The impact of COVID-19 measures on intraday electricity load curves in the European Union: A panel approach

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ABSTRACT

This paper examines the impact of the intensity of government measures introduced to reduce the spread of COVID-19 on intraday electricity load curves in 23 European countries. The econometric panel model used covers the entire period from the virus outbreak in Europe up to the release of several vaccines; therefore, the estimation considers the introduction, partial lifting, and reintroduction of the interventions. Based on the results, the impacts of the different stringency measures were similar in the 23 analysed EU member states. More stringent interventions had different effects at different times of day: the morning and evening peaks were significantly affected, as was every hour of the day. The impacts were nonlinear, meaning that different measures mutually amplified each other's impact and led to more substantial changes in electricity consumption and citizens' lives. The morning and evening peaks are also found to have decreased, causing a flattening of the load curves. In line with this result, the partial effect of an increase in the stringency index depends on the type of day (weekday or weekend), hour of the day, and initial stringency level. Overall, the lockdown measures led to a decrease in hourly electricity consumption of between 1% and 9% on weekdays and between 1% and 13% on weekends. Total daily consumption decreased by up to 9%. Understanding how hourly electricity demand reacts to different stringency measures provides valuable information in operation scheduling and capacity planning. More accurate demand forecasts can support trading decisions and help prevent extreme market mismatches.

1. Introduction

To address in a balanced way the "health versus wealth" dilemma caused by the COVID-19 pandemic [1], government decision-makers have received significant support from a large amount of quickly available data [2,3]. Infection and mortality numbers provide rapid information on the status of public health, but proxies are also needed to support decisions impacting economic activities. Traditional economic indicators, such as GDP growth, investment, or consumption, are available only at least one or two months after a given quarter has passed. On the other hand, energy consumption data are available in almost real time and are closely linked to economic and social activities [4,5]. Thus, exploring the relationship between the pandemic and the energy market is a high-priority and growing research area [6]. Within

the energy market, special attention has been given to electricity demand. Although it responds more inflexibly to economic changes than crude oil or gas demand, the availability of relevant high-frequency real-time data and the strong regional characteristics of this measure make it an excellent benchmark [7] and early warning indicator for economists.

On the other hand, electricity markets do not just provide data; they are an essential part of any modern economy, so their continuous and secure operation is key. Therefore, decision-makers and system operators need to have a clear understanding of the effects of lockdown measures. As the electricity markets within the European Union are in the process of integration, robust, multicountry analyses are receiving increasing attention both from policy-makers and academia.

This article examines the intensity of COVID-19-related mitigation measures on intraday load curves in 23 European countries over 2019 and 2020, applying a panel econometric approach. For the estimation, we employ the feasible generalised

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least squares (FGLS) method, which has previously been successfully implemented in analysing longitudinal energy panel data such as renewable energy consumption [8,9] or natural gas demand movements [10]. The results contribute to expanding scientific knowledge in the following three main areas.

First, most of the previous articles examined the first wave of the pandemic; hence, they covered the effects of introducing measures but not lifting or possibly reintroducing them. In contrast, this paper covers the period from the onset of the pandemic to the release of the vaccines, which allows more robust estimations. To this end, we use a sophisticated measure for lockdown policies that can also capture more granular differences across countries; hence, the results can provide a more detailed picture of the effects of these policies.

Second, while previous studies covered mainly individual countries, our sample is of wider scope: we seek to identify common patterns across 23 European countries. Since pandemics like the COVID-19 emergency will likely be more frequent in the future [11,12], our work can provide valuable information for decision-makers and system operators and can contribute to more effective reactions to mitigate similar situations in the future.

Third, the econometric approach, which we implement on this specific topic for the first time in the literature, allows more accurate estimation than that provided by other methods of the effects on the daily load curve. In addition, to control for seasonality and weather conditions, the model reliably predicts the nonlinear influence of intervention intensity on electricity consumption.

The article is organised as follows. Section 2 provides a short literature review, and Section 3 details the data and the methodology used. The results are presented in Section 4. Finally, Section 5 summarises the conclusions and their potential implications and limitations.

2. Literature review

Despite the short time elapsed since the outbreak of the COVID-19 pandemic, the number of country-level scientific analyses published on the relationship between the pandemic and electricity consumption is growing quickly. Early results in the literature were robust in finding that electricity demand decreased during the first wave of the pandemic [7,13]. Later, research interest turned to more focused questions. The topics of most of the studies can be classified into one or more of the following categories: (1) sectoral and regional differences in the response of electricity demand, (2) general patterns in the change in electricity demand, (3) benchmarking and improving the performance of country-level electricity demand forecasting models and algorithms, and (4) analyses that not only deal with demand but go one step further by examining more complex questions such as price responses and changes in market power or renewable energy production. The remainder of this section summarises the most important findings.

