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## Economic impacts of a supporting scheme on domestic energy consumption in Bolivia: A quasi-experimental approach

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## A Quasi-Experimental Approach

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# **Effects of an Electricity Cost Supporting Scheme on Domestic Consumption Levels and Household Welfare:**

**Quasi-experimental evidence from six Bolivian cities during the COVID-19 pandemic**





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# Abstract

The Bolivian government fostered an electricity cost supporting scheme to attenuate the effect of the nationwide full lockdown on domestic consumption during the COVID-19 pandemic (April, May, and June 2020). This paper evaluates the effect of this scheme on the levels of energy consumption during lockdown, and the monetary savings it implied for beneficiaries. The paper focuses on six of the country's most populous cities – La Paz, El Alto, Cochabamba, Santa Cruz, Tarija, and Sucre – and uses a unique dataset consisting of detailed administrative records of monthly electricity consumption registered by *every* meter in these cities from January 2018 to June 2020. By merging this unique panel dataset with microdata from the 2020 Bolivian Household Survey, this paper goes beyond average effect estimations and assesses effect distribution across population subgroups *within* these six cities. Electricity consumption was adjusted upward by beneficiaries; average increases range from 0.9% (in El Alto) to 7.3 % (in La Paz). These upward adjustments of electricity consumption are heavily concentrated among households with high demand during lockdown. The effect heterogeneity analyses reveal that the absolute gains of the supporting scheme measured in terms of bill reductions are concentrated among better-off households – as measured by income or years of schooling. However, the relative gains of the supporting scheme, as measured by bill reductions with respect to income per capita, are clearly concentrated in the worse-off part of the population.



# 1. Introduction

The rapid spread of COVID-19 forced many governments to adopt emergency measures intended to prevent the collapse of health centers during an unprecedented health crisis.

These interventions included stringent mobility restrictions; governments across the globe required people to stay at home for several months. Simultaneously, governments had to foster complementary measures to satisfy people's basic needs, including energy consumption capacities. Indeed, one measure widely implemented in different countries across Latin America and the Caribbean consisted of emergency energy cost support schemes – with consumers as final beneficiaries (see e.g. Mastropietro et al., 2020). This was the case in Bolivia, where a universal energy bill subsidy program was implemented by the government during the country's full lockdown period, which spanned April, May, and June 2020. This measure specifically targeted residential energy consumers – in contrast to industrial or commercial consumers – and consisted of full or partial reductions based on the energy bill, following a progressive negative taxation approach. It was expected that this measure would ease household budget constraints across the country, while also contributing to increased residential electricity consumption during lockdown, thereby generating positive welfare effects. To the best of our knowledge, no study has yet investigated the effects of this intervention. Therefore, the present work is the first to assess the magnitude of effects, and to provide consistent information about the natural heterogeneous energy consumption shifts across population subgroups.



In this context, this study seeks to provide an answer to the following question: **How is the supporting scheme associated with energy consumption shifts and energy expenditure during lockdown?** This question is answered by focusing on six large Bolivian cities (La Paz, El Alto, Cochabamba, Santa Cruz, Tarija, and Sucre) and using a unique panel dataset built from administrative records of monthly energy consumption registered by *every* meter in these cities from January 2018 to June 2020. In total, this analysis draws upon 41.6 million observations from approximately 5.4 million households, representing 45% of the national population.

This paper presents an assessment of the average effect of the supporting scheme and offers an analysis of different heterogeneous patterns related to it. Specifically, this paper analyzes energy consumption shifts between beneficiaries who enjoyed a full bill reduction over the entire lockdown period, and those who benefited from a partial reduction at some point over the same period. The effects for each decile of average energy consumption during lockdown are also identified. Importantly, this study also assesses the distribution of consumption shifts *within* the six considered cities. By merging administrative records with data from the 2020 Bolivian Household Survey, this study analyses effects across groups of the population defined by socioeconomic characteristics – such as income, years of schooling, and household size. Finally, the document presents a discussion about some welfare shifts associated with the supporting scheme by comparing the bill reduction with households’ disposable income. It is expected that this study will contribute to a better understanding of the scheme’s effects, thereby illuminating ways to improve similar programs in the country and across the region.

Among the most salient results, this study shows that, taking all six cities together, the average monthly energy consumption during full lockdown increased by 4.3 kWh. However, monthly energy bills were reduced by 68.6 BOB (around 10 USD) on average during the same time span. These shifts are found to be unevenly distributed across the population. Examining two household groups – the ones who enjoyed a full bill reduction and those who enjoyed a partial reduction – it is found that the former revised their energy consumption upward to a much larger extent than the latter. Moreover, households in decile 1 of energy consumption distribution during lockdown show a lower observed consumption than expected. Meanwhile, households in decile 10 showed higher than expected consumption. This observation holds true in every city, affirming that households with a relatively high energy demand during lockdown were the ones that adjusted their consumption levels upward the most. However, it is also found that the welfare shifts associated with the supporting scheme is markedly concentrated in neighborhoods with *lower* mean income levels – as defined by primary sampling units in the 2020 Bolivian Household Survey. This means that even if it is the more advantaged households that have adjusted their levels of energy consumption upward the most during lockdown, it is the more disadvantaged households that have benefited the most, relative to their income.

The document is structured as follows: Section 2 presents a brief literature overview; Section 3 describes the data and methods used to uncover the supporting scheme’s effects; Section 4 describes in detail the results; and finally, Section 5 presents concluding remarks and reflections about results.

## 2. Literature overview

The COVID-19 pandemic and stringent measures set in place by governments around the world to contain the spread of the virus have affected economic and social activities globally. Electricity is an essential input for virtually all activities, ranging from the industrial to the commercial sector, as well as for daily household activities.

This is the reason why the COVID-19 pandemic has imposed considerable direct and indirect impacts on the energy sector. Important, sudden disruptions to the economy have negatively impacted households' economic capacities through increased unemployment, income loss, and unprecedented uncertainty in investment markets (Martin et al., 2020). To mitigate these negative effects, many governments established emergency policy measures to protect people's overall purchasing power during lockdowns. These have primarily taken the form of direct universal cash transfers (see e.g. Brum and De Rosa, 2021). However, policy measures aimed to protect people's capacity to pay for electricity services were widespread around the globe long before the pandemic. This section first discusses the main relevant literature about emergency policy responses associated with the electricity sector, with particular emphasis on Bolivia. Then, a discussion of this literature clearly situates the contribution of this study in a broader context of electricity subsidies and supporting schemes.

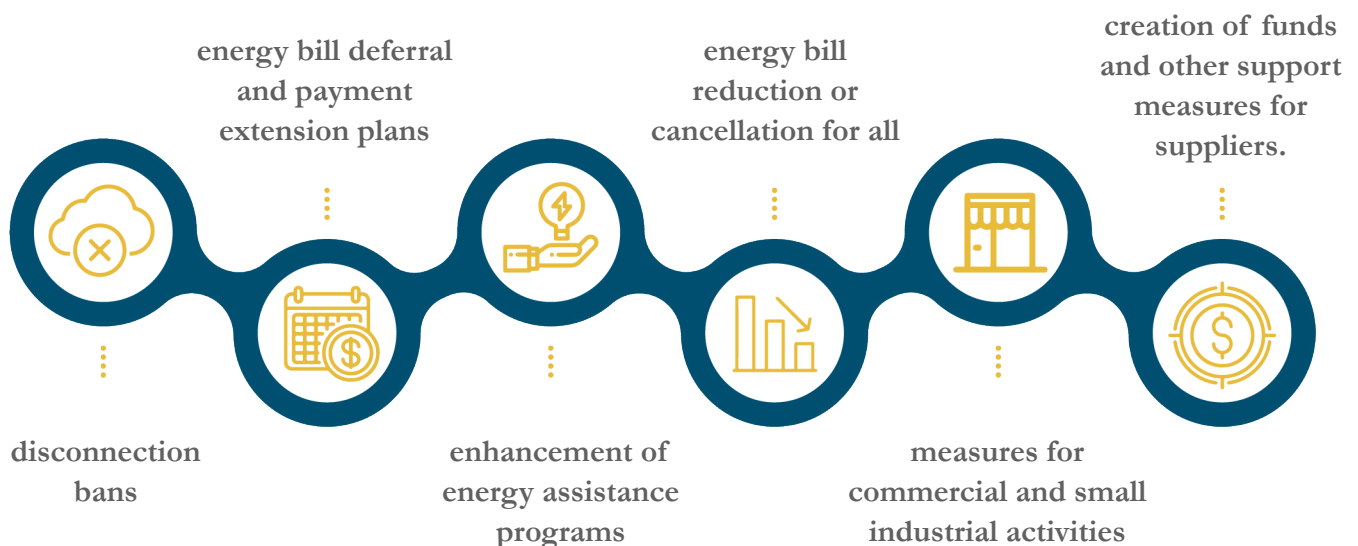
### 2.1. Emergency policy responses

Given their unprecedented, disruptive nature, the pandemic and related lockdowns have generated shifts in regular patterns of domestic energy consumption. For instance, according to Aruga et al. (2020), electricity demand in India decreased in public buildings and in industrial and commercial sectors during lockdowns, but it increased among households. They found, however, that the increase in domestic energy consumption was not visible in the eastern and northeastern regions – the poorest ones among the five regions they investigated. Similarly, Edomah and Ndulue (2020) found that the residential sector in Lagos metropolis in Nigeria increased home-based cooking, laundry, and some professional activities related with teleworking, resulting in overall higher domestic electricity consumption. Similarly, Santiago et al. (2021) found a sharp increase in electricity consumption between 8:00 and 14:00 in Spain due to the lockdown implemented from March 14 to April 30, 2020. They also show that night-time peaks were

also reconfigured in terms of duration and usage. In a similar study covering ten countries in the LAC region (including Bolivia), Sánchez Ubeda et al. (2021) found that the COVID pandemic and associated economic measures led to a sharp overall decrease of energy demand (from all economic sectors, including households). The largest monthly energy consumption drop compared to historical energy use trends was registered in Peru (-32%) and Bolivia (-26.7%) in April 2020. Sánchez Ubeda et al. (2021) also documented changes in daily consumption patterns during the COVID-19 pandemic in all ten countries under study, including night peaks that may be considered irregular or unexpected given past trends.

Clearly, lockdown measures to prevent the spread of the virus imposed by many governments led to sudden changes in socioeconomic habits, which have impacted – directly or indirectly – energy systems. Some of these shifts, such as the increase of energy consumption for cooking, are likely to be short-lived (Cheshmehzangi, 2020). However, other activities like teleworking, computer usage, and other entertainment systems are potentially longer lasting. Similarly, the increased use of heating/cooling systems is likely to be persistent over time depending on how long teleworking will continue to be practiced around the world, albeit intermittently. Empirical evidence continues to be mixed regarding the permanent or transient nature of these shifts in electricity consumption, an observation that is related to the evolving nature of the pandemic itself – the daily increase of COVID-19 cases is positively associated with increases in daily energy consumption in the study conducted by Aruga et al. (2020). According to these authors, as the number of cases declined, lockdown measures tended to relax, and energy consumption tended to return to pre-lockdown levels in India. However, this is far from certain. The containment measures to limit the spread of the virus have resulted in drastic – potentially permanent – adjustments of business activities, directly and indirectly affecting both the way the whole economy functions and people’s daily lives. These lifestyle changes may lead to long-lasting changes in societies’ daily energy demands (Kikstra et al., 2021), even if aggregated demand returns to pre-pandemic levels.

According to Mastropietro et al. (2020), policy measures to ensure domestic energy consumption capacities during lockdowns can be classified into six groups:



Among these policy measures, this study focuses on partial or full energy bill reductions for households, as it is precisely this measure as implemented in Bolivia that is the focus of this study. This supporting scheme specifically targeted domestic energy consumers during the lockdown and was implemented as a universal cost reduction of energy bills. However, the precise amount of cost reduction varied across households. Full and partial reductions were established according to the total energy bill, following a progressive negative taxation approach (see Table 1).

**Table 1: Structure of bill reductions in the supporting scheme**

| Monthly energy bill   | Reduction  |
|-----------------------|--|
| From BOB 1 to 120     | 100% of electricity consumption (inc. other rates) |
| From BOB 121 to 300   | 50% of electricity consumption                     |
| From BOB 301 to 500   | 40% of electricity consumption                     |
| From BOB 501 to 1,000 | 30% of electricity consumption                     |
| More than BOB 1,000   | 20% of electricity consumption                     |

Source: Supreme Decree N°4206, April 1, 2020 by the Constitutional Presidency of the Plurinational State of Bolivia. Official Gazette of the Plurinational State of Bolivia. [www.gacetaoficialdebolivia.gob.bo](http://www.gacetaoficialdebolivia.gob.bo)

The central government covered subsidized bills for the three months of full lockdown (April, May, and June 2020) in order to maintain operational capacity and financial stability of energy-supplying companies nationwide. Four specific elements of the energy bill were affected by this scheme: i) electricity consumption, ii) potency demand, iii) excess electricity consumption costs, and iv) a fixed minimum payment. These elements make up the entire energy bill charged to households. Other non-energy related costs appear in the bill regularly (including, for example, municipal contributions to park/street maintenance), but they were not affected by the scheme.

It is important to mention that the supporting scheme was, in fact, part of a set of policies implemented by the government to protect the people’s overall purchasing power and livelihood during strict lockdown. These policies also included water bill payments (Supreme Decree 4200), a ban of shutdowns to basic and telecommunication services (Law 1294 and Supreme Decree 4206), temporary cash transfers to vulnerable households with school-aged children, disabled people, elderly people, and informal workers within the project “*Redes de Protección Social de Emergencia por la Crisis del COVID-19*”, and the deferral of credit payments of principal and interest during and six months after the declaration of the public health emergency. It is impossible to precisely know the effect of these policies on energy demand, but one can expect that they have contributed to further easing budget constraints. However, given the relatively low responsiveness of energy demand to income shifts in the short run – due to its natural short run income and price-inelastic nature (see Zhu et al., 2018 for a comprehensive meta-analysis about this), one can expect relatively low direct effects of these complementary policies on energy demand.


## 2.2 Previous evidence of the effects of energy cost supporting schemes

Academic literature is relatively scarce with respect to the impact of supporting schemes more broadly, or subsidies on domestic energy consumption more specifically, in contexts of emergency like the one experienced during the COVID pandemic. However, there is a growing strand of literature discussing the effectiveness and scope of such emergency policy measures.

Even before the pandemic, electricity consumption subsidies were usually set in place to make energy more accessible for specific social groups that are normally at a disadvantage in terms of purchasing power (e.g., people living in rural, impoverished areas), to promote regional development, and to protect the environment (see e.g., Von Moltke et al., 2017). However, if poorly applied or designed, it is well-documented that such subsidies could also cause unwanted welfare effects, such as benefiting richer groups in the population or generating high budgetary burdens for governments (Dhakouani et al., 2020; Fattouh and El-Katiri, 2012). For instance, Marchán et al. (2017) found that only 23% of the electric energy subsidies enacted by Latin American and Caribbean governments aimed in principle to help the poorest households, ended up benefiting households in the bottom 40% of the income distribution. They estimated that, on average, governments tend to invest USD 10 to transfer USD 1 to the bottom quintile by means of this kind of subsidy. Similar evidence about the expensive, often inefficient nature of energy subsidies as a tool to transfer income to poor households was found by Feng et al. (2018), who stressed that higher income groups tend to benefit more from low energy prices across Latin America and the Caribbean, rather than lower income groups, even when accounting for both direct and indirect (through supply chains) effects of energy price reductions.

