Research article

The brazilian daylight saving time as a public policy for energy efficiency♦

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Abstract

This work aims to analyze the possible diseconomies of electricity energy induced by the end of daylight saving time in 2019. The series of electrical energy load observations for the Southeast/Midwest subsystem for each hour of the day is considered a dependent variable in multiple linear regression models. The explanatory variables mainly relate to meteorological attributes (temperature), periodicities associated with electricity consumption (daily, weekly, and annual), and economic activity. The research is based on data from the ONS (National System Operator), INMET (National Institute of Meteorology), and IPEA (Institute for Applied Economic Research) from 2017 to 2021. Daylight saving time positively impacted the reduction of consumption around the evening twilight and increased energy consumption in the late dawn and early morning. However, the net balance throughout the day is, on average, 4,976.81 MWh, corresponding to 13.47% of the power required in the Southeast/Midwest Brazilian Interconnected Power System for the 6 p.m. It is worth mentioning that around the evening twilight, the electrical system works with high load requirements.

Keywords

Daylight saving time, Load curves, Linear regression models.

Avaliação do horário de verão brasileiro como política pública de eficiência energética

Resumo

O objetivo deste trabalho é analisar as possíveis deseconomias de energia elétrica induzidas pelo fim do horário de verão em 2019. A série de observações da carga de energia elétrica

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do subsistema Sudeste/Centro-Oeste para cada hora do dia é variável dependente em um modelo de regressão linear múltipla. As variáveis explicativas referem-se principalmente aos atributos meteorológicos (temperatura), às periodicidades associadas ao consumo de energia elétrica (diária, semanal e anual) e à atividade econômica. A pesquisa é baseada em dados do ONS (Operador Nacional do Sistema), INMET (Instituto Nacional de Meteorologia) e IPEA (Instituto de Pesquisa Econômica Aplicada) de 2017 a 2021. O horário de verão reduz o consumo nas horas próximas ao crepúsculo vespertino e aumenta o consumo de energia no final da madrugada e início da manhã. Porém, o saldo líquido ao longo do dia é, em média, de 4.976,81 MWh, o que corresponde a 13,47% da potência requerida no Subsistema Sudeste/Centro-Oeste para o horário das 18h. Vale ressaltar que próximo ao crepúsculo vespertino o sistema elétrico funciona com altas exigências de carga.

Palavras-chave
Horário de verão, Curvas de carga, Modelos de regressão linear.

JEL Classification
D0, D78, C01, C29

1. Introduction

The Brazilian energy system is one of the most sustainable and renewable in the world, as half of the energy comes from hydroelectric plants. According to the national energy balance prepared by the Energy Research Company, EPE (2022), for the base year 2021, the contribution of non-renewable sources (Coal, natural gas, oil products, and nuclear) corresponds to 20% of the total offered, despite the 7th Sustainable Development Goals (SDGs) UN (2030), which indicates the need to guarantee access to cheap, reliable, sustainable, and renewable energy for all. Also, concerning price, especially in times of drought, there is difficulty in offering cheap energy.

Daylight Saving Time (DST) was introduced in Brazil in 1931 under Getúlio Vargas's government. Its main objective was to reduce energy consumption and better use solar luminosity, acting on the demand side and impacting prices. Nevertheless, part of Brazilian society has criticized this public policy, mainly for biological and trade-related reasons. The policy was extinguished in 1933 and readmitted in 1949. Once again, daylight saving time was extinct in 1968, reinstated in 1985, and prevailed until 2018.

In 2019, the Brazilian DST was revoked under the inefficiency argument. The main hypothesis for the inefficiency of DST is due to a change in the consumption profile observed in recent years. Consumption peak (the three consecutive hours of highest consumption) shifted from early evening to mid-afternoon at the end of the spring and during the summer, Lawson et al. (2017). This change is mainly a result of the greater need for ambient cooling. Li et al. (2012) state that one of the impacts of climate change on energy use in the built environment would occur in the hot summer with the cooling requirement.

In addition to the greater need for cooling, according to Grottera et al. (2018), lifestyle choices and living standards impact residential electricity consumption. It is worth noting that habits tend to change over the decades as the technology applied to electrical appliances and the population's lifestyle advances. From this perspective, the electric shower had less influence on energy costs than the rise of air conditioning usage (Gastaldello and Souza, 2014). Concerning temperature management, the new technologies regarding lighting types of equipment and electronic devices have overcome the relative relevance of lighting energy consumption (Giacomelli-Sobrinho et al., 2022).

The Ministry of Mines and Energy conducted in 2019 a study, MME (2019b), to justify the end of DST. It compares load curves for the same weekday, one month before and one month after the DST had begun.[1] The method these authors apply obtains the sum of the squares of the differences in the load values every minute and computes the t-Student statistical test. The null hypothesis states no difference in consumption before and after the DST regime. The p-value for 8 a.m. - 4 p.m. was 0.436, corroborating the null hypothesis that DST causes no impact. For the period 0 to 8 a.m. and 4 to 11 p.m., it is possible to reject the null hypothesis. MME (2019b) indicates an increase in consumption of around 0.7% after the DST begins, contributing to the recommendation to discontinue the measure. The study justifies the increase in electricity consumption due to the usage of air conditioning systems during the dawn since the resting time occurs in higher temperatures relative to the period before the DST.

[1] In Brazil, traditionally, DST starts on the second weekend of October. Thus, load observations one month before and one month after the DST start incorporate days of September and November. It is worth mentioning that these months have different characteristics in terms of, for example, temperature, luminosity, and industrial production, and all these variables affect energy consumption.

The MME (2019b) method does not consider, for instance, temperature variations and their influences on energy consumption. It argues the difficulty of combining different meteorological stations to obtain the average temperature for the subsystem. MME (2019b) also does not mention any other variables able to affect energy consumption, and how its impacts could be controlled. Three years after the end of the DST, databases have been structured to compare the effect of the DST regime in a model concerning several variables that impact energy consumption such as temperature, seasons, economic activity, covid-19 pandemic, among others.

This work aims to evaluate the effect of the discontinued Daylight Saving Time on energy consumption in Brazil. For this work, we have gathered three years of observations in which the DST was not in the course and observations for the three immediately previous years in which the Daylight Saving Time regime was implemented. The time series for load observations for each hour are dependent variables in a linear regression model. The covariates are associated with the temperature, dummy variables, seasons indicators, and economic activity index. We also conduct an assessment similar to MME (2019b) but considering the approach of the Difference in Difference methodology.

In Brazil, when first implemented in 1931, DST was applied over all the national territory. There is little need for DST near the Equator, where the proportion of light to dark hours is roughly equal year-round. So, further away from the Equator, the South and Southeast Brazilian regions show more significant reductions in electricity consumption due to DST, Harrison (2013) and MME (2022). This work focuses on the Southeast/Midwest subsystem. The SIN comprises four large subsystems (Southeast/Midwest, North, Northeast, and South). Although the most prominent expected results are to the South subsystem, the one-day average load in the Southeast/Midwest subsystem is four times the one-day average in the South subsystem.

This paper is composed of five sections, including this introduction. The second section presents the international literature on the assessment of DST. The third session presents the methodology to assess the DST as an energy-saving public policy. The fourth session presents the EDA for the daily load curves and the analysis of the estimated linear regression outcomes. The fifth session presents the work conclusions.

