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Assessment of the impact of COVID-19 lockdown measures on electricity consumption – Evidence from Portugal and Spain

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ABSTRACT

The COVID-19 pandemic caused unheard-of shifts in socioeconomic norms and interpersonal connections. Governments were compelled to place limitations on the way of life of residents and companies in order to stem the virus' spread in order to deal with this new threat. These led to stay-at-home orders in many nations and reduced industry activities to their bare minimum, which had an immediate impact on the electricity systems.

This article investigates the influence of COVID-19 on electricity consumption in Portugal and Spain, with the goal of shedding light on consumption shifts and how these are related to the stringency degree of government-imposed measures, as well as providing an overview of the first post-pandemic data. We cross information between observed electricity consumption data and numerous factors, including the Stringency Index (SI) given by the Oxford COVID-19 Government Response Tracker (OxCGRT), using an econometric model. We also investigate how government-issued alert levels influenced electricity use.

We concluded that, although Spain only felt the repercussions in 2020, Portugal saw a negative and considerable impact from restriction measures and lockdowns in 2020 and 2021. The decision to close schools was found to be the specific step that significantly reduced electricity consumption in both countries.

1. Introduction

The world has been significantly impacted by the COVID-19 pandemic, which the World Health Organization (WHO) proclaimed on March 11, 2020. More than 273 million confirmed infections and nearly 5.3 million fatalities were reported as of December 2021 [1]. The pandemic compelled nations to enact social distancing measures which closed down financial markets, workplaces, businesses, and events. Consumption and spending fell as a result of this uncertainty [2]. All industries have been touched, including those in healthcare, pharmaceuticals, agriculture, food delivery, and the energy industry [3]. The pandemic's consequences, though, have not been felt evenly in all areas, nations, or industries [4].

This study provides new insights on how the pandemic and its measures affected electricity consumption. This goal stemmed from the need to better understand the variances connected with such a remarkable event, which generated a one-of-a-kind research environment. The lessons learnt from this are intended to be useful in future emergencies that may necessitate short-term, or even long-term, scenarios of power or energy load reduction. We concentrate on four research questions: i) How did the COVID-19 containment measures impact electricity consumption?; ii) Did the restrictions have a more significant impact in 2020 than in 2021?; iii) Which measures impacted electricity consumption? and iv) Which alert levels impacted electricity consumption?

As one of the first studies to offer empirical data on Portugal and to examine a two-year impact on electricity consumption, this adds to the body of literature. This information allows us to ascertain whether the limitations and lockdowns had a different impact on the two years.

This paper is structured as follows: Section 2 surveys the relevant literature on the topic. It starts by looking at the bigger picture, reviewing the impact of the pandemic on general consumption and spending, and switches to the consequences on the energy and electricity sectors. In section 3, the methodological framework is presented. Section 4 presents the results and the relevant discussion. Finally, in section 5 we provide concluding remarks, some work limitations, and suggestions for future research.

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2. Literature review

Despite being a new topic, literature is emerging that connects the pandemic and its economic impacts to the energy and electricity sectors. Global electricity consumption declined by 1% in 2020 and, as projected, recovered in 2021 [5], while the worst affected countries took longer to recover [6]. The magnitude of the influence varies by location and country.

First off, in China, the outbreak's focal point, electricity consumption was on average 29% lower in 2020 than it was from 2015 to 2019 [7]. The mobility-restraining measures implemented to stop the virus's transmission were most detrimental to industries that depend on human mobility [8]. Consumption in India fell by 15.9% between March and June 2020 when compared to 2019 [9], returning to normal levels at the expense of the epidemic getting worse [10], which had already surpassed 2019 values by 10% in October [5]. Australia saw a 7.15% decline in electricity consumption in March 2020 [11], with Small and Medium Enterprises (SME) being the most impacted [12]. In the short-term, energy use in the USA decreased, with consumption of gasoline, jet fuel, and electricity falling by 50%, 30%, and 10%, respectively [13]. State to state differences existed in the first impact and recovery time [6]. In April 2020, overall daily consumption decreased in Ontario, Canada [14]. Consumption in Mexico decreased by 1.9% in 2020 compared to 2019 [15]. Brazil experienced a diverse reduction [16,17]. Even while the initial impact was not as significant and immediate [18], the first shutdown in the UK had a greater effect than the second [19]. Consumption fell on days when it was prohibited in Turkey [20], and four industrial zones in 2020 consumed less electricity and natural gas [21]. Due to three weeks of numerous lockdowns, Italy's electricity usage dropped by 20% [11,22], but consumption began to recover after the restrictions were removed [23]. As a result of the Spanish government's limiting actions, a decrease was noticed from February to April 2020, as well as a change in consumption pattern [24]. Electricity consumption in Portugal fell to below-average levels, with variability of roughly 12% [25]. Consumption began to recover as European governments eased restrictions. However, restrictions were reinforced in November, causing consumption to fall once more [5].

Using less energy and electricity had a number of negative effects that were felt by the environment. The Chinese economic slowdown reduced emissions [26], while renewables maintained a significant share of the energy generation mix [5]. Solar power generation, for example, broke a record in Israel [27].

In the USA, after the announcement of the first measures, generation from renewable sources outpaced coal-fired power plants. However, in July and August 2020, coal peaked [5]. Both lockdowns decreased emissions in the UK [18]. In March 2020, CO2 emissions in France fell by 6.6% [28].

Wind and solar electricity generation in Ukraine more than doubled in March 2020 compared to March 2019 [29]. During the Italian shutdown, renewables-based generation climbed from 23% to 40% [30]. In Spain, lower electricity consumption resulted in lower emissions [24]. GHG emissions in Lisbon, Portugal, dropped during the shutdown but increased again in May 2020 [31].

People employed social distancing measures and increased their time spent at home during the early stages of the pandemic. At the same moment, all non-essential businesses, workplaces, and educational institutions around the world went into complete lockdowns. In many nations, consumption of electricity increased in the residential sector while falling in the industrial and commercial sectors. During the lockdown in China, there was a decrease in the usage of public transportation, but energy use for family cooking and entertainment increased [32] and public building electricity consumption decreased [33]. The decline in the industrial and commercial sectors outpaced the increase in home consumption in Doha, Dubai [34]. Consumption in the residential sector grew in Sharjah, United Arab Emirates [35]. Data from the Australian state of Victoria indicated that as limitations were tightened, residential consumption climbed while industrial and commercial consumption decreased [12], and the similar situation occurred in Lagos, Nigeria [36].

Due to residents working and studying from home, household consumption in New York City was 15%–24% higher in 2020 than in 2019 [37], and nearly 32% higher in Austin, Texas [38]. Daily household consumption increased in Ottawa, Canada [39] and Quebec [40] during the lockdown. In Brazil, household consumption rose but industrial and transportation-related sectors contracted [16,17]. In Chile's residential sector, higher income classes had a greater increase in consumption [41]. Residential consumption rose by 17% in the UK, 11%–20% in Ireland, and public buildings by Perth and Kinross districts of Scotland during the lockdown [37,42]. The residential load grew by up to 40% in European countries [23].

In both Portugal and Spain, the loss from the industrial and commercial sectors outweighed the gain from the residential sector [25]. Particularly in Spain, the impacts were most severe during the first lockdown and milder during the second [43]. Domestic energy consumption in Warsaw, Poland [44], Ukraine, and Hungary [29] increased.

Various scholars examined the relationship between the stringency of a lockdown or mitigating actions and the variation in electricity and energy consumption. The Stringency Index (SI), developed by Hale et al. [45], or an examination of the various levels of government alert notifications are two methods used in the literature to assess stringency (ie., the severity). Lower electricity use is associated with nations scoring higher on the SI [6]. According to Ruan et al. [46], the retail industry's mobility restrictions were the primary influence on how much electricity was consumed in Philadelphia and New York City. According to Lou et al. [47], closing schools and restricting commercial activity boosted residential consumption in Arizona and Illinois by 4–5% and decreased commercial consumption by 5–8%. The tightest alert level, Alert Level 4, had the biggest and most noticeable impact in New Zealand, causing a reduction in consumption of almost 12% [48]. Stricter regulations resulted in greater load reductions in European nations [49]. The ones with the biggest effects from these measures were the stay-at-home directives, restriction on internal travel, and closures of workplaces and schools [50]. According to Yukseltan et al. [51], Turkey had greater decreases as a result of stricter regulations.

