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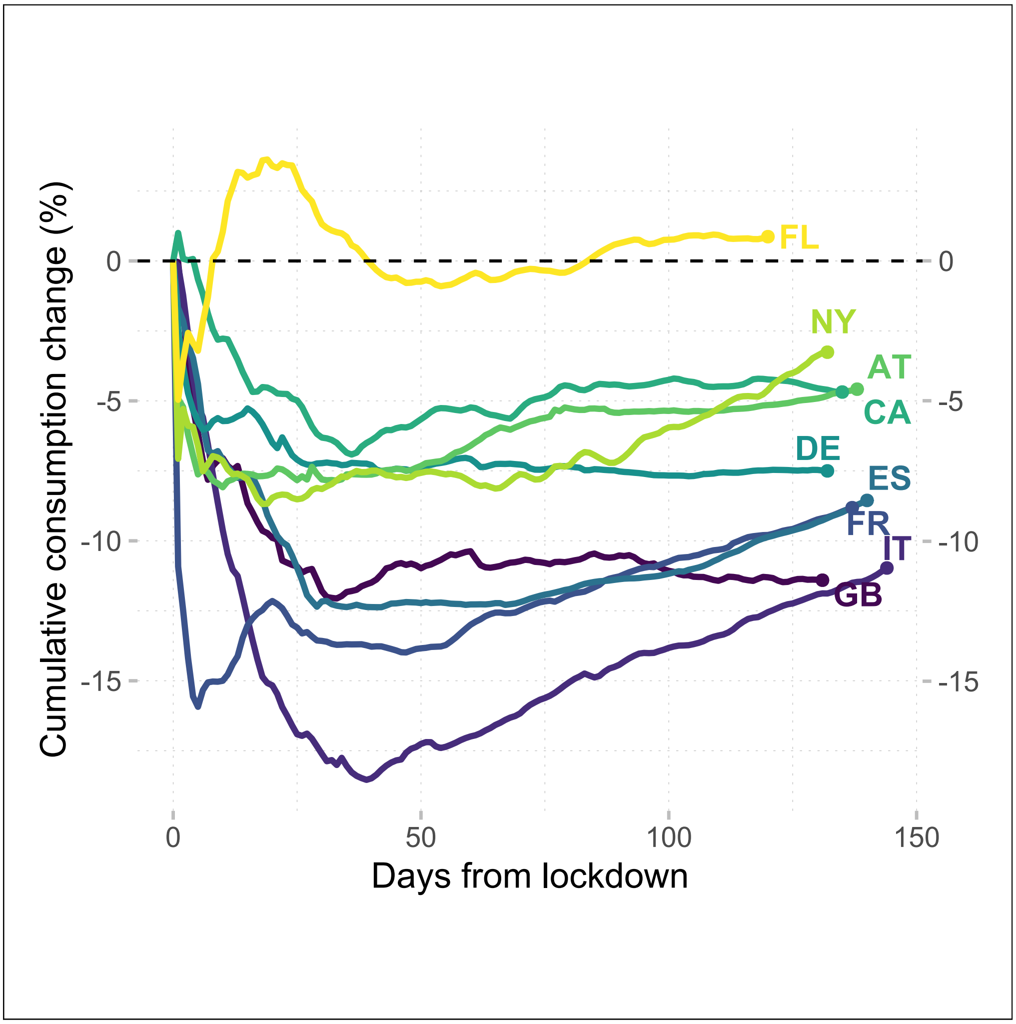

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HIGHLIGHTS

COVID-19 measures decreased electricity consumption by 3%–12% in 5 months

Most countries/states have recovered baseline levels by the end of July

Measures stringency and consumption decline are directly and non-linearly linked

Counterfactual daily electricity consumption is provided

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Impact of COVID-19 Measures on Short-Term Electricity Consumption in the Most Affected EU Countries and USA States

Javier López Prol PhD[1,3,*] and Sungmin O PhD[2]

SUMMARY

As COVID-19 spreads worldwide, governments have been implementing a wide range of measures to contain it, from movement restrictions to economy-wide shutdowns. Understanding their impacts is essential to support better policies for countries still experiencing outbreaks or in case of emergence of subsequent pandemic waves. Here we show that the cumulative decline in electricity consumption within the 5 months following the stay-home orders ranges between 3% and 12% in the most affected EU countries and USA states, except Florida, which shows no significant impact. Italy, France, Spain, California, Austria, and New York have recovered baseline consumption by the end of July, whereas Great Britain and Germany remain below baseline levels. We also show that the relationship between measures stringency and daily decline in electricity consumption is nonlinear. These results illustrate the severity of the crisis across countries and can support further research on the effect of specific measures.