2. Daylight Saving Time as public policy

DST has historically attracted strong opposition, creating tensions among political, commercial, rural, and domestic interests. While urban areas might welcome more light in the evening, rural communities are reluctant to sacrifice early morning sunlight, Harrison (2013). The literature point outs several problems associated with the DST. Kountouris and Remoundou (2014) state that daylight saving time is controversial due to its negative impact on individual well-being. Using data for Germany, they found evidence that the transition to daylight saving time negatively influences overall life satisfaction and mood, which is more intense for those who work full-time.

Harrison (2013) summarizes studies monitoring sleep duration and continuity around the spring and autumn daylight saving time (DST) transitions for several Countries. Most studies indicate changes in the quality of sleep of respondents. Coren (1996), Lahti et al. (2010), Varughese and Allen (2001) explore the relationship between DST and traffic accidents.

According to Roenneberg et al. (2019), many regions and countries are reconsidering their use of Daylight Saving Time (DST), but their approaches differ. Some, like Japan, are considering introducing this twice-a-year change in clock time. In contrast, others want to abolish the switch between DST and Standard Time but do not agree on which to use: California has proposed keeping perennial DST (i.e., all year round), and the EU debates between perennial Standard Time and perennial DST.

The principal reason for introducing daylight saving time (DST) is projected energy savings, particularly for electric lighting. Aries and Newsham (2008)'s estimates suggest a reduction in national electricity use of around 0.5% due to residential lighting reduction in the United States. They also state that there is a consensus that DST does contribute to an evening reduction in peak demand for electricity, though an increase in the morning may offset this. Rivers (2018) estimates the effect of daylight savings time on electricity demand in Ontario, Canada. The results suggest that daylight savings time reduces the demand for electricity by about 1.5% in Ontario. The reductions in electricity consumption are concentrated during the evening period. The reduction in electricity demand appears to persist for at least several weeks following the transition to daylight savings time.

Although the DST objective is to save energy, some works indicate the opposite. Sexton and Beatty (2014) study detailed individual data time use to show how American individuals change their time use in response to the abrupt shift in daylight associated with DST. They compare activities by time interval before and after the change in DST start dates that occurred in 2007 and find cautious evidence that individuals are shifting potentially energy-intensive activities earlier in the day, consistent with earlier findings of increased energy usage.

Kotchen and Grant (2011) also find that DST increases electricity demand. The findings are consistent with simulation results that identify a trade-off between reducing lighting demand and increasing heating and cooling demand. Küfeoğlu et. al (2021) show that the Daylight Saving Time policy does not lead to measurable electrical energy savings. They also claim that the findings should apply to countries such as the United States, India, Japan, Australia, or China, and continents of Africa and South America, whose latitudes are between 42.0° north and south of the equator.

Guven et al. (2021) use daily state-level panel data on electricity consumption in Australia between 1998 and 2015 . During this period, there was considerable variation in the presence and timing of DST implementation, as well as in weather conditions and cooling usage within and among states. The results show that the effect of DST on electricity consumption depends strongly on weather conditions and cooling usage. Forward DST increases electricity consumption when temperatures and air conditioner ownership are higher.

Bergland, O., & Mirza, F. (2017) look at the potential systematic variation in energy savings resulting from DST in several geographic areas varying in latitude ranging from Northern to Southern Europe. The energy savings provided by DST ranges from zero in the northernmost parts of Norway and Sweden to more than 2.5 % in many locations. The energy savings from DST decreases with latitude, especially for homogeneous groups of countries. The diversity in estimated effects cuts across geographical, cultural, and economic factors. Since the DST results depend on latitude, geographical, cultural, and economic factors, and the energy efficiency of buildings and equipment, it is necessary to evaluate the DST impact on the Brazilian case.

In terms of methodologies, according to Küfeoğlu et. Al (2021), in the literature, there are three prominent types used to measure DST policy's effect on the energy conversation. They are: i) Interrupted Time Series (ITS);

ii) Difference in Differences (DID) models and iii) multivariate regression analysis. The ITS methodology (Lopez Bernal et al., 2017; Ewusie et al., 2020) uses to evaluate multiple consecutive pre-and post-intervention observations in a single population and incorporates time by comparing slopes of trend lines before and after the intervention. Difference in Differences (DID) (Cohen Priva and Sanker, 2019; Zhou et al., 2016) is design that examines the comparison of differences in outcomes of a treated time series with an untreated series by referring controlled before-and-after an intervention. The Multiple Linear Regression (Weedmark, 2018) is a statistical method that estimates the relationship among continuous quantitative variables. Here, we adopt the Multiple Linear Regression model as method of analysis, due the fact that: i) it allows determine which factors matter most; ii) It gives information about the relevance of features, for instance, the magnitude of DST in each hour and iii) It uses data very efficiently and can make useful predictions. More details about advantages and disadvantages about each of three models can be found in Küfeoğlu et. Al (2021). We also apply a DID strategy to compare with the Multiple Linear Regression results, and with the results presented by MME (2019b).

3. Methodological approach

This section presents the method organized for this work and the data sources considered.

3.1. Data collection and processing

The data gathered for this work concerns the load curves within the investigation period, the temperature, the population in the Southeast/Midwest[2] regions of Brazil, and the Central Bank Economic Activity Index (IBC-Br).

The hourly observations of the load (in megawatt-hours (MWh)) correspond to the period from 2017/01/01 to 2021/12/31. It concerns 1,826 days or

[2] An assessment with disaggregated data into states or municipalities would better evaluate how daylight saving time works in each area. For example, the occurrence of heat islands and altitude differences are examples of variables that affect energy consumption and are not controllable with aggregated data such as the ones available. However, it is also necessary to consider that daylight saving time has to be adopted for a more significant number of states due to the difficulties in coordinating some activities like bank, public, and transport services, as well as difficulties for people crossing states.

43,824 consecutive observed values for each hour. Table 01 presents the subset of observations under the daylight saving time regime.

Table 01 - Days under Daylight Saving Time regime (2017 – 2019)

Period	Start	Finish
2016 – 2017	00:00 2016/10/16	23:59 2017/02/18
2017 – 2018	00:00 2017/10/15	23:59 2018/02/17
2018 – 2019	00:00 2018/11/04	23:59 2019/02/16

Source: Brazilian Ministry of Mines and Energy (Adaptation, 2022)

The load curves respond to meteorological variables, here we focus on temperature. The load data considered here correspond to consolidated values for the Southeast/Midwest subsystem, encompassing seven Brazilian states and presenting a considerable variation in meteorological conditions among them.

The temperature data are available on the INMET website. They correspond to records for the states' capitals that comprise the Southeast/Midwest subsystem and Brasília, as shown in Table 02. The population data projections for the subsystem region are available on the IBGE site, and Table 03 presents the IBGE projected population for each state that makes up the subsystem region. This information is geographically presented in Figure 1.