First, while overall electricity consumption has decreased, residential consumption may have increased by up to 30% in the US, China, Germany, India, and Italy [14]. This reflects the increased occupancy rate of residences. Similarly, in Australia, the stay-at-home order increased appliance use, but overall electricity consumption decreased, probably due to colder weather and reduced air conditioning usage [15]. Beyond such device usage patterns and temperature effects, Brazilian data suggest that there may be significant regional differences in the extent of the demand reduction due to the diversity of people's responses to the pandemic [16]. In the case of European countries, joint reporting platforms offer several opportunities for comparative analyses, leading to international studies taking a

primary interest in this region. Their main conclusions are that different COVID-19-related measures had different effects in each country [17,18].

Second, structural and behavioural changes in the economy are well illustrated by interday and intraday electricity consumption differences. For example, the pandemic pushed consumption to later days of the week in Ontario [19]. In addition, survey results (for New York [20] and Australia [15]) and actual consumption data (for Spain [21], Germany [22] and Italy [23]) show a flattening of intraday load curves, mainly due to the decline in the morning and evening peaks. Other studies estimate shared patterns between electricity demand and measurable predictors, e.g., spread of the disease or lockdown stringency index. These results provide useful general rules for high-level policy-making. For example, a 1% decrease in the effective reproductive number (i.e., a slowing spread of the disease) leads to a 1.62% decrease in electricity consumption loss (i.e., energy consumption deviates less from the business-as-usual scenario) [24]. The cumulative consumption decrease caused by the lockdown measures is estimated at between 3% and 12% for the US and 4% and 13% for the EU [4] and at 16.4% for the full lockdown periods in Kuwait [25].

Third, studies on the US and Germany verify that the number of confirmed cases, restraint rules, and commercial activities explain the decline in consumption well [24,26] and that these are excellent predictors in forecasting models [27,28]. Other papers compare the forecasting performance of different algorithms, including traditional econometric and/or machine learning methods [29–31].

Finally, as the mitigating measures significantly decreased electricity demand, changes on the supply side were required as well. It is crucial to evaluate how changing prices and tariffs affected social welfare. Decreasing demand should, *ceteris paribus*, lead to a decrease in prices; however, disruptions can lead to increasing market power of suppliers through grid congestions and decreasing amounts of flexible generating capacities. Suppliers' strategic behaviour and the ability to exercise market power depend on the local market structure. In the Iberian electricity market, although prices fell on average, the drop did not reflect the scale of the decline in demand [32]. In Italy, market power on both the demand and supply sides weakened during peak hours; however, for off-peak hours and emergency periods, the zonal Lerner index shows an increase in market power [33]. Somewhat surprisingly, renewable production has also been affected by the pandemic. The restriction stringency levels and number of daily confirmed deaths of COVID-19 had a significant adverse causal relationship with renewable electricity production in Denmark [27]. Other work has examined social welfare risks and the stability of distribution companies in Brazil, with the researchers finding that a credit line granted by the regulatory authority was successful in mitigating risks [34].

3. Methodology

This section first describes the energy consumption, government intervention, and weather data used in the research. Afterwards, it presents the applied panel econometric approach.

3.1. Data

The estimation is based on panel data starting at 12 am on January 1, 2019, and ending at midnight on December 31, 2020 and combining hourly electricity consumption, average temperature, and government stringency measure data for 23 European countries.

Hourly electricity consumption data were obtained from the Transparency Platform of the European Network of Transmission

Table 1

Descriptive statistics.

Variable	Obs.	Mean	St. dev.	Min.	Max.
Daily electricity consumption (MWh)	16,813	301,001	366,525	14,255	1,912,760
Government stringency index	16,813	23.8	29.9	0.0	96.3
Daily average temperature (°C)	16,813	11.0	7.9	−18.4	29.7

System Operators for Electricity (ENTSO-E) [35]. This is a comprehensive Europe-wide data source that has frequently been used in academic research, albeit with some shortcomings [36,37]. On the ENTSO-E interface, some European countries publish their data for every quarter of the hour, while others publish their data on an hourly basis. We aggregated quarter-hour consumption data to hourly frequency to consider all countries. Subsequently, countries for which the share of missing or zero consumption data exceeds 0.5 percent were removed from the database, leading to a reduction in the number of sample countries to 23. Finally, missing and zero consumption observations for the remaining countries were imputed through multivariate normal regression imputation.

Government measures related to the spread of COVID-19 were proxied using the government stringency index published as part of the Oxford COVID-19 Government Response Tracker dataset. This variable is measured on a 0–100 scale, where larger values indicate stricter government responses [38].

To control for exogenous variations in electricity consumption, we collected daily average temperature data from the NASA Power Data Access Database for all 23 countries [39]. Temperature is one of the most important determinants of short-term electricity consumption [40,41].

These data are available at the country level; therefore, they show the aggregated consumption of households and government and business entities. The analysis was executed separately for every hour of the day, but to reduce table size, we show daily averages in the descriptive statistics presented in Table 1. More detailed descriptive tables are available in the Appendix.