Energy subsidies have usually been implemented through diverse mechanisms, depending on the objectives set by governments. Broadly, they can be channeled through local energy companies or given to households, the industrial sector, or commercial businesses (Dhakouani et al., 2020). Subsidies that are conceived to primarily benefit (domestic or industrial) consumption normally aim to make energy more affordable, thus contributing to improving the living conditions of poor people, and to promoting a shift toward different uses of energy. However, there is vast evidence showing that these policies are likely to benefit richer consumers in absolute terms. Araar and Verme (2017), for instance, found that energy subsidies in some countries in the Middle East and North Africa region tended to be pro-rich in absolute terms, but tended to be more important for the poor in terms of expenditure share. Moreover, in their analysis of policies implemented during the COVID-19 pandemic, Mastropietro et al. (2020) found that bill reductions and cancellations, which were implemented by several governments around the world, provided a subsidy to all customers, including those who did not suffer any negative impact from the pandemic. Finally, it is important to mention that energy subsidies can imply high costs for the government. This is especially the case if they are implemented over a long period of time (Dhakouani et al., 2020; Narula et al., 2012), or if the government freezes energy prices for consumers while covering the rest of production costs under fluctuating international prices. However, emergency short-term measures such as those implemented during the COVID-19 period in Bolivia may have a lower impact on public budget because they were short-lived.

### 3. Data and methods



This study focuses on six of the most populous capital cities in the country, namely La Paz, El Alto, Cochabamba, Santa Cruz, Tarija, and Sucre, using comparable and internally coherent available data. The National Institute of Statistics' (NIS) 2021 estimates reflect that these six cities are home to 5.4 million people, or 45% of the national population.

In order to identify how the supporting scheme shifts domestic energy demand, and the associated welfare changes on households, the applied methodological strategy makes use of data coming from two different sources:

- A** Administrative records kept by the energy supply company in each city (DELAPAZ in La Paz and El Alto, ELFEC in Cochabamba, CRE in Santa Cruz, SETAR in Tarija, and CESSA in Sucre). These datasets contain monthly levels of energy consumption for every meter in each city between January 2018 and June 2020, as well as their precise geographical location<sup>1</sup>. This data source endows the study with a total of 3.04 million observations corresponding to 1.02 million meters in this time span.
- B** The 2020 Bolivian Household Survey Data collected by the NIS<sup>2</sup>. This survey is the only publicly available, nationally representative source of microdata to gauge living conditions. The geographical location of each meter in the administrative records mentioned above allows researchers to identify whether any given meter belongs to any of the primary sampling units (PSU) of this survey in each city, and if so, which one. It is thus possible to merge both data sources to create a PSU-level dataset containing the average patterns of energy consumption over time and key average socioeconomic characteristics, including per capita income and other living condition indicators, all of them measured post lockdown (around September 2020)<sup>3</sup>.

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<sup>1</sup> After cleaning these data from outdated/non-functional meters and outlying records, the number of total meters for which there exists full information in each city is described in Technical Appendix 7.1, and the distribution of the energy consumption that was collected through them is represented in Figure A1, found in the same appendix.

<sup>2</sup> This dataset is publicly available at: <https://www.ine.gob.bo/index.php/censos-y-banco-de-datos/censos/bases-de-datos-encuestas-sociales/>

<sup>3</sup> Details of the strategy followed to merge these two datasets are presented in Technical Appendix 7.2.

In addition, the interpretation of some results is based on primary household-level data coming from a specifically designed survey, which was collected with the purpose of complementing the other two data sources described above. The survey design ensures representativeness for the peri-urban areas in each one of the six cities considered in this study. These data provide unique information about households' socioeconomic conditions during the timespan in which the supporting scheme was active (April, May, and June 2020)<sup>4</sup>.

The applied methodological strategy consisted of five steps. More details about the formal aspects involved in each step are presented in Technical Appendix 7.3.

## STEP 1

We drew inspiration from Baron et al. (2020) to estimate average counterfactual levels of energy consumption by fitting city-specific panel data models using the energy consumption time series in the administrative records. The model used for counterfactual estimation in any city – for which the subscript is omitted for simplicity – is:

1

$$e_{it} = \alpha_0 + \alpha_i + \alpha_t + f_s(\beta, t, x_t, e_{i,t-s}) + \epsilon_{it}$$

where,  $e_{it}$  is the monthly level of electricity consumption (in kWh) recorded by meter  $i$  at time (month)  $t$ ;  $\alpha_0$  represents a constant term, and  $\alpha_i$  and  $\alpha_t$  represent meter- and time-specific effects, respectively. Function  $f_s(\cdot)$  represents a city-specific polynomial transformation of time variable  $t$ ,  $s$  lags of  $e_{it}$ , a vector of time-varying external predictors  $x_t$  (e.g., stationary transformations of relevant climate and economic variables), and a vector of parameters  $\beta$ . Finally,  $\epsilon_{it}$  is the idiosyncratic error term.

These models allowed us to predict the average demand of energy consumption in each city during the lockdown period if regular trends persisted. A parsimonious set of plausible values for  $s$  and functional forms for  $f$  were empirically explored for each city to identify the model specification that provided the best fit. External predictors included different lags of energy consumption, and variables coming from external sources, supported by existing literature (see e.g., Qarnain et al., 2020; Sánchez Ubeda et al., 2021). These were: monthly temperature in each city, a data point sourced from the National Service of Hydrology and Meteorology in Bolivia (SENAMHI)<sup>5</sup>, and the NIS Global Index of Economic Activity (IGAE, in Spanish), which measures the monthly level of economic activity in each city<sup>6</sup>. In order to arrive at meaningful counterfactual scenarios, the models did not consider IGAE levels as measured by the NIS during lockdown because they naturally captured the overall

<sup>4</sup> These unique household-level data are analyzed in much more detail in Chumacero et al. (2022), which offers a complementary analysis to the present paper, focusing on household-varying living conditions during full lockdown in Bolivia.

<sup>5</sup> See <http://senamhi.gob.bo/index.php/sismet>

<sup>6</sup> See <https://www.ine.gob.bo/index.php/estadisticas-economicas/indice-global-de-actividad-economica-igae/#1559000613762-93bd70cb-ae37>



economic contraction due to full lockdown. Rather, the models used counterfactual IGAE estimates for that period proposed by Barja et al. (2021). These estimates are clean of lockdown overall economic effects. The full estimation results for each city are presented in Appendix 7.4<sup>7</sup>.

## STEP 2

Counterfactual average levels of energy consumption during lockdown for each city if regular trends continued (denoted as  $\hat{e}_{it}$ ) were then compared with the observed average levels of energy consumption ( $e_{it}$ ). The energy consumption shift during the lockdown period,  $T$ , is denoted as  $\delta$  and estimated as follows:

2

$$\hat{\delta} = E_{i,t \in T}[e_{it}] - E_{i,t \in T}[\hat{e}_{it}]$$

Since the supporting scheme was expected to release budget constraints, one could expect  $\hat{\delta}$  to be positive in every city. To gain further understanding of the supporting scheme, this consumption change was monetized using regular energy tariffs in each city. This allowed an estimate of the amount of money that households were able to ‘save’ due to the supporting scheme.

## STEP 3

The previous step allowed the authors to estimate overall, aggregate measures of consumption adjustment in each city during lockdown. However, they naturally mask potentially important heterogeneities around them. In order to uncover a first set of heterogeneous effects, the consumption shifts presented above were recalculated conditionally on membership subgroups in each city: i) those that recorded consumption levels corresponding to a 100% bill reduction over the entire lockdown period, and ii) those that recorded consumption levels corresponding to partial bill reductions (<100%) at any point during lockdown. These changes were also monetized as in the previous step.

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<sup>7</sup> In order to create counterfactual levels of energy consumption during lockdown, several city-specific variants of Equation 1 were considered. Table A1 shows the estimation results of the preferred models for each city. These models were selected on the grounds of i) parsimony in terms of the included energy consumption lags, and economic interpretation, ii) minimum BIC and AIC information criteria among all the considered specifications in each city, and iii) the highest adjusted R<sup>2</sup> measure for goodness-of-fit.

## STEP 4

A second set of heterogeneous consumption shifts was identified by estimating differences by consumption decile during lockdown. This allowed us to better understand the distribution of effects across different profiles of energy consumers in each city. These effects were, once again, monetized following the same procedure as in the previous steps.

## STEP 5

Finally, the PSU-level dataset for each city was used to determine the welfare shifts of the supporting scheme. Having PSU-varying sets of actual and counterfactual levels of energy consumption, and the corresponding shares of energy bills in household income allowed us to apply a difference-in-difference regression framework with multiple periods.

Taking one city at a time, let us denote the dependent variable as  $y_{gut}$ . This vector may represent the collection of actual and counterfactual values of i) average level of energy consumption in PSU “u” at time “t” for household type “g”, or the mean energy bill as the income share of household type “g” in PSU “u” at time “t”. A difference-in-difference framework was applied to accommodate for specific coefficients associated with different population subgroups defined by an array of relevant socioeconomic characteristics, including income levels, education of the head of household, and household size. Heterogeneous effects of the supporting scheme could thus be estimated by fitting the following model:

3

$$y_{gut} = \lambda_0 + \lambda_u + \lambda_t + \lambda_g + \sum_g I_g \delta_g (D \times T) + \gamma \tilde{z}_{gut} + \eta_{gut}$$

where  $\lambda_0$  is a constant term,  $\lambda_u$ ,  $\lambda_t$ , and  $\lambda_g$  represent PSU-, time-, and group-fixed effects, respectively.  $D$  is a binary indicator taking a unity value if  $y_{gut}$  represents an actual observation and zero if it represents a counterfactual observation.  $T$  is a binary indicator taking a unity value for the months in which the supporting scheme was active and zero otherwise.  $I_g$  is a binary indicator of household type  $g$ . Vector  $\tilde{z}_{g,u,t}$  regroups control variables measured at the PSU level using information from the household surveys (e.g., median level of income, median housing conditions, median demographic composition, etc.). The main coefficients of interest are  $\delta_g$ , which capture energy consumption changes in group  $g$  during the entire period in which the supporting scheme was active. Finally,  $\eta_{g,u,t}$  is the idiosyncratic error term.

## 4. Results

The study yields five sets of results:

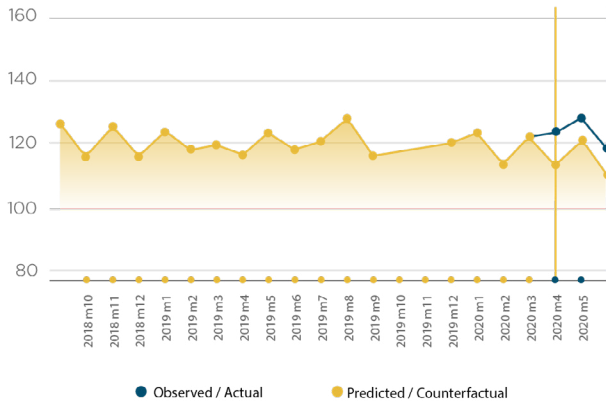
- 1 energy consumption shifts during lockdown
- 2 heterogeneous shifts across households that had partial or full bill reductions;
- 3 heterogeneous shifts across deciles of energy consumption;
- 4 heterogeneous shifts across household groups based on key socioeconomic characteristics (education, income, and household size); and
- 5 evidence of the relative welfare changes linked to the support scheme on households with different income levels.

### 4.1 Average energy consumption shifts

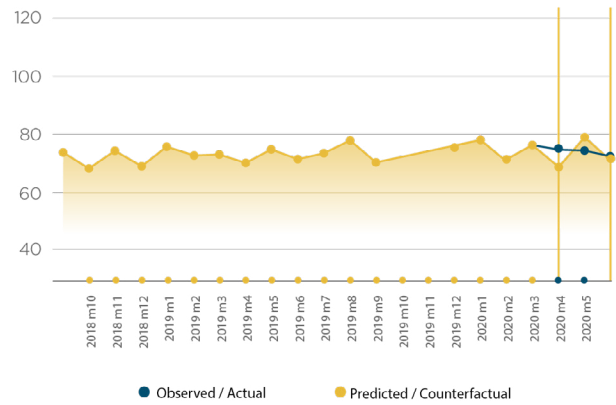
The observed and predicted energy consumption levels (plotted in Figure 1) show that each model allows us to closely reproduce the consumption dynamics before lockdown (i.e. before April 2020) in each city. Importantly, there are seasonal patterns that are particularly marked in Santa Cruz (Figure 1, panel (d)), a region with typically hot, humid weather. The models reproduce these seasonal patterns adequately, reinforcing the need to build the analysis on different specifications for each city. In Santa Cruz, for instance, in the pre-lockdown period, there was a clear drop in energy consumption from April-September, which corresponds to cold seasons in the country – autumn/winter. Air conditioners, coolers, fans, and other electronic devices are much less used during these months. Conversely, peaks of energy consumption were visible in December-May, which corresponds to the summer season. This needs to be considered in the analysis going forward. A similar pattern is observed in Tarija (panel (e)) – also a relatively hot region – but to a much lesser extent.