Table 02 - Meteorological stations of the Southeast/Midwest subsystem

Region	State	City	Station code	Station
Southeast	MG	Belo Horizonte	A251	Pampulha
		Belo Horizonte	F501	Cercadinho
	ES	Espírito Santo	A612	Vitória
	RJ	Rio de Janeiro	A602	Marambaia
		Rio de Janeiro	A621	Vila Militar
		Rio de Janeiro	A636	Jacarepaguá
		Rio de Janeiro	A652	Forte de Copacabana
	SP	São Paulo	A701	Mirante
		São Paulo	A771	Interlagos
Midwest	MS	Campo Grande	A702	Campo Grande
	MT	Cuiabá	A901	Cuiabá
	GO	Goiânia	A002	Goiânia
	DF	Brasília	A001	Brasília

Source: INMET (Adaptation, 2022)

Table 03 - Population projection (2017 – 2021)

Region	State	2017	2018	2019	2020	2021
Southeast	MG	20,908,628	21,040,662	21,168,791	21,292,666	21,411,923
	ES	3,925,341	3,972,388	4,018,650	4,064,052	4,108,508
	RJ	17,051,465	17,159,960	17,264,943	17,366,189	17,463,349
	SP	45,149,603	45,538,936	45,919,049	46,289,333	46,649,132
Midwest	MS	2,716,534	2,748,023	2,778,986	2,809,394	2,839,188
	MT	1,672,606	1,695,166	1,717,375	1,739,243	1,760,757
	GO	6,824,504	6,923,655	7,020,904	7,116,143	7,209,247
	DF	2,931,057	2,972,209	3,012,718	3,052,546	3,091,667

Source: IBGE (Adaptation, 2022)

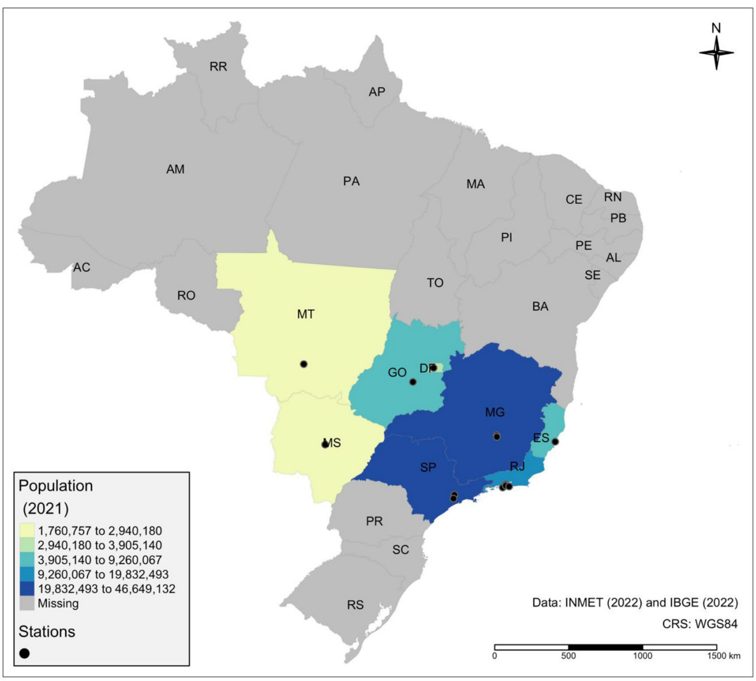

Figure 01 - Location of Meteorological stations and state population

As temperature affects energy consumption (Küfeoğlu et. Al, 2021) through, for example, ambient cooling services, the population is also an important variable to explain the load variability. The population is used as a weight to obtain a weighted average temperature variable for the Southeast/Midwest subsystem.

The first step to obtaining the hourly h weighted average temperature for a specific day t is calculating each capital's average temperature:

$$w_{thi} = \frac{\sum_{j=1}^{N} w_{th,ij}}{j}$$

Where N is the total number of meteorological stations for capital i, the weighted average temperature is obtained through the formula:

$$Temp_{th} = \frac{\sum_{i=1}^{8} x_i w_{thi}}{\sum_{i=1}^{8} x_i} \tag{1}$$

Where x_i is the projected population for each state that makes up the subsystem region.

The Central Bank Economic Activity Index (IBC-Br) aims to measure the contemporary evolution of economic activity (Bacen, 2018). It is a monthly indicator that incorporates variables considered proxies for the performance of the sectors of the economy.

3.2. Model estimates

The recorded load values for each hour are the dependent variable in a traditional linear regression models framework. A similar application can be found in Ramanathan et al. (1997). The covariates[3] are a) the average temperature, b) a set of weekday dummies, c) a harmonic related to seasons, d) a dummy for the Covid-19 pandemic period, e) IBC-Br, f) a holiday dummy and g) a dummy identifying days under the DST regime. A similar set of covariates to explain hourly load was applied in Vaz and da Silveira Filho, (2017). So, the model for the hourly load is given by:

$$\begin{aligned} Y_{th} = \beta_{0,\mathrm{h}} &+ \beta_{1,h} Temp_{th} + \beta_{2,h} D_{tSun} + \beta_{3,h} D_{tMon} + \beta_{4,h} D_{tTus} \\ &+ \beta_{5,h} D_{tWed} + \beta_{6,h} D_{tThurs} + \beta_{7,h} D_{tFri} + \beta_{8,h} D_{tSat} \\ &+ \beta_{9,h} DST_t + \beta_{10,h} \mathrm{IBC-Br_t} + \beta_{11,h} \mathrm{holiday}_t \\ &+ \beta_{12,h} Har_t + \beta_{13,h} Covid_t + \epsilon_{th} \end{aligned} \tag{2}$$

[3] The explanatory variables are all exogenous, so we do not deal with problems associated with unit roots here.

Where $\mathrm{t} = 0, \cdots, \mathrm{n}$ (the total number of observed days) and h represents the hourly interval from 12 a.m. to 11 p.m., a total of 24 models are estimated, one for each hour. The variable $Temp_{th}$ indicates the observed temperature for day t at hour h, as described in section 2.2. The variable D_{tSun} is a *dummy* assuming value one if day t is a Sunday and zero, otherwise. Analogously, D_{tMon} assumes value one if the day t is a Monday and zero otherwise. The same rule applies to the others weekday dummy variables. DST_t assumes value one if the day t is under the DST regime and zero otherwise. The $\mathrm{IBC-Br}$ index corresponds to monthly observations of the Brazilian Industrial Activity according to the Brazilian Central Bank estimates. The variable $\mathrm{holiday}_t$ is a dummy assuming value 1 if the day t is a national holiday and 0 otherwise. The variable Har_t is the harmonic variable with period $\frac{365}{4}$, to capture possible seasonal behavior induced by meteorological variables not included in the model, such as relative humidity and daylight hours. The $Covid_t$ variable takes the value 1 for the observations corresponding from 2020/03/18 to.[4]

The coefficients $\beta_{0,h}, \cdots, \beta_{13,\mathrm{h}}$ are estimate trougth Ordinary Least Squares[5] and was evaluated through a t-test at a 5% significance level.

3.3. Difference in difference methodology

The difference-in-differences (DiD) method (according to Zhou et. al. (2016)) consists of comparing differences in outcomes, before and after an intervention. For both periods, the difference of means of treated and untreated groups is evaluated (first difference). Secondly, the first difference for period after the intervention is subtracted from the first difference for period before the intervention. In the assessment of DST effectiveness, unobserved variables, such as cold fronts, heat waves, and fluctuations in industrial production, vary through the period before and after Daylight Saving Time (DST) and its variability affects energy consumption. Consequently, the difference between the two group means in the Difference-in-Differences (DiD) method would be assembled to mitigate the influence of these variables on energy consumption.

[4] The data was defined through visual inspection in graphs 06 to 09.
[5] For more details see Davidson & MacKinnon (1993).

