, which underscores the central role of digitalization in this process.

Faruqui and Sergici (2013) defined the treatment as a unique combination of a time-varying pricing design and enabling technology. However, the variation in demand response can be attributed to the rate types applied to each specification of market and demand. The rest is potentially due to other factors, such as differences in socio-demographic characteristics and climate conditions.

The impact of rate type in the demand response effectiveness depends on the rate itself and the risks associated with financial incentives. There is a challenging threshold and design to incentivize the customer to change from something they know to something they do not know. The incentive must be high enough and with low perceived risk for consumers to adopt the DR plan and change their consumption in the short-term (Lujano-Rojas et al., 2012).

The customer's perception of the demand response model is also critical for its success. Ttariff models should have an interface that allows users easy access, allowing them to correctly interpret information provided to react as requested. Models should also be flexible and compatible with the routines in people's lives. Experiments had higher impacts and achieved more significant electricity consumption reduction when households had information feedback about their electricity usage. This feedback concerns daily profile load and time series of tariff prices. In several studies, smart metering appliances were installed in households to ease the tariff model's adoption. Results indicate that access to real-time electricity prices and information on their continuous consumption levels is important to encourage the customer's response (Erickson, 2011; Stokke et al., 2010).

Still, considering the impact of the relationship between demand response and people's routines, Walker and Hope (2020) showed some barriers to behavior change in an experiment with 33 households. According to the authors, the responsibility of managing multiple activities during the night disturbed many household respondents. Customers argued that it was not feasible to deal with multiple tasks in a short period of time, and the economic compensation was not worth the effort. This challenge needs to be considered when designing the program and the required digital automatization tools to minimize the need for actual behavior change.

DR programs focusing on electricity services, such as lighting, air conditioning, dishwashers, and other appliances, can be more user-friendly or easier to understand by household consumers. A good example is a variable-peak pricing (VPP) program launched in Oklahoma. Nearly 90,000 customers there have chosen to adopt the VPP. Most agreed to install a smart thermostat provided by the utility in order to control their temperature according to the electricity price (FSR, 2020).

Asadinejad et al. (2016) show that appliance-based elasticity and customer classification reduce peak prices while increasing off-peak prices, greatly reducing price variation. In their pilot project with more than 1,400 households in the United States, Asadinejad et al. (2016) concluded that load reduction through direct control of the heating, ventilation, and air conditioning (HVAC) thermostat tends to be more effective than other devices. This is because HVAC often is the largest portion of the aggregate load, and it tends to be flexible in the short-term. Results, however, are mixed. In a large-scale online survey, Shi et al. (2020) showed a trade-off associated with the willingness of households to let third parties control their appliances. A survey of 1,575 North American households investigated residential customers' engagement in household activities, energy consumption habits, and willingness to participate in incentive-based demand response programs. The study considered two DR programs: an incentive-based one with automatic control of the thermostat temperature setting of HVAC and hot water usage; and a price-based one involving manual curtailment behavior. The study showed the resistance of households to have their appliances controlled. Moreover, challenges were observed for programs where a thermostat controller was installed in rented dwelling units with seniors or babies sensitive to temperature changes.

Another element that needs to be considered is weather conditions, especially with respect to air conditioning and heating management. According to Bartusch et al. (2011), households experienced an electricity cost reduction two times higher in summer than in winter. Experiments showed that load shifting was more effective for regions with well-defined seasons, especially during the summer.

In sum, residential DR programs are quite heterogeneous, as are their results. The household's circumstances, its appliances, and the program design matter. Price incentives can work, but they need to be conceptualized and marketed in a way that's acceptable to consumers. For instance, residential consumers tend better to understand the conceptualization of peak/off-peak duality to make decisions. DR programs tend to be more successful in the residential sector if they bring significant incentives to the residential consumer, lower risk perception, rely on user-friendly AMI tools, have a good communication campaign to explain potential program benefits to consumers, include tips on how to change energy consumption patterns to respond to electricity price signals, or provide additional HVAC temperature control instruments.

After reviewing the specific applications of demand response to the residential sector and different pilot experiences that have been implemented, the study now turns its attention to provide evidence for the potential adoption of those programs and what the preferences and characteristics of a LAC consumer open to demand response programs are. Understanding how to engage residential customers and encourage their voluntary adoption is crucial to the success of a residential DR program. The engagement question is the focus of the experiment developed in the study, whose methodology is presented in the next section.

5

Methodology and design of the demand response experiment

This section aims to contribute to the design of potential DR policies with experimental insights. This section will discuss the following questions: How can policymakers and energy distribution firms better engage with households to encourage a better understanding of DR incentives? What are the preferred DR plans offered to consumers by utilities? What are the perceptions of these plans? The experiment uses lessons from the literature on psychological interventions to inform and motivate conscious decision-making concerning DR programs.

5.1 The theoretical background of the methodology

Recent scientific research (Costa, 2012; Gunther et al., 2010; Gustafsson & Gyllenswärd, 2005; Holmes, 2009; Langevin et al., 2013; Wada et al., 2012, Dillahunt & Mankoff, 2014) has provided initial evidence of the effeicacy of psychological interventions to optimize households' energy consumption rates. For instance, researchers have provided information and feedback to consumers through visualizations, termed eco-feedback (Holmes, 2009). Interventions based on energy consumption feedback (Vassileva et al., 2012) have had a significant role in raising energy awareness, reducing energy consumption by around 10%, relative to the control condition.

The current study uses behavioral theory and methods to test existent (Paunesku et al., 2015; Sherman et al., 2013) and novel psychological interventions to reduce energy consumption among middle- and low-income consumers. Behavior change interventions are tools to achieve behavior change, developed by researchers to help policymakers and practitioners identify and design successful campaigns. Behavioral science insights in the hands of expert practitioners can help people make better choices than they would make on their own. Interventions like those follow the vantage point or a practitioner who has identified specific behavioral goals, such as reducing energy consumption (Cohen & Andrade, 2018).

Recent research stipulates that for behavior change to be initiated and sustained from a behavioral perspective, the advocated behavior must reach adequate accessibility, desirability, and feasibility levels. Figure 3 summarizes the biggest influences of behavior change based on Andrade (2015).

Figure 3. Influences of Behavior Change

Source: Prepared by the authors; adapted from Andrade (2015).

This work aims to understand how low- and medium-income consumers react to DR plans after receiving full information about their purposes and benefits. The tested behavioral interventions can be applied in several DR strategies: services' pricing/promotion, product portfolio, advertising/campaigns, or communications between these firms and their clients.

5.2 Experimental design

The main study follows one factor (peak-hours/off-hours plan) between-subjects design, relying on self-reported measures. The procedure was designed in Qualtrics and, thus, followed an online approach. Participants accessed the study through the Qualtrics link and participated at their convenience. Participants were informed that their personal information would be kept confidential.

5.2.1 Sample

As is often the case with behavior studies, a third-party company recruited participants for this study. The company focused on recruiting low- and mid-low-income consumers from its database of participants in 11 countries. The company follows the countries' socioeconomic criteria for defining participants who can be more willing to accept DR programs.

A total of 5,298 subjects from 11 LAC countries (Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Mexico, Panama, Paraguay, Peru, and Uruguay) participated in the survey. Table 1 shows the sample's breakdown per country. The survey was conducted digitally via internet. Given this, the survey biases the sample toward consumers with access to electricity and the internet. However, as DR programs require the existence of electricity and probably the internet, that bias does not seem to be a big issue.

For the sake of granting high external validity of the study's findings, participants who did not complete the study's main dependent variables and/or did not pay at least part of their household electric bill were excluded (a total of 801 and 561 participants, respectively). Their exclusion also helps ensure an accurate gauge of the electricity cost burden. In general, most interviewees came from urban areas, which is also precisely where DR policies can be applied most effectively.

The final sample was composed of 3,936 participants who reached the end of the study. The sample is approximately evenly distributed among countries, with percentages ranging from 4.41% (Mexico) to 11.92% (Brazil). Therefore, the sample seems heterogenic, with a robust number of participants per country. Table 1 summarizes those numbers.

Table 1. Sample by Country

	Total	Who pays the bill		Who paid the bill and completed the survey		
Country	#	#	% of those who started	#	% of those who pay	Distribution of those who paid the bill and completed the questionnaire
Argentina	539	480	89.05%	407	84.79%	10.32%
Bolivia	500	463	92.60%	399	86.18%	10.12%
Brazil	777	639	82.24%	470	73.55%	11.92%
Chile	477	435	91.19%	382	87.82%	9.69%
Colombia	514	493	95.91%	450	91.28%	11.41%
Costa Rica	457	411	89.93%	289	70.32%	7.33%
Mexico	247	221	89.47%	174	78.73%	4.41%
Panama	510	464	90.98%	392	84.48%	9.94%
Paraguay	388	329	84.79%	286	86.93%	7.25%
Peru	427	390	91.33%	351	90.00%	8.90%
Uruguay	462	412	89.18%	343	83.25%	8.70%
Total	5298	4737	89.41%	3943	83.24%	100%

Source: Authors' design based on experiment data

Table 2 presents the sample's demographic characteristics. The average age of the respondents was 32.38 years, and 57.96% were female. About two-thirds of the respondents declared themselves non-white, and only 34.45% were officially married. With respect to income, the recruiting process selected only low- and mid-low-income consumers [11].

Table 2. Summary Statistics

	Observations	Mean or %	SD	Min	Max
Age	3,353	32.38	9.87	18	85
Gender (Male)	3,356	42.04%		0	1
Race (White)	3,356	33.10%		0	1
Marital Status (Married)	3,356	34.45%		0	1

Source: Authors' design based on experiment data

5.2.2 Main goals and predictions

This study draws on concepts from decision sciences (Abrahamse et al., 2005; Cohen & Andrade, 2018; Karlan et al., 2010) to explore ways to trigger consumers' willingness-to-shift activities and reduce their electricity consumption during peak hours. The success of time-of-use pricing, where consumers are charged higher rates during peak usage, depends on many factors. The goal was to test which type of time-of-use-based plan could lead to targeted consumers' higher likelihood of adoption. This study predicts that plans with clear and salient goals for reducing electricity bills will be preferred among the sample of low- to mid- income consumers.

Consumers must manage their consumption to successfully reduce or avoid increasing their electricity bills under a time-of-use-based plan. This study also tested interventions to make consumers more equipped to handle their consumption and deal with the increased (reduced) electricity tariff during peak (off-peak) hours. More precisely, the experiment relies upon different types of behavioral intervention (e.g., reminders, information about consumption price) to assess which interventions would make consumers more likely to change their consumption from peak to off-peak hours. Participants are expected to report being more likely to switch consumption in accordance with DR incentives when they receive reminders with information about electricity service costs (i.e., cost of the use of an appliance for a period) or their actual electricity consumption, compared to when receiving only reminders of the peak time-hours.

11. The results show that the study has a good representation in the sample of low- and mid-low-income participants. For example, in the case of Brazil, the socioeconomic profile of the sample is quite similar to the socioeconomic profile of the Brazilian population of the National House-holdBudget Survey in Brazil for the years 2017-2018. The comparison allows us to decide that the sample is robust and capable of representing low- and medium-income households. In this study, participants declared an average income per capita of USD 200/month, which is compatible with the 3rd-4th decile of the Brazilian population according to the Brazilian Family Budget Survey. In addition, participants replied that they would pay USD28 per month for their electricity bill and it would only be equivalent to the amount paid for the 5th decile of the Brazilian population, also according to the Brazilian FamilyBudget Survey. Finally, in terms of education, 5% of the sample have not studied or have less than a high school education; 60% completed or are completing high-school; and 25% already completed or are completing undergraduate studies. These results reflect that the sample presents a socioeconomic profile compatible with the profile of households with lower and middle incomes. Therefore, the sample seems robust with respect to representing the target audience of the study – lower- and middle-income households. More details are available in Annex A.1.