Figure 1: Observed and expected levels of energy consumption by city

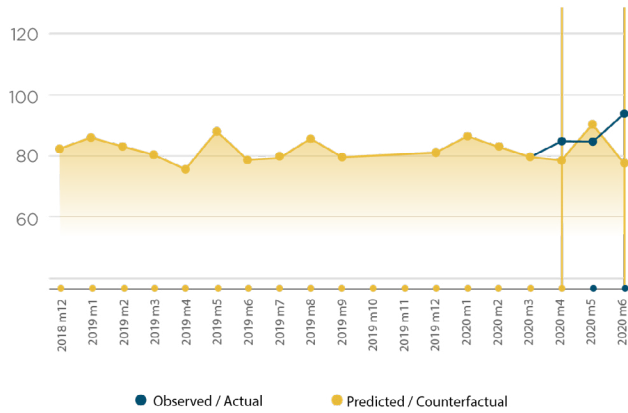
(a) La Paz



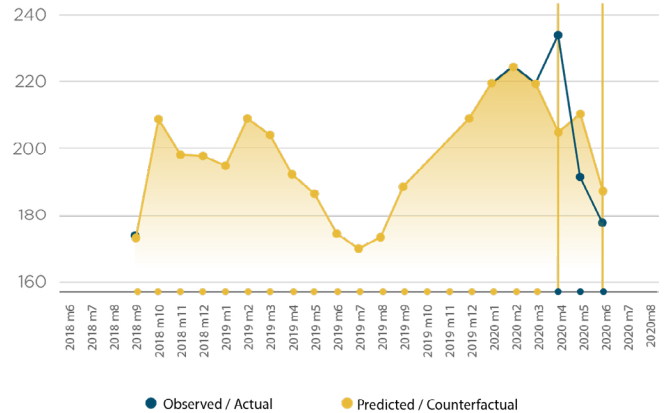
(b) El Alto



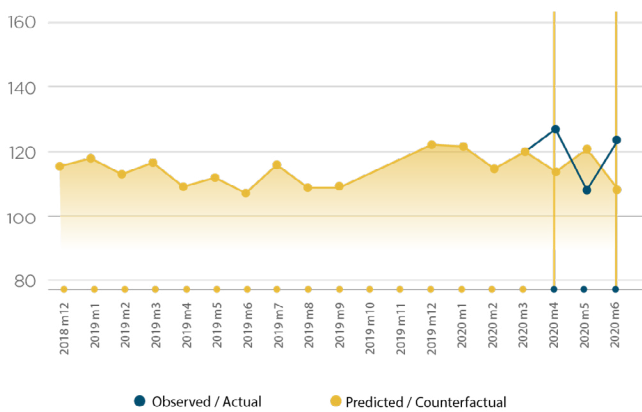
(c) Cochabamba



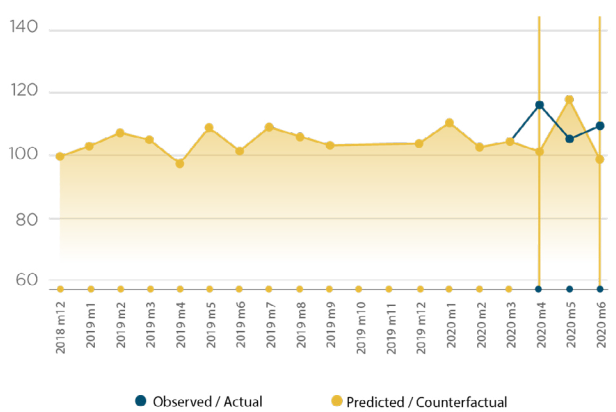
(d) Santa Cruz



(e) Tarija



(f) Sucre



Source: Authors' design based on administrative records

The results show that there were clear differences between observed and expected energy consumption when regular trends continued during lockdown. There were some peaks of observed energy consumption in different months during lockdown for different cities. Such peaks occurred in April for Tarija, Sucre, and Santa Cruz, in May for La Paz, and June for Cochabamba. These differences may be related to the way energy consumption is recorded throughout the country: workers from the energy supplying companies make a visual inspection of the meter levels to establish the bill. It was impossible to implement this human resource-intensive strategy of data collection in a normal way during the strict lockdown, as human mobility was severely restricted for all citizens. This may have pushed energy supplying companies to register estimated consumption values for some meters during lockdown. Companies took different approaches to cope with this limitation. For instance, in Cochabamba, these estimated values consisted of a sixth-month average of consumption levels just before lockdown<sup>8</sup>.



The discussion above is important because it points to the inaccuracy of monthly assessments within the lockdown period. It is clearly preferable to aim to identify the *average* effect across the entire lockdown period. Table 2 shows the average observed monthly energy consumption during lockdown and its expected counterpart in each city. The difference between these average consumption levels (denoted as  $\hat{\delta}$  in Table 2) represents the mean adjustment by households in terms of monthly energy consumption. This difference captures the combined effect of strict lockdown and the supporting scheme, which cannot be disentangled as they are perfectly contemporaneous – there is no measurable time span in which the scheme was active without having a full lockdown or vice-versa. Thus  $\hat{\delta}$  should be interpreted as a measure of the overall change in households' habits and daily activities caused by both strict lockdown and the scheme's existence. In column 1 of Table 2 we can see that monthly average changes in energy consumption during lockdown ranged between 0.2 kWh (Santa Cruz) and 8.4 kWh (Cochabamba).

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<sup>8</sup> See <https://www.lostiempos.com/actualidad/economia/20200421/elfec-80-usuarios-se-beneficiara-descuento-del-100-su-factura>

**Table 2: Estimated effects by city – monthly average over the lockdown period**

| Level                      | # of obs         | # of meters      | $\hat{\delta}$ | $\hat{\delta} \times F$ | $\hat{\Delta}$ |
|----------------------------|------------------|------------------|----------------|-------------------------|----------------|
|                            |                  |                  | [KWH]          | [BOB]                   | [BOB]          |
| <b>Six cities combined</b> | <b>3,045,240</b> | <b>1,015,080</b> | <b>4.3</b>     | <b>7.12</b>             | <b>68.57</b>   |
| Cochabamba                 | 473,991          | 157,997          | 5.6            | 11.6                    | 66.6           |
| La Paz                     | 679,605          | 226,535          | 8.4            | 7.9                     | 67.4           |
| Santa Cruz                 | 856,998          | 287,879          | 0.2            | 5.20                    | 85.7           |
| Sucre                      | 184,029          | 61,343           | 4.4            | 6.0                     | 59.7           |
| Tarija                     | 125,718          | 41,906           | 5.48           | 14.65                   | 66.54          |
| El Alto                    | 724,899          | 242,067          | 0.7            | 0.4                     | 53.1           |

Notes:

i)  $\hat{\delta}$  represents the difference between the average energy consumption with the supporting scheme and its estimated counterpart, over the entire lockdown period

ii)  $\hat{\delta} \times F$  represents the difference between the monetized average energy consumption and its estimated counterpart, over the entire lockdown period.

iii)  $\hat{\Delta}$  represents the difference between the average bill without the scheme and the average bill with the scheme over the entire lockdown period.

Source: Authors' design based on administrative records

Using each city's regular monthly tariffs,  $F$ , it was possible to estimate monetized changes in electricity consumption during lockdown. These changes were calculated as the difference between the estimated monetary consumption without the scheme and that with the scheme; they are denoted as  $\hat{\delta} \times F$ . The tariff structure generally consisted of a baseline kWh price for low consumption, and a variable price component that increased with consumption levels. The second column of Table 2 shows that the monthly average monetized consumption effect ranged from BOB 0.4 in El Alto to BOB 14.6 in Tarija. Note that this monetized value was only a component of the value for payment as it appeared on the energy bill, which is subject to the supporting scheme.

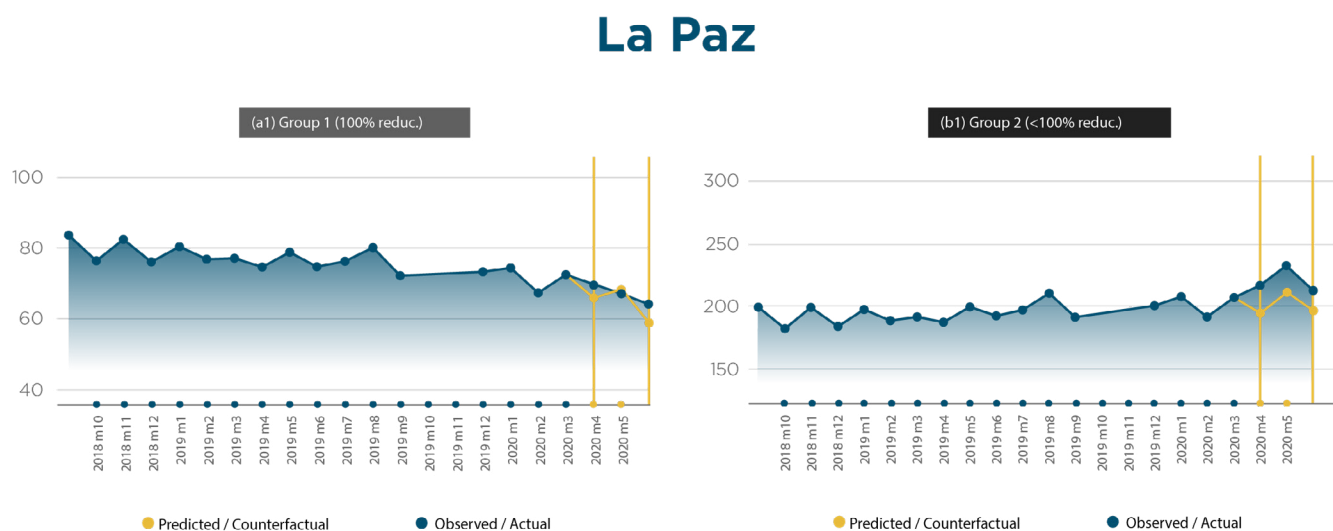
To further understand the monetary effects of the supporting scheme, it is useful to analyze the difference between the monthly average energy bill during lockdown without the scheme, and that with the scheme. This difference is denoted as  $\hat{\Delta}$  in Table 2 and it represents the amount of money that households were able to avoid spending while maintaining energy consumption observed during lockdown. The third column of Table 2 shows that this monthly average bill reduction ranged from BOB 53 in El Alto to nearly BOB 86 in Santa Cruz.

## 4.2. Conditional average effects: Beneficiary groups

Although the summary measures presented above are useful to get a general sense of the households' adjustment in terms of energy consumption, they naturally masked heterogeneities within cities.

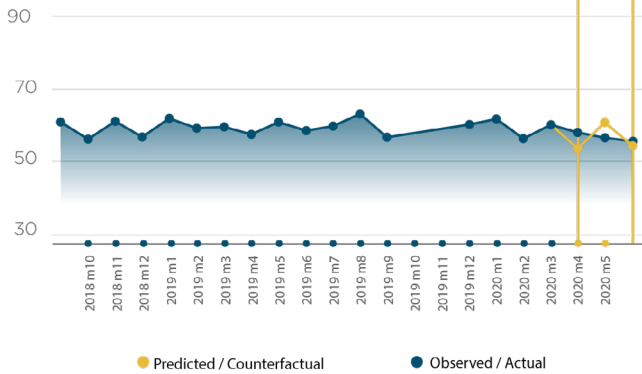
The results presented in this section focus on consumption adjustments within two different meter subgroups: those that had 100% bill reduction (group 1) and those that had less than 100% reduction (group 2). It was found that both groups recorded higher-than-expected consumption levels during lockdown in all cities except for group 2 in Santa Cruz. It was also found that households in group 1 revised their energy consumption upward to a much larger extent than those who benefited from partial bill reductions. The actual and predicted levels of energy consumption for each group are presented in Figures 2a and 2b.

Figure 2(a): Observed and expected levels of energy consumption by city and meter group

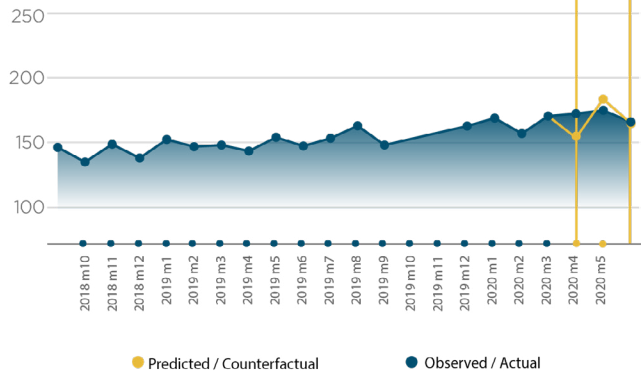


# El Alto

(a2) Group 1 (100% reduc.)

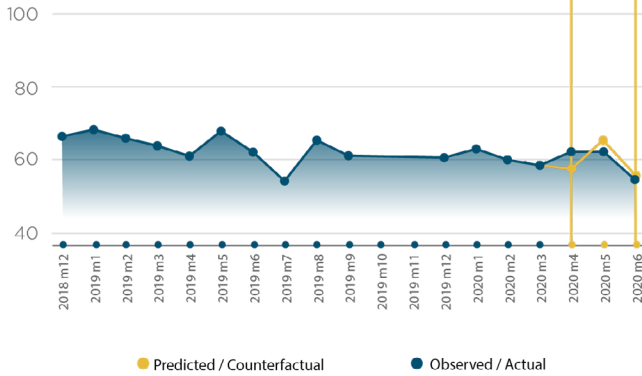


(b2) Group 2 (<100% reduc.)

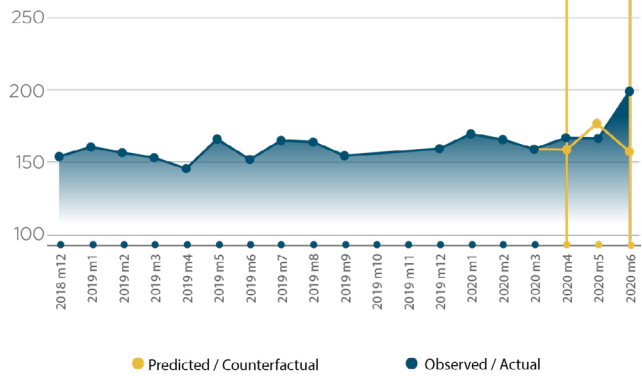


# Cochabamba

(a3) Group 1 (100% reduc.)

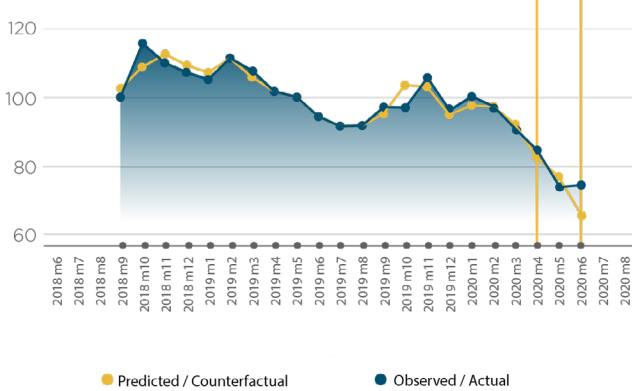


(b3) Group 2 (<100% reduc.)

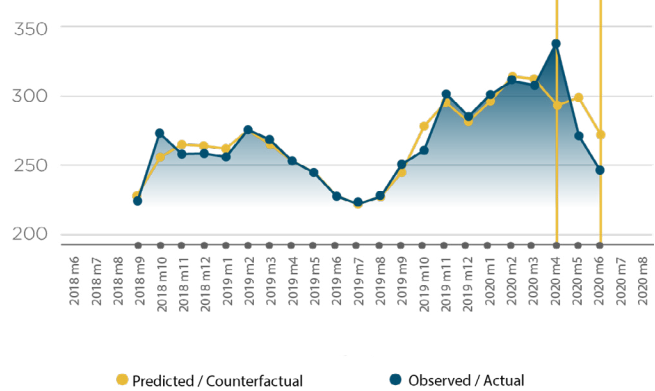


# Santa Cruz

(a1) Group 1 (100% reduc.)