An important task in the Difference-in-Differences is to define the control group properly. The DST policy is not applied to Brazilian North and Northeastern regions, however, these regions are dissimilar from the Brazilian Southeast/Midwest in terms of population, meteorological conditions, altitude, and latitude. The work presented in MME (2019b) states that there is no evidence of the effectiveness of DST from 8 a.m. to 4 p.m., so we use this set of hours as a control group, say $H_{ct} = \{8,9,\cdots,16\}$ hours unities to test the results presented by MME (2019b). The remaining set of hours from 0hs to 7 a.m. and 4 p.m. to 11 p.m. is the treatment group, that we call $H_{tr} = \{0,1,\cdots,7,17,\cdots,23\}$ hours unities.

The difference between the two means of the groups in the DiD method is the subtraction of the average affected hour's load $h_a \in H_{tr}$ by the average unaffected hour's load $h_u \in H_{ct}$ for thirty days before and after the beginin of the daylight saving time. We denote generically each date $t = (n, w)$ as a number of days n away from beginin of the daylight saving time and the weekday w related to this date. Write the beginning of the daylight saving time as $t^* = (n^*, w^*)$. More precisely, let t be an index representing the date around t^* with $n^* = 0$. Write T as the set of all dates, that is,

$$T \subset \{(n, w): -30 \leq n \leq 29 \text{ and } w \in W\}$$

where W is the set of weekdays. Note that each weekday is related with each period away from t^*. Define the set of dates after and before t^* as

$$T_{-} = \{(n, w) \in T: -30 \leq n \leq -1\} \quad and \quad T_{+} = \{(n, w) \in T: 0 \leq n \leq 29\}$$

We calculate the average load in the set of affected hours $h \in H_{tr}$ and unaffected $h \in H_{cr}$ for $t \in T_{-}$ as

$$\bar{Y}_t^{tr-} = \frac{1}{15}\sum_{h \in H_{tr}} Y_{th} \text{ for } t \in T_{-} \text{ and } \bar{Y}_t^{ct-} = \frac{1}{9}\sum_{h \in H_{ct}} Y_{th} \text{ for } t \in T_{-}$$

where $\bar{Y}_t^{tr-}$ is the average load over the treatment group and $\bar{Y}_t^{ct-}$ is the average load over the control group, both defined before t^*. The same is done for $t \in T_{+}$ as follows:

$$\bar{Y}_t^{tr+} = \frac{1}{15}\sum_{h \in H_{tr}} Y_{th} \text{ for } t \in T_{+} \text{ and } \bar{Y}_t^{ct+} = \frac{1}{9}\sum_{h \in H_{ct}} Y_{th} \text{ for } t \in T_{+}$$

Where $\bar{Y}_t^{tr_+}$ is the average load in the treatment group and $\bar{Y}_t^{ct-}$ is the average load in the control group both defined after t^*. The first difference of the DiD method is then given by:

$$\Delta_1\bar{Y}_t^- = \bar{Y}_t^{tr_-} - \bar{Y}_t^{ct_-} \text{ for } t \in T_- \text{ and } \Delta_1\bar{Y}_t^+ = \bar{Y}_t^{tr_+} - \bar{Y}_t^{ct_+} \text{ for } t \in T_+$$

A standard second difference would account for the weekday difference in energy consumption and not only in the DST effect since energy consumption is weekday-dependent. Furthermore, it may occur different numbers of observations for each weekday. We therefore consider the second difference adjusting to deal with these specificities. To do so, define $I_{\bar{w}}: T \to W$ as the indicative function which for each date $t = (n, w) \in T$ gives $I_{\bar{w}}(t) = 1$ if $w = \bar{w}$ and 0 otherwiswe for all $t \in T$. For a specific weekday w, we calculate:

$$\Delta_2\bar{Y}_w^+ = \frac{1}{\sum_{t\in T_+} I_w(t)} \sum_{t\in T_+} \Delta_1\bar{Y}_t^+ \times I_w(t) \text{ and } \Delta_2\bar{Y}_w^- = \frac{1}{\sum_{t\in T_-} I_w(t)} \sum_{t\in T_-} \Delta_1\bar{Y}_t^- \times I_w(t)$$

The second difference is then given by:

$$DiD_w = \Delta_2\bar{Y}_w^+ - \Delta_2\bar{Y}_w^-$$

Finally, we test if the seven observations obtained above are statistically equal to zero, in a t-test with 5% significance.

3.4. Recommendation of DST as a public policy for reducing energy consumption

Figure 1 presents in a summarized manner the methodological steps adopted in this work. The first step is to define the focused dataset, the hourly loads, temperature, the population for the Brazilian Southeast/Midwest region, and the IBC-Br. The second step consists of collecting loads in MWh, temperatures in degrees Celsius, observed for each hour from 2017/01/01 to 2021/12/31. Also, it was collected the population information for Brazilian capitals of the Southeast/Midwest region. The third step consists of a descriptive analysis of the hourly observations of the load to confirm the covariates of the linear regression model. The estimated coefficients in the model and their statistical significance are the inputs used in evaluating DST as a public policy for energy saving.

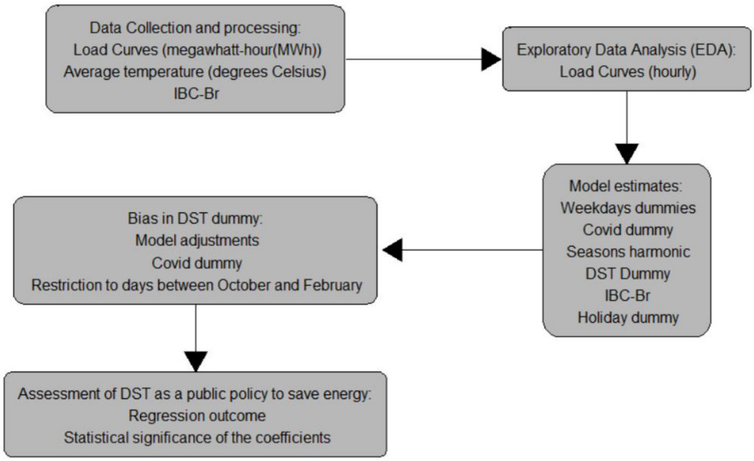

Figure 01 – Methodological approach

4. Results and discussion

4.1. EDA for the electricity load curves

Graphical analyses were performed, stratifying the structure of the historical series for load curves at different time cut-offs, different seasons, the COVID-19 effect, and the existence of the DST regime in the analyzed periods. All the figures are based on consolidated values (MWh) for the Southeast and Midwest subsystem, composed of seven Brazilian states.

Figure 02 shows a set of daily load curves for the week running from 2021/09/29 to 2021/05/10. The daily load curves present a well-defined shape. The minimum demand occurs at dawn, precisely between 3 a.m. and 4 a.m. Gradually, consumption rises until 10 a.m. From 10 a.m. until 4 p.m., electricity consumption presents stability. The highlighted region, between 4 p.m. and 6 p.m., shows, for weekdays, a reduction in consumption. It is due to the return of workers to their homes. Around 6 p.m., the demand increases again, and, in general, the peak hour occurs between 6 p.m. and 8 p.m. For this specific week, it is possible to observe that the consumption peak occurs during the evening on Wednesday and Thursday.