Government measures related to the pandemic did not change within a day; therefore, daily data can be used for every hour of a given day. In the case of temperature, we use the daily average temperature for every hour in the day. The rationale behind this choice is that heating and cooling are very important drivers of electricity consumption, but their usage depends on the average temperature over a longer time horizon (e.g., one or several days), not the actual temperature itself [42]. For example, if the temperature is above 25°C around noon in wintertime but air conditioners are not normally turned on, taking the actual temperature into consideration might bias our analysis.

Based on the descriptive statistics, electricity consumption differs primarily based on the size and population of the countries. The daily average temperature shows substantial differences across countries driven mainly by geographical location, while government restrictions show similar values across countries, with a mean of approximately 20–30 and a maximum of approximately 70–90 (on a scale of 0–100).

The database contains the following 23 EU countries: Austria, Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

3.2. Model

Hourly electricity consumption shows high volatility within a day. Therefore, we decide to estimate separate models for every hour of the day. In this way, it is possible to identify the effect of the lockdown measures on hourly consumption and estimate different effects within a day. This can shed light on how daily load profiles were altered during the pandemic.

The effects of the COVID-19-related measures might not be linear, as less severe restrictions (e.g., compulsory wearing of face masks on public transport) might not substantially alter citizens' lives and daily routine and, hence, their electricity consumption. Once everyday life is impacted heavily by restrictions (e.g., with closures of primary and secondary schools), citizens must re-organise their daily routines and activities, which can have a significant impact on their electricity consumption. Furthermore, restrictions on economic activities (e.g., mandatory closures of restaurants) can enhance this effect and reduce the consumption of corporations. To capture this nonlinearity of different stringency levels, we apply a quadratic specification for the stringency index. This choice is supported by findings in prior literature [4].

In the case of temperature, previous literature [43–47] suggests that its effect is nonlinear, as both heating and cooling require a significant amount of energy. A quadratic relationship can also be assumed in this case, but we apply a more flexible approach and create 5°C bins, similarly to Deschênes and Greenstone [43].

Based on the abovementioned considerations, the resulting empirical model is as follows:

$$\ln(E_{it}) = \alpha + \beta_1 GovStringency_{it} + \beta_2 GovStringency_{it}^2$$
$$+ \sum_j \gamma_j Temp_{itj} + D_t + Year_t + c_i + u_{it},$$

where E_{it} represents electricity consumption in a given hour in country i on day t, $GovStringency_{it}$ is the value of the government stringency index in country i on day t, $Temp_{itj}$ represents the temperature dummy variables taking the value of 1 if the daily average temperature was in the jth bin in country i on day t and 0 otherwise, D_t is the day-of-week fixed effect, $Year_t$ is the year fixed effect (for 2019 and 2020), c_i is the country fixed effect, and u_{it} is the idiosyncratic error term.

Different panel model approaches are available to estimate this equation. One of the most critical problems, endogeneity, does not arise in this case, as all the variables are predefined; hence, neither simultaneity nor reverse causality can emerge in this case.

However, due to the relatively long panel coverage (731 days) and the fact that hourly electricity consumption is similar on subsequent days, autocorrelation cannot be ignored. Traditional panel methods were developed for panels containing a large number of cross-sectional observations and only a few time periods. In the current case, the time dimension is substantially larger than the number of countries involved; therefore, autocorrelation might be observable in the error term. Additionally, due to the differences in electricity consumption volumes across the 23 countries analysed, the error term is likely heteroscedastic.

Furthermore, in the case of energy markets, cross-sectional dependence is receiving increasing attention. Since this study focuses on the European energy market, where market integration is already high and national networks are connected to each other, cross-sectional dependence in the error term cannot be ignored [48].

These problems are commonly addressed in prior literature by estimating feasible generalised least squares (FGLS) regressions [8–10,49–53]. The FGLS method can account for first-order

serial correlation, heteroscedasticity, and cross-sectional correlation in the error term. Since the FGLS method does not require demeaning or first-differencing the data, time independent variables can also be estimated with this method. However, to account for time and country fixed effects, we use the least squares dummy variable approach and add year and country dummy variables to the regression model, as shown in the equation above. Therefore, the applied FGLS model is a standard least squares dummy variable model with a specific error term structure. Since in this case, N (the number of countries) is fixed and T (the number of time periods) tends to infinity, the estimation procedure is less complicated, as the individual time series make it possible to estimate cross-sectional covariances and autocorrelation. This FGLS estimator is consistent and asymptotically normally distributed; hence, the usual test statistics can be applied [54].

Finally, considering the very different electricity load patterns on weekdays and weekends, we estimate two sets of models, one for weekdays (Monday to Friday) and one for weekends (Saturday and Sunday). Since different models are estimated for every hour of the day to capture the changing electricity consumption patterns within the days, 48 models are estimated.

4. Results

4.1. Changes in electricity load curves

Electricity consumption was significantly altered in 2020 in comparison to that in 2019 (Fig. 1). The first wave of the pandemic (i.e., the springtime of 2020) showed very large consumption variations relative to the levels in the previous year. The difference decreased substantially in the summer period, and electricity consumption recovered to the pre-pandemic level in line with the partial elimination of the restrictions, while it started to slowly increase as an increasing number of countries reintroduced restrictions in the second wave of the pandemic. However, the second wave demonstrated much lower changes in consumption patterns, which might be due to the gradual introduction of the restrictions and the political focus on maintaining economic activities.