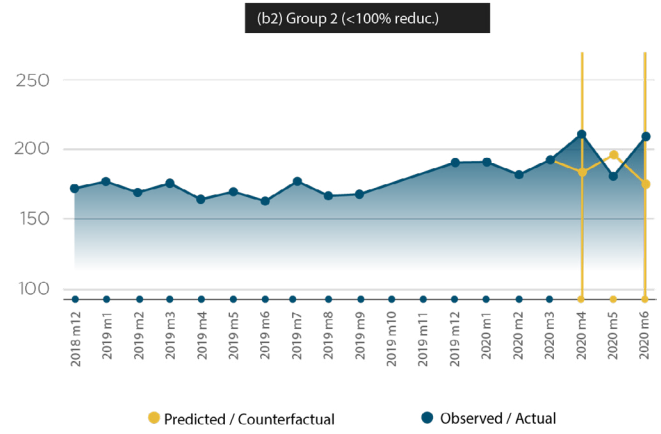
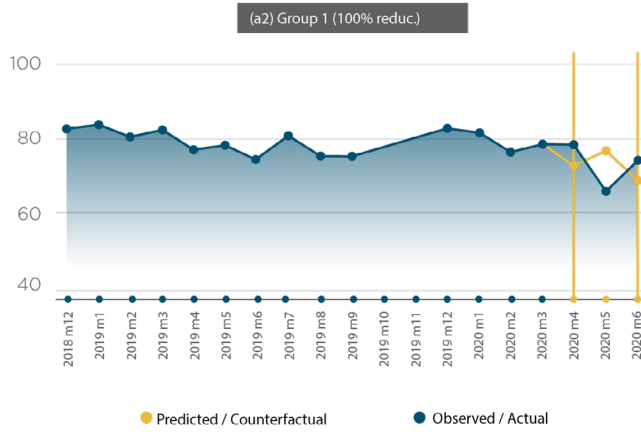


(b1) Group 2 (<100% reduc.)

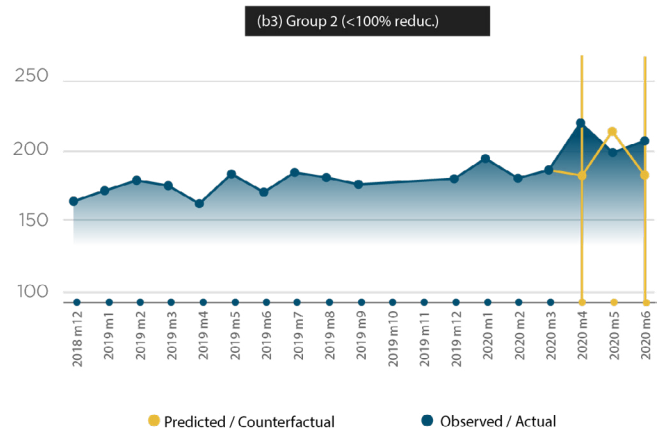
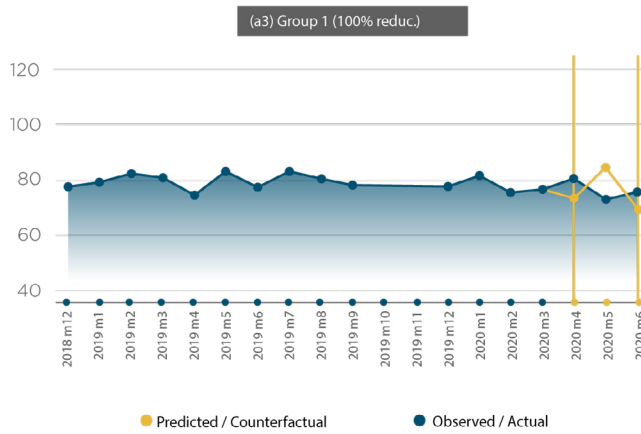




# Tarija



# Sucre



Source: Authors' design based on administrative records

Households in group 2 (i.e., households with high energy bills) revised their energy consumption upward to a much larger extent than those in group 1. This is an interesting result, which shows that the increase in demand cannot be entirely explained by the supporting scheme. It also suggests that electricity demand elasticity tends to be non-linearly related with income. Again, this result holds for every city except for Santa Cruz (see Table 3, column corresponding to  $\hat{\delta}$ ). For instance, the monthly average energy adjustment for group 1 in La Paz was 2.5 kWh, while that for group 2 was 19.4 kWh. The only exception to this pattern was Santa Cruz, where households in group 2 reduced their average energy consumption, while those in group 1 increased it. This heterogeneity needs to be explored further in the future, using more granular data.

**Table 3: Estimated effects by city and by meter subgroup**

| City                       | $\hat{\delta}$ |              | $\hat{\delta} \times F$ |              | $\hat{\Delta}$ |              |
|----------------------------|----------------|--------------|-------------------------|--------------|----------------|--------------|
|                            | [KWH]          |              | [BOB]                   |              | [BOB]          |              |
|                            | Group 1        | Group 2      | Group 1                 | Group 2      | Group 1        | Group 2      |
| <b>Six cities combined</b> | <b>1.19</b>    | <b>11.73</b> | <b>2.92</b>             | <b>10.54</b> | <b>52.85</b>   | <b>91.11</b> |
| Cochabamba                 | 0.2            | 13.3         | 3.0                     | 16.0         | 52.2           | 87.3         |
| La Paz                     | 2.5            | 19.4         | 4.4                     | 13.8         | 55.6           | 87.6         |
| Santa Cruz                 | 1.6            | -0.1         | 3.4                     | 1.4          | 54.4           | 106.7        |
| Sucre                      | 0.7            | 16.0         | 1.7                     | 13.1         | 50.6           | 85.9         |
| Tarija                     | 0.06           | 15.40        | 4.03                    | 20.92        | 52.88          | 90.16        |
| El Alto                    | 0.3            | 3.6          | 0.2                     | 1.4          | 48.8           | 77.4         |

Notes:

i) Group 1 is formed of meters with full bill reduction, and Group 2 is formed of those with partial bill reduction. ii)  $\hat{\delta}$  represents the difference between the average energy consumption and its estimated counterpart, over the entire period. iii)  $\hat{\delta} \times F$  represents the difference between the monetized average energy consumption and its estimated counterpart, over the entire period. iv)  $\hat{\Delta}$  represents the difference between the average bill without the scheme and the average bill with the scheme, over the entire period.

Source: Authors' design based on administrative records.

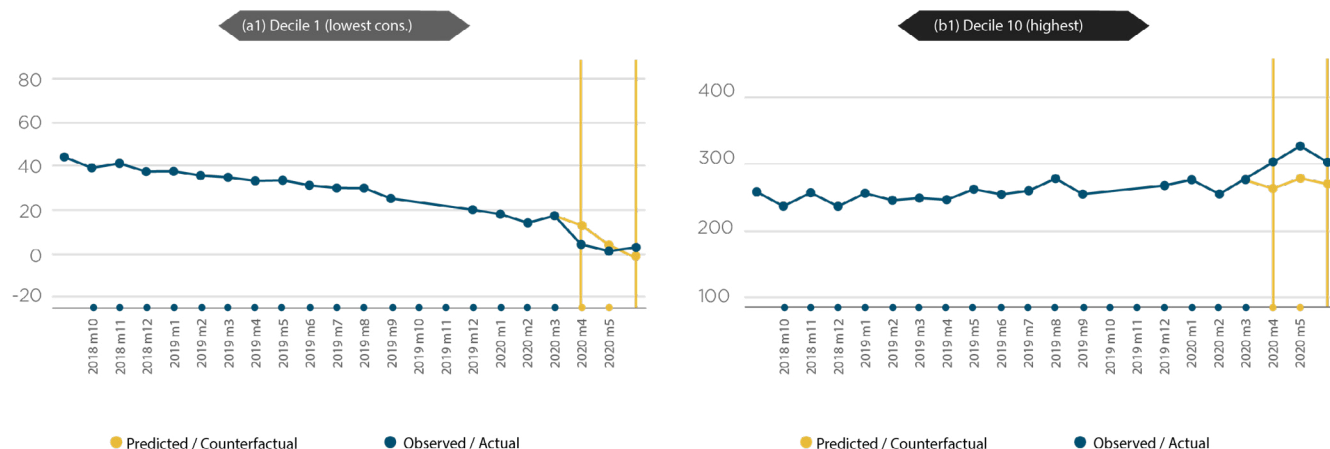
These results were also reflected in the monetized consumption levels using each city's tariffs. In Table 4, the column related to  $\hat{\delta} \times F$  shows how households in group 2 that revised their consumption upward also paid more for this increase than those households in group 1. Santa Cruz was also an exception, as the increase in the monetized consumption was larger in group 1. Finally, turning to the monetary effects by meter subgroup, Table 3 column related to  $\hat{\Delta}$  shows that households in group 2 benefited from a larger bill reduction than those in group 1. This result held for every city; in Santa Cruz, for instance, households in group 2 had an average bill reduction of more than BOB 106.7, while those in group 1 managed to avoid spending around BOB 54.4 on average.

## 4.3. Conditional average effects of energy consumption deciles

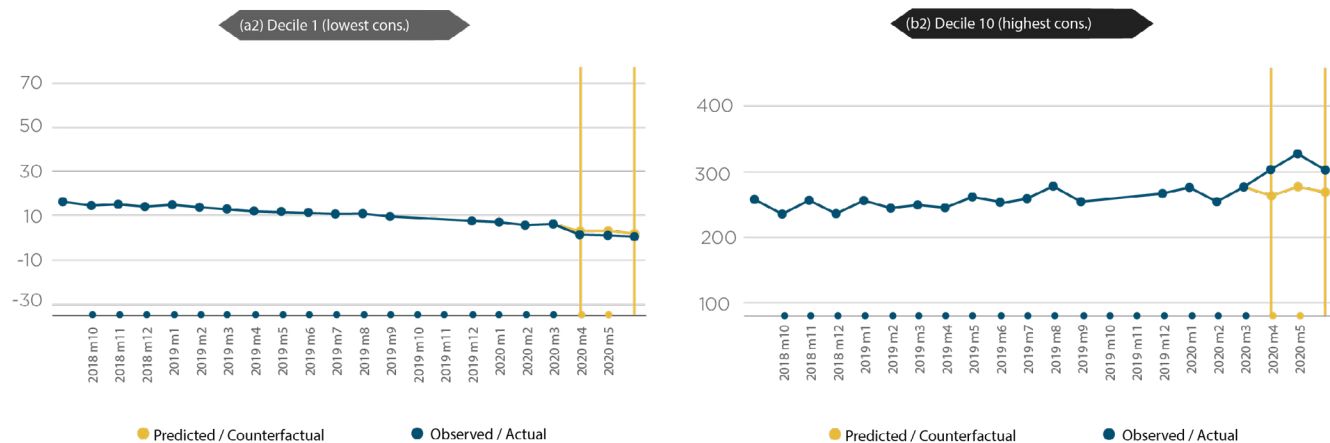
Digging deeper into the scheme’s heterogeneous effects, the study considered the average consumption adjustments in each decile of the observed average consumption schedule during lockdown. Figures 3a (La Paz, El Alto, and Cochabamba) and 3b (Santa Cruz, Tarija, and Sucre) show the actual and expected levels of energy consumption for deciles one (lowest consumption levels) and ten (highest consumption levels).

Figure 3(a): Observed and expected levels of energy consumption by city and decile

### La Paz



### El Alto



# Cochabamba

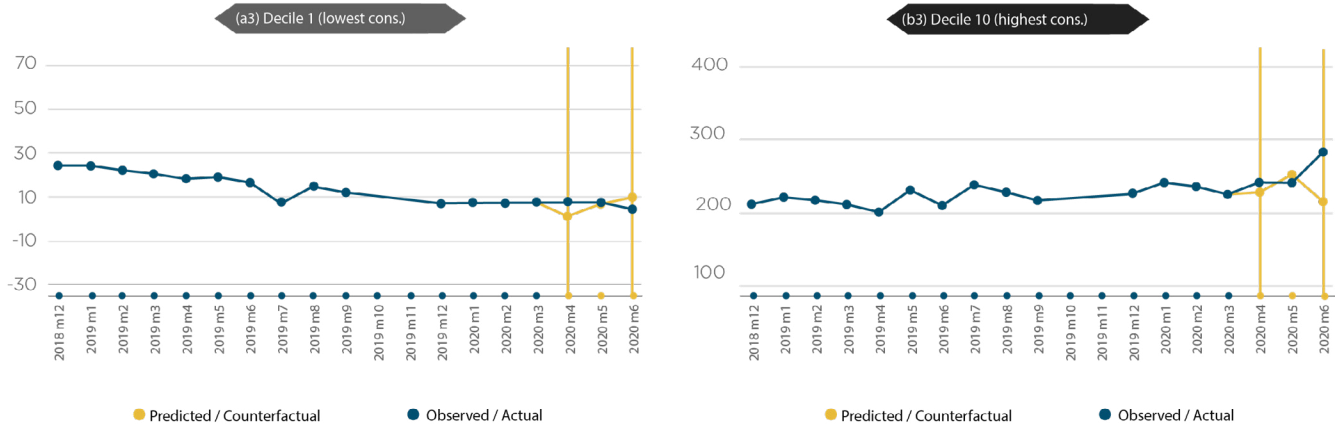
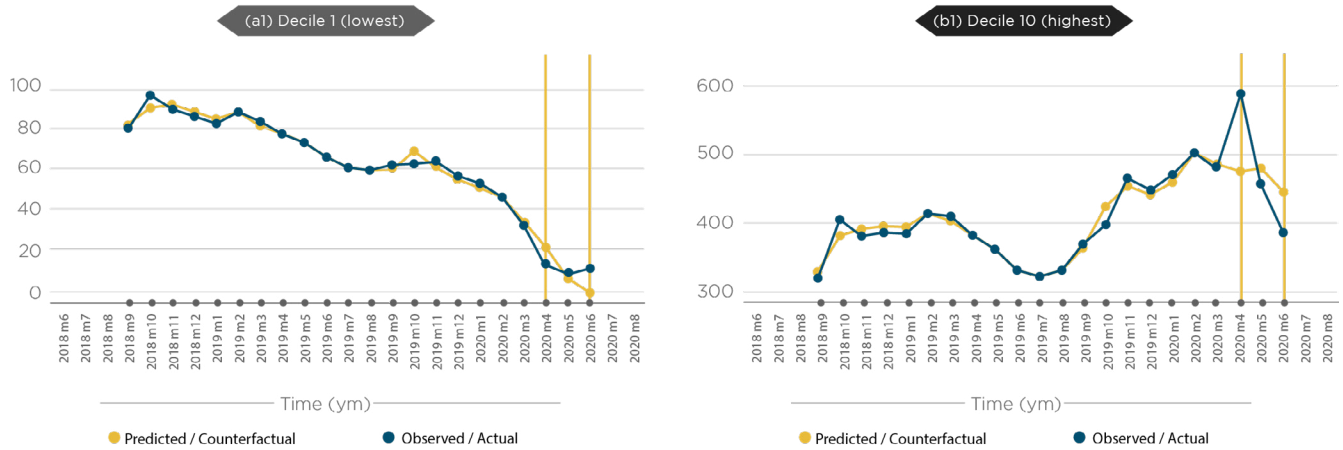
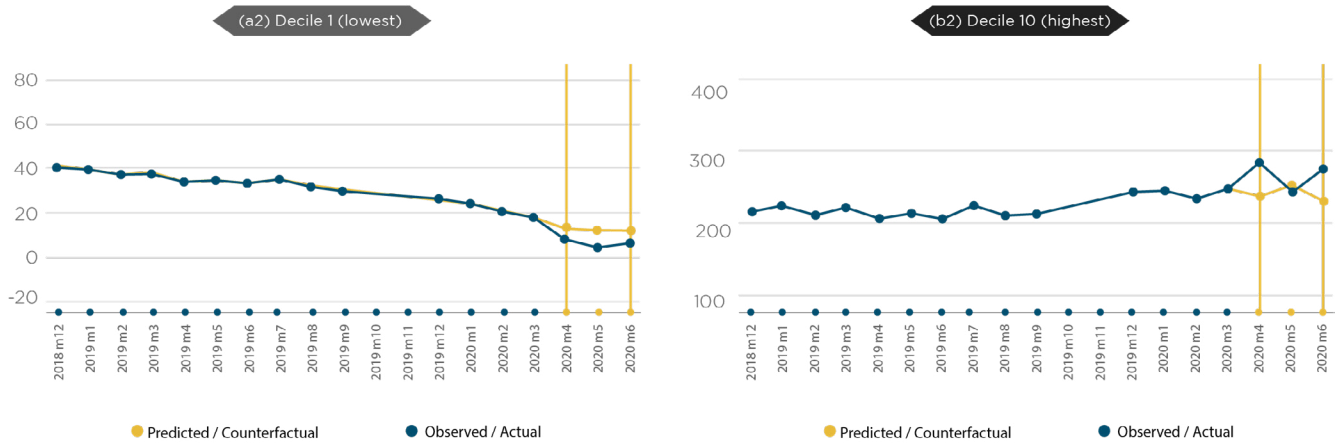