Figure 02 also makes clear how weekdays affect energy consumption. The Monday dawn presents the smaller consumption for the period from 12 a.m to 5 a.m.. The Saturday dawns, specifically from 12 a.m to 4 a.m. is similar to weekdays, but with a consumption reduction from 4 a.m to 6 a.m. instead of the increase observed for weekdays. The Sunday curve presents the lower level of consumption for all time except in the dawn period. For the weekends, the smaller consumption occurs around 6 a.m., which is a time of increasing consumption for weekdays. Saturday and Sunday do not present the typical reduction in consumption between 4 p.m. and 6 p.m.

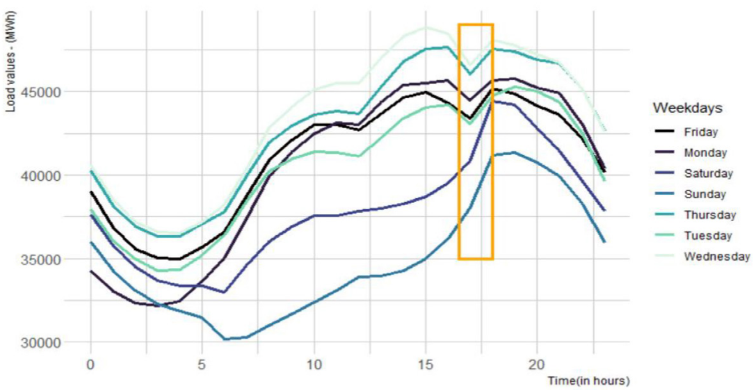

Figure 02 – Observed load curves for the week running from 2021/09/29 to 2021/05/10
Source: Own elaboration with ONS data 2021a

Figure 03 shows load curves for seven specific dates, (2018/02/13, 2018/03/06, 2018/03/13, 2018/03/20, 2018/07/03, 2018/07/10, and 2018/07/17), all of which are Tuesdays. The first four refer to summer Tuesdays, and the last three ones to winter Tuesdays. The figure's objective is to show how the seasons affect the load curve shape for the same weekday and also show how the holiday affect electricity consumption. It is remarkable that the peak hours for the winter curves is at night, and for summer, it is during the evening. The summer in Brazil run from December to March, so 2018/02/13 is a summer day. The effect of the holiday is to shift the load curve downwards. This effect is less intense for the morning hours than the others. The inflection in consumption around 6 pm on non-holiday summer days is not observed for a holiday.

The peak of consumption on holidays occurs at night instead of in the afternoon as on non-holiday summer days.

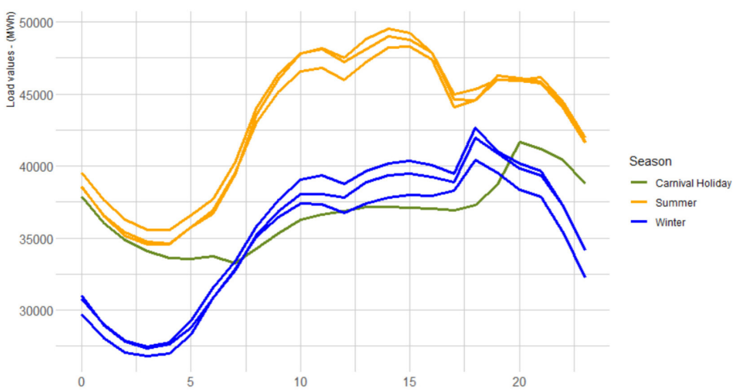

Figure 03 - The observed load curves for six specific dates: 2018/02/13, 2018/03/06, 2018/03/13, 2018/03/20, 2018/07/03, 2018/07/10, and 2018/07/17

Source: Own elaboration with ONS data 2021a

Figure 04 shows the graphs for each load time series observed. The series are grouped by day periods, dawn (Panel A), morning (Panel B), evening (Panel C), and night (Panel D). The U-shape in a one-year interval is typical for all graphs. It reflects the continuous reduction in energy consumption until target the minimun in June/July, months with lower temperatures in Brazil climate. The variability for morning observed values is higher than that observed for dawn. The load observations for the evening present a variability similar to that observed in the morning. However, they do not shift through the Y-axes as the series observed for the morning. The variability underlying observed values at night and dawns are similar. Nevertheless, the valley observed in the middle of the year is less intense at the night series. It occurs because the load used during the night is associated with lighting and electronic devices, which respond less intensively to the temperature.

The valley observed in 2020 differs from the others. It is deeper and starts earlier. This anomaly is due to the covid-19 pandemic and will be better analyzed in the next section. The red vertical line highlights the beginning of Covid-19 social measures of isolation.

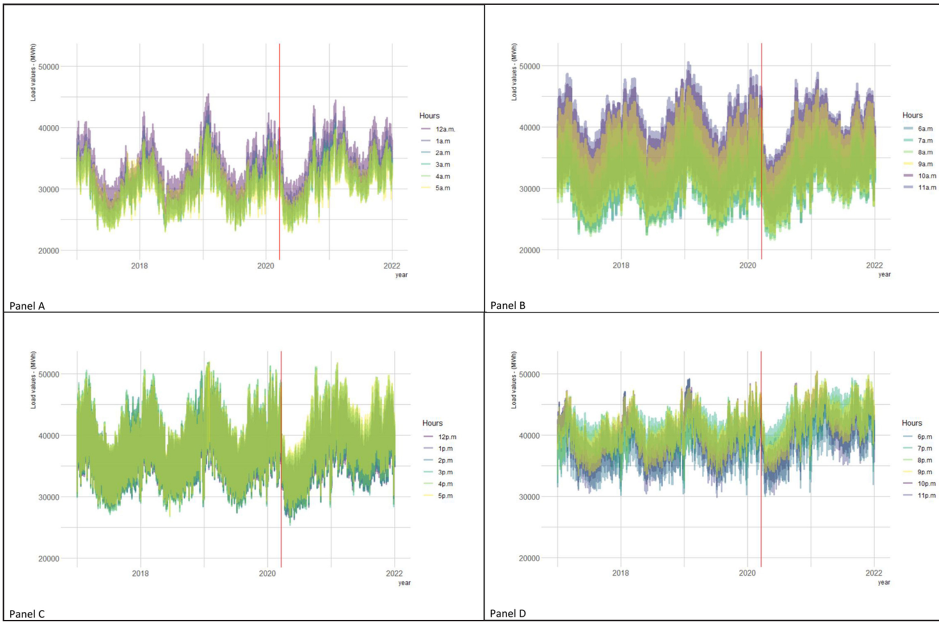

Figure 04 - Time series observed for each hour for the period 2017/01/01 to 2021/12/31.

4.1. Covid effect

The Covid-19 pandemic also substantially changed the electricity consumption profile. Figure 05 shows the change in the shape of the load curve after the confirmation of coronavirus community transmission in 2020/03/20, in the national territory and the first decrees determining social isolation, mainly in Brazil's southeast capitals. In Figure 05, Week 1 runs from 2020/03/08 to 2020/03/14 and corresponds to a typical summer week. The consumption peak occurs during the evening, and the level of consumption is higher than 45.000 MWhs. Week 2 runs from 2020/03/15 to 2020/03/21. It typically behaves as a summer week until the black line, which indicates the confirmation by the Ministry of Health of the community transmission of the coronavirus in Brazil. Curves for week 3 and week 4 present a considerable reduction in the level of consumption due to the beginning of social isolation. The peak stays around 42500 MWhs. The measures to contain the coronavirus transmission also change the load curve shape—the consumption peak changes to the early night.