3. Methods

3.1. Empirical model

As our goal is to study the impact of the different levels of lockdown and the strictness of containment policies on the actual and observed electricity consumption, we resort to the model used by Do et al. [52]. This study designed electricity forecasting models (hereafter called model, for shortness) that use environmental and economic factors and is easily expandable to include multiple additional variables. Therefore, this model uses the following variables:

The dependent variable, f_{daily}, is actual and observed electricity consumption.[1]

Heating Degree Days (HDD) and Cold Degree Days (CDD) represent temperature and are used to separate the cold and heat branches of the electricity consumption in terms of duration and intensity. This method has been used in Refs. [53–56]. Using T_{ref} as the reference temperature 18 °C, common in the literature [55,56], and the average temperature for Lisbon, Portugal, and Madrid, Spain, HDD and CDD are calculated using equations (1) and (2):

$$CDD = \max\left(T - T_{ref}, 0\right) \tag{1}$$

[1] We should note that there is no data at daily frequency that disaggregates total electricity consumption into domestic and non-domestic.

$$HDD = \max\left(T_{ref} - T, 0\right) \tag{2}$$

To include the economic trend, we use Industrial Production (IP). This was calculated using data from the Index for Industrial Production of the Organization for Economic Co-operation and Development (OECD), which covers production in mining, manufacturing, and public utilities, excluding construction. As this Index is a short-term economic indicator, we calculated a 90-day moving average.

For weekdays (W) and months (M), we use dummy variables. Wednesday is day 1 and January is month 1. These dummies are an alternative for capturing seasonality.

Another way used for seasonality in the load component is Hours of Daylight (HDL), as used in Ref. [57], calculated through equations (3) and (4), as in Ref. [58]. By first calculating the sun's inclination angle λ_t:

$$\lambda_t = 0.4102 \sin\left(\frac{2\pi}{365}(l_t - 80.25)\right) \tag{3}$$

Where l_t ε [1365] and 1 represents January 1st, etc. δ is the latitude. Because we used the central value of latitudes for Portugal and Spain which are similar (respectively 39 and 40) hours of daylight for each day are approximately the same for each of the referred countries

$$HDL_t = 7.722\ arccos\left(-\tan\left(\frac{2\pi\delta}{360}\tan(\lambda_t)\right)\right) \tag{4}$$

During the holidays there is a drop in consumption [59]. Therefore, we account for Holidays (Ht) as a binary dummy variable [55] and the lagged dummy (H_{t-1}), because of the effect on adjacent days [60] which can be explained as people can take advantage of the holiday to take a work-break in the days preceding it.

Time trend is incorporated through time.

Model 1. (eq. (5)) is the base model:

$$f_{daily}(t) = \alpha_1 + \alpha_2 HDD_t + \alpha_3 CDD_t + \alpha_4 IP_{t-1} + \sum_{\substack{i=1 \\ i\neq 3}}^{7} \alpha_5 W_{i,t} + \alpha_6 H_t + \alpha_7 H_{t-1} + \sum_{j=2}^{12} \alpha_8 M_{j,t} + \alpha_9 HDL_t + \alpha_{10} time_t + \varepsilon_t \tag{5}$$

Model 2. (eq. (6)) is the correction of first-order autocorrelation, enabling robust standard errors and including the lagged dependent variable $f_{daily_{t-1}}$:

$$f_{daily}(t) = \alpha_1 + \alpha_2 HDD_t + \alpha_3 CDD_t + \alpha_4 IP_{t-1} + \sum_{\substack{i=1 \\ i\neq 3}}^{7} \alpha_5 W_{i,t} + \alpha_6 H_t + \alpha_7 H_{t-1} + \sum_{j=2}^{12} \alpha_8 M_{j,t} + \alpha_9 HDL_t + \alpha_{10} time_t + \alpha_{11} f_{daily_{t-1}} + \varepsilon_t \tag{6}$$

The methodological novelty consists of the addition of the lockdown stringency level, using the database OxCGRT, which offers information about government responses to the pandemic over time, in a form of combined data and indices regarding measures. To quantify and compare the policy measures [45], introduced a continuously updated dataset, which contains, among others, government policies related to closure and containment. Among several indices, the Stringency Index is a useful tool that can measure lockdown policy stringency. The SI therefore reflects how strict those measures are and how they affect people's behavior, combining eight indicators of containment and closure policies (C) and one for health measures (H), described in Table 1.

Table 1
Stringency Index (SI) components.

ID	Name	Value info
C1	School closing	0 - No measures 1 – Recommended closing, or open with alterations 2 - Require closing (only some levels, eg just high schools) 3 - Closing all levels
C2	Workplace closing	0 – No measures 1 – Recommended closing, or work from home 2 – Require closing, or work from home, for some sectors 3 - Require closing, or work from home, except essential workplaces
C3	Cancel public events	0 - No measures 1 - Recommended cancelling 3- 2 - Require cancelling
C4	Restrictions on gatherings	0 - No restrictions 2- 1 - Restrictions on very large gatherings (above 1000 people) 2 - Restrictions between 101 and 1000 people 3 - Restrictions between 11 and 100 people 4 - Restrictions of 10 people or less
C5	Close public transport	0 - No measures 1 - Recommended closing, or reduce 2 - Require closing, or prohibiting most citizens from using
C6	Stay at home requirements	0 - No measures 1 - Recommended not leaving house 2 - Recommended not leaving house, with exceptions (exercise, grocery shopping or essential trips) 3 - Require not leaving house, with minimal exceptions (only once per week, or one person at a time)
C7	Restriction on internal movements	0 - No measures 1 - Recommended not to travel between regions/cities 2 - Internal movement restrictions in place
C8	International travel controls	0 - No measures 1 - Screening 2 - Quarantine arrivals from high-risk regions 3 - Ban on arrival for some regions 4 - Ban on all regions or total border closure
H1	Public information campaigns	0 - No Covid-19 public information campaign 1 - Public officials urging caution about Covid-19 2 - Coordinated public information campaign

SI is, then, calculated using equation (7).

$$I = \frac{1}{9}\sum_{j=1}^{9} I_j \tag{7}$$

Model 3. (eq. (8)) adds the SI variable.

$$f_{daily}(t) = \alpha_1 + \alpha_2 HDD_t + \alpha_3 CDD_t + \alpha_4 IP_{t-1} + \sum_{\substack{i=1 \\ i\neq 3}}^{7} \alpha_5 W_{i,t} + \alpha_6 H_t + \alpha_7 H_{t-1} + \sum_{j=2}^{12} \alpha_8 M_{j,t} + \alpha_9 HDL_t + \alpha_{10} time_t + \alpha_{11} f_{daily_{t-1}} + \alpha_{12} SI_t + \varepsilon_t \tag{8}$$

Model 4. (eq. (9)) aims to study the impact of SI for each year.

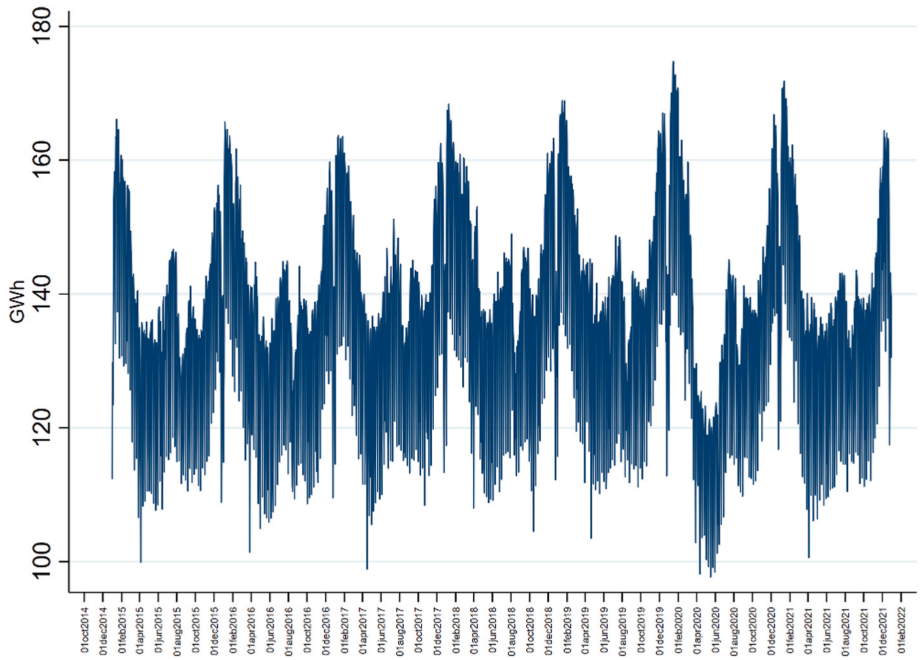

Fig. 1. Portuguese daily electricity consumption 2015–2021. Data source: [61].