Figure 3(b): Observed and expected levels of energy consumption by city and decile

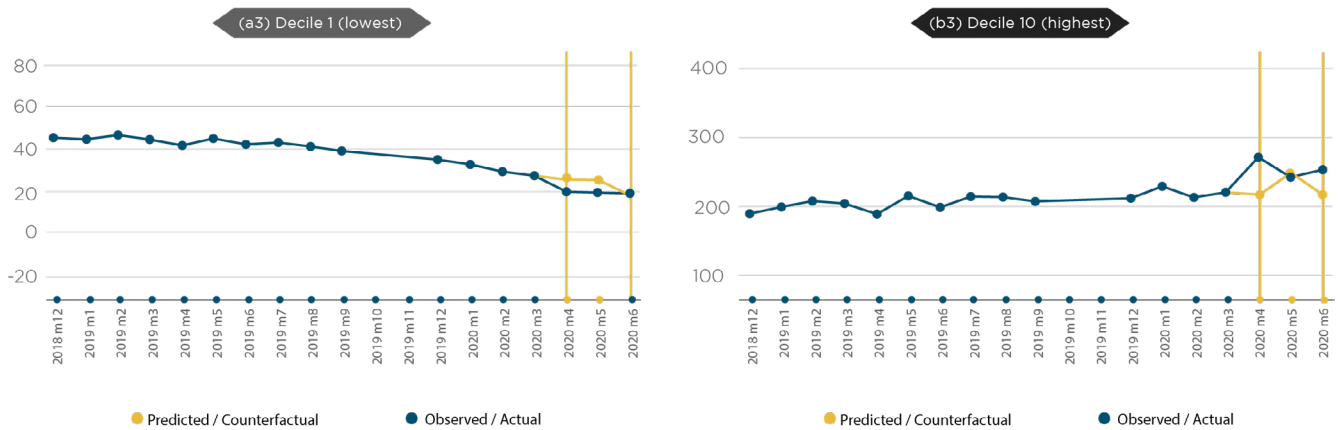
# Santa Cruz



# Tarija



# Sucre



Source: Authors' design based on administrative records

The observed average consumption during lockdown in decile 1 was lower than the expected consumption, while it was higher than expected in decile 10. This held true in every city. As shown in Figure 4, an average increase in energy consumption was visible only in meters sitting in the fifth decile or higher in the consumption distribution. Clearly, households that had a relatively high energy demand during lockdown were the ones that adjusted their consumption levels upward the most<sup>9</sup>. Even if the correlation between income and energy consumption is not perfect, this result shows that higher-income households tend to have higher levels of energy consumption; this can be due to ownership of electric/electronic appliances. This heterogeneity of consumption adjustments can be explained by indirect income effects triggered by short-term price shifts; adjustment capacity can increase, for instance, with ownership of electric/electronic appliances.

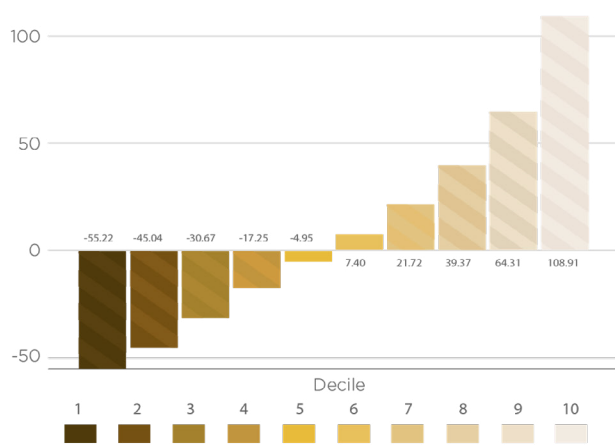
Households that had a relatively low demand for energy during lockdown decreased their demand with respect to the expected levels. For instance, the monthly average consumption adjustment downwards in decile 1 was around 40- 50 kWh in most cities, while it went down by more than 95 kWh in Santa Cruz.

These results may have at least a two-fold explanation. On the one hand, they may be due to temporary human movement within cities, whereby people living alone relocated into dwellings with extended family - most likely in the same city, as domestic travel was also severely restricted. On the other hand, the results may also reflect temporary tenant relocation and/or ending of rent contracts by small families, students, or single people.

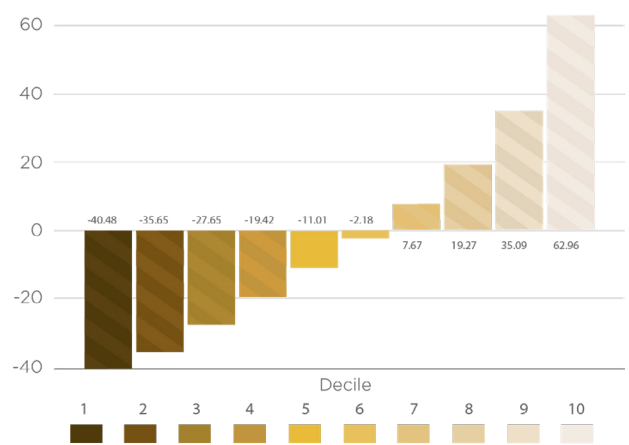
<sup>9</sup> In most cities, the average adjustment in the tenth decile was around 80-90 kWh, but in Santa Cruz it was over 145 kWh.

Figure 4: Effects on energy consumption (kWh/month) by decile and city

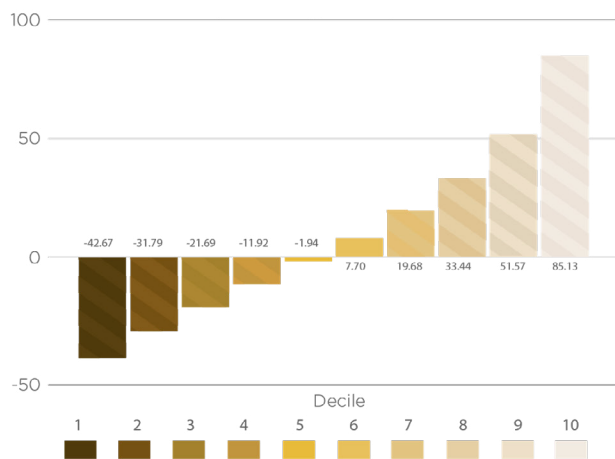
### La Paz



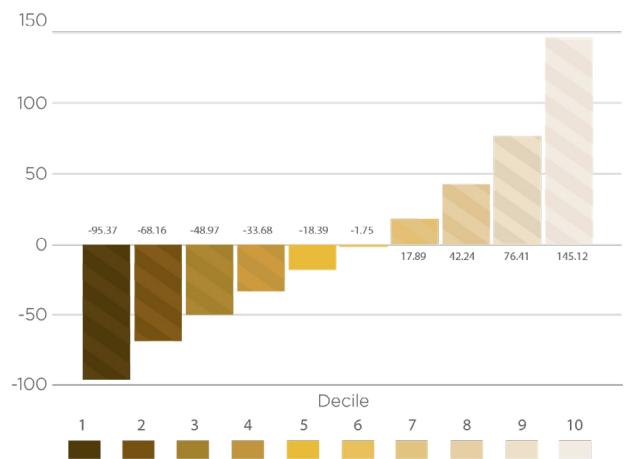
### El Alto



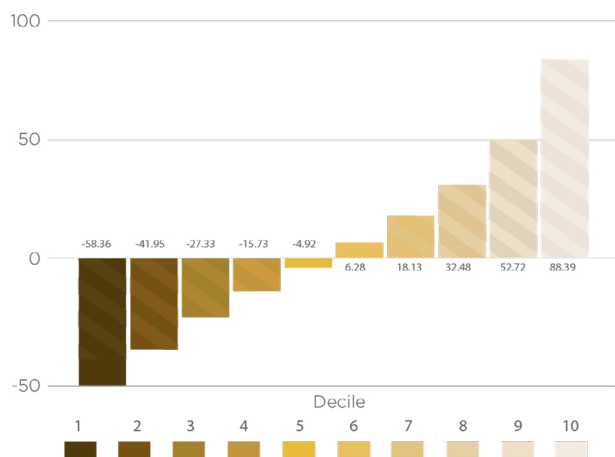
### Cochabamba



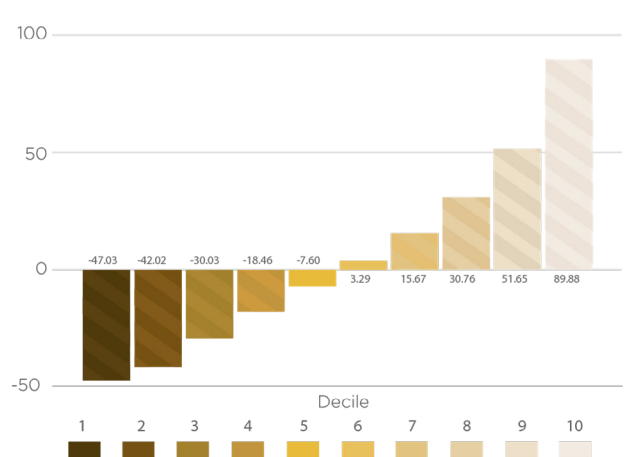
### Santa Cruz



### Tarija



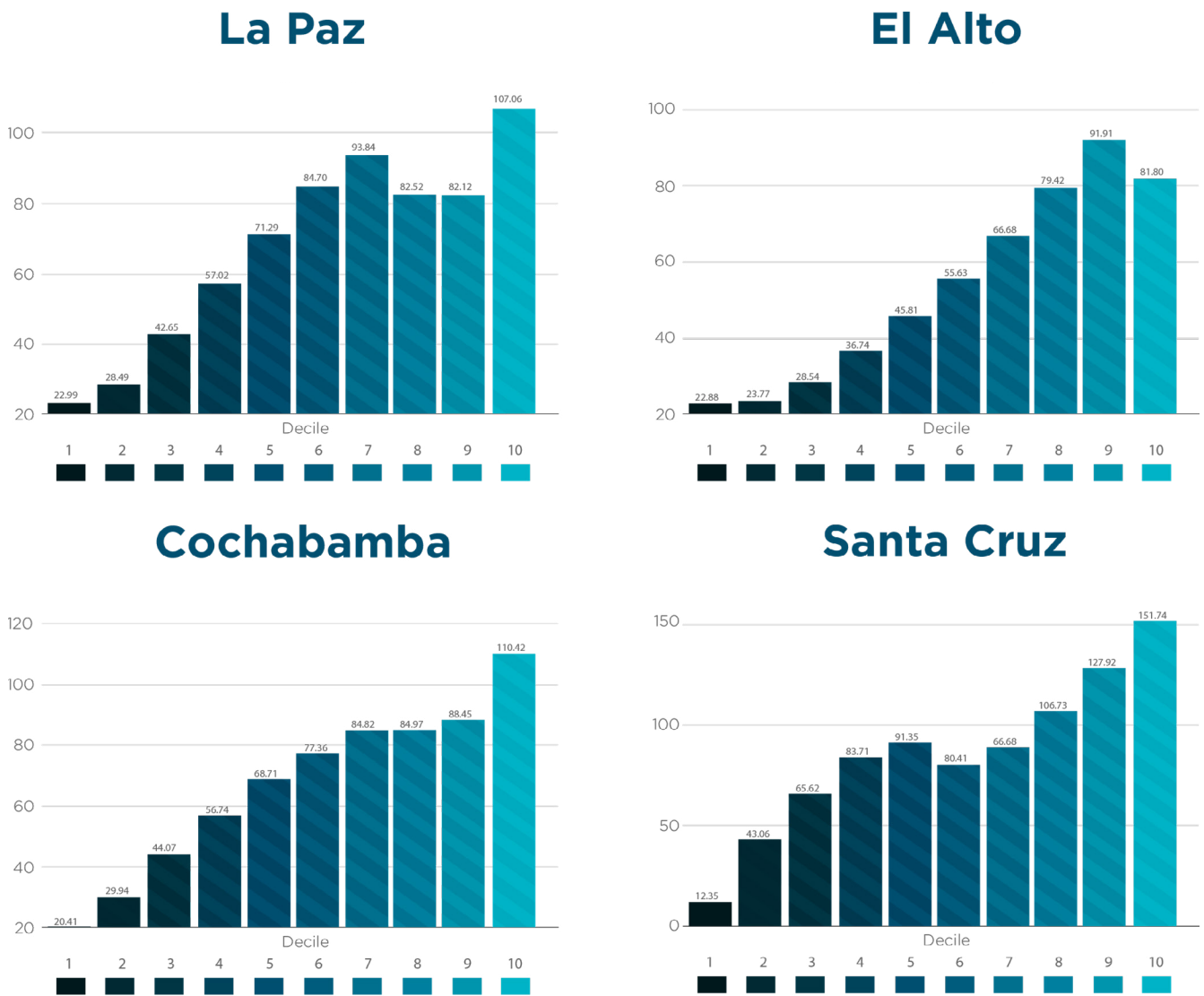
### Sucre



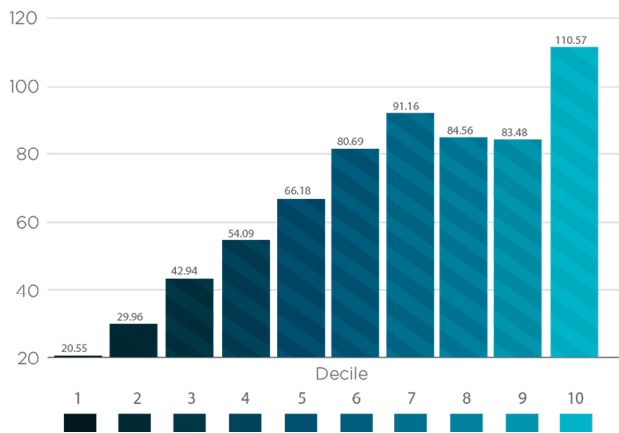
Source: Authors' design based on administrative records

Turning to monetized effects by decile, Figure 5 shows that meters sitting in the higher deciles granted their users larger bill reductions. For instance, while meters in the first decile in Cochabamba registered consumption levels that allowed users to avoid spending around BOB 20 per month, on average, this ‘saving’ rose to more than BOB 110 for users with meters in the tenth decile. Similar results were found in all cities. However, it is interesting to notice that this trend was not monotonic; in Sucre, for instance, the average ‘saving’ per month is highest for users of meters sitting in the eight decile (BOB 95).