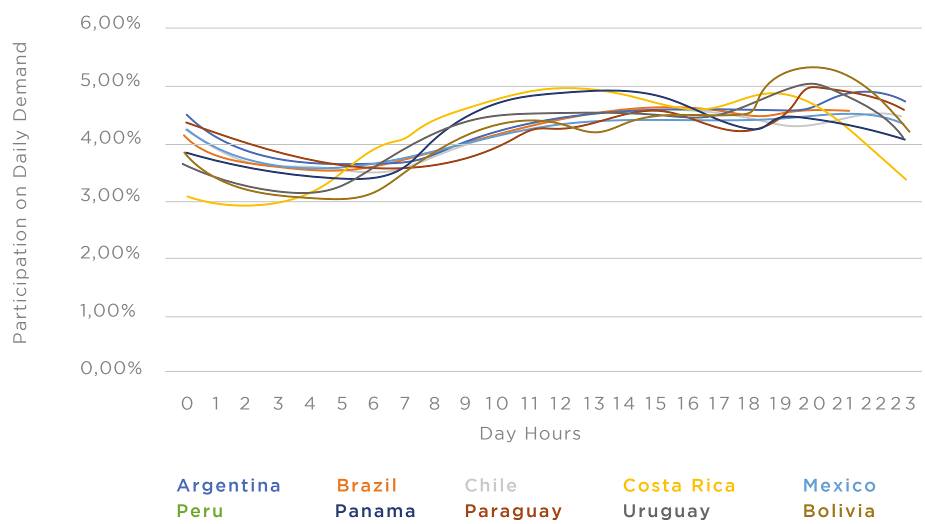
Electricity suppliers and policymakers need to be aware of consumers' sensitivity to peak-hours price increases if they aspire to design a more effective plan. In addition, the ratios between peak-hours and off-peak hours rate and the flat rate are also important to mitigate peak hours consumption. For that reason, the questionnaire seeks to assess consumers' price sensitivity to peak-hours tariffs by addressing the following question: How much increase is needed to make consumers more willing to reduce peak hours consumption? The authors assume that even a small increase in the peak-hours tariff will increase the reported intention to switch consumption when the increase is salient for consumers. The study thus anticipates that consumers' reported intention to switch consumption will not parallel growth with the peak-hours tariff increase.

The paper also aimed to explore the psychological impacts on consumers' price sensitivity. For that reason, the questionnaire assessed consumers' perception of fairness of a higher tariff during peak hours, and whether this increases their willingness to adjust consumption. Although the sample comprises mid- and low-income consumers, the study also aims to test potential interactions of consumers' income and the main outcomes of interest.

5.2.2.1 Target hours for demand management

In order to adjust the treatments of the experiment, the distribution of peak hours of every country was examined based on data from national operators. Below, Figure 4 shows how every country has a particular interval where potential demand response policies should target shifting the load more effectively. As shown below, the weekday load profile of every country is similar, but its patterns vary slightly.

Figure 4: Relative Distribution of Electricity Consumption across the Day



Source: Authors' design, using available data from national grid operators

Since the experiment aims to identify potential adopters of DR programs, the hours targeted were adjusted to encompass the top three-hour consumption period during a weekday in each country. While peak hours interval time extended beyond the three hours, the focus was around the peak hour and the prior and posterior hour to lower the load's crest. Additionally, a choice was made to focus on hours traditionally associated with residential sector consumption and the period where the hours could be selected disregarded the mid-day consumption rise related to industrial and commercial establishments.

The selected hours for each country were: Argentina, 20-23; Bolivia 18-21; Brazil 17-20; Chile, 20-23; Colombia, 18-21; Costa Rica, 18-21; Mexico, 19-22; Peru, 18-21; Panama, 17-20; Paraguay, 19-22; Uruguay, 19-22. In each country, hours were selected according to the highest concentration of electricity consumption[12].

5.2.2.2 Experiment Procedure

The procedure was a quantitative approach with an exploratory, experimental design and survey, relying on behavioral interventions and self-reported measures. The decision to run a study with experimental behavioral methods provided high methodological robustness. Even with financial and time constraints, the indication is the experimental approach. Experiments aim to measure the relationship of the independent variable to the dependent variable (Wilson et al., 2010). Scientific research often aims to study the effect of one variable on another one. The variables in a study of a cause-and-effect relationship are called the independent and dependent variables. The independent variable is the cause, the dependent variable is the effect, and its value depends on changes in the independent variable. In experimental research, the researcher manipulates or changes the independent variable to measure the effect of this change on the dependent variable (Wilson et al., 2010).

In the experiment, members of the sample frame were invited to participate in a study on residential electricity consumption. They were informed that the Inter-American Development Bank was conducting that experiment for academic and public policy purposes in partnership with academic researchers. Individuals who agreed to participate would make hypothetical decisions in an online survey and provide information about themselves. Participants took around ten minutes to complete the entire study. Those who did not complete the study were excluded from the sample because they did not reply to the controls employed in each analysis.

This study aimed to assess the behavior of those in charge of household electricity payment decisions. Therefore, the questionnaire also asked other questions about the value of respondents' electricity bills (i.e., "How much is the average monthly electricity bill in your household?"; "How much was the lowest electricity bill you have ever paid?", "How much was the highest electricity bill you have ever paid ?") and the appliances they have at home (i.e., electric heater, air conditioning, fan, computer (laptop, notebook, tablet), smartphone, internet access, access to electricity from the grid, own electricity meter). Participants who indicated not paying any share of their electricity bill were also excluded from the data analysis. Participants responded whether they pay their electricity bill, and how much they contribute (i.e., 0%, 1% to 49%, 50% or 51% to 100%).

After responding to these questions, participants responded to one question to assess their perception of fairness of a higher tariff for peak hours. Participants were informed that there are periods when energy suppliers have additional costs to fulfill clients' use. Those periods are known as peak times. The questionnaire then asked them to judge whether they perceive it as fair that an energy supplier charges a higher tariff during peak times if they provide a discount during off-peak times.

After this question, the questionnaire tested participants' sensitivity to a peak-hours price increase. The experiment asked participants how likely they were to change their peak times consumption to off-peak times if the tariff is 20% higher during peak times compared to off-peak times. The same question is asked for a peak-hours tariff increase of 40, 60, 80, and 100% to test participants' price sensitivity.

12. Colombia's hours were selected based on information published on the national operator's website, XM.

Participants also responded to questions that tested their current knowledge of peak hours tariffs (i.e., “Do you know the electricity peak times in your region?” and “Do you know how much more expensive the tariff by kWh charged by your energy supplier during peak times is relative to off-peak times?”) and their current electricity plan (i.e., “Does your energy supplier, in your current energy plan, charge you a higher fee for the use of electric appliances during peak times?”). The experiment then informed participants about the peak hours in their region and asked them to respond whether these matched the days/times they use more electricity in their household. 44.8% of the participants indicated when the hours were where most electricity was consumed in their region. Still, only 35.8% knew if their provider was charging them a higher tariff during that period of consumption.

At this point in the survey, the participant had to choose between two types of plans: a flat-tariff plan or a Demand Response plan (DR plan). The manipulation was which time-of-use-based plan. Whereas the flat-tariff plan was always the same for all participants, the survey randomly assigned participants to one of five different DM plans.

Figure 5 shows what those participants read for each tariff plan. The texts in the treatments are translations of those offered in the survey. The original texts can be found at the end of this document (Annex A.2). The original survey was conducted in Spanish and Portuguese. The experiment then presented the differences between the flat-tariff plan (control option) and DM plans (condition options).

In the flat-tariff plan, which was characterized as a control plan and was shown as an option for all participants, the electricity tariff is the same for all day-time hours. Most Latin American household consumers have their electricity consumption billed based on a flat-tariff plan. Regarding DM plans, there were five conditional options. Each participant was exposed to only one DM plan, and they were compelled to decide between that DM plan and the flat-tariff plan. Figure 5 shows how the plans were presented to participants. The five DM plans are described below:

- **Condition 1 - The Peak-hours Tariff Plan:** The rate is more expensive during three peak hours and cheaper during the other 21 off-peak hours each day. As in Australian DM plans[13], the peak hour rate is almost triple the off-peak rate and 80% higher than the flat tariff, and the off-peak tariff is 30% lower than the flat tariff. Considering a consumer whose monthly electricity consumption is equal to 150 kWh/ month and whose demand is equal to 500 W/h during the peak hours and 167 W/h during the off-peak hours, a reduction of 33% in electricity consumption during peak hours would result in a reduction of up to 21% in the total electricity bill (in the case the consumer only decides to reduce consumption). Suppose the consumer decides to move 33% of their peak-time consumption to an off-peak period. In that case, that plan will reduce the total electricity bill by 21%.

- **Condition 2 - The Brazilian Peak-hours Tariff Plan:** The rate is more expensive during three peak hours and cheaper during the other 21 off-peak hours each day. This plan is similar to the previous Peak-hours Tariff Plan, even though this one replicates the condition of the Brazilian DM plan instead of those of the Australian DM plans. Therefore, the peak hour rate is almost triple the off-peak rate and double the flat tariff, while the off-peak tariff is 20% lower than the flat tariff. Considering a consumer whose monthly electricity consumption is equal to 150 kWh/ month and whose demand is equal to 500 W/h during the peak hours and 167 W/h during the off-peak hours, a reduction of 33% in the electricity consumption during peak hours would result in a discount of up to 4% in the total electricity bill (in the case the consumer only decides to reduce consumption).

13. A more detailed account of the Australian DM plans is available at https://www.energymadeeasy.gov.au/.

- **Condition 3 - AC Control Plan:** The consumer who decides to join this plan allows the distributor to turn off their AC (if necessary) during the three peak hours of each day. As compensation, the consumer receives a discount of 21% on their electricity bill. Based on the Brazilian Household Budget Survey survey 2017-2018 (IBGE, 2020), households who own an air conditioning unit declared a monthly electricity consumption between 185 kWh/month and 333 kWh/month. Also, concerning the data from IBGE (2020), a simple bottom-up model was built in order to estimate the participation of each piece of equipment in the total electricity consumption as to understand the average power and time of use of each domestic appliance. As a result, the authors estimate that air conditioning is responsible for 33% of electricity consumption during peak hours. Turning off the air conditioning during peak hours would reduce peak-hour consumption by 33%. Therefore, the AC Control Plan has the same result as the Peak-hours Tariff Plan. This plan was offered as a condition in the experiment only for the air conditioning consumer.

- **Condition 4 - Heater Control Plan:** The consumer who decides to join this plan allows the distributor to turn off their heater (if necessary) during the three peak hours of each day. As compensation, the consumer receives a discount of 21% on their electricity bill. Considering that the heater consumes electricity similarly to air conditioning, the authors estimated that the heater is responsible for 33% of the electricity consumption during peak hours. As a result, turning off the heater during peak hours would reduce peak-hour consumption by 33%. Therefore, the Heater Control Plan produces the same results as the Peak-hours Tariff Plan. The only difference is the way the plan is explained to the client. This study assumes that the explanation of the reduction of heater use during peak times, as an example, makes it easier for consumers to understand the pros and cons of the plan. This plan was offered as a condition in the experiment only for the participant/consumer with a heater.

- **Condition 5 - Peak-hours Saving Goal Plan:** The consumer who adopts this plan faces an explicit challenge. If they manage to reduce their high-end consumption by 33%, they receive a 21% discount on their monthly electricity bill. Suppose they maintain the same level of consumption or reduce consumption but fail to reach the consumption reduction target during peak hours. In that case, their consumption continues to be billed at a flat rate. However, suppose there is an increase in peak hour consumption during. In that case, the consumer's monthly electricity bill may be subject to a penalty of up to 8%. The creation of this condition aimed to assess how consumers reacted to the existence of a goal to be pursued. In other words, the idea was to analyze if the presence of a goal could make the plan more transparent and more attractive to the client and increase the adhesion to a DM program.

After opting for one of the plans in one of the above five conditions, participants indicated which information would be more beneficial for their household to reduce consumption during peak times. Subsequently, they responded to items that tapped into their perceptions of the quality of the electricity supply to their household and why they might be interested in reducing electricity during peak hours. The randomized treatment was applied. The remainder of the questions were applied in the same order to every surveyed person.

Before they finished the survey, participants responded to some demographic questions, including: racial background, gender identity, age, educational attainment, place of residence, individual and household gross monthly income, civil status, occupation, and what portion of their total monthly income is devoted to paying their energy bill. Afterward, participants receive a thanks message.

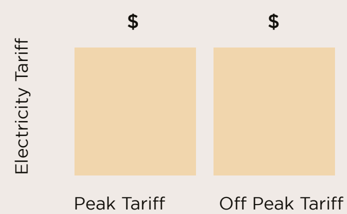
The next section will evaluate the different responses based on the randomized condition, the plan selection that every person was exposed to concerning other control variables.

Figure 5. Experimental Conditions

Flat-tariff plan (all the participants had this plan as Option A):

Plan A

Your electricity tariff is the same for all hours of the day.



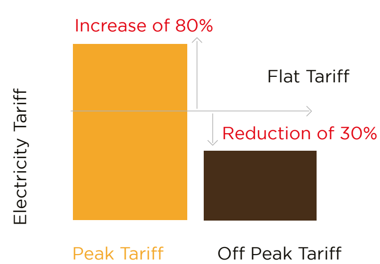
Time-of-use plans (Participants were randomly assigned to one of these plans as Option B):

Condition 1– Peak hours tariff plan

Plan B

Your electricity rate is more expensive during peak hours and cheaper during off peak hours. The peak hour rate is almost triple the off-peak rate and the double the flat tariff, while the off-peak tariff is 30% lower than the flat tariff.