$$f_{daily}(t) = \alpha_1 + \alpha_2 HDD_t + \alpha_3 CDD_t + \alpha_4 IP_{t-1} + \sum_{\substack{i=1 \\ i\neq 3}}^{7} \alpha_5 W_{i,t} + \alpha_6 H_t + \alpha_7 H_{t-1} + \sum_{j=2}^{12} \alpha_8 M_{j,t} + \alpha_9 HDL_t + \alpha_{10} time_t + \alpha_{11} f_{daily_{t-1}} + \alpha_{12} 2020SI_t + \alpha_{13} 2021SI_t + \varepsilon_t \tag{9}$$

Through Model 5 (eq. (10)) SI broken down into the months of 2020 and 2021.

$$f_{daily}(t) = \alpha_1 + \alpha_2 HDD_t + \alpha_3 CDD_t + \alpha_4 IP_{t-1} + \sum_{\substack{i=1 \\ i\neq 3}}^{7} \alpha_5 W_{i,t} + \alpha_6 H_t + \alpha_7 H_{t-1} + \sum_{j=2}^{12} \alpha_8 M_{j,t} + \alpha_9 HDL_t + \alpha_{10} time_t + \alpha_{11} f_{daily_{t-1}} + \alpha_{12} 2020SIJan_t + \alpha_{13} 2020SIFeb_t + \ldots + \alpha_{34} 2021SINov_t + \alpha_{35} 2021SIDec_t + \varepsilon_t \tag{10}$$

Model 6. (eq. (11)) follows a different approach of Model 3. This time, the SI is broken down into its individual components.

$$f_{daily}(t) = \alpha_1 + \alpha_2 HDD_t + \alpha_3 CDD_t + \alpha_4 IP_{t-1} + \sum_{\substack{i=1 \\ i\neq 3}}^{7} \alpha_5 W_{i,t} + \alpha_6 H_t + \alpha_7 H_{t-1} + \sum_{j=2}^{12} \alpha_8 M_{j,t} + \alpha_9 HDL_t + \alpha_{10} time_t + \alpha_{11} f_{daily_{t-1}} + \alpha_{12} C1_t + \alpha_{13} C2_t + \alpha_{14} C3_t + \alpha_{15} C4_t + \alpha_{16} C5_t + \alpha_{17} C6_t + \alpha_{18} C7_t + \alpha_{19} C8_t + \alpha_{20} H1_t + \varepsilon_t \tag{11}$$

Models 7 and 8 were built to assess how the different lockdown levels impact electricity consumption. The State-issued Alert Levels are dummy variables which add information about the periods of adoption of each alert level. In Portugal the state-issued alert levels, from the strictest to the least strict, were Emergency, Calamity, Contingency, and Alert. In Spain, the alert levels varied between regions, however we considered the nationwide alarm period defined by the national government.

Therefore, Model 7 adds information about the alert levels adopted by the Portuguese government in eq. (12a) and by Alarm periods decreed by the Spanish government in equation (12b).

$$f_{daily}(t) = \alpha_1 + \alpha_2 HDD_t + \alpha_3 CDD_t + \alpha_4 IP_{t-1} + \sum_{\substack{i=1 \\ i\neq 3}}^{7} \alpha_5 W_{i,t} + \alpha_6 H_t + \alpha_7 H_{t-1} + \sum_{j=2}^{12} \alpha_8 M_{j,t} + \alpha_9 HDL_t + \alpha_{10} time_t + \alpha_{11} f_{daily_{t-1}} + \alpha_{12} Alert_t + \alpha_{13} Contigency_t + \alpha_{14} Calamity_t + \alpha_{15} Emergency_t + \varepsilon_t \tag{12a}$$

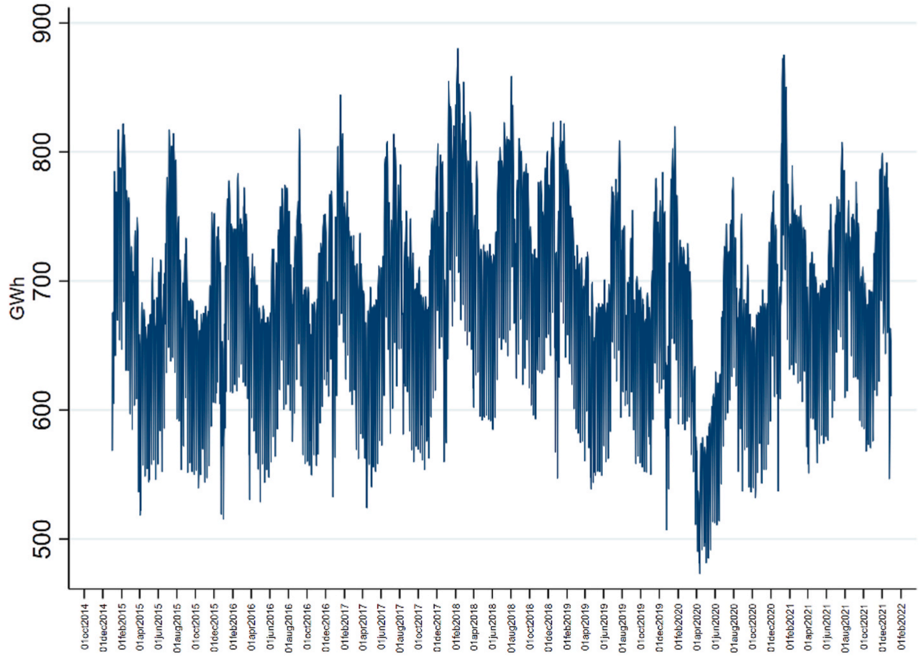

Fig. 2. Spanish daily electricity consumption 2015–2021 Data source [64].

$$f_{daily}(t) = \alpha_1 + \alpha_2 HDD_t + \alpha_3 CDD_t + \alpha_4 IP_{t-1} + \sum_{\substack{i=1 \\ i\neq 3}}^{7} \alpha_5 W_{i,t} + \alpha_6 H_t + \alpha_7 H_{t-1} + \sum_{j=2}^{12} \alpha_8 M_{j,t} + \alpha_9 HDL_t + \alpha_{10} time_t + \alpha_{11} f_{daily_{t-1}} + \alpha_{12} Alarm1_t + \alpha_{13} Alarm2_t + \varepsilon_t \tag{12b}$$

Model 8. (equations (13a) and (13b)) goes a step further by comparing the period of adoption of each alert level with the SI and attempting to quantify the strictness of each alert level. In Spain, the national Alarm period as established by the national government did not cover the entire period, therefore we bridged the SI with the Alarm and non-Alarm periods, in contrast to Portugal, where the Alert levels encompassed all periods since the beginning of the COVID-19 crisis.

$$f_{daily}(t) = \alpha_1 + \alpha_2 HDD_t + \alpha_3 CDD_t + \alpha_4 IP_{t-1} + \sum_{\substack{i=1 \\ i\neq 3}}^{7} \alpha_5 W_{i,t} + \alpha_6 H_t + \alpha_7 H_{t-1} + \sum_{j=2}^{12} \alpha_8 M_{j,t} + \alpha_9 HDL_t + \alpha_{10} time_t + \alpha_{11} f_{daily_{t-1}} + \alpha_{12} SIAlert_t + \alpha_{13} SIContigency_t + \alpha_{14} SICalamity_t + \alpha_{15} SIEmergency_t + \varepsilon_t \tag{13a}$$

$$f_{daily}(t) = \alpha_1 + \alpha_2 HDD_t + \alpha_3 CDD_t + \alpha_4 IP_{t-1} + \sum_{\substack{i=1 \\ i\neq 3}}^{7} \alpha_5 W_{i,t} + \alpha_6 H_t + \alpha_7 H_{t-1} + \sum_{j=2}^{12} \alpha_8 M_{j,t} + \alpha_9 HDL_t + \alpha_{10} time_t + \alpha_{11} f_{daily_{t-1}} + \alpha_{12} SIAlarm1_t + \alpha_{13} SIAlarm2_t + \alpha_{14} SINoAlarm_t + \varepsilon_t \tag{13b}$$

3.2. Data collection

The study period was decided to be from January 1st, 2005 through December 31st, 2021, with all data collected publicly available.