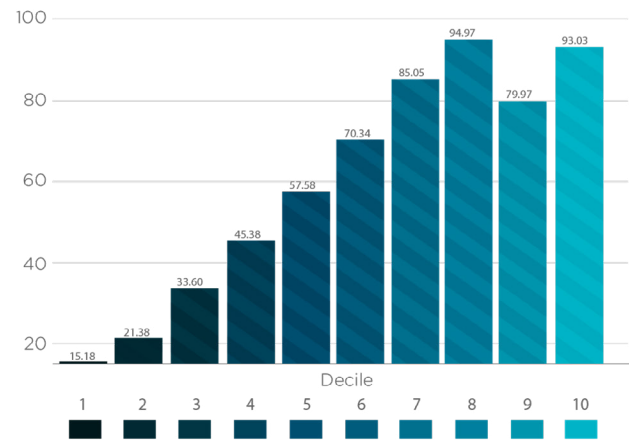
**Figure 5: Effects as measured by monthly bill reduction by energy consumption decile and city**



## Tarija



## Sucre



Source: Authors' design based on administrative records

## 4.4. Heterogeneous effects based on key socioeconomic characteristics: Using Household Survey data

This section presents an analysis based on the dataset combining administrative records and the 2020 Household Survey data in order to gain a better understanding of the aforementioned results. These results are fit six variants of equation 3, which aim to identify heterogeneous effects on i) energy consumption and ii) a money-based welfare assessment among different population subgroups defined by three key socioeconomic characteristics:

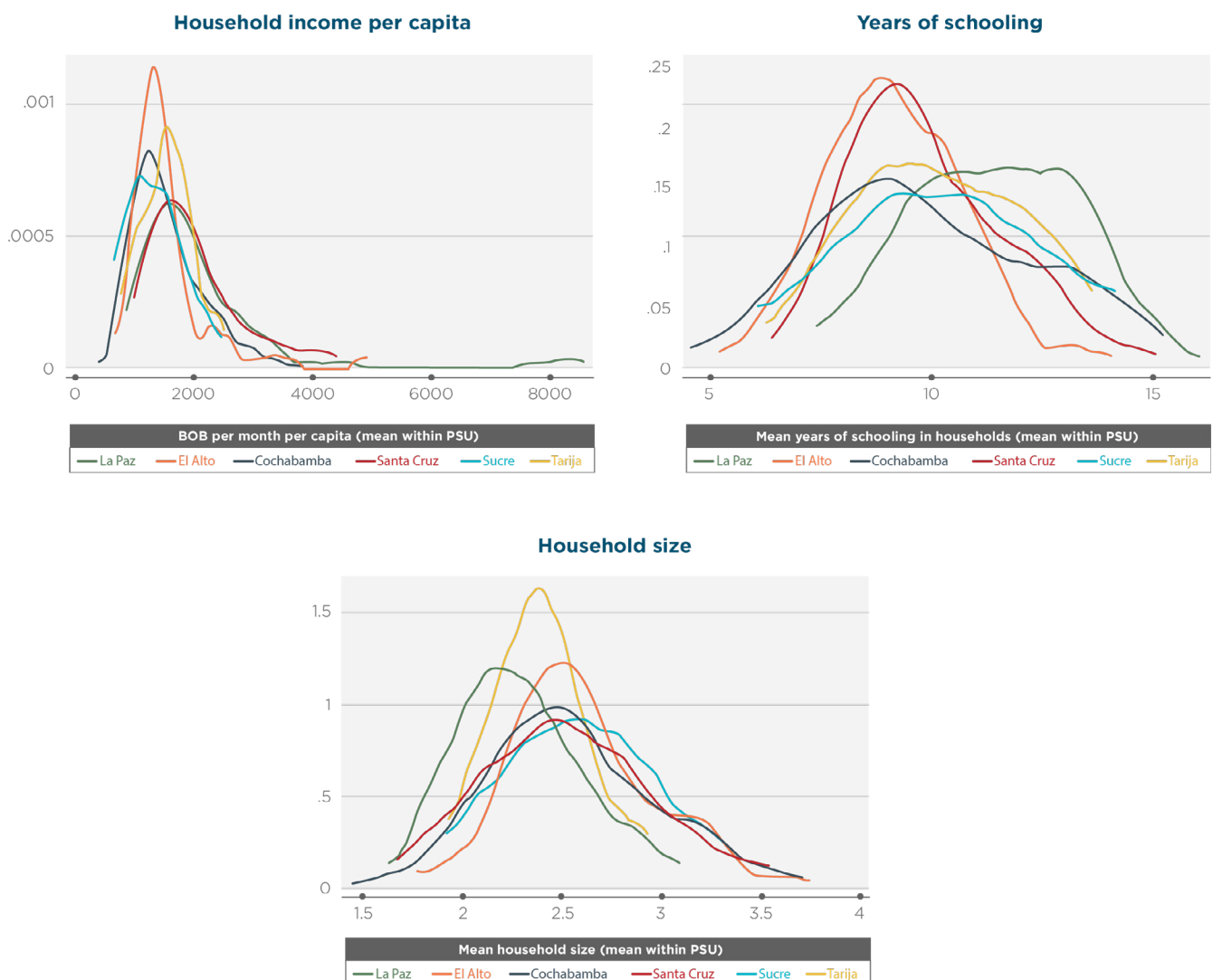
- A** *monthly income per capita*, which was used to separate PSUs into two groups for each city: those who were relatively well-off – above the median income level – and those who were relatively worse-off – below the median income level. The distributions of the mean income level by PSU in each city were plotted in Figure 6 panel (a). It was skewed toward the higher income values, particularly in La Paz.



**B** *mean years of schooling within households*, which complements the previous variable to separate relatively advantaged and disadvantaged PSUs. Years of schooling are highly correlated with income levels, but the former may also capture other non-monetary socioeconomic conditions defining relative welfare advantages. The distribution of mean years of schooling by PSU was plotted in Figure 6 panel (b). We can see that years of schooling were much more evenly distributed across PSUs around the mean for each city compared to monthly income per capita. It also highlighted that, overall, years of schooling were higher in La Paz.

**C** *household size* as measured by the average number of its members was the third relevant PSU-grouping variable. As shown in Figure 6 panel (c), households tended to be relatively small in all cities – the median household size was consistently around 2.5

**Figure 6: Distribution of key socioeconomic characteristics (mean within PSU)**



The first three variants of equation 3 took monthly energy consumption as the dependent variable, and their estimation results are presented in Table 4. The results showed that energy consumption adjustments upward during lockdown across cities are mostly concentrated in the above-median PSUs in terms of monthly income per capita and years of schooling.

Statistically significant upward consumption adjustments among these socioeconomic subgroups were consistently found in all six cities. The sharpest adjustments occurred in La Paz (10.6 kWh/month), Tarija (7.6), and Cochabamba (7.1). The mildest, but statistically significant adjustment, was found in El Alto (3.8).

Similar upward consumption adjustments are less widespread among below-median PSUs in terms of income and years of schooling. In fact, consumption adjustments were not found to be statistically significant if one focused on these socioeconomic groups in Tarija and El Alto. There were significant adjustments in Cochabamba and La Paz, but they were lower than the adjustments found for above-median PSUs.

**Table 4: Heterogeneous effects on energy consumption (kWh/month)**

**(a) Socioeconomic groups defined by household p/c income (BOB/month)**

| Effect on ...      | Cochabamba | El Alto   | La Paz     | Santa Cruz  | Sucre     | Tarija    |
|--------------------|------------|-----------|------------|-------------|-----------|-----------|
| below median group | 5.434 ***  | -0.357    | 7.462 ***  | -12.323 *** | 5.279 *** | 0.405     |
| above median group | 7.141 ***  | 3.804 *** | 10.582 *** | 6.483 ***   | 5.364 *** | 7.651 *** |
| Median p/c income  | 1443       | 1390      | 1788       | 1742        | 1250      | 1563      |
| Within R2          | 0.165      | 0.0307    | 0.782      | 0.558       | 0.286     | 0.171     |
| Obs.               | 666        | 366       | 378        | 498         | 114       | 186       |

**(b) Socioeconomic groups defined by years of schooling**

| Effect on ...            | Cochabamba | El Alto   | La Paz     | Santa Cruz  | Sucre     | Tarija    |
|--------------------------|------------|-----------|------------|-------------|-----------|-----------|
| below median group       | 4.827 ***  | -0.839    | 6.345 ***  | -11.942 *** | 4.104 *** | -2.022    |
| above median group       | 7.687 ***  | 4.563 *** | 10.266 *** | 16.196 ***  | 6.483 *** | 9.589 *** |
| Median schooling (years) | 9.6        | 9.1       | 11.5       | 9.6         | 9.9       | 9.9       |
| Within R2                | 0.165      | 0.307     | 0.782      | 0.558       | 0.287     | 0.171     |
| Obs.                     | 666        | 366       | 378        | 498         | 114       | 186       |

(c) Socioeconomic groups defined by household size

| Effect on ...         | Cochabamba | El Alto   | La Paz    | Santa Cruz | Sucre      | Tarija    |
|-----------------------|------------|-----------|-----------|------------|------------|-----------|
| below median group    | 6.257 ***  | 3.764 *** | 9.773 *** | 11.807 *** | 10.518 *** | 6.342 *** |
| above median group    | 6.040 ***  | -0.776    | 8.446 *** | -8.863 *** | 1.802      | 0.850     |
| Median household size | 2.5        | 2.5       | 2.3       | 2.5        | 2.6        | 2.4       |
| Within R2             | 0.165      | 0.307     | 0.782     | 0.558      | 0.285      | 0.171     |
| Obs.                  | 666        | 366       | 378       | 498        | 114        | 186       |

Note: \*\*\* p-value<0.001, \*\* p-value<0.05, \* p-value<0.10

Source: Authors' own based on administrative records

Below-median PSUs in terms of income and schooling in Santa Cruz were the only socioeconomic group for which we found a significant energy consumption adjustment downward during lockdown (-12.3 kWh/month). This may be due particularly important income restrictions in these households.

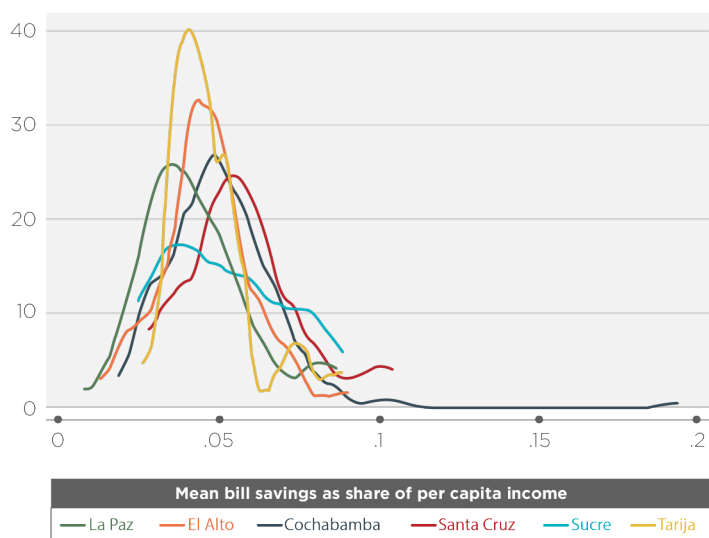
It is worth noting that higher consumption adjustments were consistently found in well-off households. All these results further reinforce the idea that the demand elasticity of households depends on their income, potentially due to ownership of electric and electronic appliances. It is also interesting to stress that, across cities, PSUs sitting below the median household size distribution were consistently home to people who adjusted their energy consumption upward during lockdown the most. In fact, there were no statistically significant consumption adjustments in households above the median size in El Alto, Sucre, and Tarija. Again, households sized above the median in Santa Cruz showed a distinctive pattern in that they significantly adjusted their consumption levels downward (-8.9 kWh). As household size was negatively correlated with purchasing power in the country, this result may reinforce the idea that these households suffered particularly harsh disposable income restrictions during strict lockdown.

## 4.5. Welfare effects of the support scheme

To better understand the effects of the support scheme on welfare, this section presents an analysis of the distribution of average energy consumption shifts as a share of mean household income per capita by PSU in each city.

The average effect of the program on monthly income was similar across cities, registering at between 4% and 5%. The distribution of these shares in all six cities is depicted in Figure 7. The highest ones were found in Sucre (5%), Cochabamba (5%), Santa Cruz (4.9%), and Tarija (4.7%). The lowest mean shares were found in La Paz and El Alto (4%). It is important to note that these shares were relatively uniformly distributed around the mean in all cities, except in La Paz, where the distribution of shares was clearly right skewed. There are some households (in the lowest income regions) in this city for which the energy bill savings fostered by the supporting scheme represented around 19% of their monthly income.

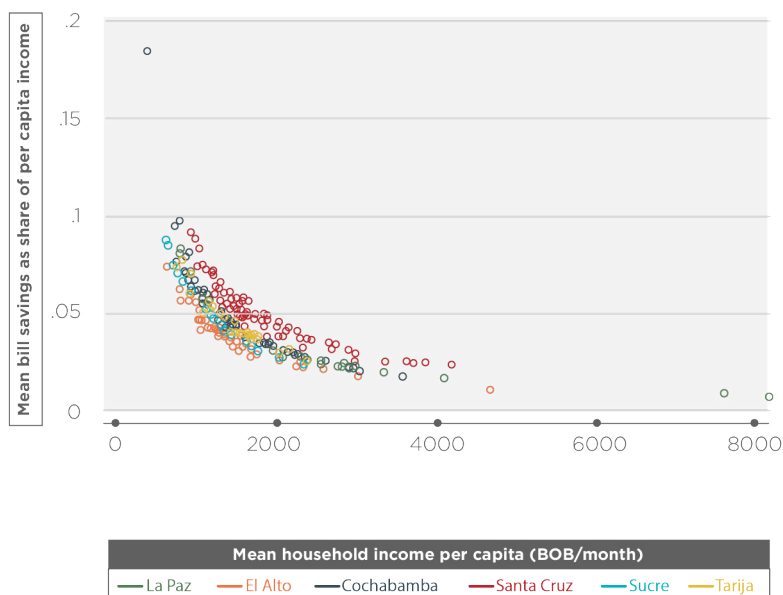
**Figure 7: Effect as share of mean energy bill savings in household income per capita**



Source: Authors' own based on administrative records

Indeed, the results showed a clear progressive relative effect of the supporting scheme in benefit of the poorest households. Plotting the share of energy bill savings against the mean income level (see Figure 8), the analysis pointed out a clear negative relationship whereby the welfare effect of the supporting scheme was markedly concentrated in PSUs with lower mean income levels. This was the case in all six cities. This means that even if more advantaged households (in terms of income or schooling levels) adjusted their levels of energy consumption upward during lockdown, it was actually the more disadvantaged households that had the higher effect on their income. They were, indeed, the beneficiaries with highest welfare shift from the supporting scheme in relative terms.