4.2. Panel regression estimates

The previous subsection indicated that government measures likely impacted electricity load curves. Panel regressions were applied to verify the causal effects. The aim of our research is to identify general patterns across EU countries and, at the same time, allow as much flexibility as possible to capture the real effects of the restrictions. Therefore, we decided to estimate 24 models for the 24 hours of the day, as the effect of the restrictions on the electricity load curve is likely not homogeneous [21–23].

Due to the significant number of parameters estimated, the results are presented in the Appendix, and Table 2 shows the most important estimates only. The effect of the parameters of interest, COVID-19-related restrictions, is generally negative and significant but not in all cases. In the weekday subsample, the results indicate a decreasing effect between 12 am and 4 am; i.e., a low level of restrictions led to a decrease in energy consumption, but introducing stringent government measures did not alter consumption afterwards. For other parts of the day, the negative effect is often not linear, meaning that stricter government measures disproportionately decreased electricity consumption. Finally, in a small number of cases, neither the linear nor the quadratic terms are individually significant. However, the Wald F test assessing the joint significance of the stringency index and its squared term shows highly significant results in all cases, indicating that COVID-19-related government measures impacted electricity demand in every hour of the day. Therefore, we decide to use the point estimates for calculating partial effects and the estimated load curves.

Table 2
Regression results for the government stringency index.

Hour of the day	Weekday		Weekend	
	Government stringency index	Square of government stringency index	Government stringency index	Square of government stringency index
0.00–0.59	−0.000892*** (0.000202)	0.000004** (0.000002)	−0.000869*** (0.000233)	0.000000 (0.000002)
1.00–0.59	−0.001102*** (0.000209)	0.000006*** (0.000002)	−0.000906*** (0.000238)	0.000000 (0.000002)
2.00–2.59	−0.001165*** (0.000212)	0.000007*** (0.000002)	−0.000784*** (0.000250)	−0.000001 (0.000002)
3.00–3.59	−0.001143*** (0.000217)	0.000007*** (0.000002)	−0.000771*** (0.000236)	−0.000002 (0.000002)
4.00–4.59	−0.001095*** (0.000222)	0.000006** (0.000002)	−0.000954*** (0.000241)	0.000000 (0.000003)
5.00–5.59	−0.001061*** (0.000247)	0.000003 (0.000002)	−0.001191*** (0.000251)	0.000002 (0.000002)
6.00–6.59	−0.000781*** (0.000289)	−0.000002 (0.000003)	−0.00089*** (0.000255)	−0.000001 (0.000003)
7.00–7.59	−0.00054* (0.000319)	−0.000004 (0.000003)	−0.000528** (0.000258)	−0.000006** (0.000003)
8.00–8.59	−0.000357 (0.000316)	−0.000005* (0.000003)	−0.000349 (0.000256)	−0.000009*** (0.000003)
9.00–9.59	−0.000291 (0.000302)	−0.000006* (0.000003)	−0.000334 (0.000254)	−0.000009*** (0.000003)
10.00–10.59	−0.000179 (0.000295)	−0.000007** (0.000003)	−0.000298 (0.000261)	−0.000011*** (0.000003)
11.00–11.59	−0.000249 (0.00029)	−0.000006* (0.000003)	−0.000291 (0.000271)	−0.000009*** (0.000003)
12.00–12.59	−0.00019 (0.000294)	−0.000006** (0.000003)	−0.000376 (0.000281)	−0.000007** (0.000003)
13.00–13.59	−0.000257 (0.000299)	−0.000006* (0.000003)	−0.000395 (0.000282)	−0.000006** (0.000003)
14.00–14.59	−0.000284 (0.000304)	−0.000005* (0.000003)	−0.000267 (0.000293)	−0.000007** (0.000003)
15.00–15.59	−0.000221 (0.000313)	−0.000007** (0.000003)	−0.0002 (0.000309)	−0.000008** (0.000003)
16.00–16.59	−0.000142 (0.000316)	−0.000007** (0.000003)	−0.000194 (0.000334)	−0.000008** (0.000003)
17.00–17.59	−0.000439 (0.000312)	−0.000005* (0.000003)	−0.00053 (0.000331)	−0.000004 (0.000003)
18.00–18.59	−0.000237 (0.000296)	−0.000007** (0.000003)	−0.00041 (0.000327)	−0.000006* (0.000003)
19.00–19.59	−0.000528* (0.000271)	−0.000003 (0.000003)	−0.000525* (0.000293)	−0.000004 (0.000003)
20.00–20.59	−0.000756*** (0.000242)	0.000001 (0.000002)	−0.00079*** (0.000248)	0.000000 (0.000002)
21.00–21.59	−0.000648*** (0.000213)	0.000000 (0.000002)	−0.000872*** (0.000219)	0.000002 (0.000002)
22.00–22.59	−0.000638*** (0.000195)	0.000001 (0.000002)	−0.000735*** (0.000209)	0.000001 (0.000002)
23.00–23.59	−0.000706*** (0.000199)	0.000001 (0.000002)	−0.000803*** (0.000225)	0.000001 (0.000002)

Standard errors (robust for serial correlation, heteroscedasticity, and cross-sectional correlation) are in parenthesis.
*p < 0.1.
**p < 0.05.
***p < 0.01.