The Portuguese daily electric load data is from Ref. [61]. Fig. 1 illustrates it with thermal energy generation and renewable energy network feed-in. The level of consumption in 2020 was the lowest since 2005 and was 3.7% lower than in 2019. It fell throughout the lockdown and then leveled off in the second part of the year [62]. Even though the pandemic's effects were still seen in 2021, consumption increased by 1.7% over 2020 but lagged behind 2019 levels [63]. Renewable energy output increased to 58% in 2020 from 51% in 2019, owing primarily to reduced consumption [62]. In 2021, electricity generated by renewable sources accounted approximately 59% of total energy production as the last two coal-fired power stations were shut down and the capacity of wind farms and photovoltaic installations was increased [63].

The Spanish daily electric load data (Fig. 2) is from Ref. [64]. Consumption was 5.5% lower in 2020 than in 2019 [65], although it recovered modestly in 2021, standing 2.5% higher [66]. The reduction in consumption led to an all-time high in renewable energy generation of 46.7% in 2021, surpassing the previous records of 45.5% in 2020 as well as 38.9% in 2019 [66].

HDD and CDD are calculated using the daily average temperature. Data for Lisbon, Portugal, comes from Ref. [67], and data for Madrid, Spain, comes from Ref. [68].

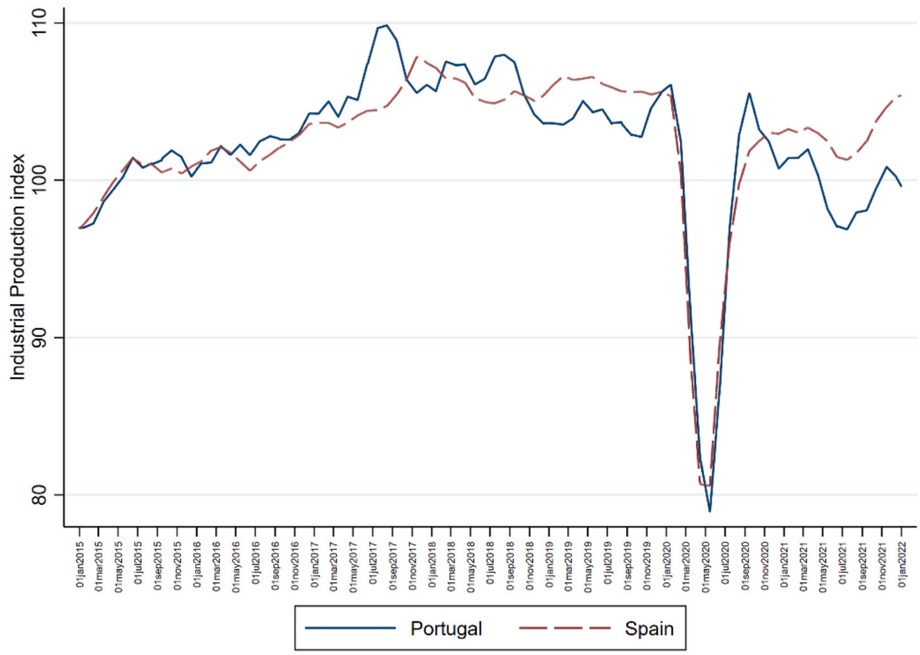

Fig. 3. Industrial production (IP) - Portugal and Spain.

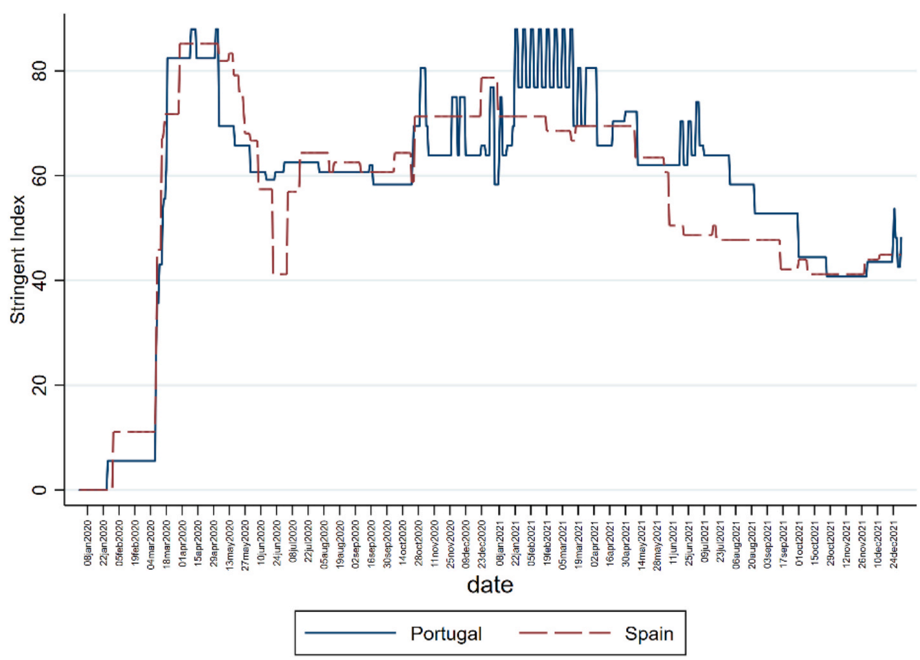

Fig. 4. Stringent index - Portugal and Spain.

The Industrial Production Index, used to determine IP (Fig. 3), was retrieved from Ref. [69].

Data regarding public holidays in Portugal and Spain was retrieved from [70,71].

All data about the degree of stringency of the measures, both as SI (Fig. 4) and as individual measures, was acquired from the OxCGRT database. Values for the period from 2015 to 2019 are nil because the epidemic did not start until 2020.

Figs. 5 and 6 show official information about alert levels from the Portuguese [72] and Spanish [73,74] governments. Spain reported its first continental verified case on March 26 while Portugal confirmed its first cases on March 2 [75]. States of exception were declared by both nations.

The most severe warning level, Emergency, was then proclaimed twice in Portugal. The first time, the authorities put the population under strict lockdown conditions and closed down all non-essential economic activity. To control the virus, nearly every precaution was taken, resulting in a straight line for a brief period in March and April 2020. Stringency had an average value of 83.27. The lockdown was less severe the second time, and just a partial shutdown was implemented, yielding an average value of 72.55 (Table 2). Several measures were altered every few of weeks at this time. One example is C7, which prohibited travelling across regions except on weekends for particular periods, resulting in multiple ups and downs at the start of 2021 (see

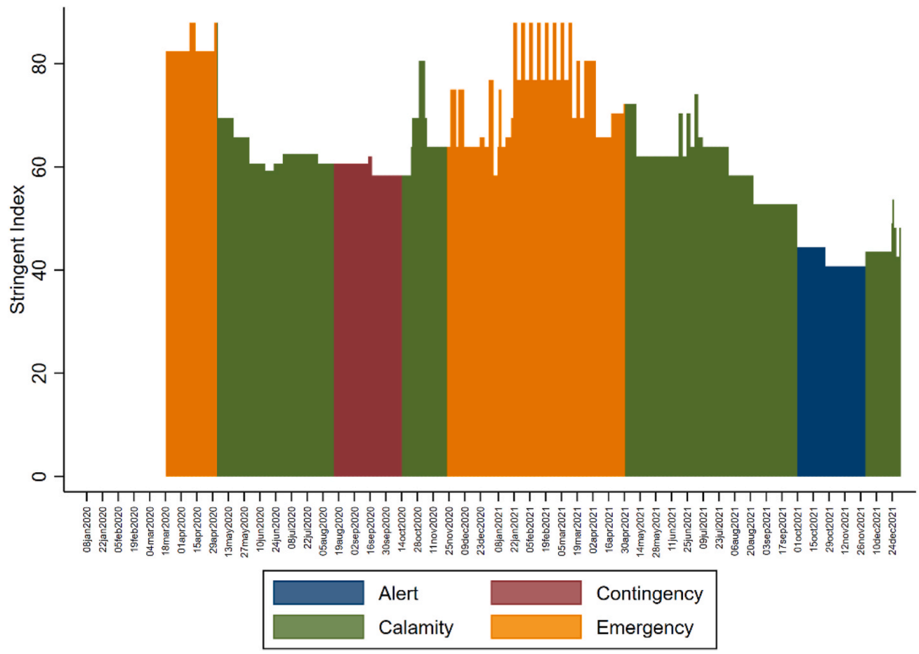

Fig. 5. Alert levels with stringency quantification (Portugal).