If you reduce your consumption in 33% during peak times, you can have a reduction of up to 21 % in your total electricity bill.

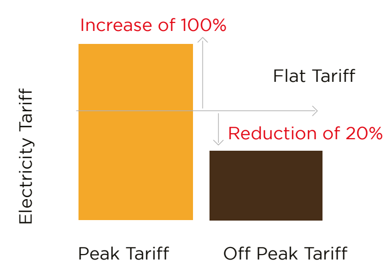


Condition 2 – Peak hours (Brazilian) tariff plan

Plan B

Your electricity rate is more expensive during peak hours and cheaper during off peak hours.

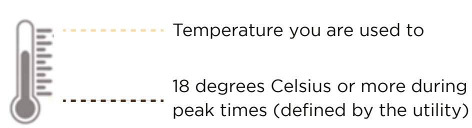
The peak hour rate is almost triple the off-peak rate and the double the flat tariff, while the off-peak tariff is 20% lower than the flat tariff. If you reduce your consumption in 33% during peak times, you can have a reduction of up to 4 % in your total electricity bill.

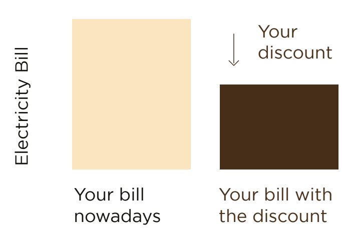


Condition 3 – Heater control plan

Plan B

During peak times, you allow the utility to switch your heater off (if needed) and you receive a discount of up to 21% in your total electricity account.

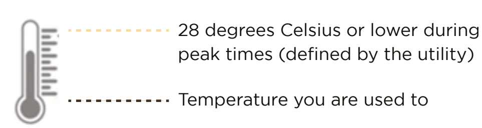


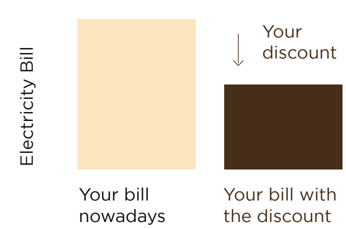


Condition 4 – AC control plan

Plan B

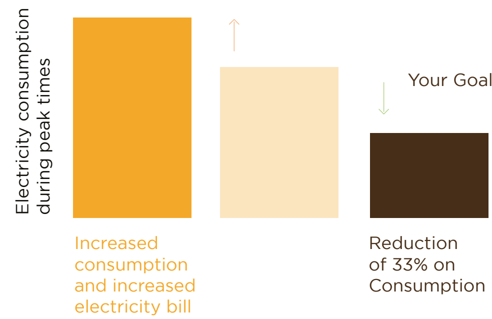
During peak times, you allow the utility to switch your air conditioning off (if needed) and you receive a discount of up to 21% in your total electricity account.





Condition 5 – Peak-hours saving goal plan

Suppose you reduce consumption by 33% during peak times. In this case, you can receive a discount of up to 21% on your monthly electricity bill. If you do not change your consumption, your electricity bill will continue to be the same. However, your bill will be more expensive if you increase your consumption during peak times.



Source: Authors' design

6

Results and Discussion

This section explores the experiment results through statistical analysis and is divided into five parts. At first, it looks at the composition of the experiment participants. The second examines the role of consumers' perception over DR acceptability and likelihood of adopting behavioral changes with respect to electricity consumption. The third evaluates price sensitivity to see how keen these users might be to change their consumption as DR policies might increase prices at some times of the day. The fourth looks at the likelihood of adopting communication tools, which are essential to a successful DR policy. Finally, a brief section profiling the participants who accepted the demand response plan in the experiment is included.

6.1 Main Experiment: Preferred peak-hour plan

The authors analyzed the likelihood of participants opting for a DR time-of-use tariff-based electricity plan when a non-DR flat-tariff plan was available. Each participant needed to choose between two types of plans[14]. The manipulation was based on the DR type of time-of-use and utility-based plans presented in the last section. Whereas the flat-tariff plan was always the same for all participants, the survey randomly assigned participants to one of five different DR-based plans . Figure 6 summarizes the choices interviewees faced.

14. The authors have run all tests, including demographics as control variables, to provide further robustness to results, and to prevent any demographic differences among treatment conditions. The results seem to be guarded against cultural or country variations because they are robust even after controlling for country differences and participants' demographic differences.

Figure 6: Summary of Experimental Conditions

CONDITION 1: Flat-tariff plan vs. Peak-hours tariff plan (was shown to n=1,059 participants)

CONDITION 2: Flat-tariff plan vs. Brazilian Peak-hours Tariff Plan* (shown to n=842)

CONDITION 3: Flat-tariff plan vs. Peak-hours saving goal plan (shown to n=1,018)

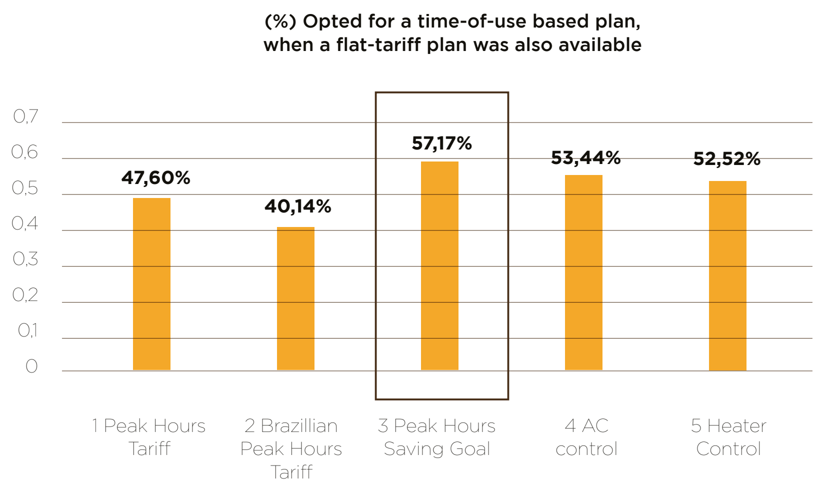
CONDITIONS 4 & 5: Flat-tariff plan vs. Peak-hours AC or heater control plans

(shown to n=668 & 356 = 1,024)

Answers were coded as one (1) if the respondent preferred the time-of-use-based-plan, or zero (0) if the consumer opted for the flat rate. The chi-square test showed that adoption of the alternative plan is not distributed equally among conditions $(\chi^2\ (4) = 60.19, p<0.001)$. The chi-square test evaluates whether at least one condition is different from the others, but does not show which conditions are different. Figure 7 shows the main results.

The peak hours saving goal plan was more frequently chosen (57.2%) by consumers willing to reduce their electricity bill, ranking as the proposed DR plan with the highest level of acceptability in this study. The peak hours plan (2) inspired by the Brazilian Peak-hours Tariff Plan was chosen less frequently. These differences are, in all cases, statistically significant in accordance with customarily required levels indicated in the literature $(p<0.001)$.

Figure 7: Main Results from Experiment



Source: Authors' design based on experiment data

The authors ran logistic regressions using the peak hours plan as the baseline comparison among other time-of-use plans to provide further statistical robustness to this finding with respect to the most acceptable DR plan. The advantage of the logistic model compared to the chi-square is the inclusion of controls, which reduce possible alternative explanations and deliver a more robust result. Controls are variables reported by participants (e.g., participants' income, race, gender, percentage of the electricity bill they usually pay) that can be used to minimize the exogenous effects on dependent variable changes (i.e., the decision regarding a time-of-use plan). With the controls, it is possible to explain only by the independent variables (i.e., the type of a time-of-use plan). Compared to the chi-square test, logistic regression allows for comparing all alternatives individually rather than grouped.

There were two models: one 'controlled' the participants' country and demographics; the other did not identify the country of residence as a control. The dependent variable Choice of plan would be assumed as "1" if the interviewee chose the DR plan, and "0" if the interviewee chose to remain with a flat-tariff plan. Thus, the model estimated is as follows:

$$Choice\ of\ plan = \alpha + \beta\_1\ White\ Tariff + \beta\_2\ Goal + \beta\_3\ AC + \beta\_4\ Heater + X'\delta + \theta + \varepsilon$$

in which $\beta\_1, \beta\_2, \beta\_(3\ )and\ \beta\_4$ are the coefficients of interest, and $X'\delta$ is the vector of control variables (natural logarithm of household income in dollars, perceived electricity burden, age, and dummies for males, marital status, and those who pay half or more of the bill). The coefficient θ denotes the country effects in the second model. Table 3 presents the results.

Table 3. Logistic Regression Results

Time-of-use based plans	Model 1:	Model 2:
	Without country controls	With country controls
BrazilianPeak Hours Tariff	-0.290** (0.108)	-0.291** (0.109)
Saving Goal	0.376*** (0.099)	0.376*** (0.100)
AC Control	0.183 (0.116)	0.172 (0.117)
Heater Control	0.144 (0.135)	0.142 (0.136)
Observations	3,045	3,045
Pseudo-R^2	0.0109	0.0152
Controls	Yes	Yes
Country Controls	No	Yes

* p<.05, ** p<.01, *** p<.001. Standard errors in parentheses. Controls were omitted due to non-significant values—Peak Hours Tariff Plan used as the baseline.

Source: Authors' design, using experiment data

Even after controlling for participants' demographics only (Model 1) and participants' country of residence (Model 2), the Saving Goal Plan remains the preferred DR plan by consumers in Latin American countries over a flat plan. The Peak Hours DR Plan (2) remains less likely to be chosen by consumers in these countries than the other DR time-of-use-based and appliance-based plans. These results are robust even after the inclusion of demographic and country controls. In summary, consumers prefer the DR Saving Goal Plan over the alternative. They significantly dislike the DR Brazilian Peak Hours Tariff Plan. Regarding DR AC or Heater Control options, consumers seem not to have particular likes or dislikes, which suggests that the plans could gather support if they are promoted well.

6.2 Psychological perception of the sense of agency and moderation effects

With these results in mind and with the role of agency mentioned in past sections regarding the efficacy of DR, the variables of the five plans offered are sorted into two categories: (1) those where the user has control over their goals (i.e., the peak hours plan and the Brazilian White Tariff plan), and, thus, have a higher sense of agency, and (2) those in which there is a sense of others' agency, in which the electricity supplier suggests the goals or exerts external control over consumption (i.e., the goal plan and the HVAC control plans). Hence, there is a dummy variable called "agency," which assumes the value of one (1) if consumers control and define their reduction goals under the plan, and zero (0) if the electricity provider sets the reduction goal or the use of HVAC to meet the reduction in bill value. The dependent variable is a dummy for adopting the alternative plan compared to the flat-rate plan. Thus, the baseline logistic regression is as follows (which is very similar to the previous specification):

$$Choice\ of\ plan = \alpha + \beta Agency + X'\delta + \theta + \varepsilon$$

The authors also tested interactions of this effect with the income variable, the perceived electricity burden (i.e., % of the electricity bill over the household income), and the fairness of peak hours measure (i.e., a variable that assesses consumers' perception that charging a higher rate during peak hours is fair). Results are presented in Table 4, below.

Table 4. Results from Agency Logistic Regressions

	Model 1	Model 2	Model 3	Model 4
Agency	-0.396*** (0.074)	-0.512*** (0.134)	-0.428*** (0.100)	-0.512*** (0.135)
Agency x Fairness		0.049 (0.048)		
Agency x Perceived Burden			0.153 (0.318)	
Agency x Income				0.049 (0.048)
Observations	3,045	3,045	3,045	3,045
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Pseudo-R²	0.01	0.01	0.01	0.01

Source: Authors' design using experiment data

The first coefficient shows that plans in which the provider sets reduction goals or HVAC temperature performs better than those in which agency lies with the consumer. In other words, consumers are less (vs. more) likely to choose the plan when consumers (vs. the provider) exert control over it. None of the interactions were significant, which shows a very homogeneous effect of those types of plans among different demographics.

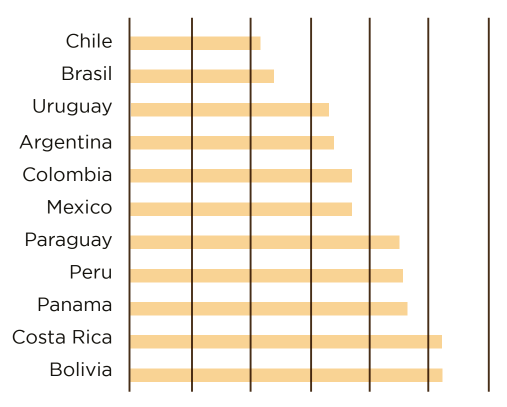
Unlike the Shi et al. (2020) survey results, this experiment found that consumers are interested in plans that offer the utility the ability to control consumers' electricity consumption across all models. This preference becomes clearer still when controlling for fairness and burden perception. When considering the consumers' income, consumers preferred tariff plans controlled by the provider over flat plans. This result points toward the need to explore other plans that reduce consumers' necessity to manage their plan consumption, providing solutions guided by electricity providers when designing DR policies. The difference observed with results of a survey in the US points out the need to further explore whether cultural elements play a role in the willingness of households to opt into automatic control programs[15].