4.3. Panel regression results for weekdays

The regression results indicate that the daily average temperature has a nonlinear effect on electricity consumption. Compared to the consumption associated with the reference category of 10–15°C, electricity consumption is significantly higher if the temperature is lower. If the daily average temperature is below −10°C, consumption is *ceteris paribus* larger by 2%–6% depending on the hour of the day. If the temperature is approximately 0°C, this increase is only approximately 1%–2%. When the daily average temperature is above the reference category, first, we can see a significant but moderate (less than 1%) decline in consumption. However, when the daily average temperature is above 25°C, we
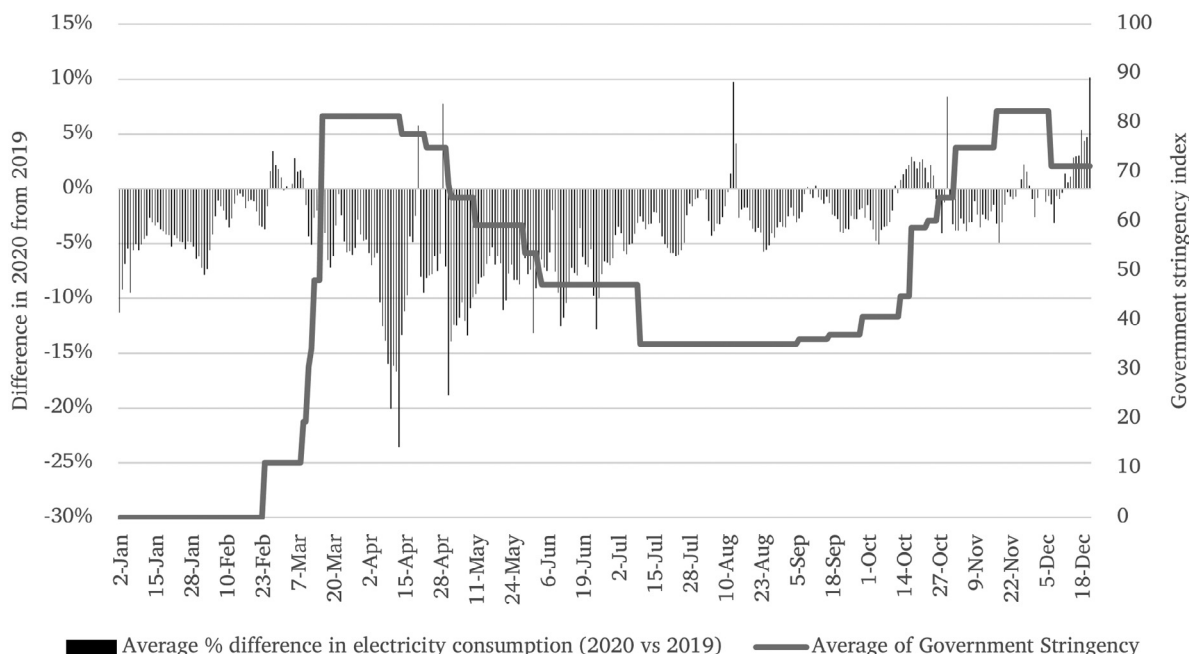
Fig. 1. Average percentage difference in electricity consumption in 2020 and 2019 and the level of the government stringency index. *Notes:* Average percentage difference is the average of the hourly consumption differences of the 23 countries considered: $\sum_i \sum_h \frac{con_{i,h,t,2020} - con_{i,h,t,2019}}{con_{i,h,t,2019}} / (\sum i + \sum h)$, where $con_{i,h,t,2019}$ refers to electricity consumption in country i in hour h in day t in 2019.

can also observe an increase in electricity consumption of up to 2.5%. These results are in line with those in prior literature [43–47], confirming that heating and cooling require a significant amount of additional energy that leads to a consumption rise.

Since the government stringency index has a quadratic effect on electricity consumption, we illustrate both the partial effects and the estimated load curves using visualisation. The partial marginal effect (PME) of the stringency index, showing the change in electricity demand if the index increases by 1 unit, depends on both the hour of the day and the starting index value (Fig. 2).