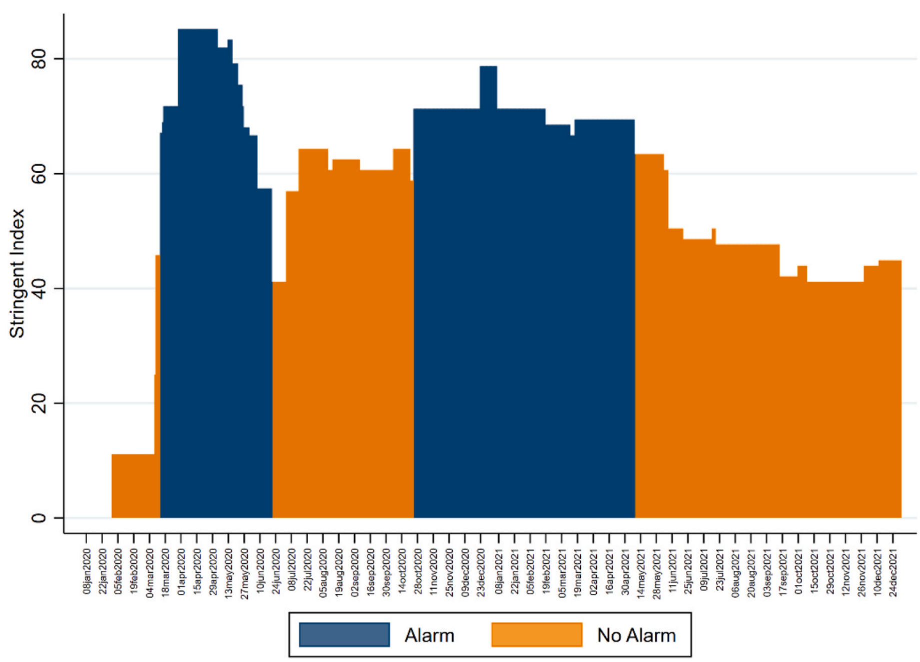

Fig. 6. Nationwide Alarm periods with stringency quantification (Spain).

Table 3).

In Spain, the state of alarm (the least severe of the three constitutional exceptions: alarm, emergency, and siege) was declared twice across the country: in 2020 from March 14 to June 21 and from October 25 to May 9 of the following year. The first state of alarm featured a statewide lockdown as well as restrictions on mobility and activity outside the home. Only those who could not work from home were permitted to leave their homes, and even then, only to acquire necessities, go to work, or receive medical care. Certain economic activities and closed specific public spaces and establishments, such as bars and restaurants, were suspended [73]. Regional governments were permitted to change these hours if they felt it was necessary, but a national curfew that prohibited mobility between the hours of 11 p.m. and 6 a.m. was implemented because of the second state of alarm. There were also limits on social gatherings, and restrictions on mobility between regions [74].

4. Results

As was described in Section 3, we created 8 models, from which we took the most significant findings (Tables 4–11).

According to Model 3 data, the SI had a large and negative impact on Portugal (Table 4), as projected. In other words, the more stringent the containment measures, the greater the reduction in consumption. This

Table 2
Alert levels and respective Stringency interval (Portugal).

Alert level	Time interval	Stringency interval	Average	Standard deviation
Emergency	March 19, 2020 – May 2, 2020	82.41–87.96	83.27	2.03
Calamity	May 3, 2020–July 31, 2020	59.26–69.44	63.63	4.13
Contingency	August 1, 2020–October 14, 2020	58.33–60.65	59.87	1.19
Calamity	October 15, 2020 – November 8, 2020	58.33–80.56	67.22	8.18
Emergency	November 9, 2020–April 30, 2021	63.89–87.96	72.55	8.51
Calamity	May 1, 2021–September 30, 2021	52.78–74.07	60.80	5.98
Alert	October 1, 2021–November 30, 2021	40.74–44.44	42.26	1.83
Calamity	December 1, 2021–December 31, 2021	45.59–53.70	44.39	2.44

Table 3
Alarm periods and respective Stringency interval (Spain).

Alert level	Time interval	Stringency interval	Average	Standard deviation
1st Alarm Period	March 14, 2020–June 21, 2020	41.2–85.19	75.52	10.34
2nd Alarm Period	October 25, 2020 – May 9, 2021	63.43–78.7	70.91	2.56

Table 4
Portugal - results from models 1, 2, and 3.

	Model 1	Model 2	Model 3
Const	132.351***	45.175***	49.035***
	(27.11)	(11.8)	(11.28)
fdaily$_{t-1}$		0.713***	0.709***
		(37.91)	(37.83)
HDD	0.158**	0.044	0.044
	(2.41)	(0.897)	(0.87)
CDD	0.506***	0.260***	0.262***
	(8.44)	(9.186)	(9.08)
IP$_{t-1}$	0.556***	0.158***	0.126***
	(25.23)	(9.21)	(5.87)
H	−17.297***	−13.677***	−13.681***
	(-30.97)	(-14.38)	(-14.37)
H$_{t-1}$	−6.838***	6.001***	5.945***
	(-11.95)	(7.07)	(6.96)
HDL	−0.066***	−0.027***	−0.027***
	(-9.41)	(-5.66)	(-5.76)
Time	0.0014***	0.0004***	0.0007***
	(10.08)	(3.92)	(4.27)
SI			−0.013**
			(-2.41)
R^2	0.8758	0.9440	0.9442
Observ.	2556	2556	2556
AR(1)	2634.51	0.3765	0.4794
	[0.0000]	[0.5395]	[0.4888]
White	1132.56	1095.37	1131.53
	[0.0000]	[0.0000]	[0.0000]

Notes: *t-statistics* in parentheses (*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$); *p-values* in square brackets. Augmented Dickey-Fuller (ADF) test including both a constant and a trend: fdaily, HDD, CDD, IP, H and HDL are stationary with p-value <0.05.

Table 5
Spain - results from models 1, 2 and 3.

	Model 1	Model 2	Model 3
Const	167.011***	76.253***	78.285***
	(5.19)	(4.05)	(3.74)
fdaily$_{t-1}$		0.761***	0.761***
		(47.13)	(37.98)
HDD	4.951***	1.886***	1.890***
	(16.09)	(8.35)	(7.47)
CDD	6.904***	2.898***	2.898***
	(19.82)	(14.87)	(15.18)
IP$_{t-1}$	4.74***	1.111***	1.090***
	(31.36)	(9.23)	(6.77)
H	−62.357***	−35.639***	−35.635***
	(-16.94)	(-6.846)	(-6.73)
H$_{t-1}$	−26.003***	22.048***	22.055***
	(-7.10)	(5.17)	(5.16)
HDL	0.028	−0.047**	−0.047*
	(0.610)	(-2.03)	(-1.77)
Time	0.0006	0.0002	0.0004
	(0.675)	(0.47)	(0.43)
SI			−0.0072
			(-0.22)
R^2	0.7777	0.9188	0.9188
Observ.	2556	2556	2556
AR(1)	3469.44	0.0018	0.0015
	[0.0000]	[0.9658]	[0.9681]
White	1003.78	1088.98	1153.17
	[0.0000]	[0.0000]	[0.0000]

Notes: *t-statistics* in parentheses (*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$); *p-values* in square brackets. Augmented Dickey-Fuller (ADF) test including both a constant and a trend: f_{daily}, HDD, CDD, IP, H and HDL are stationary with p-value <0.05.

discovery is consistent with the findings of other publications, including [49,50].

For Spain (Table 5), the impact is negative, but it is not significant, which contradicts the findings of [9,23], which revealed that the lockdown measures lowered electricity consumption from February to April 2020. However, our research is not limited to a three-month period. Instead, it examines the impact of these measures over a two-year window, concluding that the lockdown policies had no relevant effect in Spain.

SI in Model 4 (Tables 6 and 7) was divided into years. The findings reveal that Portugal's electricity consumption suffered significantly and negatively as a result of the containment policies in 2020 and 2021 (Table 6), while for Spain this negative and severe influence only occurred in 2020 and not 2021 (Table 7).

The manner the pandemic developed in both countries may be a factor in this result. Portugal had a sharp surge in new infections and deaths in late 2020 and early 2021 (Fig. 7), even more pronounced than in the first months of the epidemic, prompting the government to implement new restrictions that eventually led to a partial lockdown in early 2021. The pandemic peak in Spain at the end of 2020 and early 2021 was lower than in Portugal, which could be explained by prevention and fear growth factors having a more active role, but that might have reduced the fear factor in Spain through 2021 leading to a lift of the Alarm period and a faster decrease in the stringency measures in Spain than in Portugal (see Fig. 4).