6.3 Price sensitivity

Price sensitivity is key to understanding how effective DR programs might be, as well as to assessing price calibration once implemented to achieve expected results. Five scenarios were tested in which prices during peak hours are 20%, 40%, 60%, 80%, and 100% higher than off-peak hour pricing. The likelihood of reducing consumption during peak hours was assessed using a seven-point Likert scale [16]. This study then estimated OLS models using the fairness of peak hours measure, the perceived electricity burden, and the household income's natural logarithm in US dollars. This part of the experiment aimed to understand the full self-perceived behavior modification resulting from different pricing plans applied to consumers' current electricity costs.

Experiment participants had, on average, reported a perceived burden of the electricity bill of about 9.4% of their income. The sampled countries with the lowest relative burden were Chile, at 9.03%, and Brazil, at 9.08%. The highest relative burdens were recorded in Bolivia, at 9.65%, and Costa Rica, which also registered as 9.65%. These figures are reflected in Figure 8, below. The survey measured the standard deviation followed by Colombia.

Figure 8. The average percentage of income dedicated to paying the electricity bill

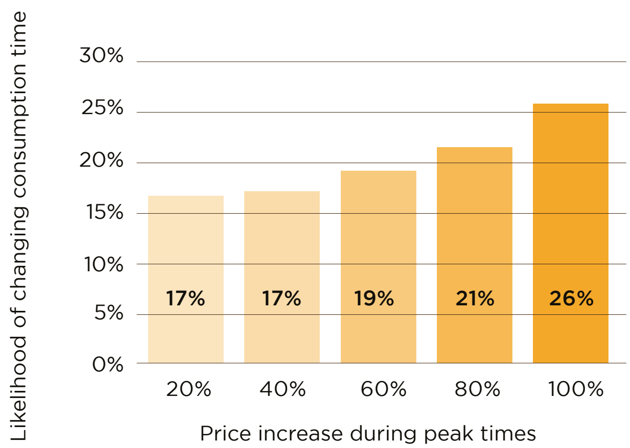


Source: Authors' design using experiment data

15. Such is the case of the Brazilian White Tariff (Tarifa Branca, in Portuguese), which favored standard peak hours pricing and that by their own account. The study points out that, if reformulated, the White Tariff could have more adopters and bring more benefits to the electric system.
16. Defined as the following levels: extremely improbable, moderately improbable, slightly improbable, nether probable nor improbable, slightly probable, moderately improbable, and extremely probable.

As shown below in Figure 9, 17% of participants were likely to reduce consumption if the price increased by 20%. In comparison, 26% of participant consumers declared that they would likely change their consumption patterns if the price doubled.

Figure 9. Likelihood of Changing Consumption Time



Source: Authors' design using experiment data

In this case, an Ordinary Least Square (OLS)[17] model was estimated to explain how the variation of the Likelihood of Reducing Consumption is explained by the fairness perception, perceived burden of the electricity bill, and income. The specification is formulated below and regression results are shown in Table 5.

$$\text{Likelihood of Reduction} = \alpha+\beta\_1 \text{ Fairness}+\beta\_2 \text{ Perceived Electricity Burden}+\beta\_3 \ln(\text{Income})+X'\delta+\theta+\varepsilon$$

Table 5: Results from Price Sensitivity

DV:	Likelihood of Reducing Consumption (more price sensitive)				
Price Increase	**20%**	**40%**	**60%**	**80%**	**100%**
Fairness	0.128*** (0.021)	0.136*** (0.023)	0.142*** (0.024)	0.121*** (0.025)	0.101*** (0.025)
Perceived Burden	0.424** (0.151)	0.552*** (0.150)	0.444** (0.159)	-0.343* (0.169)	0.037 (0.182)
Income	0.033* (0.014)	0.027* (0.014)	0.016 (0.015)	0.026 (0.015)	0.010 (0.017)
Observations	3,020	2,933	2,929	2,907	2,916
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
R^2	0.03	0.03	0.03	0.02	0.01

Source: Authors' design using experiment data

17. The Ordinary Least Square (OLS) model was chosen instead of a logistic regression because the dependent variable was a 7-point scale rather than a dummy variable. It required moving away from dummy variables to capture the full variability of the subjects at tcurrent sampling levels.

The perception of the fairness of the peak hours extra charge (or off-peak hours discount) is heavily correlated to the likelihood of reduced consumption. People who perceive the DR tariff as fair tend to reduce consumption more.This highlights the importance of making consumers understand the purpose of DR programs, since understanding might signify support and efficacy.

The situation is reversed when looking at the perceived participation of the electricity bill over the income. In other words, people who use a higher percentage of their income to pay their bills are less likely to reduce energy usage during peak hours. This effect seems to be caused because this measure captures the effect of income. People with lower incomes are also those with a greater percentage of their income paying their energy bills. Recruitment for this study focused on engaging low- and mid-income participants. Low-income people are in the lower-income deciles, and those higher in income are not wealthy, but middle-income (except for a few outliers). The authors thus interpret those with lower vs. higher income in the sample. Those with lower income in the sample (i.e., very poor) may not have much to change in their consumption; therefore, they have less room to reduce their consumption in peak hours. In other words, they have less “discretionary” energy consumption to reduce.

Most people with more income in the sample are not wealthy (and price is important for them), and they might have more room to change when compared to those participants in the sample who have lower incomes. Participants reported the percentage of their salary used to pay their electricity bill (i.e., Perceived Electricity Burden). This paper assumes that the lower the income, the higher the Perceived Electricity Burden. In other words, the lower the income, the higher the percentage of salary that goes toward paying their electricity bill. Hence, an inverse relationship would be confirmed by analyzing a regression with Perceived Electricity Burden as a dependent variable and participants' income as an independent variable. The direct correlational effect is significant ($P<.005$). Therefore, the experiment has evidence that the higher the income, the lower the Perceived Electricity Burden. In conclusion, the authors infer that Perceived Electricity Burden is also a proxy for participants' income: i.e., lower the perceived burden and higher income.

In line with this rationale, Table 5 shows the effect of Perceived Burden and Income on the Likelihood of Reducing Consumption. The negative impact of Perceived Burden on price sensitivity is in line with the interpretation that those with higher Perceived Burden have lower income. The increase of the Perceived Burden decreases price sensitivity because higher Perceived Burden is associated with lower income. Those poor might have less “discretionary” energy consumption to reduce[18].

The significant effect of income is on the first increase level (20%) and second increase level (40%) (Table 5). Effect of income does not seem to impact further increases significantly. In the sample, families with higher income seem to be more sensitive to price and change behavior in this initial increase.

Households with lower income in the sample seem to be unable to change their consumption because their electricity consumption is already the minimum necessary to meet basic electricity requirements for subsistence. This means they have less room to reduce their consumption more in peak hours. Meanwhile, participants with more income in the sample (those who are not wealthy and are probably part of a middle-income class) respond better to changes in prices, having a little more room to change their behavior when compared to those with lower income in the sample. This means that even a smaller increase of 20% can reduce energy consumption in middle-income households during peak hours.

Since the source of the change seems to differ, this suggests that differently applied policies and programs could be marketed to consumers segmented along these demographic lines. In Annex A.3, you can find a discussion about the effect of participants' income, perceived fairness of peak hours tariffs, and perceived electricity burden on their price sensitivity.

18. Further studies considering household appliances are necessary to explore better this hypothesis.

6.4 Effect of reminders

The presence of informational strategies might help consumers better change their behavior to maximize their savings and, by extension, improve the efficacy of the DR policy in accordance, an outcome that would be congruent with findings from the literature. Five possible interventions were analyzed on a five- point Likert scale,[19] two of which provided only reminders, and three that provided reminders with information. Table 6 shows five different reminders. The intervention reveals the preferred method of communication to the consumer, enabling them to enact some form of real-time decision-making over which electricity-consuming activities perform. Options ranged from a more simplistic form of communication to a more dynamic one. The aim here was to help inform potential DR design decisions when communicating with residential consumers. A paired t-test analysis was also performed comparing the pure reminders to reminders with price information. The paired t-test allows comparison of the means of two conditions, in this case, the pure reminders to the reminders with information. Results showed that, indeed, when participants receive information, they declare that they are more likely to reduce energy consumption $(\text{Mean}_{info}=3.79,\ \text{Mean}_{remider}=3.68,\ t(3841)=9.44,\ p<0.001)$. There was also a comparison between app notification versus significant text messages $(t=21.30,\ p<.0001)$. The app proved to be better suited than text messages to obtain informational awareness of shifting prices generated by DR policies.

Table 6: Mean Effect of Different Consumptions Reminder

Media	Reminder Type	Content	Observations	Mean	Min	Max
Text message	Pure reminder	A text message with a reminder when Peak Hours begin and end	3,343	3.55	1	5
	Pure reminder	A text message with a reminder when electricity price reaches a threshold	3,342	3.63	1	5
	Reminder with price information	A text message with info on the electricity price paid for the most electricity-consuming appliances	3,353	3.74	1	5
	Reminder with price information	A text message with information on current and forecasted consumption	3,339	3.82	1	5
App notification	Reminder with price information	App notification with information on current and forecasted consumption	3,339	4.00	1	5

Source: Authors' design using experiment data

19. According to Preedy and Watson (2010), a five-point Likert scale is a type of psychometric response scale in which responders specify their level of agreement with a statement, typically in five points: (1) Strongly disagree; (2) Disagree; (3) Neither agree nor disagree; (4) Agree; (5) Strongly agree.

6.5 Who are those more accepting?

One of the questions about promoting DR to residential users is what type of consumer, with which type of electricity consumption behavior, would be most likely to participate in DR plans. The operating hypothesis was that consumers with high electricity-consuming appliances, such as HVAC, would be more aware of electricity costs and, consequently, propose adopting a DR plan. To the surprise of the study's authors, there was no significant difference between the appliances and the energy sources of DR- accepting participants and non-DR accepting participants. However, this paper includes that data since this material composition can be important when devising potential policies and might interest policymakers. 26.9 % of DR accepting participants had AC.

Analogously and under the same hypothesis, the survey investigated the different fuels used for cooking, heating, and water warming. Results were likewise non-significant, but the distributions can be found in Table 7 below.

Table 7: Profile of Fuels Used by Experiment Participant by the Preference of DR

	DR Accepting			DR Rejecting		
	Electricity	Gas	Other	Electricity	Gas	Other
Heating	43.55%	11.73%	44.72%	43.2%	10.99%	45.81%
Cooking	18.54%	71.21%	10.25%	17.9%	74.04%	8.06%
Warming water	41.97%	37.98%	20.05%	44.62%	33.85%	21.53%

Source: Authors' design using experiment data

7

Conclusions and lessons learned

Consumer empowerment is one of the radical transformations digitalization can bring to the electricity sector. Historically, consumers (especially small consumers) have been considered price takers, especially in the short-term. In the context of the energy sector, consumers were not expected be empowered in their daily decisions.

Due to this history, regulators and policymakers assume that clients cannot react to short-term price variations. It has also been assumed that costs are higher than the value that households' responses can bring to the system. Consequently, regulations and policies hinder short-term price signals (and sometimes forbid them) to protect consumers. However, these kinds of assumptions can lead to a vicious cycle. Without price signals, consumers do not change their behavior, which justifies regulators' assumptions about the passive role of consumers. Meanwhile, consumers usually do not know about changes in electricity costs, nor that it could be possible to pay less if they change their behavior. Historically, this logic has been justified by the high transaction costs associated with demand response.

So, what has changed (or is changing)? First, digitalization and advanced metering infrastructure (AMI) allow utilities and consumers to track their electricity consumption in real-time and to make pre-set decisions based on prices/costs. AMI substantially decreases the transaction cost associated with demand response. Second, the growth of variable renewables increases the difference of peak and off-peak electricity costs substantially. It means the potential of economic savings associated with demand response increases. In the energy transition process in which renewables need to increase exponentially over the next few decades, the value of demand flexibility will increase. Third, the combination with other technologies that allow price arbitrage, such as storage and electromobility, empowers consumers and increases their potential to deliver the flexibility the electricity system requires.

In this context, demand response (DR), enabled by the electricity sector's digitalization, is part of the future of the electricity sector. DR can increase system efficiency in dealing with variability while increasing affordability.