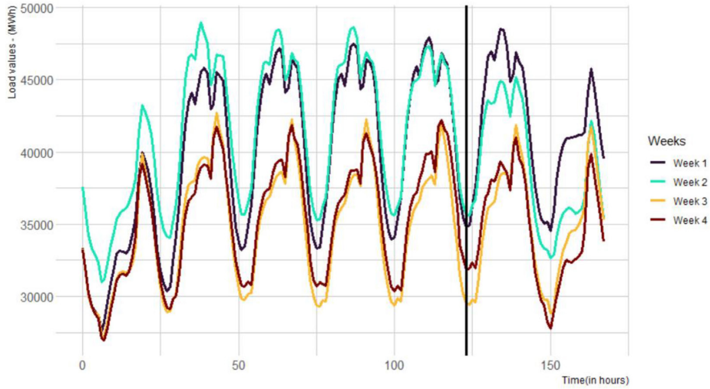

Figure 05 - Load curves close to the beginning of measures to restrict social circulation due to Covid-19.

4.2. Regression analysis outcomes for electricity load curves

Figure 06 shows the estimated coefficients for the weekday dummies for each hour. These coefficients describe the standard behavior of consumption for each weekday. The lowest consumption occurs in the dawn and early morning, and the highest occurs in the late afternoon and early evening. All coefficients are statistically significant at a 5% significance level. The Breusch-Pagan test was performed for the each estimated equation and indicates the presence of heterocedastic erros. So, the p-values presented hereafter are based on robust erros.

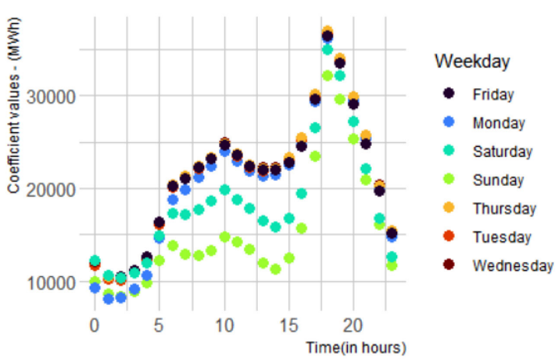

Figure 06 – Weekdays dummies values

Table 4 - The unrestricted model estimated coefficients for temperature, DST dummy, Harmonic component, and covid-19 dummy. It is estimated one regression equation for each hour.

Time	*Temp*	*DST*	*Har*	*Covid*
12 a.m.	1028,17***	-42,29*	-337,96***	1453,85***
1 a.m.	1025,43***	119,42	-262,74***	1478,69***
2 a.m.	992,25***	306,90	-236,74**	1388,49***
3 a.m.	943,73***	507,68***	-252,85***	1323,23***
4 a.m.	887,81***	860,91***	-313,66***	1208,15***
5 a.m.	767,28***	1082,25***	-485,09***	534,19***
6 a.m.	650,67***	1355,54***	-301,78***	18,86
7 a.m.	703,75***	1344,56***	-483,45***	411,11**
8 a.m.	794,8***	931,87***	-513,27***	180,26
9 a.m.	838,74***	639,15***	-587,02***	-199,66*
10 a.m.	804,1***	-78,29*	-478,39***	-791,3***
11 a.m.	814,5***	-287,42*	-485,07***	-1024,57***
12 p.m.	785,8***	564,59***	-547,8***	-487,86***
1 p.m.	790,4***	972,17***	-689,83***	-167,24*
2 p.m.	777,07***	1088,63***	-850,55***	99,82
3 p.m.	713,22***	1171,89***	-908,25***	474,5**
4 p.m.	615,98***	713,24***	-789,24***	776,92***
5 p.m.	411,44***	-247,08*	-200,42**	585,54***
6 p.m.	236,51***	-2457,63***	-558,19***	424,98**
7 p.m.	337,81***	-1630,53***	-725,85***	1394,05***
8 p.m.	489,19***	23,43	-600,73***	1330,48***
9 p.m.	670,42***	-97,58*	-552,3***	1168,04***
10 p.m.	857,83***	-59,31*	-428,64***	1124,64***
11 p.m.	987,36***	-62,41*	-388,41***	1290,87***

Legend (statistical significance of the t-test): 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1'' 1
Source: Data from this search

The temperature-estimated coefficients are all statistically significant at a 5% significance level, see Table 4. The highest coefficient value is for 1 a.m.; they decrease until 7 a.m. From 8 a.m., the coefficient increases until 10 a.m. and reaches relative stability until 4 p.m. The lowest coefficient values occur around 7 p.m. The load around the peak hour responds less intensively to temperature relatively other times of the day. This behavior evidences the effect of public lighting onset, which does not depend on temperature. Public lighting can be postponed or delayed according to the season, which presents a correlation with temperature but does not vary in intensity according to the season and so on with the temperature.

Furthermore, it shows the effect of people's habits, who, after work, go home and use electrical equipment.

The harmonic component coefficient, also presented in Table 4, captures the variability in consumption induced by seasons, which are not necessarily reflected in temperature. The variable is statistically significant to explain the load for hours between 1 p.m. and 7 p.m. and also the load observed at 2 a.m. and 3 a.m.

The coefficient associated with the pandemic dummy captures how the each hour respond to the social and economic changes induced by the measures to reduce the virus transmission. The coefficient is not statistically significant, with a 5% level, for 6 a.m., 8 a.m. and 2 p.m. The pandemic period causes an reduction in energy consumption for 9 a.m, 10 a.m., 11 a.m, 12 p.m. and 1 p.m. Throughout the rest of the time, the effect of the pandemic is the increase the energy consumption.

The p-value of the F test are all next to zero, that is, for the estimated equation for each hour, we can reject the null hypotheses that all the coefficient are jointly equal to zero.

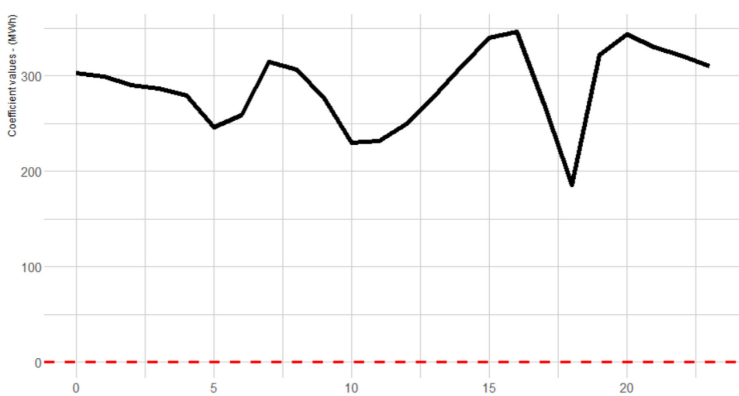

Figure 07 – The IBC-Br estimated coefficient

Source: Data from this search

Figure 07 shows the IBC-Br estimated coefficient. In Figure 7 and all ones hereafter, we add a red dotted line to highlight the zero intending to easily observe the negative and positive values of the coefficients. Since it is a monthly periodicity indicator, it captures an intraday effect not directly caused by the IBC-Br observations. Even without an exact interpretation of the intraday effect, the indicator is essential to capture changes in the level of consumption resulting from changes in industrial production throughout the year and among years.