In Model 5, SI was broken down into months, starting in 2020. Table 6 shows that for Portugal, the most significant months in 2020 were January, March, April, May, June, July, and September, while the most crucial months in 2021 were February, March, April, May, June, July, September, and October. The results in Spain (Table 7) demonstrate that the actions had a considerable impact in February, September, October, and November 2020, as well as September 2021.

Unexpectedly, January 2020 in Portugal and September 2021 in Spain produce a different conclusion from what we anticipated, since the findings reveal that they had a beneficial influence on power consumption, indicating that harsher regulations led to an increase in

Table 6
Portugal - results from models 4 and 5.

	Model 4	Model 5	Model 5	*Cont.*	Model 5	*Cont.*
Const	49.737***	60.659***	***SI_1.20***	0.451***	***SI_1.21***	−0.008
	(11.02)	(10.43)		(5.55)		(-0.82)
$fdaily_{t-1}$	0.709***	0.689***	***SI_2.20***	−0.050	***SI_2.21***	−0.016**
	(37.32)	(35.28)		(-0.38)		(-2.03)
HDD	0.046	0.049	***SI_3.20***	−0.046***	***SI_3.21***	−0.040***
	(0.91)	(0.96)		(-4.01)		(-5.25)
CDD	0.265***	0.289***	***SI_4.20***	−0.049***	***SI_4.21***	−0.027***
	(9.13)	(9.44)		(-4.12)		(-2.87)
IP_{t-1}	0.121***	0.046	***SI_5.20***	−0.061***	***SI_5.21***	−0.013*
	(5.44)	(1.32)		(-3.98)		(-1.76)
H	−13.680***	−13.751***	***SI_6.20***	−0.053***	***SI_6.21***	−0.024***
	(-14.36)	(-14.26)		(-3.47)		(-2.67)
H_{t-1}	5.94***	5.618***	***SI_7.20***	−0.036***	***SI_7.21***	−0.030***
	(6.93)	(6.64)		(-3.98)		(-3.36)
HDL	−0.028***	−0.029***	***SI_8.20***	−0.017	***SI_8.21***	−0.007
	(-5.79)	(-6.01)		(-1.29)		(-0.55)
Time	0.0007***	0.0009***	***SI_9.20***	−0.031***	***SI_9.21***	−0.026**
	(4.23)	(4.50)		(-4.83)		(-2.13)
SI2020	−0.017**		***SI_10.20***	−0.007	***SI_10.21***	−0.021*
	(-2.32)			(-1.28)		(-1.73)
SI2021	−0.011**		***SI_11.20***	−0.007	***SI_11.21***	−0.016
	(-2.01)			(-0.79)		(-0.67)
			SI_12.20	0.003	***SI_12.21***	−0.006
				(0.12)		(-0.16)
R^2	0.9442	0.9450				
Observ.	2556	2556				
AR(1)	0.4857	1.0209				
	[0.4859]	[0.3123]				
White	1166.44	1369.48				
	[0.0000]	[0.0000]				

Notes: *t-statistics* in parentheses (*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$); *p-values* in square brackets. Augmented Dickey-Fuller (ADF) test including both a constant and a trend: fdaily, HDD, CDD, IP, H and HDL are stationary with p-value <0.05. In Model 4, linear restriction test: b[SI2020]-b[SI2021] = 0 and p-value >0,05.

Table 7
Spain - results from models 4 and 5.

	Model 4	Model 5	Model 5	*Cont.*	Model 5	*Cont.*
Const	110.735***	117.868***	***SI_1.20***	−0.134	***SI_1.21***	0.039
	(4.63)	(2.74)		(-0.56)		(0.73)
$fdaily_{t-1}$	0.752***	0.747***	***SI_2.20***	−0.670**	***SI_2.21***	−0.016
	(43.79)	(43.23)		(-2.04)		(-0.32)
HDD	1.941***	1.931***	***SI_3.20***	−0.149	***SI_3.21***	−0.006
	(8.46)	(8.46)		(-1.20)		(-0.13)
CDD	2.961***	3014***	***SI_4.20***	−0.141	***SI_4.21***	0.021
	(14,99)	(14,58)		(-1.094)		(0.33)
IP_{t-1}	0.848***	0.807**	***SI_5.20***	−0.084	***SI_5.21***	0.012
	(5.65)	(2.29)		(-69)		(0.23)
H	−35.94***	−36.109***	***SI_6.20***	−0.094	***SI_6.21***	0.066
	(-6.89)	(-6.89)		(-0.69)		(0.91)
H_{t-1}	21.498***	21.196***	***SI_7.20***	−0.072	***SI_7.21***	0.114
	(5.07)	(5.03)		(-0.88)		(1.42)
HDL	−0.0482**	−0.049**	***SI_8.20***	−0.079	***SI_8.21***	0.042
	(-2.13)	(-2.15)		(-1.23)		(0.498)
Time	0.0005	0.0008	***SI_9.20***	−0.111**	***SI_9.21***	0.160**
	(0.52)	(0.43)		(-2.13)		(2.16)
SI2020	−0.0897**		***SI_10.20***	−0.105*	***SI_10.21***	0.040
	(-2.21)			(-1.89)		(0.44)
SI2021	0.039		***SI_11.20***	−0.134***	***SI_11.21***	0.001
	(1.23)			(-3.13)		(0.01)
			SI_12.20	−0.029	***SI_12.21***	0.296
				(-0.27)		(0.16)
R^2	0.9193	0.9196				
Observ.	2556	2556				
AR(1)	0.0271	0.0409 [0.8398]				
	[0.8692]					
White	1163.89	1344.98 [0.0000]				
	[0.0000]					

Notes: *t-statistics* in parenthesis (*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$); *p-values* in square brackets. Augmented Dickey-Fuller (ADF) test including both a constant and a trend: fdaily, HDD, CDD, IP, H and HDL are stationary with p-value <0.05. In Model 4, linear restriction test: b[SI2020]-b[SI2021] = 0 and p-value >0,05.

Table 8
Portugal - results from model 6.

	Model 6		Cont.
Const	50.747***	***C1 – Schools closing***	−0.504**
	(4.29)		(-2.13)
$fdaily_{t-1}$	0.697***	***C2 – Workplace closing***	−0.758
	(37.47)		(-1.53)
HDD	0.036	***C3 – Cancel public events***	1.231
	(0.73)		(0.84)
CDD	0.265***	***C4 – Restrictions on gatherings***	−1.080***
	(9.13)		(-2.82)
IP_{t-1}	0.128***	***C5 – Close public transport***	0.513
	(5.74)		(0.73)
H	−13.696***	***C6 – Stay at home requirements***	0.364
	(-14.21)		(1.31)
H_{t-1}	5.748***	***C7 – Restriction on internal movements***	−0.250
	(6.98)		(-1.31)
HDL	−0.028***	***C8 – International travel controls***	0.819
	(-5.74)		(0.95)
Time	0.0006***	***H1 – Public information campaigns***	0.180
	(3.26)		(0.25)
R^2	0.9447		
Observ.	2556		
AR(1)	2.1774		
	[0.1402]		
White	1231.13		
	[0.0000]		

*Notes: t-statistics in parentheses (*p < 0.1, **p < 0.05, ***p < 0.01); p-values in square brackets. Augmented Dickey-Fuller (ADF) test including both a constant and a trend: fdaily, HDD, CDD, IP, H and HDL are stationary with p-value < 0.05.*

Table 9
Spain - results from model 6.

	Model 6		Cont.
Const	104.235***	***C1 – Schools closing***	−5.085**
	(2.99)		(-2.34)
$fdaily_{t-1}$	0.751***	***C2 – Workplace closing***	−1.828
	(43.44)		(-1.08)
HDD	1.965***	***C3 – Cancel public events***	3.748
	(8.32)		(0.81)
CDD	3.001***	***C4 – Restrictions on gatherings***	0.078
	(14.44)		(0.06)
IP_{t-1}	0.913***	***C5 – Close public transport***	−1.250
	(3.23)		(-0.24)
H	−35.87***	***C6 – Stay at home requirements***	−0.317
	(-6.90)		(-0.33)
H_{t-1}	21.569***	***C7 – Restriction on internal movements***	−1.866
	(5.10)		(-1.41)
HDL	−0.049**	***C8 – International travel controls***	2.459
	(-2.17)		(0.99)
Time	0.0002	***H1 – Public information campaigns***	−0.692
	(0.13)		(-0.33)
R^2	0.9194		
Observ.	2556		
AR(1)	0.0394		
	[0.8427]		
White	1238.59		
	[0.0000]		

Notes: *t-statistics* in parentheses (*p < 0.1, **p < 0.05, ***p < 0.01); *p-values* in square brackets. Augmented Dickey-Fuller (ADF) test including both a constant and a trend: fdaily, HDD, CDD, IP, H and HDL are stationary with p-value <0.05.

consumption. The only active measure in Portugal in the end of January 2020 (Fig. 8) was the health education campaign (H1). When its value is 1, public health authorities advise the population to be careful with COVID-19. One possible explanation for the positive signal and importance is that when this measure was implemented in January 2020, before the pandemic, electricity consumption surged due to some sort of anticipation of economic and domestic activities.