The PME behaves differently during different periods of the day. From midnight to 6 am, the PME is stronger at lower stringency levels. When the stringency index is 0, a one-point increase in stringency decreases hourly electricity consumption by between 0.08% and 0.12%. However, if the one-point increase occurs from a higher initial stringency level, the partial electricity consumption change is lower, and there is no significant decrease if the starting level of stringency is very high (above 75). Between 8 am and 6 pm, the PME is stronger at higher stringency levels. At maximum stringency, the value of the PME is between −0.13% and −0.16%,[1] while at 0 stringency, it is between −0.01% and −0.05%, in some cases more than 10 times lower. This result clearly reinforces that stricter government measures disproportionately reduce electricity consumption during the daytime. Between 7 pm and 12 am, the partial effects are largely identical (between −0.05% and −0.11%), regardless of the initial level of the stringency index.

To summarise the weekday PME characteristics, we can conclude the following.

- At low levels of the stringency index, the partial (decreasing) effect on electricity consumption is larger in mornings and evenings and is weaker during the daytime.

- At medium levels of the stringency index, the partial (decreasing) effect is rather flat during the whole day (between −0.10% and −0.04%).
- At higher levels of the stringency index, the partial (decreasing) effect is very strong in working hours, is moderate in the evening, and is low or even insignificant at dawn and in the early morning.

Although the PMEs do not seem to be particularly substantial in magnitude, since the government stringency index ranges from 0 to 96.3, the marginal effects add up to rather substantial differences in electricity consumption. Fig. 3 illustrates how the average load curve was altered at different levels of the government stringency index (for better comparability, we rescale the cross-country average predicted consumption of the 23 EU countries to have a maximum of one). Fig. 4 explicitly shows the estimated change in consumption due to COVID-19-related restrictions. The consumption decrease is low during the night and in the early hours of the day. In working hours, the differences are higher, and the effect size also grows as the restrictions become more stringent. The highest estimated difference in consumption between a stringency index level of 0 and 100 is −8.2%, which is a substantial reduction.

Considering total daily electricity consumption, we can observe a 1%, 3%, 5% and 7% decrease from the level in the no-restriction case if the stringency index is 25, 50, 75 and 100, respectively.

4.4. Panel regression results for weekends

Analysing the weekend subsample, the effect of temperature is much more substantial than its effect on weekdays. When the daily average temperature is very low (below −10°C), electricity consumption is 10% to 20% higher than that of the reference category (10–15°C). The direction of the change is, however, similar to what is observable on weekdays. When the daily average temperature rises, electricity consumption *ceteris paribus* decreases. When the daily average temperature is approximately 0°C, the

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[1] Since the stringency index cannot go above 100, the partial effect is one sided here: only a one-point decrease in the index is meaningful.
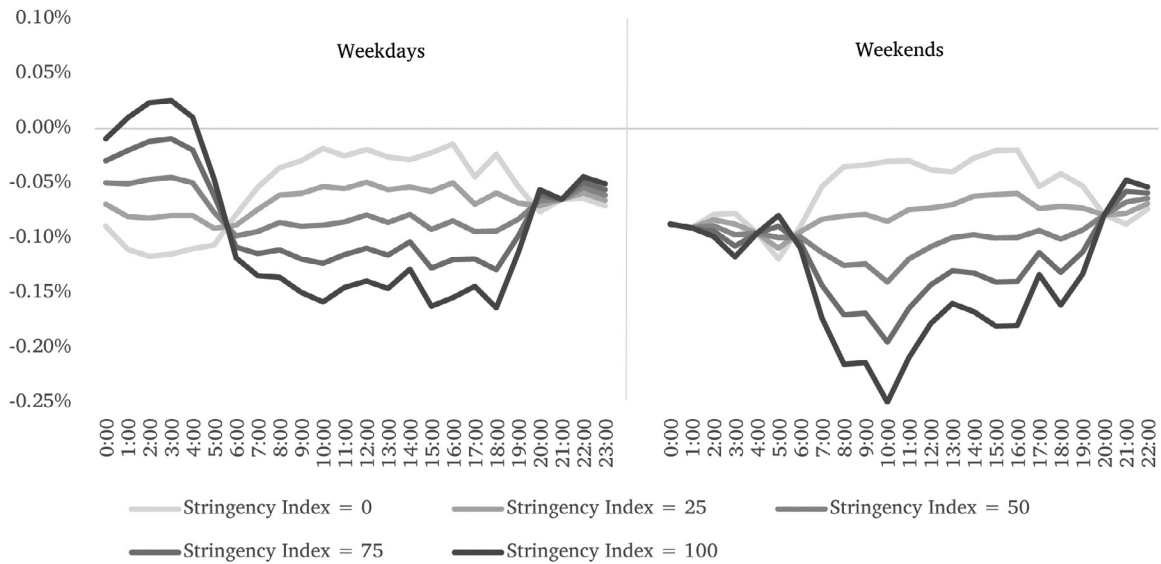
Fig. 2. Partial effects of a 1-unit increase in the government stringency index on daily load curves.
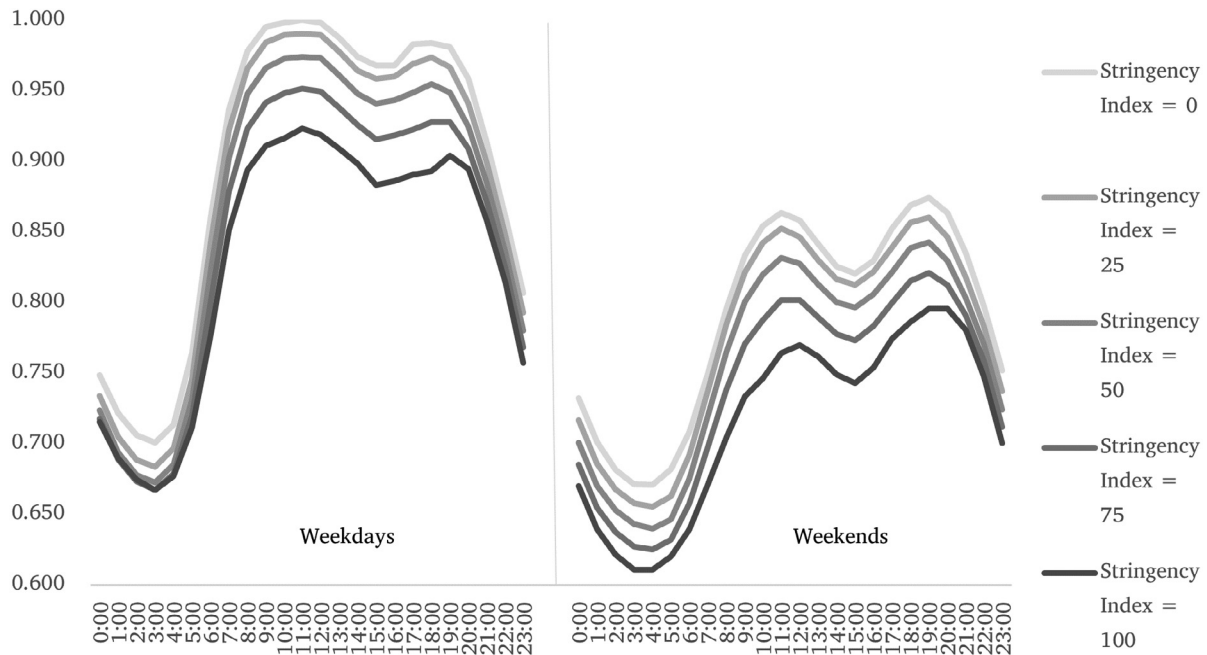