Incentives for DR programs can be based on prices (price-based DR programs) or contracts (contract incentive-based DR programs). The price-based DR programs normally consider differentiated electricity rates per day-time, also known as Time-of-Use (ToU) tariffs. In this case, while tariffs during peak times are higher in order to cover the supply costs, the tariff is even lower during off-peak times than the conventional flat rate. Therefore, in DR programs with price-based incentives, consumers can naturally react to different electricity rates. Conversely, in contract incentive-based DR programs, the consumer signs a contract that gives the distributor the right to impose consumption limits during some hours of the day in exchange for a discount on the electricity tariff or total bill. Contract incentive-based DR programs can provide discounts on the electricity tariff or bill if the consumer achieves a pre-defined target of consumption reduction.

Demand response policies have been shown to be successful in commercial and industrial settings. Implementing DR programs for industrial and commercial sectors has already taken root in several LAC countries. Results from cost evaluations in Jamaica have shown how beneficial these incentives can be to reduce the exposure of factories and businesses to unaffordable electricity costs.

The success of DR programs can be replicated in the residential sector, especially with advances in AMI. In the residential sector, voluntary-adoption price-based DR programs tend to be more common due to their simplicity. LAC countries such as Brazil, Costa Rica, and Uruguay, have already implemented some DR programs for households. Most of those DR programs are based on ToU tariffs and voluntary consumer adoption. In other words, the consumer can choose to move from a flat tariff program to a ToU tariff program. Such a program has limited adoption, however. Understanding barriers and potential mechanisms to overcome them is key to improving adoption.

Based on our analysis, the success of the DR programs is expected to increase exponentially over the years. However, the experiment reinforced that the success of those programs will depend on the existence of significant incentives to the residential consumer. Success will also rely on user-friendly AMI tools, a good communication campaign to explain the program's potential benefits to consumers, the inclusion of tips on how to change energy consumption patterns to respond to electricity price signals, or the provision of additional HVAC temperature control instruments. In addition, the dissemination of DR programs with incentive-based contracts could further increase adoption and the efficacy of DR programs in the residential sector because this type of DR program seems easier for the consumer to understand and more attractive due to its clear discount on the electricity tariff/bill, as pointed out by past experiences.

In order to analyze the likelihood of lower- and middle-income households adopting a DR plan in LAC, this study developed an experiment giving the consumer a choice to move to a DR plan with a sample of consumers from 11 countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Mexico, Panama, Paraguay, Peru, and Uruguay.

The main results of the experiment estimate that households could have good acceptance and understanding of DR programs. Most interviewees understand that it would be fair to cover supply costs if electricity rates were higher during peak times. More than 50% of interviewees would be willing to switch to a DR plan in some experimental conditions. Those conditions included DR programs with targeted or limited incentives, such as the Peak Hour Saving Goals and the Peak Times HVAC Control.

Viewing the results through the lens of income, middle-income consumers tend to have a higher sensitivity to variations in electricity prices, reacting to even very low tariff increases. Even modest variations in price (20% during peak hours) are effective in shifting electricity consumption behavior for middle-income consumers. However, lower-income consumers perceive a higher burden of electricity. With these insights in mind, it is logical to think that DR programs are an interesting opportunity to reduce electricity bill burden in lower-income households. At the same time, however, lower-income households also have less flexibility to reduce their consumption during peak times since they are bound to more essential activities. DR policies and regulations need to take these findings into account to capture this positive potential market without introducing or exacerbating burdens of lower-income consumers. In the next steps, the authors suggest analyzing the potential residential market for DR programs and developing DR plans according to electricity consumption blocks to capture the heterogeneity of energy consumption patterns.

It is important to highlight the importance of an awareness campaign to inform energy customers about the benefits and reasoning behind the DR policy as a means of increasing its success. Interviewees in this study demonstrated high acceptance of informational instruments (such as text reminders and notifications from an app that allowed them to track their electricity consumption). Consumer participants demonstrated a preference for digitalization and, specifically, the use of apps, to track their consumption; however, the findings do not exclude the value of text messages. Implementing these informational instruments would improve consumers' perceived fairness of the DR programs and their awareness about their electricity consumption behavior during the day/month/year, as well as associated costs. In other words, those instruments could help consumers manage their electricity consumption better and be more engaged in consumption pattern changes. The implementation of informational instruments might contribute significantly to the adoption and efficacy of DR programs.

In summary, this study has provided insight into how to devise DR policies to increase their acceptance by potential residential consumers. The information shared herein included experimental data, literature reviews, and policy precedents. LAC has seen some DR policies enacted, aimed at different sectors. As varied DR designs and precedents in other regions suggest, there is potential to further develop DR in new LAC countries and sectors. DR programs must be considered a potential and effective solution to reduce LAC electricity service costs and increase their affordability in the short- and medium-term.

Bibliography

ABRAHAMSE, W., STEG, L., VLEK, C., & ROTHENGATTER, T. (2005). A review of intervention studies aimed at household energy conservation. Journal of Environmental Psychology, 25(3) , pp. 273–291. https://doi.org/10.1016/j.jenvp.2005.08.002

ACUÑA, D., KORENKO, J., & KORENKO L. (2016). EnerHomGy: gestión de la demanda eléctrica domiciliaria. Tésis de Grado. Facultad de Ingeniería. Universidad de la República: Uruguay.

ALBADI, M.H., & EL-SAADANY, E.F. (2008). A summary of demand response in electricity markets. Electric Power Systems Research, 78(11), pp. 1989–1996. https://doi.org/10.1016/j.epsr.2008.04.002

ANDRADE, E. B. (2015). Consumer emotions. In M. I. Norton, D. D. Rucker, & C. Lamberton (Eds.), The Cambridge handbook of consumer psychology (pp. 90–121). New York: Cambridge University Press. https://doi.org/10.1017/CBO9781107706552.004

ANTONIO, K. M., RAVILLARD, P., CHUECA, E., LOPEZ, D., & HALLACK, M. (2020). Enhancing affordability of Peruvian households: Evidence from retrofit lighting. Washington, D.C.: Inter-American Development Bank.

BARTUSCH, C., WALLIN, F., ODLARE, M., VASSILEVA, I., & WESTER, L. (2011). Introducing a demand-based electricity distribution tariff in the residential sector: Demand response and customer perception. Energy Policy, 39(9), pp. 5008–5025.

BATLLE, C., & RODILLA, P. (2009). Electricity demand response tools: Current status and outstanding issues. European Review of Energy Markets, 3(2), pp. 1–27.

BORENSTEIN, S., JASKE, M., & ROSENFEL, A. (2002). Dynamic pricing, advanced metering and demand response in electricity markets. University of California Energy Institute, Center for the Study of Energy Markets (CSEM) Working Paper Series. no. 105, pp. 1–64, October.

CASTRO ABRIL, M. (2020). Intermittent renewable energy, hydropower dynamics and the profitability of storage arbitrage. Washington, D.C.: Inter-American Development Bank.

CAVALLO, E., POWELL, A., & SEREBRISKY, T. (2020). From structures to services: The path to better infrastructure in Latin America and the Caribbean. Washington, D.C.: Inter-American Development Bank.

COHEN, J. B., & ANDRADE, E. B. (2018). The ADF framework: A parsimonious model for developing successful behavior change interventions. Journal of Marketing Behavior, 3(2), pp. 81–119. https://doi.org/10.1561/107.00000046

COSTA, F. (2012). Can rationing affect long-run behavior? Evidence from Brazil, December 2011. Costa, http://dx.doi.org/10.2139/ssrn.2028684

DILLAHUNT, T. R., & MANKOFF, J. (2014). Understanding factors of successful engagement around energy consumption between and among households. CSCW '14: Proceedings of the 17th ACM conference on computer supported cooperative work and social computing. pp. 1246–1257. https://doi.org/10.1145/2531602.2531626

DRANKA, G. G., & FERREIRA, P. (2020). Load flexibility potential across residential, commercial, and industrial sectors in Brazil. Energy, vol. 201, June. https://doi.org/10.1016/j.energy.2020.117483

EID, C., KOLIOU, E., VALLES, M., RENESES, J., & HAKVOORT, R. (2016). Time-based pricing and electricity demand response: Existing barriers and next steps. Utilities Policy, 40, pp. 15–25, 2016. https://doi.org/10.1016/j.jup.2016.04.001

EUROPEAN COMMISSION – EC. (2016). Impact assessment study on downstream flexibility, price flexibility, demand response and smart metering, DG Energy, pp. 192, 2016, July.

FARUQUI, A., & SERGICI, S. (2010). Household response to dynamic pricing of electricity: A survey of 15 experiments. Journal of Regulatory Economics, 38(2).

FARUQUI, A., & SERGICI, S. (2013). Arcturus: International evidence on dynamic pricing. The Electricity Journal, 26(7), pp. 55–65.

FARUQUI, A., & BOURBONNAIS, C. (2020). The tariffs of tomorrow. IEEE Power Energy Magazine, pp. 18–25, June.

FEDERAL ENERGY REGULATORY COMMISSION – FERC. (2018). Assessment of demand response and advanced metering. Staff Report. November.

FLORENCE SCHOOL OF REGULATION - FSR. (2020). Time of use and dynamic pricing rates in the US. Available: https://fsr.eui.eu/time-of-use-and-dynamic-pricing-rates-in-the-us/.

GAGNE, D., SETTLE, E., AZNAR, A., & BRACHO, R. (2018). Demand response compensation methodologies: Case studies for Mexico. Technical Report. Golden, CO: National Renewable Energy Laboratory (NREL), pp. 58, June.

GELLINGS, C. W. (1985). The concept of demand-side management for electric utilities. Proceedings of the IEEE, 73(10), pp. 1468–1470.

GOLDENBERG, C., DYSON, M., & MASTERS, H. (2018). Demand flexibility the key to enabling a low-cost, low-carbon grid insight brief. White Paper. Basalt, CO: Rocky Mountain Electricity Institute.

GUNTHER, B., JÖRG, P., & LINDA, S. (2010). Energy usage and socio-economic conditions in Mozambique – Evidence from GTZ electrification project regions.

GUSTAFSSON, A., & GYLLENSWÄRD, M. (2005). The power-aware cord: Energy awareness through ambient information display. Conference on Human Factors in Computing Systems - Proceedings, p. 1423–1426. Available at: https://doi.org/10.1145/1056808.1056932

HALE, E., BIRD, L., PADMANABHAN, R., & VOLPI, C. (2018). Potential roles for demand response in high-growth electric systems with increasing shares of renewable generation potential roles for demand response in high-growth electric systems with increasing shares of renewable generation. Technical Report. Golden, CO: National Renewable Energy Laboratory - NREL, vol. NREL/TP-6A, December.

HOLMES, T. G. (2009). Eco-visualization: Combining art and technology to reduce energy consumption. Proceedings of the 6th Conference on Creativity & Cognition, Washington, D.C., USA, June. https://doi.org/10.1145/1254960.1254982

INTERNATIONAL ENERGY AGENCY – IEA. (2021). Demand response. Paris: IEA. Available at: https://www.iea.org/reports/demand-response

INTERNATIONAL ENERGY AGENCY – IEA. (2018). World Energy Outlook 2018: Highlights. Paris: IEA.

JANSEN, L. L., ANDREADOU, N., PAPAIOANNOU, I., & MARINOPOULOS, A. (2020). Smart grid lab research in Europe and beyond. International Journal of Energy Research, 44(3), pp. 1307–1336. https://doi.org/10.1002/er.4818

JIMENEZ MORI, R. A,. & YÉPEZ-GARCÍA, A. (2020). How do households consume energy? - Evidence from Latin American and Caribbean Countries. Washington, D.C.: Inter-American Development Bank.

KARLAN, D. S., MCCONNELL, M., MULLAINATHAN, S., & ZINMAN, J. (2010). Getting to the top of mind: How reminders increase saving. Management Science, 62(12), March. https://doi.org/10.1287/mnsc.2015.2296

LANGEVIN, J., GURIAN, P. L., & WEN, J. (2013). Reducing energy consumption in low-income public housing: Interviewing residents about energy behaviors. Applied Energy, 102, pp. 1358–1370. https://doi.org/10.1016/j.apenergy.2012.07.003

LUJANO-ROJAS, J. M., MONTEIRO, C., DUFO-LÓPEZ, R., & BERNAL-AGUSTÍN, J. L. (2012). Optimum residential load management strategy for real time pricing (RTP) demand response programs. Energy Policy, 45, pp. 671–679.

OCONNELL, N., PINSON, P., MADSEN, H., & OMALLEY, M. (2014). Benefits and challenges of electrical demand response: A critical review. Renewable and Sustainable Energy Reviews, 39, pp. 686–699.

PREEDY, V.R., & WATSON R.R. (2010). Handbook of disease burdens and quality of life measures. New York: Springer. DOI: https://doi.org/10.1007/978-0-387-78665-0_6363.
RAVILLARD, P., CARVAJAL, F., LOPEZ SOTO, D., CHUECA MONTUENGA, E., & HALLACK M. (2019). Towards greater energy efficiency in LAC: Progress and policies. Washington, D.C.: Inter-American Development Bank.