**Figure 8: Effect as a share of household income per capita**



Source: Authors' own based on administrative records

The larger positive effect of the supporting scheme on the least well-off households, in relative terms, was corroborated by model-based heterogeneous assessments. Three additional variants of equation 3 were estimated, positing the share of energy bills in household income as the dependent variable. The estimation results are presented in Table 5. The supporting scheme generated widespread significant welfare benefits in all six cities, and these benefits have consistently been larger among the relatively more disadvantaged population subgroups. For instance, PSUs that were home to households sitting below the median per capita income benefited from energy bill reductions representing between 6.7% (Santa Cruz) and 4.5% (El Alto) of household income. Meanwhile, households sitting over the median per capita income benefited from reductions representing 3.2% (Santa Cruz) and 2.7% (El Alto). A similar pattern was found for households sitting below and above the median in terms of years of schooling. This was to be expected, given the high correlation between schooling and income, and it confirms the higher relative welfare effect of the supporting scheme on the comparatively more disadvantaged population subgroups. This result was further reinforced by a higher effect on households sized above the median, which was consistent across cities. In La Paz for instance, the supporting scheme generated a 4.7% reduction of the energy bill share in income for the more sizeable households, while this reduction was 3.7% in smaller households.

**Table 5: Heterogeneous effects on energy bills as share of household income per capita**

**(a) Socioeconomic groups defined by household p/c income (BOB/month)**

| Effect on ...      | Cochabamba | El Alto    | La Paz     | Santa Cruz | Sucre      | Tarija     |
|--------------------|------------|------------|------------|------------|------------|------------|
| below median group | -0.061 *** | -0.045 *** | -0.055 *** | -0.067 *** | -0.059 *** | -0.059 *** |
| above median group | -0.034 *** | -0.027 *** | -0.031 *** | -0.041 *** | -0.032 *** | -0.037 *** |
| Median p/c income  | 1443       | 1390       | 1788       | 1742       | 1250       | 1563       |
| Within R2          | 0.002      | 0.029      | 0.213      | 0.434      | 0.413      | 0.289      |
| Obs.               | 666        | 366        | 378        | 498        | 114        | 186        |

**(b) Socioeconomic groups defined by years of schooling**

| Effect on ...            | Cochabamba | El Alto    | La Paz     | Santa Cruz | Sucre      | Tarija     |
|--------------------------|------------|------------|------------|------------|------------|------------|
| below median group       | -0.060 *** | -0.044 *** | -0.055 *** | -0.055 *** | -0.065 *** | -0.053     |
| above median group       | -0.037 *** | -0.031 *** | -0.036 *** | -0.041 *** | -0.037 *** | -0.042 *** |
| Median schooling (years) | 9.6        | 9.1        | 11.5       | 9.6        | 9.9        | 9.9        |
| Within R2                | 0.002      | 0.029      | 0.213      | 0.434      | 0.413      | 0.289      |
| Obs.                     | 666        | 366        | 378        | 498        | 114        | 186        |

**(c) Socioeconomic groups defined by household size**

| Effect on ...         | Cochabamba | El Alto    | La Paz     | Santa Cruz | Sucre      | Tarija     |
|-----------------------|------------|------------|------------|------------|------------|------------|
| below median group    | -0.040 *** | -0.034 *** | -0.037 *** | -0.043 *** | -0.042 *** | -0.041 *** |
| above median group    | -0.058 *** | -0.043 *** | -0.047 *** | -0.054 *** | -0.057 *** | -0.058 *** |
| Median household size | 2.5        | 2.5        | 2.3        | 2.5        | 2.6        | 2.4        |
| Within R2             | 0.002      | 0.029      | 0.213      | 0.434      | 0.413      | 0.289      |
| Obs.                  | 666        | 366        | 378        | 498        | 114        | 186        |

Note: \*\*\* p-value<0.001, \*\* p-value<0.05, \* p-value<0.10

Source: Authors' own based on administrative records

## 5. Final remarks

This paper presents an analysis of the effects of the supporting scheme on energy consumption during the period of full lockdown (April, May, and June 2020) in six populous Bolivian cities: La Paz, El Alto, Cochabamba, Santa Cruz, Tarija, and Sucre. The study shows that the effects of the supporting scheme followed patterns that are important to inform policymaking, and many of them were consistent across all six cities.



On average, consumers adjusted their energy demand upward in five of the six cities. The sharpest rise compared to the expected energy demand during lockdown was found in La Paz (+8.4 kWh) and Cochabamba. The only exception is Santa Cruz, where consumption was adjusted downward. This case requires further analysis for better understanding, as it can be related to households' habits and climate.

Increases in electricity demand were found to be comparatively mild among households that benefited most from the program in relative terms. In general, meters that registered consumption levels compatible with a full bill reduction consistently across the lockdown period showed consumption adjustments that were lower than those with a partial reduction. This means that households with high energy consumption during lockdown increased their demand the most. In absolute terms, this was reflected in higher bill reductions for consumers with the highest energy demand. The only exception to this result was found in Santa Cruz. In this city, households with high levels of energy consumption decreased their demand during lockdown. However, these households still had the highest bill reduction across all the considered cities, which shows how high their energy demand was.

On average, observed consumption levels in the lower deciles (which included combined lockdown effects and scheme effects) were clearly lower than the expected consumption level for these deciles (without lockdown and scheme effects), and this was true for all six cities. Conversely, the actual consumption in the higher deciles was higher than the expected consumption level. This may be explained by relocation to different dwellings or by temporary tenant relocation and/or ending of rent contracts. Even if correlation between high energy consumption and high purchasing power was not perfect, it can be expected to be quite high. As a consequence, these results show that the wealthiest households revised their energy consumption upward during lockdown. Indeed, this was true in absolute terms – they benefited from the highest bill reductions as a result of the supporting scheme. However, if the bill reduction with the mean income levels in ‘neighborhoods’ is considered, the analysis shows that it is the least wealthy households that experienced the highest effects, because the support was relatively if compared with their income. For instance, in Cochabamba, the support scheme represented around 20% of average income for lower income ‘neighborhoods’. The percentage could have actually been much higher for some lower income householders, as a consequence of the inequality with neighbors and the decrease of the income level during the pandemic. As a result, the relative welfare gains could be considered more concentrated in the least well-off population.

The entire population benefited from bill reductions that increased their liquidity and purchasing power in times in which it was highly needed. The supporting scheme was applied as a universal indirect cash transfer, an emergency policy measure. This analysis shows, however, that in the future, a more targeted policy for households with lower purchasing power (or to neighborhoods with lower purchasing power) could be a more efficient expenditure and potentially a more equitable distribution of opportunities to adjust the demand for energy upward, if needed. As a potentially fruitful avenue to explore, one way of operationalizing a finer-tuned targeted version of the program would be to have longer support periods for the least well-off households.



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## 7. Appendices

### 7.1. Administrative records: A descriptive analysis

The raw data include monthly administrative records of five electricity distribution companies that distribute electricity to different municipalities in five departments: (i) DELAPAZ, that distributes energy to La Paz and El Alto; (ii) CRE, to Santa Cruz; (iii) ELFEC, to Cochabamba; (iv) SETAR to Tarija; and (v) CESSA to Chuquisaca. Initially, these databases did not have the same number of observations between months, so during the merging, a small percentage of data was lost. For the months covered by the study, the database was comprised of around two million energy meters of residential and non-residential categories in all municipalities within the five departments mentioned before. For this reason, a comprehensive selection of only residential categories was performed, and only six cities of interest were left in the database.

From this exercise, the data of the six cities combined include around 1.3 million energy meters. Out of those, further filtering was performed to ensure that all meters corresponded to natural individuals (i.e. they did not correspond to churches, schools, community buildings, firms or other organizations), resulting in a database with 1.1 million energy meters.

Applying the interquartile rule to define outliers over the pooled consumption distribution in each city, we found that a total of 4% of meters reported atypically high measured levels of energy consumption. We did not consider these records in our analysis, as they risked blurring the regular consumption patterns that we sought to understand.

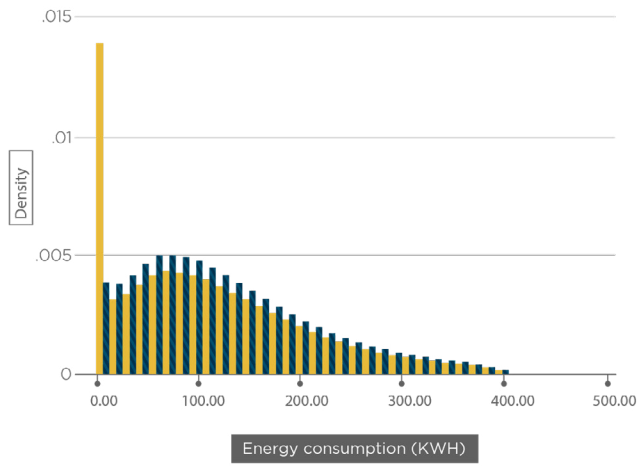
Also, a total of more than 500,000 meters (2.2 million observations) systematically recorded zero energy consumption. From these observations, 35,000 were observations with zero energy consumption in all 43 months of analysis. The later meters were also excluded from our analysis, as they represented either empty dwellings or outdated records.

Taking these data characteristics into account, we ended up with a total of 1.02 million meters (43.6 million observations) as the universe of domestic energy consumption in the six cities combined. We had a full panel dataset for these meters, with the rest forming an incomplete panel dataset.

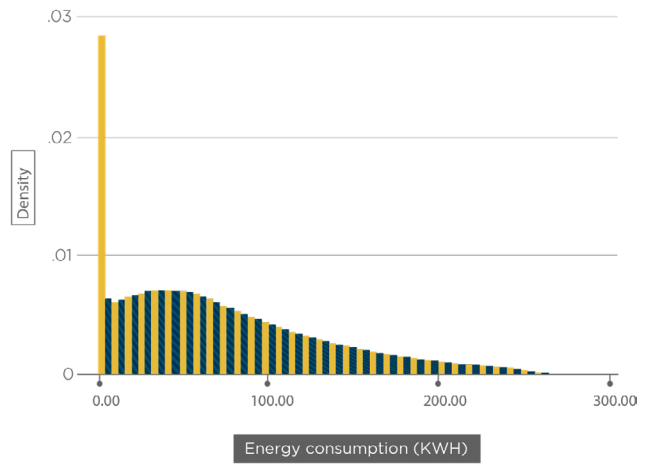
The pooled distribution of energy consumption for each city is depicted in Figure A1.

Figure A1: Distribution of Energy Consumption (no outliers):

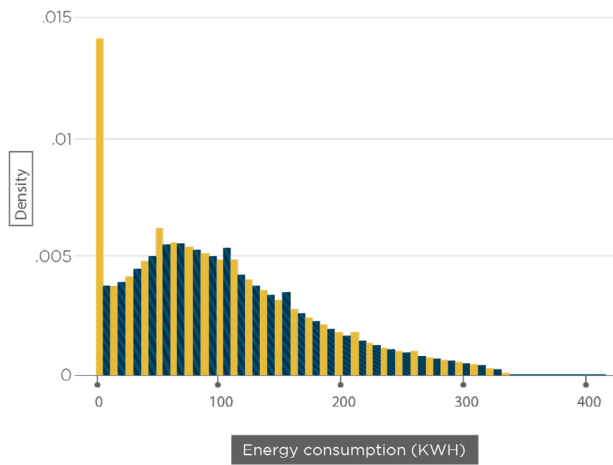
(a) La Paz



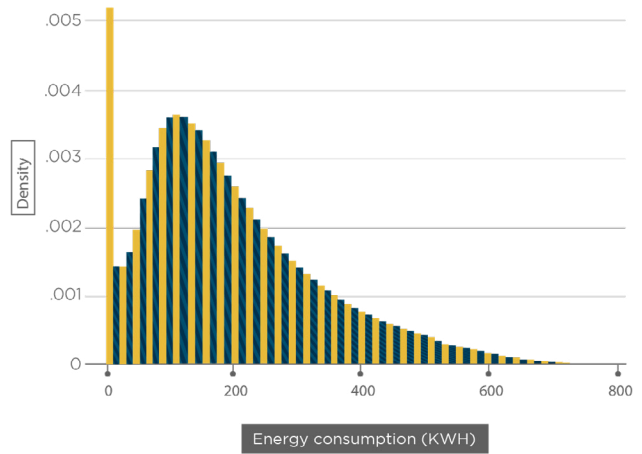
(b) El alto



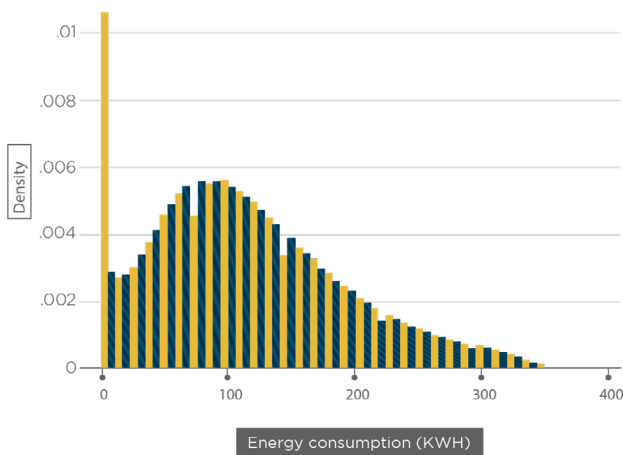
(c) Cochabamba



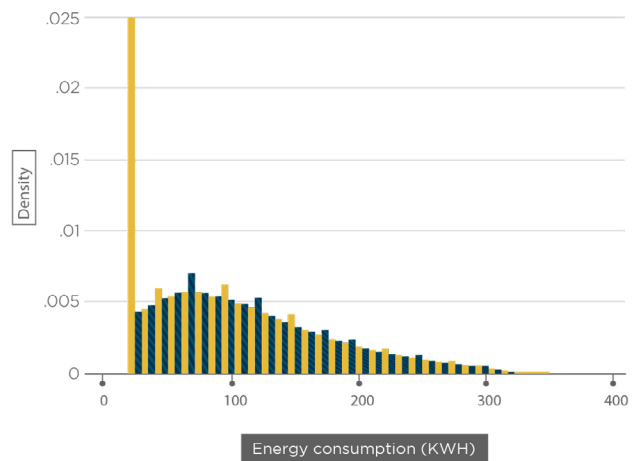
(d) Santa Cruz



(e) Tarija



(f) Sucre



## 7.2. Combining administrative records and Household Survey data

The process to combine the electricity consumption administrative records with the data from the Household Survey conducted in 2020 required working in several sequential phases:

- Identify the PSUs that corresponded to the cities that were the object of analysis. In this case, the National Institute of Statistics denied the possibility of providing the list of these PSUs. This fact prompted the need to work on the identification based on previous work carried out in which the way to identify the PSUs was deduced from the code included in the variable 'folio'.
- Once the PSUs corresponding to each of the cities were identified, the latitude and longitude coordinates were obtained (using the central point of each PSU).
- In parallel, the latitude and longitude coordinates corresponding to each of the included addresses where the energy meters were located were obtained from the electricity consumption database. To obtain these data, the Apps Script geocode function included in Google Sheets was used, which allowed obtaining coordinates from Google Maps.