Fig. 3. Average daily load curves under different levels of the government stringency index (rescaled).

increase in electricity consumption over that in the reference category is of between 2% and 10%. Once the temperature is between 15°C and 25°C, electricity consumption is approximately 1% lower than that of the reference category.

The effect of the government stringency index is shown using the same figures as for weekdays. The PME shows stronger effects as the stringency index increases during the daytime (Fig. 2). There is a rather substantial difference in the PME between lower and higher stringency levels. The strongest PME on weekends at maximum stringency is −0.25% (at 10 am), while the weakest at minimum stringency is −0.02% (at 4 pm). The midday effect of the restrictions is more or less similar to what is observed for weekdays. The partial effect is higher when stringency increases. In contrast, the effects at earlier and later hours are different.

To summarise the weekend PME characteristics, we can state the following.

- Between 8 pm and 6 am, the effect of the initial stringency level is not determinant, and an increase in stringency leads to a similar decrease in the level of electricity consumption regardless of the measures already in place.
- During the daytime, very substantial nonlinear effects are observable, meaning that the starting level of the stringency index is crucial. When the starting level is already high, further measures lead to larger marginal decreases in electricity consumption than those observed when the starting point is lower.

During weekends, the consumption change increases when the stringency index is higher and generally becomes more balanced throughout the day (Fig. 3). Hence, the flattening of the daily load curve is not as substantial as the one that we observe
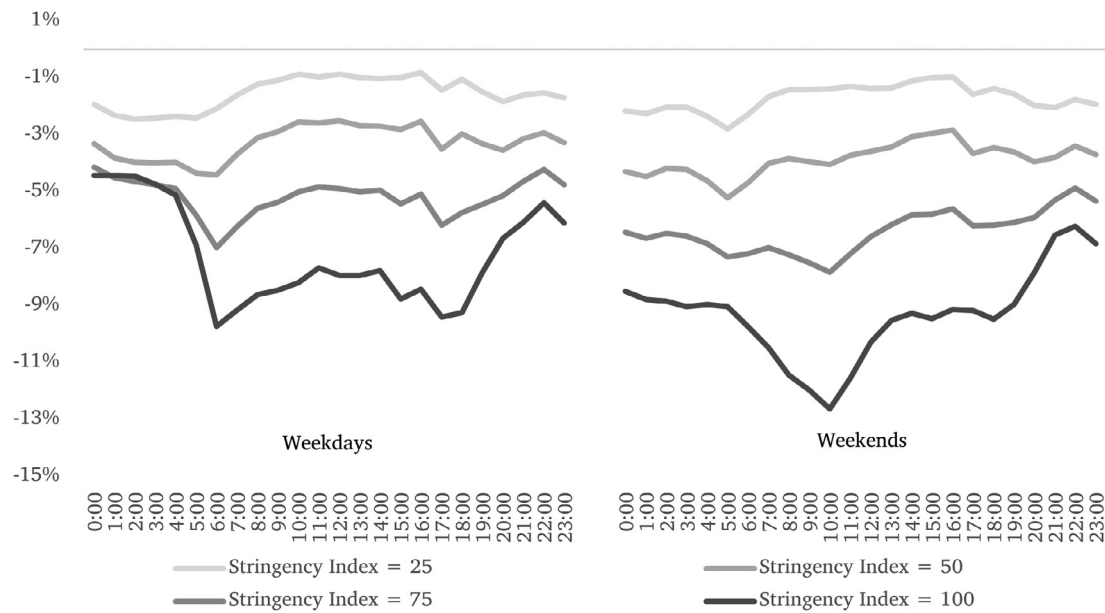
Fig. 4. Estimated consumption decrease relative to the level with no COVID-19-related restrictions (stringency index = 0).