RODAS-GALLEGO, E., & MEJÍA-GIRALDO, D. (2020). Market-based Impact of a demand response program in the Colombian power market. IEEE Latin America Transactions, 18(03), pp. 537-544, March. https://doi.org/10.1109/TLA.2020.9082725

SANCHEZ Ú.E., PORTELA, G., MUÑOZ, J., SAN ROQUE, A., CHUECA, J. E., & Hallack M. (2021). Impacto del COVID-19 en la demanda de energía eléctrica en Latinoamérica y el Caribe. Washington, D.C.: Inter-American Development Bank. https://publications.iadb.org/es/impacto-del-covid-19-en-la-demanda-de-energia-electrica-en-latinoamerica-y-el-caribe

SATCHWELL, A., BARBOSE, G., GOLDMAN, C., HLEDIK, R., & FARUQUI, A. (2013). Incorporating demand response into Western interconnection transmission planning. Berkeley, CA: Lawrence Berkeley National Laboratory.

SCHIL W., PAHLE M., & GAMBARDELLA C., (2017). Start-up costs of thermal power plants in markets with increasing shares of variable renewable generation. Nature energy.

STOFT, S. (2002). Power system eonomics. IEEE Press.

STOKKE, A. V., DOORMAN, G. L., & ERICSON, T. (2010). An analysis of a demand charge electricity grid tariff in the residential sector. Energy Efficiency, 3(3), pp. 267–282. https://doi.org/10.1007/s12053-009-9071-9

VANTHOURNOUT, K., DUPONT, B., FOUBERT, W., STUCKENS, C., & CLAESSENS, S. (2015). An automated residential demand response pilot experiment, based on day-ahead dynamic pricing. Applied Energy, 155, pp. 195–203.

VASSILEVA, I., ODLARE, M., WALLIN, F., & DAHLQUIST, E. (2012). The impact of consumers' feedback preferences on domestic electricity consumption. Applied Energy, 93, pp. 575–582. https://doi.org/10.1016/j.apenergy.2011.12.067

VAZQUEZ C., HALLACK M., & VAZQUEZ, M. (2017). Price computation in electricity auctions with complex rules: An analysis of investment signals. Energy Policy, 105(C), 550-561.

WADA, K., AKIMOTO, K., SANO, F., ODA, J., & HOMMA, T. (2012). Energy efficiency opportunities in the residential sector and their feasibility. Energy, 48(1), pp. 5–10. https://doi.org/10.1016/j.energy.2012.

WALKER, I., & HOPE, A. (2020). Householders' readiness for demand-side response: A qualitative study of how domestic tasks might be shifted in time. Energy and Buildings, 215, p. 109888. https://doi.org/10.1016/j.enbuild.2020.109888

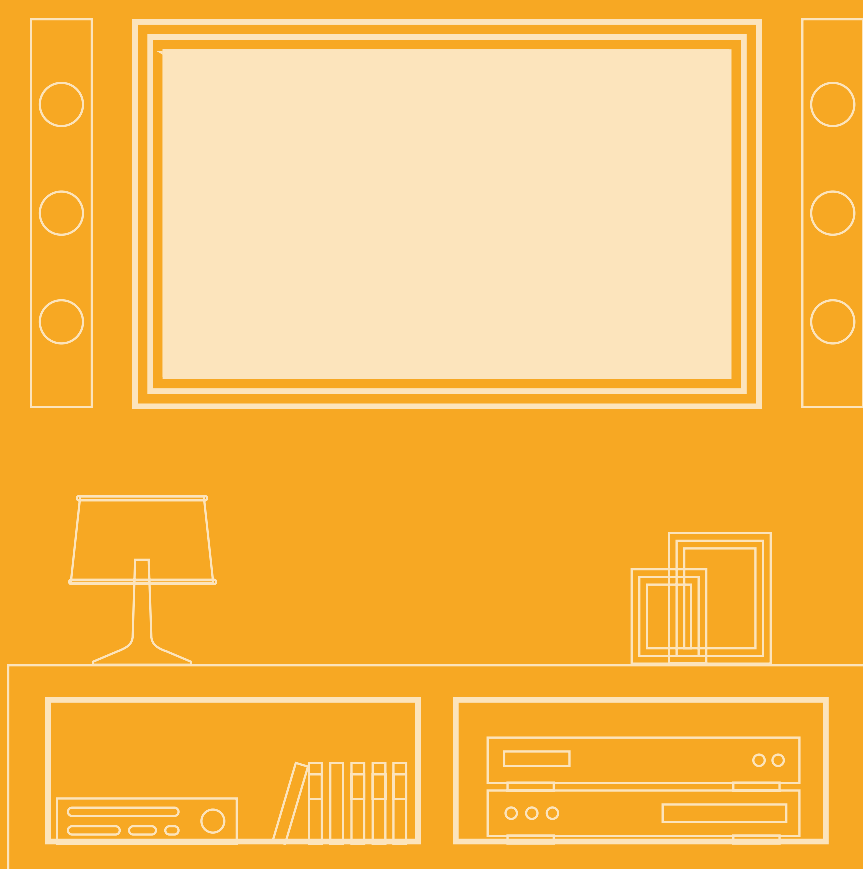
WANG, Y., LIN, H., LIU, Y., SUN, Q., & WENNERSTEN, R. (2018). Management of household electricity consumption under price-based demand response scheme. Journal of Cleaner Production, 204, pp. 926–938. https://doi.org/10.1016/j.jclepro.2018.09.019

WEBER, S., PUDDU, S., & PACHECO, D. (2017). Move it! How an electric contest motivates households to shift their load profile. Energy Economics, 68, pp. 255–270.

WILSON, T.D., ARONSON, E., & CARLSMITH, K. (2010). The art of laboratory experimentation. Handbook of Social Psychology, pp. 49–79. https://doi.org/10.1002/9780470561119.socpsy001002

US DEPARTMENT OF ENERGY – US DOE. (2006). Benefits of demand response in electricity markets and recommendations for achieving them. pp. 13–14, February.

ANNEX



A.1 Average per capita income and household electricity bill cost:

A comparison between the sample results and the Brazilian household budget survey

This is the socioeconomic profile of the experiment's sample from Brazil, excluding outliers[20] .

(a) Monthly Per capita income (entire household)

10% of the sample: earn less than USD20 - >	equivalent to the 1st income decile of the Brazilian Household Budget Survey 2017-2018.
25% of the sample: earn less than USD40 - >	equivalent to the 1st income decile of the Brazilian Household Budget Survey 2017-2018.
50% of the sample: earn less than USD80 - >	equivalent to the 2nd income decile of the Brazilian Household Budget Survey 2017-2018.
75% of the sample: earn less than USD130 - >	equivalent to the 3rd income decile of the Brazilian Household Budget Survey 2017-2018.
90% of the sample: earn less than USD230 - >	equivalent to the 5th income decile of the Brazilian Household Budget Survey 2017-2018.
Mean = earn USD200 ->	between the 3rd and the 4th income decile of the Brazilian Household Budget Survey 2017-2018.

The monthly per capita income per Brazilian household decile is shown below (Table A.1.1). The data is from the Brazilian Household Budget Survey 2017-2018[21] .

20. The household overall income mean seems to be elevated because of some outliers. More precisely, a very small group of participants in the sample reported an extremely high household income (e.g., around 10-15 participants reported household income from USD30k to 100k), and it is very likely that they included digits by mistake. Therefore, a small number of participants is impacting the mean income, pushing it higher than it would be otherwise. However, as income was an open-ended question, the study considers the possibility that respondents could have included a 0 or ,00 by mistake. Household income higher than USD20k represented around 5% of the sample.
21. The exchange rate was 3,22 reais per dollar from the Brazilian Central Bank for the day of January 15, 2018, available at: http://www.ipeadata.gov.br/ExibeSerie.aspx?serid=38590&module=M

Table A.1.1. Per capita Income per Brazilian Household Decile, 2018.

Per capita Income* - Brazil - POF 2017-2018				
Variable	Mean	Std. Dev.	Min	Max
Decil 1	$ 50.75	$ 17.26	$ -	$ 76.21
Decil 2	$ 96.98	$ 11.70	$ 76.21	$ 116.50
Decil 3	$ 137.14	$ 11.68	$ 116.52	$ 157.34
Decil 4	$ 178.13	$ 12.43	$ 157.34	$ 200.30
Decil 5	$ 226.42	$ 14.90	$ 200.31	$ 251.42
Decil 6	$ 277.71	$ 15.32	$ 251.42	$ 304.34
Decil 7	$ 339.93	$ 21.15	$ 304.36	$ 378.45
Decil 8	$ 434.47	$ 35.33	$ 378.46	$ 502.53
Decil 9	$ 618.48	$ 77.87	$ 502.54	$ 777.92
Decil 10	$ 1,766.66	$ 1,911.39	$ 777.94	$ 74,396.94

* Values in Dollars (December 15th, 2020)

Source: Brazilian Household Budget Survey – POF 2017-2018.

(b) Household Monthly Electricity Bill Cost (entire household)

10% of the sample: pay less than USD12 (R$60) on average per month -> equivalent to the 2nd income decile of the Brazilian Household Budget Survey 2017-2018.

25% of the sample: pay less than USD18 (R$90) on average per month -> equivalent to the 3rd income decile of the Brazilian Household Budget Survey 2017-2018.

50% of the sample: pay less than USD24 (R$120) on average per month -> equivalent to the 4th income decile of the Brazilian Household Budget Survey 2017-2018.

75% of the sample: pay less than USD36 (R$180) on average per month -> equivalent to the 6th income decile of the Brazilian Household Budget Survey 2017-2018.

90% of the sample: pay less than USD50 (R$250) on average per month -> equivalent to the 8th income decile of the Brazilian Household Budget Survey 2017-2018.

Mean = pay USD28 (R$140) on average per month -> equivalent to the 5th income decile of the Brazilian Household Budget Survey 2017-2018.

The cost of the Brazilian household electricity bill is presented per decile (Table A.1.2.).

Table A.1.2. Average Monthly Electricity Bill Cost per Household Decile, 2018

Monthly Electricity Bill Cost* per Household- Brazil - POF 2017-2018				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Decil 1	$ 7.81	$ 2.50	$ 0.75	$ 11.52
Decil 2	$ 14.50	$ 1.58	$ 11.53	$ 17.07
Decil 3	$ 19.54	$ 1.38	$ 17.08	$ 21.93
Decil 4	$ 24.55	$ 1.49	$ 21.94	$ 27.13
Decil 5	$ 29.84	$ 1.66	$ 27.13	$ 32.83
Decil 6	$ 35.84	$ 1.90	$ 32.83	$ 39.29
Decil 7	$ 43.25	$ 2.50	$ 39.29	$ 47.89
Decil 8	$ 53.61	$ 3.42	$ 47.90	$ 59.99
Decil 9	$ 69.10	$ 6.34	$ 60.00	$ 82.45
Decil 10	$ 121.12	$ 47.73	$ 82.45	$ 568.65

* Values in Dollars (December 15th, 2020)

A.2. Experiment questionnaire in original format

Start of Block: Consentimento

consent_form **DOCUMENTO DE CONSENTIMIENTO INFORMADO**
Comportamiento de consumo eléctrico residencial

El propósito de esta investigación es conocer su opinión y hábitos de consumo eléctrico. Se lleva a cabo con fines académicos y de política pública cuyos datos serán analizados como parte de una colaboración con el Banco Interamericano de Desarrollo (BID).

Si participa, tomará decisiones hipotéticas en una encuesta en línea y proporcionará cierta información sobre usted.

Responder el cuestionario le puede tomar unos 10 minutos.
Sus datos serán confidenciales y sus respuestas siempre serán analizadas de forma anónima, junto con las respuestas de otros encuestados, nunca de forma individual. Su participación es totalmente voluntaria y no implica riesgos anticipados. Si en algún momento tiene dudas sobre la investigación o su participación, puede contactar a los investigadores: Jorge Jacob (Investigador): jorgejacob@gmail.com, Rodrigo Leite: rodrigo.de.oliveira.leite@gmail.com, Jesus Montuenga (BID): JESUSCHU@iadb.org, Mariana Weiss (BID): MARIANAWE@iadb.org

part_consent ¿Está de acuerdo en participar en este estudio?

- ☐ Si (4)
- ☐ No (5)

Skip To: End of Survey If ¿Está de acuerdo en participar en este estudio? = No
End of Block: Consentimento

Start of Block: partic_billshare

partic_billshare

Gracias por participar. ¡Vamos a empezar!

Comenzaremos con algunas preguntas sobre el uso actual de electricidad en su hogar.
¿Qué porcentaje de la factura de electricidad total de su hogar paga al mes habitualmente?