As has already been mentioned, Spain in 2021 saw little impact from the containment measures. Consequently, one explanation for what happened in September 2021 is that as the pandemic progressed, people learned to adapt to their new circumstances, and electricity consumption increased as the economy recovered.

In Model 6 SI is broken down into its constituents. Schools closing (C1) and gathering restrictions (C4) were the only measures that impacted significantly the electricity consumption in Portugal (Table 8), while in Spain (Table 9) just school closing (C1) was significant.

Models 7 and 8 (Tables 10 and 11) were designed to evaluate the effects of the various Alert Levels chosen by the Portuguese government and the national alarm state imposed by the Spanish government.

In the case of Portugal, only Contingency - the second least stringent of the four possible levels - had a significant impact. However, in order to have a better grasp of the real stringency of each alert level, we cross-referenced data with the Stringency Index, from which the research variables used in Model 8 were derived. Based on these findings, we believe that the most severe emergency level, Emergency, also had a substantial impact. This was the case possibly because the Contingency alert level was enforced for a short period of time (from August 1st, 2020, to October 14th, 2020) and its stringency level was barely lower than the second strictest level, Calamity (Fig. 5). This is consistent with the results found before those public restrictions had an negative and significant impact and it was on level 4 out of 4, meaning that meetings were restricted to groups of 10 people or less. Furthermore, typically Portugal has many foreign tourists in the summer, but in 2020 this was not the case due to international travelling restrictions, so these two reasons might be the cause of negative impact on electricity consumption found for the Contingency level.

In the case of Spain, the data confirmed model 4 in Table 7, where the pandemic only had an impact in the first year, and in this case, during the first period of Alarm. As already indicated the pandemic peak in Spain at the end of 2020 beginning of 2021 was not as high as in Portugal, and by the end of the year, not only were the restrictions smaller, as previously explained, but also the fear factor was lower than during the first Alarm period, indicating that the economy and habits had adapted to the new situation.

In both cases could be argued that the results found in Tables 8 and 9 for school closing could be a reflex of these alert periods. In Annex A we performed a robustness analysis where we included the components of the stringent indexes and the alert periods, and the school closings negative effect continue to be negative. The significance of the effects of the different periods changed, showing the effects declaring the different periods are not as robust as the effects of the measures taken.

5. Conclusions

The global impact of the COVID-19 pandemic was felt most acutely in 2020 and 2021. Many authors have begun to document its effects, particularly those on the electricity and energy sectors. Countries that implemented shelter-at-home policies saw a reduction in load. The rise in residential consumption was inadequate to overcome the decline in the industrial and commercial sectors. This reduction in overall consumption resulted in lower emissions and changes in the energy generation mix, with renewable energy sources briefly increasing their proportion. However, the economic rebound that followed the lockdowns allowed electricity consumption to return to 2019 levels and surpass them by the end of 2020.

Portugal and Spain were the subjects of this study. It included a wider time span than other literature, covering the pandemic and measures in 2020 and 2021, as well as two additional years. The econometric model used in the methodological framework, as in Ref. [52], assessed electricity consumption and allowed for innovative upgrading. The OxCGRT Stringency Index, which quantified lockdown stringency, was one of the additions.

Despite the many similarities in terms of stringency rules, it is crucial to emphasize that Portugal and Spain have different results. The impact of the restriction orders on electricity consumption in Portugal persisted

Table 10
Portugal - Results from models 7 and 8.

	Model 7		*Cont.*	*Model 8*		*Cont.*
Const	46.712***	***Alert***	0.022	48.005***	***SIAlert***	−0.004
	(10.67)		(0.04)	(10.99)		(-0.38)
$fdaily_{t-1}$	0.709***	***Contingency***	−0.857**	0.707***	***SIContingency***	−0.016**
	(37.29)		(-2.19)	(37.31)		(-2.54)
HDD	0.044	***Calamity***	−0.216	0.044	***SICalamity***	−0.008
	(0.86)		(-0.48)	(0.87)		(-1.24)
CDD	0.262***	***Emergency***	−0.719	0.263***	***SIEmergency***	−0.013**
	(9.21)		(-1.43)	(9.14)		(-2.16)
IP_{t-1}	0.149***			0.138***		
	(6.46)			(6.19)		
H	−13.690***			−13.685***		
	(-14.39)			(-14.36)		
H_{t-1}	5.942***			5.920***		
	(6.93)			(6.91)		
HDL	−0.027***			−0.027***		
	(-5.72)			(-5.74)		
Time	0.0006***			0.0007***		
	(3.25)			(3.91)		
R^2	0.9441			0.9442		
Observ.	2556			2556		
AR(1)	0.4934			0.5373		
	[0.4825]			[0.4636]		
White	1181.73 [0.0000]			1168.61		
				[0.0000]		

Notes: *t-statistics* in parentheses (*p < 0.1, **p < 0.05, ***p < 0.01); *p-values* in square brackets. Augmented Dickey-Fuller (ADF) test including both a constant and a trend: fdaily, HDD, CDD, IP, H and HDL are stationary with p-value <0,05.

Table 11
Spain - Results from models 7 and 8.

	Model 7		*Cont.*	*Model 8*		*Cont.*
Const	16.73	***Alarm1***	−5.604*	48.06	***SIAlarm1***	−0.137*
	(0.74)		(-1.76)	(1.61)		(-1.71)
$fdaily_{t-1}$	0.759***	***Alarm2***	−0.276	0.759***	***SIAlarm2***	−0.0261
	(37.76)		(-0.15)	(37.71)		(-0.89)
HDD	1.908***			1.928***	***SINoAlarm***	−0.0386
	(7.53)			(7.52)		(-0.89)
CDD	2.908***			2.903***		
	(15.19)			(15.21)		
IP_{t-1}	0.936***			0.763***		
	(6.08)			(3.45)		
H	−35.66***			−35.62***		
	(-6.74)			(-6.73)		
H_{t-1}	22.00***			22.03***		
	(5.14)			(5.15)		
HDL	−0.0454*			−0.0452***		
	(-1.73)			(-1.73)		
Time	0.0005			0.00149***		
	(0.93)			(1.28)		
R^2	0.9188			0.9189		
Observ.	2556			2556		
AR(1)	0.003			0.002		
	[0.9572]			[0.9674]		
White	1161.99 [0.0000]			1182.25		
				[0.0000]		

Notes: *t-statistics* in parentheses (*p < 0.1, **p < 0.05, ***p < 0.01); *p-values* in square brackets. Augmented Dickey-Fuller (ADF) test including both a constant and a trend: fdaily, HDD, CDD, IP, H and HDL are stationary with p-value <0,05.

until 2020 and 2021. School closures and gathering limitations were the specific actions that had the greatest impact. Only two alert levels—Emergency, the level at which lockdown is ordered, and Contingency, the second-least strict of the four warning levels—had a considerable detrimental impact. For Spain the containment measures had a detrimental effect in 2020 but not in 2021. Given that no big lockdown was implemented in 2021, unlike in Portugal, it may indicate that the pandemic evolved favorably, and the fear element subsided. The sole noteworthy action, which also applied to Portugal, was the schools closing.

Our findings are significant and will be useful to public decision-makers in future emergencies and in normal times when the management or reduction of electricity load is required, such as the proper management and coordination of school timetables, which was the measure with the greatest impact across the different models tested. Furthermore, if one or more such actions must be taken, the effects on electricity load are understood ahead of time. As a result, critical market participants can forecast future electric consumption.

Future research ideas include extending this work to examine the effects of electricity reduction due to COVID-19 on other dimensions, such as pollution, and duplicating this methodology in countries where data on electricity consumption are available and broken down by residential, industrial, and commercial sectors.