The final objective was to identify as many energy meters as possible around the central point of each PSU. To achieve this goal, near neighbors were found using Stata's *'geonear'* command, a tool that finds near neighbors using geodetic distances. Once the near neighbors were found, the addresses included in the records of the electricity consumption bases were assigned to the corresponding PSUs.

Finally, the merge of the prepared databases was performed using the PSU variable as a parameter.

## 7.3. Econometric framework

Creating valid counterfactual scenarios for our analysis amounts to consistently estimating the expected level of expenditure on electricity during April, May, and June 2020 had the supporting scheme not been implemented. Our analysis focused on estimating the expected level of domestic electricity consumption during the supporting scheme period. To predict these consumption levels, we used monthly panel data collected by the electricity providers in six cities: Cochabamba, La Paz, El Alto, Santa Cruz, Sucre, and Tarija.

### 7.3.1. Counterfactual estimation

We drew inspiration from the methodology applied in Baron et al. (2020) to evaluate the impact of school closures in Florida on the report of child maltreatment during the pandemic-related lockdown episodes in this American state. We used monthly panel data collected by electricity providers in the form of administrative records for urban and peri-urban areas to fit the following model:

A1

$$e_{it} = \alpha_0 + \alpha_i + \alpha_t + f_s(\beta, t, x_t, e_{it-s}) + \epsilon_{it}$$

where,  $e_{it}$  is the level of electricity consumption (in kWh) recorded by meter “i” at time (month) “t,”  $\alpha_0$  represents a constant term, and  $\alpha_i$  and  $\alpha_t$  represent meter- and time-specific effects, respectively. Function  $f_s$  represents a polynomial transformation of time variable “t,” s lags of  $e_{it}$ , a vector of time-varying external predictors  $x_t$  (e.g. stationary transformations of relevant climate and economic variables), and a vector of parameters  $\beta$ . Finally,  $\epsilon_{it}$  is the idiosyncratic error term. A parsimonious set of plausible values for s and functional forms for f were empirically explored to identify the model specification that provided the best fit.

For notation clarity in the remainder of the document, let us collect the full set of parameters in vector  $\theta_1 = [\alpha_0, \alpha_i, \alpha_t, \beta]$ , so that equation (A1) can be rewritten in a general way as:

A2

$$e_{it} = g(\theta_1, s, t, x_t) + \epsilon_{it}$$

Equation (A2) was estimated for relevant meter subsets in order to create counterfactual levels of electricity consumption i) at the city level, and ii) for different types of supporting scheme beneficiaries in each city.

To arrive at counterfactual estimates of electricity consumption at the city level, we fit equation (A2) with data corresponding to the subset of meters i such that  $i \in p$  with  $p \in P = \{\text{El Alto, La Paz, Cochabamba, Santa Cruz, Sucre, Tarija}\}$ . Thus, the counterfactual level of aggregate consumption in city p at time t, denoted as  $\hat{e}_{pt}$ , is estimated as  $\hat{e}_{pt} = E_{i \in p} [\hat{e}_{it}]$ , where  $\hat{e}_{it} = g(\hat{\theta}_1, s, t, x_t)$  was the predicted value of electricity consumption as per equation (A2).

We followed the same idea to arrive at counterfactual estimates of electricity consumption for different types of supporting scheme beneficiaries. Let us denote as B the set of relevant beneficiary types. These can be defined, for instance, by their electricity bill reduction during lockdown; thus,  $B = \{100\%, 50\%, 40\%, 30\%, 20\%, 0\%\}$ . Beneficiary types can also be defined as deciles of the distribution of average energy consumption during lockdown.

In a general way, the counterfactual level of aggregate consumption for beneficiary type  $b \in B$  in city  $p$  was denoted as  $\hat{e}_{bpt}$  and estimated as  $\hat{e}_{bpt} = E_{i \in b \cap i \in p} [\hat{e}_{it}]$ . The key identifying assumption of the proposed method for counterfactual estimation was that in the absence of both full lockdown measures in the country and cost support policies, the actual levels of electricity consumption should not have diverged from their regular dynamic patterns in each city and for each beneficiary type.

Using geo-localization information, it was possible to merge administrative records of energy consumption with the Household Survey in Bolivia. The exact location of each energy meter allowed us to identify those belonging to each primary sampling unit in the Household Survey (PSU, denoted as  $u$ ) in every city. Naturally, the PSUs in the Household Survey only included a subset of the meters that were included in the administrative records, thus resulting in some information loss. However, taken together, the PSUs were precisely defined to represent the average living conditions of people in the considered cities, including several consumption patterns. It was thus expected that they would also allow us to generate a representative sample of meters from the administrative records – which are, in fact, the universe of meters. This is a testable hypothesis that we discussed in detail while we presented the data used for our study.

Once the relevant subset of meters was matched to the PSUs in the Household Survey, it was possible to revise equation (A1), which was estimated for each city separately, by adding PSU-specific effects,  $\alpha_u$ :

A3

$$e_{iut} = \alpha_0 + \alpha_i + \alpha_t + \alpha_u + f_s(\beta, t, x_t, e_{it-s}) + \epsilon_{it}$$

The addition of this effect re-defined the vector collecting the full set of parameters as  $\theta_2 = [\alpha_0, \alpha_i, \alpha_t, \alpha_u, \beta]$ , so that equation (A3) could be rewritten in a general way as:

A4

$$e_{iut} = g(\theta_2, s, t, x_t) + \epsilon_{it}$$

We could thus estimate the counterfactual level of electricity consumption in PSU  $u$  at time  $t$  as  $\hat{e}_{ut} = E_{i \in u} [\hat{e}_{iut}]$  where  $\hat{e}_{iut} = g(\hat{\theta}_2, s, t, x_t)$  is the predicted value of electricity consumption as per equation (A4).

## 7.3.2. Effect estimation

Once valid counterfactual average levels of energy consumption were identified, the supporting scheme effect could be estimated simply by comparing the actual and counterfactual levels of energy consumption i) for each city, and ii) for each beneficiary type in each city, for every month during lockdown (T). Denoting the effect in city p at time t as  $\delta_{pt}$ , we have:

A5

$$\hat{\delta}_{pt} = E_{i \in p}[e_{it}] - E_{i \in p}[\hat{e}_{it}] = e_{pt} - \hat{e}_{pt}, \forall t \in T$$

Denoting the effect for beneficiary type b in city p at time t as  $\delta_{bpt}$ , we have:

A6

$$\hat{\delta}_{bpt} = E_{i \in b \cap i \in p}[e_{it}] - E_{i \in b \cap i \in p}[\hat{e}_{it}] = e_{bpt} - \hat{e}_{bpt}, \forall t \in T$$

We also explored the usefulness and adequacy of estimating an average effect across all the lockdown period T. Thus, for city p we have:

A7

$$\hat{\delta}_p = E_{t \in T \cap i \in p}[e_{it}] - E_{t \in T \cap i \in p}[\hat{e}_{it}] = e_p - \hat{e}_p$$

and for each beneficiary type in city p we have:

A8

$$\hat{\delta}_{bp} = E_{i \in b \cap i \in p \cap t \in T}[e_{it}] - E_{i \in b \cap i \in p \cap t \in T}[\hat{e}_{it}] = e_{bp} - \hat{e}_{bp}$$



### 7.3.3. More detailed heterogeneous effects using Household Survey data

Having the PSU-varying set of actual and counterfactual levels of electricity consumption allowed us to apply a difference-in-difference regression framework with multiple periods.

Taking one city at a time, let us denote the average level of electricity consumption in PSU  $u$  at time  $t$  as  $y_{ut}$ . If this level corresponds to the observed (actual) consumption level, then  $y_{ut} = E_{icu} [e_{iut}] = e_{ut}$ . If this level corresponds to the counterfactual consumption level, then  $y_{ut} = \hat{e}_{ut}$  defined previously.

The canonical difference-in-difference model can thus be posited as:

A9

$$y_{ut} = \lambda_0 + \lambda_u + \lambda_t + \delta(D \times T) + \gamma z_{ut} + v_{ut}$$

where  $\lambda_0$  is a constant term,  $\lambda_u$  and  $\lambda_t$  represent PSU- and time-fixed effects, respectively.  $D$  is a binary indicator taking a unity value if  $y_{ut} = e_{ut}$  and zero if  $y_{ut} = \hat{e}_{ut}$ .  $T$  is a binary indicator taking a unity value for the months in which the supporting scheme was active and zero otherwise. Vector  $z_{ut}$  are control variables measured at the PSU level using information from the Household Survey (e.g., median level of income, median housing conditions, median demographic composition, etc.). The main coefficient of interest was  $\delta$ . Finally,  $v_{ut}$  the idiosyncratic error term.

In order to uncover some potential heterogeneous effects, we proposed to extend the canonical difference-in-difference model in (A9) to accommodate for specific coefficients associated with different household types. These types were defined based on analytical relevance, but preliminary, one may think of income quantiles or household size. For now, let us denote as  $y_{gut}$  the outcome variable for household type  $g$  in PSU  $u$  at time  $t$ . Heterogeneous effects can thus be estimated by fitting the following model:

A10

$$y_{gut} = \lambda_0 + \lambda_u + \lambda_t + \lambda_g + \sum_g I_g \delta_g (D \times T) + \gamma \tilde{z}_{gut} + \eta_{gut}$$

where  $\lambda_g$  denotes household type fixed effects, and  $\delta_g$  represents the effect for household type  $g$ , which is activated by means of household type binary indicator  $I_g$ . Finally,  $\eta_{gut}$  represents the appropriate idiosyncratic error term.

## 7.4. Estimation results

Table A1: Full estimation results by city – preferred models

|                         | Cochabamba  | El Alto    | La Paz      | Santa Cruz | Sucre       | Tarija     |
|-------------------------|-------------|------------|-------------|------------|-------------|------------|
| Jan (ref)               |             |            |             |            |             |            |
| Feb                     | -3.634***   | -19.05***  | 17.50***    | 37.15***   | -18.11***   | -13.75***  |
| Mar                     | 6.457**     | -28.15***  | -143.7***   | 37.75***   | -121.6***   | -31.05***  |
| Apr                     | -4.075**    | -22.88***  | -205.8***   | -0.171     | -109.6***   | -30.56***  |
| May                     | -2.629**    | -25.61***  | -132.9***   | 3.853      | -50.94***   | -16.08***  |
| Jun                     | -18.05***   | -44.54***  | -174.9***   | 10.88      | -81.73***   | -27.46***  |
| Jul                     | -21.57***   | -34.36***  | -162.9***   | -0.185     | -34.23***   | -6.353***  |
| Aug                     | -7.598***   | -35.79***  | -136.0***   | 19.53      | -70.70***   | -25.35***  |
| Sep                     | -0.785      | -36.10***  | -186.2***   | 25.44      | -108.8***   | -31.23***  |
| Oct                     | 2.237       | -25.28***  | -178.4***   | 49.67      |             |            |
| Nov                     |             | -3.866***  | -40.87***   | 19.94      |             |            |
| Dec                     | 6.721**     | -23.17***  | -79.84***   | 35.01      | -108.1***   | -23.63***  |
| Trend 2                 |             |            |             | 0.000156   |             |            |
| Year = 2018 (ref)       |             |            |             |            |             |            |
| Year = 2019             | 6.637***    | -0.351***  | -25.40***   | 11.63      | -31.72***   | -3.588***  |
| Year = 2020             | 5.884***    | 2.792***   | -32.79***   | 11.43      | -31.95***   | -2.047     |
| Cons. Lag 1             | 0.282***    | 0.359***   | 0.419***    | 0.436***   | 0.385***    | 0.357***   |
| Cons. Lag 2             | 0.0805***   | 0.0824***  | 0.0768***   | 0.123***   | 0.0959***   | 0.111***   |
| Cons. Lag 3             | 0.0407***   | 0.0292***  | 0.0179***   | -0.0646*** | 0.0228***   | 0.0209***  |
| Cons. Lag 4             | -0.0186***  | 0.00268*   | -0.00988*** | 0.00452*** | -0.0134***  | -0.00850** |
| Cons. Lag 5             | 0.00193     | 0.00929*** | 0.00782***  | 0.00679*** | -0.00054    | -0.0146*** |
| Cons. Lag 6             | 0.0167***   | 0.00338**  | -0.00219    | -0.0366*** | -0.00172    | -0.0176*** |
| Cons. Lag 7             | -0.00426*** | -0.0114*** | -0.0116***  | 0.0145***  | -0.0169***  | -0.0133*** |
| Cons. Lag 8             | -0.000754   | -0.0141*** | -0.0116***  | -0.0263*** | -0.0152***  | -0.0177*** |
| Cons. Lag 9             | -0.0104***  |            |             |            | -0.00599*** | -0.000546  |
| Cons. Lag 10            | -0.0398***  |            |             |            | 0.00195     | -0.00173   |
| Cons. Lag 11            | 0.0137***   |            |             |            | -0.00608*** | 0.00440*   |
| Temperature             | -3.950***   | -5.781***  | -23.10***   | 1.374***   |             | 0.11       |
| $\Delta$ IGAE           | -0.178***   | 0.259***   | 2.517***    | -0.350***  | 1.791***    | 0.425***   |
| $\Delta$ IGAE Lag 1     |             | -0.124***  | 1.662***    | 0.412***   | 0.314***    |            |
| Constant                | 135.5***    | 111.1***   | 476.6***    | -36.99     | 153.9***    | 85.60***   |
| Obs.                    | 2264733     | 4122172    | 3665245     | 4513292    | 810924      | 561908     |
| Adjusted R <sup>2</sup> | 0.167       | 0.267      | 0.311       | 0.381      | 0.267       | 0.255      |
| AIC                     | 21140590.6  | 36242866.6 | 34961219.2  | 48080052.3 | 7314306.4   | 5283706.1  |
| BIC                     | 21140906.4  | 36243184.2 | 34961533.9  | 48080238.8 | 7314584.9   | 5283975.9  |

Notes: \*\*\*, p-value<0.001, \*\*, p-value<0.05, \*, p-value<0.1.  $\Delta$  denotes the first difference of the variable to ensure stationarity.



# **Effects of an Electricity Cost Supporting Scheme on Domestic Consumption Levels and Household Welfare:**

**Quasi-experimental evidence from six Bolivian cities during the COVID-19 pandemic**