- ☐ 0% - No pago nada de la factura. (1)
- ☐ 1% a 49% - Pago menos de la mitad de la factura. (4)
- ☐ 50% - Pago la mitad de la factura. (5)
- ☐ 51% a 100% - Pago más de la mitad de la factura. (6)

End of Block: partic_billshare

Start of Block: partic_billvalue

partic_billvalue_avg

¿Cuál es el valor promedio de la factura de electricidad de su hogar por mes? (Considerando los últimos dos años)

[Responda solo en números, en su moneda local. No incluya centavos (ej .: 150).]

____

____

partic_billvalue_hig

¿Cuál fue el valor máximo que pagó por su factura de luz eléctrica? (Considerando los últimos dos años)

[Responda solo en números, en su moneda local. No incluya centavos (ej .: 150).]

____

____

partic_billvalue_low

¿Cuál fue el valor mínimo que pagó por su factura de luz eléctrica? (Considerando los últimos dos años)

[Responda solo en números, en su moneda local. No incluya centavos (ej .: 150).]

____

____

Page Break
partic_appliances Indique si tiene o no los siguientes artículos en su hogar:

	Si (1)	No (2)
Calentador eléctrico (49)	☐	☐
Aire econdicionado (66)	☐	☐
Ventilador (68)	☐	☐
Computadora (laptop, notebook, tableta) (28)	☐	☐
Celular con acceso a internet (Smartphone) (37)	☐	☐
Servicio de internet (44)	☐	☐
Acceso a la red eléctrica (45)	☐	☐
Contador eléctrico particular (69)	☐	☐

End of Block: partic_billvalue

Start of Block: timeofusetariff_fairness

timeofusetariff_fair

Lea atentamente la siguiente información:

Los proveedores de electricidad son empresas que suministran electricidad a los hogares. Por lo general, cobran la misma tarifa por cada unidad de electricidad utilizada (kWh), independientemente del tiempo de uso.

Sin embargo, en algunas horas del día la utilización de electricidad por los hogares en una ciudad es la más alta (las horas punta). Durante estos horarios, los proveedores de electricidad tienen costos adicionales para cumplir el uso de sus clientes.

part_timeofuse_fairn Teniendo eso en mente, por favor, marque los siguientes elementos:

Es justo que un proveedor de electricidad cobre una tarifa más alta durante las horas de pico (pico). (4)

- ☐ Totalmente en Desacuerdo (18)
- ☐ En Desacuerdo (19)
- ☐ Algo en Desacuerdo (20)
- ☐ Ni de Acuerdo Ni en Desacuerdo (21)
- ☐ Algo de Acuerdo (22)
- ☐ De Acuerdo (23)
- ☐ Totalmente de Acuerdo (24)

Page Break

part_timeofuse_sensi En caso de que un proveedor de energía cobre a su hogar una tarifa por la electricidad más alta durante las horas pico.

¿Qué posibilidades hay de que reduzca su consumo en horas de pico a horas de donde que no sean pico si su tarifa es?:

20% más durante las horas de pico, en comparación con las horas donde no se da el pico. (1)

- ☐ Extremadamente Improbable (32)
- ☐ Moderadamente Improbable (33)
- ☐ Ligeramente Improbable (34)
- ☐ Ni probable Ni Improbable (35)
- ☐ Poco Probable (36)
- ☐ Moderadamente Probable (37)
- ☐ Muy Probable (38)

40% más durante las horas de pico, en comparación con las horas donde no se da el pico. (4)

- ☐ Extremadamente Improbable (32)
- ☐ Moderadamente Improbable (33)
- ☐ Ligeramente Improbable (34)
- ☐ Ni probable Ni Improbable (35)
- ☐ Poco Probable (36)
- ☐ Moderadamente Probable (37)
- ☐ Muy Probable (38)

60% más durante las horas de pico, en comparación con las horas donde no se da el pico. (5)

- ☐ Extremadamente Improbable (32)
- ☐ Moderadamente Improbable (33)
- ☐ Ligeramente Improbable (34)
- ☐ Ni probable Ni Improbable (35)
- ☐ Poco Probable (36)
- ☐ Moderadamente Probable (37)
- ☐ Muy Probable (38)

80% más durante las horas de pico, en comparación con las horas donde no se da el pico. (6)

- ☐ Extremadamente Improbable (32)
- ☐ Moderadamente Improbable (33)
- ☐ Ligeramente Improbable (34)
- ☐ Ni probable Ni Improbable (35)
- ☐ Poco Probable (36)
- ☐ Moderadamente Probable (37)
- ☐ Muy Probable (38)

Precio 100% más alto (el doble) durante las horas de pico, en comparación con las horas donde no se da el pico. (7)

- ☐ Extremadamente Improbable (32)
- ☐ Moderadamente Improbable (33)
- ☐ Ligeramente Improbable (34)
- ☐ Ni probable Ni Improbable (35)
- ☐ Poco Probable (36)
- ☐ Moderadamente Probable (37)
- ☐ Muy Probable (38

End of Block: timeofusetariff_fairness

Start of Block: timeofusetariff_awareness part_timeofuse_awa .

	Si (30)	No (31)
¿Sabe a qué hora es la hora de pico de uso de electricidad en su región? (2)	☐	☐
¿Sabe cuánto más caro cobra su proveedor de energía la tarifa por kWh durante las horas de pico en relación con las horas fuera de pico? (3)	☐	☐
¿Tiene su ciudad o región una tarifa con valores que diferencia cuando realiza uso eléctrico en horario de pico y fuera de él? (11)	☐	☐

End of Block: timeofusetariff_awareness

Start of Block: peaktime_info

peaktime_info La hora de picos de uso de electricidad en su región es:

De 7 hasta 10h de la noche (= 3 horas al día)
Teniendo en cuenta eso, responda las siguientes preguntas.

partic_time_mostuse ¿Corresponde este periodo de horas de pico a la hora del día en que su hogar consume más electricidad (por ejemplo, electrodomésticos)?

☐ SÍ. Usamos más electricidad durante esta hora de punta. (4)

☐ SÍ, EN PARTE. Usamos tanta electricidad dentro del horario de pico como fuera de el. (5)

☐ NO. No utilizamos más la electricidad durante esta hora de pico. (6)

End of Block: peaktime_info

Start of Block: cond_heater

cond_heater Imagine que su proveedor de electricidad ofrece estos dos planes para su hogar. ¿Qué plan elegirías? [Horas pico en su región: 7 hasta 10h de la noche] Duración total = 3 horas

☐ Plan A Tu tarifa es la misma independientemente de la hora del día. (2)

☐ Plan B Durante las horas de pico, permites que tu proveedor de electricidad apague tu calentador (solo si tu proveedor lo necesita) y tienes un descuento de hasta un 21% en tu factura total de la luz. (4)

End of Block: cond_heater

Start of Block: cond_horasdepico

cond_horasdepico Imagine que su proveedor de energía ofrece estos dos planes para su hogar. ¿Qué plan elegirías?

[Horas pico en su región: 7 hasta 10h de la noche] Duración total = 3 horas

☐ Plan A Tu tarifa es la misma independientemente de la hora del día. (1)

☐ Plan B Su tarifa es más cara durante las horas de pico y más barata fuera de estas horas pico. La tarifa de las horas de pico es casi el triple que las horas de menor actividad. Si reduce su uso en un 33% durante las horas de pico, su factura total de la luz se reduce en un 21%. (2)

End of Block: cond_horasdepico

Start of Block: cond_goal

cond_goal Imagine que su proveedor de electricidad ofrece estos dos planes para su hogar. ¿Qué plan elegirías?

[Horas pico en su región: 7 hasta 10h de la noche] Duración total = 3 horas

☐ Plan A Tu tarifa es la misma independientemente de la hora del día. (1)

☐ Plan B Si reduce su uso en un 33% durante las horas de pico, su tarifa disminuirá y su factura total de la luz se reducirá hasta en un 21%. Sin embargo, si continúa con su consumo eléctrico la factura total de la luz se mantiene, pero si aumenta su uso durante las horas de pico ,su factura total de la luz aumenta. (2)

End of Block: cond_goal

Start of Block: cond_peakhours_Brazil

cond_peakhours_Brazi Imagine que su proveedor de electricidad ofrece estos dos planes para su hogar. ¿Qué plan elegirías?

[Horas pico en su región: 7 hasta 10h de la noche] Duración total = 3 horas

☐ Plan A Tu tarifa es la misma independientemente de la hora del día. (1)

☐ Plan B Su tarifa es más cara durante las horas de pico y más barata fuera de estas horas pico. La tarifa de las horas de pico es casi el triple que las fuera de estas horas pico. Si reduce su uso en un 33% durante las horas de pico, su factura total de la luz se reduce en hasta 4%. (2)

End of Block: cond_peakhours_Brazil

Start of Block: cond_AC

cond_AC Imagine que su proveedor de electricidad ofrece estos dos planes para su hogar. ¿Qué plan elegirías?

[Horas pico en su región: 7 hasta 10h de la noche] Duración total = 3 horas

☐ Plan A Tu tarifa es la misma independientemente de la hora del día. (1)

☐ Plan B Durante las horas de pico, permites que tu proveedor de electricidad apague tu aire acondicionado (solo si tu proveedor lo necesita) y tienes un descuento de hasta un 21% en tu factura total de la luz. (2)

End of Block: cond_AC

Start of Block: DV_prefered_reminder

DV_prefered_interven

Ahora, imagine que le gustaría reducir el consumo de electricidad de su hogar durante las horas de pico.

¿Qué tipo de información proporcionada por el proveedor de electricidad cree que sería más eficaz para que su hogar redujera el consumo durante las horas de pico?

Mensajes de texto con información sobre qué electrodomésticos suelen consumir más electricidad y cuánto se paga aproximadamente por ellos. (33)

☐ Definitivamente No (23)
☐ Probablemente No (24)
☐ Tal Vez (25)
☐ Probablemente Sí (26)
☐ Definitivamente Si (27)

Mensajes de texto recibidos cuando comienzan y termina las horas de pico. (34)

- ☐ Definitivamente No (23)
- ☐ Probablemente No (24)
- ☐ Tal Vez (25)
- ☐ Probablemente Sí (26)
- ☐ Definitivamente Si (27)

Un mensaje de texto cuando el precio de la electricidad es superior a un límite estimando el horario pico. (35)

- ☐ Definitivamente No (23)
- ☐ Probablemente No (24)
- ☐ Tal Vez (25)
- ☐ Probablemente Sí (26)
- ☐ Definitivamente Si (27)

Un mensaje de texto con tu consumo actual y previsión de la factura de la luz a final de mes. (36)

- ☐ Definitivamente No (23)
- ☐ Probablemente No (24)
- ☐ Tal Vez (25)
- ☐ Probablemente Sí (26)
- ☐ Definitivamente Si (27)

Una aplicación para el celular con notificaciones de tu consumo de electricidad y él pronostican el costo final de su factura de la luz. (37)

- ☐ Definitivamente No (23)
- ☐ Probablemente No (24)
- ☐ Tal Vez (25)
- ☐ Probablemente Sí (26)
- ☐ Definitivamente Si (27)

End of Block: DV_prefered_reminder

Start of Block: manp_check

manipulation_check En esta investigación mostramos dos planes hipotéticos de consumo de luz. ¿Cuál de los siguientes planes era uno de ellos?