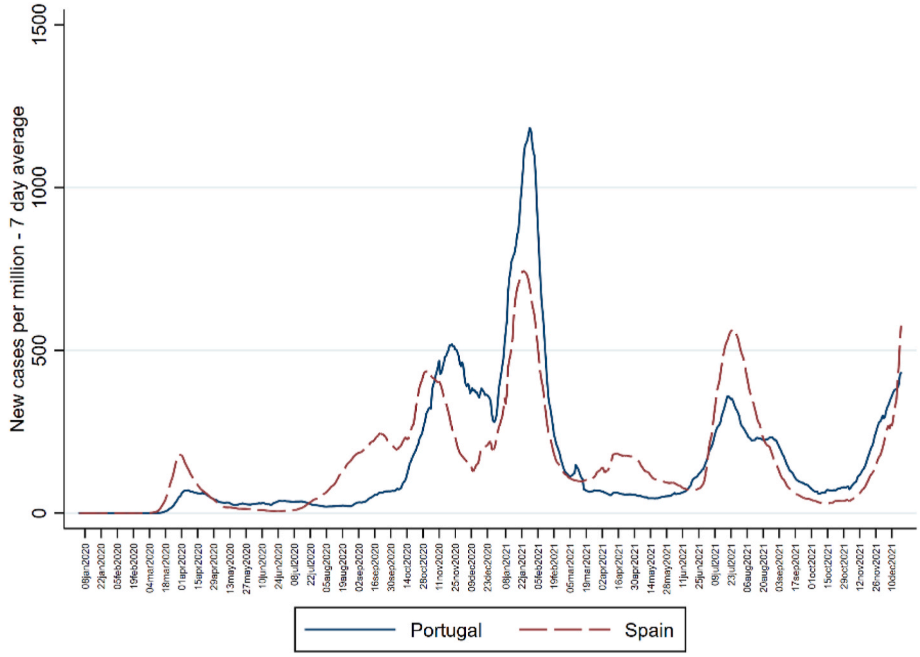

Fig. 7. COVID 19 new cases per million – 7-day average (source: [76]).

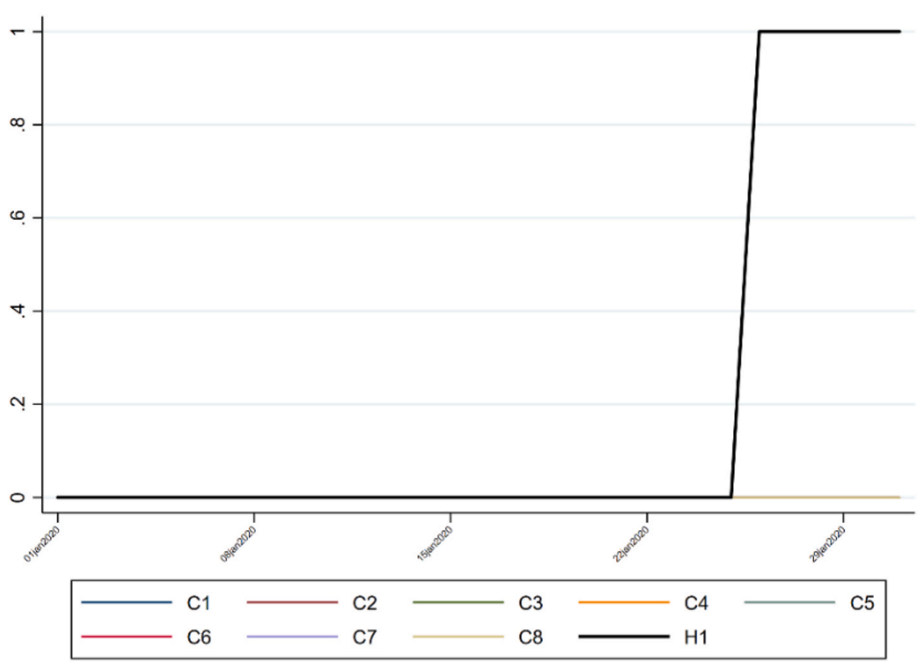

Fig. 8. Measures adopted in Portugal - January 2020.

Credit author statement

Patrícia Pereira da Silva: Conceptualisation, Writing – Original Draft, Methodology, Validation, Investigation, Writing - Review & Editing. **Pedro André Cerqueira:** Conceptualisation, Methodology, Data collection, Validation, Investigation, Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

Table 1A
Portugal

	Model A Portugal	Model B Portugal
Const	38.99***	38.99***
	(7.81)	(7.75)
$fdaily_{t-1}$	0.690***	0.691***
	(28.42)	(28.50)
HDD	0.0501	0.0487
	(1.00)	(0.98)
CDD	0.275***	0.275***
	(9.68)	(9.71)
IP_{t-1}	0.143***	0.142***
	(5.71)	(5.58)
H	−13.73***	−13.72***
	(-14.24)	(-14.24)
H_{t-1}	5.622***	5.631***
	(7.52)	(7.54)
HDL	−0.0283***	−0.0282***
	(-5.65)	(-5.63)
Time	0.000539***	0.000546***
	(3.00)	(3.02)
C1 – Schools closing	−0.833***	−0.670***
	(-2.99)	(-2.73)
C2 – Workplace closing	0.131	0.230
	(0.22)	(0.36)
C3 – Cancel public events	5.357**	5.137**
	(2.40)	(2.26)
C4 – Restrictions on gatherings	−1.249**	−1.189**
	(-2.34)	(-2.11)
C5 – Close public transport	1.032	1.273*
	(1.53)	(1.78)
C6 – Stay at home requirements	0.0122	0.178
	(0.05)	(0.69)
C7 – Restriction on internal movements	−0.299	−0.0955
	(-1.09)	(-0.33)
C8 – International travel controls	−1.775	−1.907
	(-1.13)	(-1.22)
H1 – Public information campaigns	0.893	0.785
	(1.30)	(1.17)
Alert	−6.288***	
	(-3.23)	
Calamity	−2.482*	
	(-1.69)	
Emergency	−2.202	
	(-1.44)	
Contingency	−3.392**	
	(-2.07)	
SIAlert		−0.136***
		(-3.10)
SICalamity		−0.0400*
		(-1.67)
SIEmergency		−0.0367
		(-1.59)
SIContingency		−0.0550**
		(-2.07)
R2	0.945	0.945
Observ.	2556	2556
AR(1)	0.943	0.936
	[0.342]	[0.336]
White	1362.83	1323.91
	[0.000]	[0.000]

t statistics in parentheses; p-value between squared parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2A
Spain

	Model 1A Spain	Model 1B Spain
Const	42.06	41.75
	(1.10)	(1.08)
$fdaily_{t-1}$	0.751***	0.751***

(*continued on next page*)

Table 2A (*continued*)

	Model 1A Spain	Model 1B Spain
	(36.68)	(36.59)
HDD	1.970***	1.972***
	(7.82)	(7.83)
CDD	2.998***	2.992***
	(15.71)	(15.73)
IP_{t-1}	0.913***	0.920***
	(2.87)	(2.86)
H	−35.85***	−35.84***
	(-6.76)	(-6.76)
H_{t-1}	21.58***	21.58***
	(5.05)	(5.05)
HDL	−0.0501*	−0.0503*
	(-1.90)	(-1.90)
Time	0.000209	0.000179
	(0.13)	(0.11)
C1 – Schools closing	−5.605*	−4.759
	(-1.66)	(-1.33)
C2 – Workplace closing	−1.636	−0.561
	(-0.82)	(-0.20)
C3 – Cancel public events	3.727	3.987
	(0.75)	(0.73)
C4 – Restrictions on gatherings	−0.172	0.486
	(-0.13)	(0.28)
C5 – Close public transport	−0.444	1.391
	(-0.08)	(0.20)
C6 – Stay at home requirements	0.147	1.199
	(0.14)	(0.50)
C7 – Restriction on internal movements	−1.557	−0.837
	(-0.80)	(-0.28)
C8 – International travel controls	2.886	3.742
	(1.08)	(1.11)
H1 – Public information campaigns	−0.721	0.618
	(-0.41)	(0.16)
ESAlarm1	−1.778	
	(-0.31)	
ESAlarm2	−2.101	
	(-0.62)	
SIAlarm1		−0.256
		(-0.46)
SIAlarm2		−0.243
		(-0.47)
SINoAlarm		−0.238
		(-0.42)
R2	0.920	0.920
Observ.	2556	2556
AR(1)	0.045	0.050
	[0.843]	[0.824]
White	1251.81	1269.44
	[0.000]	[0.000]

t statistics in parentheses; p-value between squared parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

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