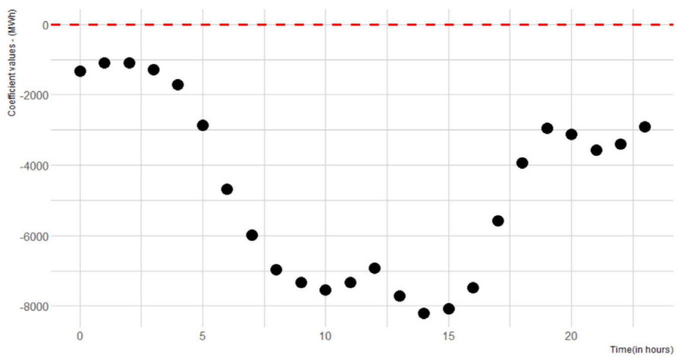

Figure 08 – The Holiday estimated coefficient
Source: Data from this search

Figure 08 presents the holiday estimated coefficient. The holiday dummy coefficient assumes negative values for all days, indicating that consumption is lower than average on holidays. As expected, the morning hours respond less to the holiday dummy. The coefficient increases in absolute value throughout the morning until approximately 18 hours. The night hours also vary relatively less on holidays compared to other hours.

The DST dummy estimated coefficient is a binding value to the objective proposed in this work. It is presented in Figure 09. Negative/positive coefficient values indicate consumption below/above the average for days in which the dummy assumes a value of 1.

The unrestricted model has a positive and significant coefficient from 2 a.m. to 9 a.m. and 12 p.m. to 4 p.m. The statistically significant coefficients for the remaining time are all negative or non-significant. However, it is essential to note that the dummy for DST also assumes a zero value for the days between March and September, characterized by milder temperatures and less need for cooling. The days under the DST regime are hotter than the average temperature. This implies a demand for cooling services, which leads to higher energy consumption. Thus, the daylight saving time dummy may capture an effect induced by the season and not exactly due to the validity of daylight saving time. In this case, the dummy values are biased.

To control this possible bias, the regression model described in equation 3.1 was estimated only for the days between October and February. Table 5 reports the coefficients estimated for Temperature (Temp), the DST dummy (DST), the Harmonic (Har), and the Covid dummy (Cov). In this restricted model, the DST dummy objective is to answer about the DST performance for days with the same meteorological characteristics. When estimating the model for days between October and February, the Dummy coefficients are positive and significant only for 6 a.m., which reinforces the increase in consumption of lighting services at this time. For all other times, the significant coefficient is negative, and it has to be highlighted the performance of the DST coefficient for 7 p.m.

The exposed results show that the DST regime fulfills its purpose: to reduce consumption at peak times, in the late afternoon and early evening. To measure the energy economy, we divide the DST dummy coefficient of the restricted model by the weekday dummy to measure the energy economy. For example, for 6 p.m., the reduction for Sunday (the day with the lowest average consumption during the peak time) is 8.17%. At the same time, on a Thursday (the day with the highest average consumption of the week at 6 p.m.), it is 7.11%. For the 7 p.m. time, the consumption reduction on Sunday is 7%, and on Thursday, it is 6%. Although daylight saving time reduces consumption in the late afternoon and early evening, it has the effect of a greater need for artificial lighting around 6 p.m.

To verify the average net balance of energy savings induced by daylight saving time, we sum all the statistically significant estimated coefficients (95% confidence) for the DST dummy in the restricted model. The net balance of savings was 4,976.81 MWh. For comparison purposes, the amount saved over a day corresponds to 13.47% of the power required in the system for 6 p.m. on a Thursday (one of the times and days with the highest energy consumption).

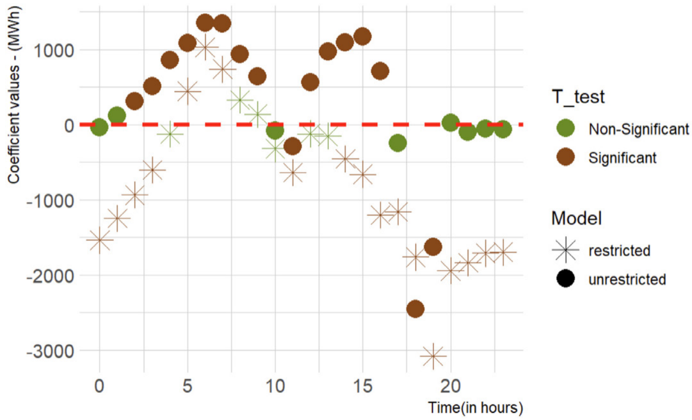

Figure 09 – Daylight Saving Time dummy values for irrestricted and restricted model.
Source: Data from this search

Table 5 - Estimated coefficients of the model restricted to the days observed between October and February. It is estimated one regression equation for each hour.

Time	Temp	DST	Har	Covid
12 a.m.	1193,57***	-1538,45***	296,58.	612,97**
1 a.m.	1201,98***	-1248,9***	302,02.	636,2***
2 a.m.	1181,95***	-937,04***	246,54.	571,31**
3 a.m.	1138,94***	-603,97***	152,32	559,69**
4 a.m.	1070,56***	-124,97*	17,78	525,5**
5 a.m.	1023,78***	443,64**	-348,71**	113,72
6 a.m.	898,53***	1027,48***	-348,28**	-133,28*
7 a.m.	862,65***	738,32***	-361,76***	20,34
8 a.m.	1009,67***	325,91.	-433,78***	-95,62*
9 a.m.	1156,06***	137,67	-677,22***	-320,11*
10 a.m.	1160,73***	-321,07*	-787,35***	-739,22***
11 a.m.	1017,58***	-639,5***	-570,1***	-980,45***
12 p.m.	889,75***	-121,63*	-401,33***	-643,64***
1 p.m.	865,36***	-154,77*	-310,1**	-550,33**
2 p.m.	841,8***	-458,29*	-220,2*	-537,53**
3 p.m.	766,82***	-661,53***	-79,8*	-409,13*
4 p.m.	677,01***	-1205,45***	121,92	-261,67*
5 p.m.	513,1***	-1160,97***	165,01	-54,47*
6 p.m.	344,99***	-1764,1***	-1031,77***	392,04.
7 p.m.	351,13***	-3081,74***	-139,77*	305,81.
8 p.m.	516,6***	-1946,35***	344,39***	171,71
9 p.m.	728,36***	-1840,67***	274,28.	197,74
10 p.m.	979,2***	-1712,27***	337,29**	246,9
11 p.m.	1138,65***	-1697,11***	356,7**	392,92.

Legend (statistical significance of the t-test): 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1'' 1
Source: Data from this search

4.3. Difference in difference methods results

Table 6A presents statistics for 2017 and 2018, during which DST was implemented. It shows that the average consumption in the post-DST period exceeds that in the pre-DST period for both the treatment group (Affected hours) and the control group (Unaffected hours). The mean of the first difference (Affected hours - Unaffected hours) is higher in absolute value during the post-DST period, as can be seen comparing -2.925,75 with -3.518,25 for 2017, and -2.798,25 with -3.636,85 for 2018 in Table 6. This finding indicates an increase in afternoon consumption for days during summer afternoons, as illustrated in Figure 03. Additionally, the 2018 averages of the second difference (average first difference for each weekday in the post-DST period minus the average first difference for each weekday in the pre-DST period) are greater in absolute value compared to those from 2017, -584,98 and -875,98, for 2017 and 2018, respectively. The set of observations for the second difference is statistically significantly different from zero according to the t-test, according table 6A.