- ☐ Si reduce su consumo electrico en un 33% durante las horas de pico, su factura total de luz puede reducirse hasta en un 21%. (21)
- ☐ Si reduce su consumo electrico en un 33% durante las horas de pico, su factura total de luz puede reducirse hasta en un 4%. (22)
- ☐ Si reduce su consumo electrico en un 33% en horas pico, su tarifa disminuye y su factura total de luz se puede reducir hasta en un 21%. Si no altera su consumo su factura de la luz no cambia. (23)
- ☐ Si deja que su proveedor de electricidad apague su aire acondicionado o calentador en los horarios de pico, obtendrá un descuento de hasta el 21% en su factura total de luz. (24)

End of Block: manp_check

Start of Block: partic_consumption_motives

partic_consumption_m

Indique en qué medida está de acuerdo o en desacuerdo con los siguientes puntos:

Me gustaría reducir consumo de electricidad en mi hogar por cuestiones medioambientales. (1)

- ☐ Totalmente en Desacuerdo (11)
- ☐ En Desacuerdo (12)
- ☐ Algo en Desacuerdo (13)
- ☐ Ni de Acuerdo Ni en Desacuerdo (14)
- ☐ Algo de Acuerdo (15)
- ☐ De Acuerdo (16)
- ☐ Totalmente de Acuerdo (17)

Me gustaría reducir consumo de electricidad en mi casa para ahorrar dinero. (2)

- ☐ Totalmente en Desacuerdo (11)
- ☐ En Desacuerdo (12)
- ☐ Algo en Desacuerdo (13)
- ☐ Ni de Acuerdo Ni en Desacuerdo (14)
- ☐ Algo de Acuerdo (15)
- ☐ De Acuerdo (16)
- ☐ Totalmente de Acuerdo (17)

Me gustaría reducir el consumo de electricidad en mi casa, pero es muy difícil porque tengo que educar a otras personas que viven conmigo. (3)

- ☐ Totalmente en Desacuerdo (11)
- ☐ En Desacuerdo (12)
- ☐ Algo en Desacuerdo (13)
- ☐ Ni de Acuerdo Ni en Desacuerdo (14)
- ☐ Algo de Acuerdo (15)
- ☐ De Acuerdo (16)
- ☐ Totalmente de Acuerdo (17)

He tenido dificultades en los últimos años para pagar mi factura de luz. (5)

- ☐ Totalmente en Desacuerdo (11)
- ☐ En Desacuerdo (12)
- ☐ Algo en Desacuerdo (13)
- ☐ Ni de Acuerdo Ni en Desacuerdo (14)
- ☐ Algo de Acuerdo (15)
- ☐ De Acuerdo (16)
- ☐ Totalmente de Acuerdo (17)

Normalmente evito usar dispositivos electrónicos debido al costo de la electricidad. (6)

- ☐ Totalmente en Desacuerdo (11)
- ☐ En Desacuerdo (12)
- ☐ Algo en Desacuerdo (13)
- ☐ Ni de Acuerdo Ni en Desacuerdo (14)
- ☐ Algo de Acuerdo (15)
- ☐ De Acuerdo (16)
- ☐ Totalmente de Acuerdo (17)

Me gustaría usar el aire acondicionado o la calefacción con más frecuencia en mi casa. (7)

- ☐ Totalmente en Desacuerdo (11)
- ☐ En Desacuerdo (12)
- ☐ Algo en Desacuerdo (13)
- ☐ Ni de Acuerdo Ni en Desacuerdo (14)
- ☐ Algo de Acuerdo (15)
- ☐ De Acuerdo (16)
- ☐ Totalmente de Acuerdo (17)

part_perc_use_same En comparación con personas con el MISMO nivel socioeconómico que el tuyo, ¿cómo crees que es tu consumo de electricidad?

- ☐ SUPERIOR al consumo promedio de los demás. (1)
- ☐ IGUAL al promedio de los demás. (13)
- ☐ INFERIOR al consumo promedio de los demás. (2)

part_perc_use_high En comparación con personas con el nivel socioeconómico SUPERIOR que el tuyo, ¿cómo crees que es tu consumo de electricidad?

- ☐ SUPERIOR al consumo promedio de la gente como yo. (1)
- ☐ IGUAL al promedio de la gente como yo. (13)
- ☐ INFERIOR al consumo promedio de la gente como yo. (14)

---

partic_elect_supplie ¿Cuál es el nombre de su proveedor de electricidad?
(Si no recuerda, déjelo en blanco)

---

partic_electr_source ¿Cuál es la principal fuente de energía que utiliza en su casa para

Calentar la casa (1)

- ☐ Energía Eléctrica (1)
- ☐ Gas Canalizado (4)
- ☐ Bombona de Gas (5)
- ☐ Leña (7)
- ☐ Otros (8)
- ☐ Ninguno (9)

Cocinar (2)

- ☐ Energía Eléctrica (1)
- ☐ Gas Canalizado (4)
- ☐ Bombona de Gas (5)
- ☐ Leña (7)
- ☐ Otros (8)
- ☐ Ninguno (9)

Calentar Agua (3)

- ☐ Energía Eléctrica (1)
- ☐ Gas Canalizado (4)
- ☐ Bombona de Gas (5)
- ☐ Leña (7)
- ☐ Otros (8)
- ☐ Ninguno (9)

---

partic_Interr_freq

Respecto al suministro de energía eléctrica en su hogar el año pasado ...

En promedio, ¿con qué frecuencia ha tenido cortes de electricidad?

- ☐ Diario (11)
- ☐ 4-6 veces por semana (12)
- ☐ 2-3 veces por semana (13)
- ☐ Una vez por semana (14)
- ☐ Una vez al mes (15)
- ☐ Nunca (16)

partic_Interr_durati .

En promedio, ¿cuánto duraron las interrupciones y apagones del suministro eléctrico? (1)

- ☐ 0 (1)
- ☐ 1-3min (2)
- ☐ 4-15min (3)
- ☐ 16-40min (4)
- ☐ 41-59min (5)
- ☐ 1-3h (6)
- ☐ 4-10h (7)
- ☐ 11-23h (8)
- ☐ 1-2 días (9)
- ☐ 3-5 días (10)
- ☐ 6 días o más (11)

¿Cuánto duró el apagón eléctrico o corte de luz más largo? (2)

- ☐ 0 (1)
- ☐ 1-3min (2)
- ☐ 4-15min (3)
- ☐ 16-40min (4)
- ☐ 41-59min (5)
- ☐ 1-3h (6)
- ☐ 4-10h (7)
- ☐ 11-23h (8)
- ☐ 1-2 días (9)
- ☐ 3-5 días (10)
- ☐ 6 días o más (11)

---

partic_interr_conse Sobre los costos asociados a estos apagones eléctricos o cortes de luz:

¿Se dañó algún equipo? (1)

- ☐ Sí (1)
- ☐ No (2)
- ☐ No tuve interrupciones (3)

¿Ha recibido una compensación económica por la interrupción del servicio eléctrico? (7)

- ☐ Sí (1)
- ☐ No (2)
- ☐ No tuve interrupciones (3)

¿Ha recibido una compensación económica por el equipo dañado por el corte de luz? (8)

- ☐ Sí (1)
- ☐ No (2)
- ☐ No tuve interrupciones (3)

¿Fue necesario contactar al distribuidor o regulador para solucionar el problema? (9)

- ☐ Sí (1)
- ☐ No (2)
- ☐ No tuve interrupciones (3)

Page Break

End of Block: partic_consumption_motives

Start of block: demographics

todelete_13 Antes de terminar, responda a estas preguntas demográficas:

---

race ¿Cuál es su origen racial?
▼ Asiático (5) ... Prefiero no contestar (9)

---

gender ¿Cuál es su identidad de género?
▼ Masculino (1) ... Otro (13)

---

age ¿Cuál es tu edad? (En años | solo números enteros)
▼ 18 (1) ... 85 o más (68)

---

education

¿Cuál es el nivel educativo más alto que ha alcanzado?
▼ Educación Básica Incompleta (1) ... Prefiero no contestar (10)

nacionalidad ¿Dónde vive actualmente?
▼ Argentina (7) ... Otro (110)

---

state_live ¿En qué ESTADO/PROVINCIA vive actualmente?

Page Break

*

partic_income ¿Cuál es su ingreso total en un mes antes de impuestos? [Responda solo en números, en su moneda local. No incluya centavos (ej .: 150).]

---

partic_incomeshare_b

¿Cuánto de su ingreso mensual total se dedica a pagar su factura de energía? [Responda solo en números, en su moneda local. No incluya centavos (ej .: 150).]
▼ 5% o menos (7) ... 101% o más (18)

*

partic_income_hh ¿Cuál es el ingreso total de TODOS los miembros de su hogar en un mes antes de impuestos? (Incluidos sus ingresos y los de otros miembros de su familia). [Responda solo en números, en su moneda local. No incluya centavos (ej .: 150).]

---

partic_residents_hh ¿Cuántas personas en total viven o se quedan en su casa?
▼ 1 (1) ... 12 o más (15)

Page Break

*

civil_status ¿Está casado, viudo, divorciado, separado o nunca se casó?
▼ Casado (1) ... Nunca Casado (5)

---

*

work
¿Qué enunciado describe mejor su situación laboral actual?
▼ Trabajando (Trabajo Asalariado) (1) ... Sin trabajo (Otro) (10)

End of Block: demographics

Start of Block: Thanks

Thanks ¡Muchas gracias por su participación!

End of Block: Thanks

A.3 The effect of participants' income, perceived fairness of peak hours tariffs, and participants' perceived electricity burden on their price sensitivity

First, the paper examined the effect of participants' income (Table A.3.1), perceived fairness of peak hours tariffs (Table A.3.2), and participants' perceived electricity burden (Table A.3.3) on their willingness to reduce consumption during on-peak hours (a proxy for their electricity consumption-related price sensitivity). The effect of each one of these variables was analyzed separately. Then, these three variables were assessed together in the same regression (Table A.3.4). All these regressions control for variations in consumers' demographics.

When analyzed separately, participants' income impacts their price sensitivity, especially an initial price increase (Table A.3.1). Participants' perceived fairness of peak hours tariffs (Table A.3.2) and participants' perceived electricity burden (Table A.3.3) also impact their price sensitivity and almost all price increase levels. Comparing the tables, participants' income (Table A.3.1) has a less stable impact on participants' price sensitivity relative to participants' perceived fairness (Table A.3.2) and participants' perceived electricity burden (Table A.3.3), since these two variables impact participants in more price increases.

To check the final effect on the price sensitivity of each one of these variables, the paper relies on regression models including all these three variables together (Table A.3.4). Table A.3.4 shows that participants' income significantly affects participants' price sensitivity, but only on the first price increase. For the remaining levels of increase, the effect of income does not appear to reach significance when these other variables are considered. Thus, income had a less stable effect on their price sensitivity when compared to the effect of fairness and perceived electricity burden, that more consistently impacted participants' price sensitivity.

Table A.3.1. Impact of Income on Willingness of Reducing Consumption During Peak Hours

Price increase	Model 20%	Model 40%	Model 60%	Model 80%	Model 100%
DV: Willingness to reduce consumption during peak hours (more price sensitive)					
Income	0.031**	0.025	0.020	0.022	0.008
	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)
Controls1	Yes	Yes	Yes	Yes	Yes
# Observations	3,078	2,988	2,985	2,961	2,969
R-squared	0.019	0.018	0.011	0.011	0.008

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05,
1 Controlled for consumers' age, gender, race, social status, country, and % of the bill paid
Source: Authors' design, using experiment data

Table A.3.2. Impact of Fairness on Willingness to Reduce Consumption During Peak Hours (more price-sensitive)

Price increase	Model 20%	Model 40%	Model 60%	Model 80%	Model 100%
DV: Willingness to reduce consumption during peak hours (more price sensitive)					
Fairness	0.140***	0.130***	0.134***	0.113***	0.100***
	(0.020)	(0.020)	(0.022)	(0.023)	(0.025)
Controls1	Yes	Yes	Yes	Yes	Yes
Observations	3,699	3,603	3,593	3,570	3,577
R-squared	0.026	0.023	0.019	0.015	0.011

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05,
1 Controlled for consumers' age, gender, race, social status, country, and % of the bill paid
Source: Authors' design, using experiment data

Table A.3.3. Impact of Perceived Burden of the Electricity Bill on Willingness to Reduce Consumption During Peak Hours (more price-sensitive)

Price increase	Model 20%	Model 40%	Model 60%	Model 80%	Model 100%
DV: Willingness to reduce consumption during peak hours (more price sensitive)					
Perceived Burden	-0.372***	-0.572***	-0.459***	-0.389**	-0.127
	(0.140)	(0.141)	(0.149)	(0.157)	(0.169)
Controls1	Yes	Yes	Yes	Yes	Yes
# Observations	3,552	3,464	3,455	3,432	3,442
R-squared	0.016	0.018	0.011	0.009	0.006

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05,
1 Controlled for consumers' age, gender, race, social status, country, and % of the bill paid
Source: Authors' design, using experiment data

Table A.3.4. Impact of Income, Fairness and Perceived Burden of the Electricity Bill on Willingness to Reduce Consumption During Peak Hours (more price-sensitive)

Price increase	Model 20%	Model 40%	Model 60%	Model 80%	Model 100%
DV: Willingness to reduce consumption during eak hours (more price sensitive)					
Fairness	0.128***	0.136***	0.142***	0.121***	0.101***
	(0.023)	(0.023)	(0.024)	(0.025)	(0.027)
Perceived Burden	-0.424***	-0.552***	-0.444***	-0.343**	-0.037
	(0.151)	(0.151)	(0.159)	(0.169)	(0.182)
Income	0.033**	0.027	0.016	0.026	0.010
	(0.014)	(0.014)	(0.015)	(0.015)	(0.017)
Controls1	Yes	Yes	Yes	Yes	Yes
Observations	3,020	2,933	2,929	2,907	2,916
R-squared	0.033	0.035	0.026	0.020	0.013

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05,
1 Controlled for consumers' age, gender, race, social status, country, and % of the bill paid
Source: Authors' design, using experiment data