for weekdays. However, a higher decreasing effect in the forenoon peak (−13%) develops as the stringency index increases (Fig. 4).

Taking total daily electricity consumption into consideration, we can observe a 2%, 4%, 6% and 9% decrease from the level in the no-restriction case if the stringency index is at 25, 50, 75 and 100, respectively.

5. Conclusions

This paper examined the impact on intraday electricity consumption of measures initiated to reduce the spread of COVID-19 in 23 European countries. The database used covers the entire period from the outbreak of the disease in Europe until vaccines became available, i.e., the first introduction of the measures, their partial lifting and their reintroduction in the second wave of the pandemic. In our panel econometric approach, in addition to controlling for weather and calendar effects, we estimated separate regressions for every hour of the day using FGLS methodology.

Our results confirmed that common patterns, considered a consequence of government interventions, are observable in daily electricity load curve changes in the 23 European countries.

Government interventions affected load curves in the same way that we have seen in single-country analyses [21–25], indicating that it is worth taking a wider geographical approach and considering related markets together. These general patterns consist of declining evening and morning peaks, hence showing a flattening of the curve. The effects are nonlinear and differ across hours of the day and between weekdays and weekends. The flattening of the load curve is more powerful on weekdays, but the decrease in consumption is larger on weekends. This is because a larger difference is observable in the marginal effects between peak and off-peak hours on weekdays.

Overall, lockdown measures led to a decrease in hourly electricity consumption of between 1% and 9% on weekdays and 1% and 13% on weekends, depending on the level of the stringency measures and the hour of the day. Total daily consumption decreased by up to 9%, which is rather substantial. Based on our analysis, EU countries show similar patterns; therefore, it is worth considering the EU electricity market as a whole in evaluating the effects of stringency measures.

The results have some key policy implications. Since electricity demand decreased substantially while the stringency measures were in force, electricity producers and transmission system operators should be aware of this. Capacity planning requires substantial adjustments compared to the baseline scenario that requires flexibility in production and transmission system management. A more flexible operation can also be valuable in managing renewable energy sources [21]. Furthermore, power plant operation and maintenance schedules can also be modified as lower demand requires less production capacities. System operators and energy producers should create resilience plans to quickly address the challenges as it was proposed by other researchers, too [55,56]. These plans should be executed already at the introduction of the stringency measures to mitigate the impact and to provide more accurate demand forecasts to avoid extreme market mismatches and price spikes.

Additionally, our results verified the nonlinear impact of stringency measures on electricity demand. The evidence of nonlinear effects supports the assumptions that different restriction measures (e.g., stay-at-home recommendations and school closures) may mutually amplify each other's impact. This indicates that less stringent measures or a more gradual introduction of the measures can provide more time for system operators and electricity producers to adjust their operations to the more substantial changes [24]. Therefore, governments should seek to optimise the severity of their measures. Even a marginally less restrictive measure can have a significantly lower effect on electricity consumption and therefore probably on business actors, citizens, and GDP growth.

Finally, we can conclude that the intensity of the interventions had a similar effect on the load curves in all 23 European countries considered. That is, most citizens and companies, regardless of the country in which they are located, seem to have responded similarly to the restrictions. The universality of the effects is promising because it suggests that lessons learned from the evaluation of COVID-19 interventions will be useful in future pandemics [11,12] or other crises requiring similar measures. A possible reason for the identified relationship is that EU countries have similar cultural and developmental roots, and their energy markets are connected to each other. Analysing the effects

in more heterogeneous regions is a promising area for future research.

CRediT authorship contribution statement

Zombor Berezvai: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Olivér Hortay:** Conceptualization, Validation, Data curation, Writing – original draft. **Tamás Szőke:** Conceptualization, Validation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Olivér Hortay is the Head of Energy and Climate Policy Division at Századvég Gazdaságkutató Zrt. (a policy think tank). The other authors have no competing interests.

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Appendix A. Supplementary data

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