Traditionally, in Brazil, Daylight Saving Time (DST), except in 2018, always commenced at 00:00 on the second weekend of October. Based on this pattern, hypothetical DST start dates were projected for 2019, 2020, and 2021 as October 12th, October 10th, and October 9th, respectively. The objective of this exercise is to replicate the DiD method for the years when the DST was not in force and use it to validate the DiD method during the period of DST validity, that is, a placebo exercise. Table 6B presents results obtained like those in Table 6A. In Table 6B, the average energy consumption during the hours affected by DST was slightly lower than those for unaffected hours. It marks a deviation from the patterns observed in 2017 and 2018. This change in consumption probably is due to the COVID-19 pandemic, which changed daily consumption patterns, as illustrated in Figure 5.

The annual average of the first differences exhibits an increasing trend over the three years. In contrast, the average of the second differences is smaller in absolute value compared to the corresponding values observed in 2017 and 2018. It suggests that, for the years when DST was not implemented, the values observed for post-DST and pre-DST are more similar. This conclusion is supported by the t-test results, which indicate that the difference between post-DST and pre-DTS observations is statistically insignificant.

Table 6A - A set of means categorized by treatment and control group, first and second differences of DID method, and t-test. Observations for 2017 and 2018, years of DST ongoing.

	Mean in MWh for the treatment group (Affected hours)	Mean in MWh for the Control group (Unaffected hours)
Pre-DST	37267,19	36196,77
Pos-DST	39509,77	38637,25
Mean by year for the first difference (MWh)		
	2017	2018
Pre-DST	-2.925,75	-2.798,25
Pos-DST	-3.518,25	-3.636,85
Mean by year for the second difference (MWh)		
	2017	2018
	-584,98	-875,98
	t-statistic	p-value
2017-2018	3.6027	0.003215

Table 6B - A set of means categorized by treatment group and control group, first and second differences of DID method, and t-test. Observations for years 2019, 2020, and 2021 in which DST are out of validity.

	Mean in MWh for the treatment group (Affected hours)	Mean in MWh for the Control group (Unaffected hours)	
Pre-DST	36959,8	40372,5	
Pos-DST	38549,7	38.654,7	
Mean by year for the first difference (MWh)			
	2019	2020	2021
Pre-DST	-2839,07	-1587,68	-1041,72
Pos-DST	-2879,56	-1535,94	-669,21
Mean by year for the second difference (MWh)			
	2019	2020	2021
	-285,36	-170,62	178,97
	t-statistic	p-value	
2019-2020-2021	0.5362	0.6008	

Figure 10 illustrates the hourly mean of the observed load for the thirty days preceding the onset of Daylight Saving Time (DST) and the first thirty days under the DST regime for 2017 and 2018. In 2017, there was a decrease in consumption near the hours leading up to evening twilight. The reduction in consumption during the afternoon in the period under DST is probably not due to DST. Theoretically, this policy should not influence consumption during this time of day. In 2018, an increase in consumption was observed near morning twilight. In contrast to 2017, afternoon consumption during the post-Daylight Saving Time (DST) period in 2018 was comparatively higher than in the pre-DST period. Given that DST does not influence consumption at this time, a plausible explanation is the occurrence of higher temperatures. This factor may also account for the apparent absence of a DST effect near evening twilight. Figure 10 reinforces the necessity of control by the variables that affect consumption to evaluate the DST policy correctly.

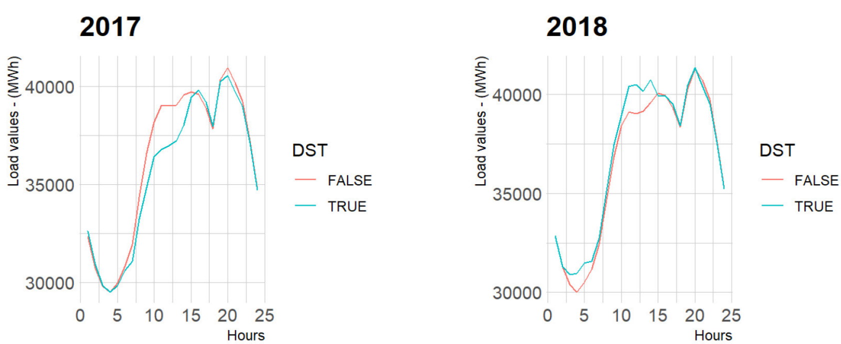

Figure 10 - Hourly mean of the observed load for the thirty days preceding the onset of Daylight Saving Time (DST) and the first thirty days under the DST regime for 2017 and 2018.

5. Conclusion and Policy Implications

The MME (2019b) states that there is no evidence of the effectiveness of DST from 8 a.m. to 4 p.m. This result has been expected since the DST objective is to act on the demand related to lighting services. The MME (2019b) also states that for the complementary period (12 a.m. to 8 a.m. and 4 p.m. to 11 p.m.), there are two effects: the first refers to the nocturnal interval, in which the best use of natural lighting reflects in energy savings; the second refers to an increase in electricity consumption, at dawn, possibly caused by the increase in temperature to which the population is exposed during their nocturnal rest period and, consequently, by the increase in energy consumption by the greater use of refrigeration equipment, in particular air conditioning.

Due to the difficulties in combining different meteorological stations to obtain the average temperature for the subsystem, the methodology applied in MME (2019b) does not consider the temperature in its calculation. However, the MME (2019b) states that the anticipation of one hour of remaining time leads to higher electricity consumption during dawn. The statements are contradictory because the variability in the temperature through two months (MME (2019b) compares curves one month before and one month after daylight saving time begins) can be higher and with more reason can affect the energy consumption and so must be controlled to avoid bias. Furthermore, here, we highlighted other variables to explain the energy consumption and which must be used in any evaluation of the DST effectiveness.

The results indicate that the DST dummy coefficient is negative in the linear regression model. This result implies that methods controlled by the set of variables that affect energy consumption show positive results for DST policy for the Brazilian Southeast/Midwest subsystem. The DiD methodology also corroborates our results, pointing out that the load means for the pre-DST and post-DST periods are statistically different. It is necessary to reinforce that the effectiveness of the DST is closely related to the daylight, which is maximum, for Brazil, on December, 21. So, methodologies based only on the neighborhood of the DST beginning can underestimate its effect.

In terms of energy savings, we can conclude, from this work, that daylight saving time is recommended. The result presented in MME (2019a) pointed out that regardless of gender, age group, education, and belonging or not economically active, the population prefers the end of DST for several idiossincratic reasons. Therefore, this is a significant cost associated with its adoption. Other factors such as loss of productivity should be considered when calculating the cost-benefit of this government policy. The tests performed here only provide a counterpoint to what was previously established in MME (2019b) and a more detailed analysis of the magnitudes of the negative and positive effects of the DST should be performed. This could be a future study complementary to this paper. This work only brings many methodological improvements compared to the evaluation made by the Ministry of Mines and Energy, MME (2019b).

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CONFLITO DE INTERESSE

Os autores declaram não terem quaisquer conflitos de interesse.

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