INTRODUCTION

From social distancing guidelines to strict lockdowns and paralyzation of non-essential economic activity, governments worldwide have taken a wide range of measures to halt the spread of the COVID-19 pandemic (Hale et al., 2020a). These measures have multiple implications. Global CO_2 emissions decreased by 17% during forced confinements (Le Quéré et al. 2020), and global GDP is expected to decline by 3% in 2020 as a result of the pandemic (IMF, 2020a). The economic contraction in advanced countries will double the world average, and it could be as high as 9% in the most affected countries, such as Italy. As an illustration, the strongest impact of the 2003 SARS coronavirus epidemic was in China and Hong Kong with GDP losses of 1.1% and 2.6%, respectively, and a global GDP decline of less than 0.1% (Lee and McKibbin, 2004). Given the unprecedented nature of this crisis, governments are uncertain about the economic impacts of the implemented measures (IMF, 2020b). The unfolding outbreaks in other countries (World Health Organization, 2020) beyond the ones studied here and the potential emergence of subsequent pandemic waves (Kluge, 2020) reveal the urgency to improve our knowledge about the potential impacts of the containment measures.

Given the relationship between electricity consumption and GDP (Hirsh and Koomey, 2015) and the real-time availability of electricity consumption data, analyzing the evolution of electricity consumption may serve as an early warning indicator to assess the impact of containment measures on overall economic activity. Early attempts to track the evolution of electricity consumption during the pandemic have been made by the Bruegel institute (McWilliams and Zachmann, 2020), which provides information on temperature-adjusted peak-hour electricity consumption in European countries compared with the previous year. There are also studies assessing early impacts in the United States (Agdas and Barooah, 2020) and Europe (Cicala, 2020). The International Energy Agency provides a broader analysis of the impact of COVID-19 on the energy sector (IEA, 2020), and Gillingham et al., 2020 estimate the short- and long-term impacts on energy and the environment in the United States. Several media outlets have also provided information on the fall of electricity consumption in different countries compared with previous years' weekly or monthly averages (Morison, 2020; Bui and Wolfers, 2020). Most recently, Ruan et al., (2020) estimated the impact of COVID-19 on electricity consumption in the United States. Our studies concur in providing a counterfactual baseline estimation but differ in the input data, estimation method, and spatial coverage and resolution.

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Given that electricity consumption is determined by many factors such as temperature, trends, seasonal cycles, calendar effects, and short-term dynamics (Fan and Hyndman, 2012), ignoring such factors would bias the results (See Figure S14). Additionally, the resulting data and a reproducible method should be publicly available to support further research. For these reasons, we forecast baseline daily electricity consumption in a counterfactual "business as usual" scenario in which COVID-19 did not take place and then compare the forecast with actual electricity consumption in the nine most impacted European countries and USA states. We estimate daily electricity consumption with country-specific dynamic harmonic regressions with Fourier terms for complex seasonality, quadratic temperature, and calendar effects (Hyndman and Athanasopoulos, 2018). This allows us to build a reliable counterfactual baseline scenario with test accuracy ranging between 2.7% and 4.6% mean average percentage error (see Tables S1–S9), which is within the range of the 1-day ahead forecast accuracy benchmark set in the literature (Jun and Ergün, 2011). We have evaluated the most widely used time series forecast methods and opted for the dynamic harmonic regression as it provides the best accuracy results and lowest spread across countries (see Transparent Methods in the Supplemental Information for details).

Our approach enables a reliable estimation of counterfactual baseline electricity consumption against which to compare actual data. We analyze the decline in electricity consumption in the most affected European countries and USA states and link it with the stringency of the measures taken to contain the pandemic. We find that all the studied countries/states, except Great Britain and Germany, have recovered baseline electricity consumption by the end of July 2020. Furthermore, we reveal the non-linear relationship between the stringency of the containment measures and the decline in electricity consumption. This could entail that moderate measures may have only a small effect on electricity consumption and thus economic activity. Moreover, data and code used for our analysis are publicly available so the estimation can be extended to other countries/states and support further research on the effect of specific measures, the evolution of economic activity or the relationship with other high-frequency indicators.

RESULTS

Electricity Consumption Decline

Figure 1 shows the cumulative change in electricity consumption since the lockdown/stay-home order in each country/state until the end of July 2020. The severity of both the outbreaks and the lockdown and complementary measures taken by governments to halt the COVID-19 spread differ widely across countries, and therefore the electricity consumption evolution also varies. Most of the studied countries have experienced a negative cumulative impact of between 3% and 12% within the 5 months following the start of the crisis, except Florida, which has not suffered a significant negative impact with respect to the baseline scenario.

Figure 2 provides greater detail for each particular country/state, presenting the daily percentage change in electricity consumption compared with the expected counterfactual baseline (see Figure S4) for the actual and forecast electricity consumption in absolute terms. Countries are sorted and colored (darker to lighter) according to the cumulative impact during the study period as shown in Figure 1. The dates of the national/state-wide lockdowns/stay-home orders are indicated on each of the panels by vertical dotted lines. Additionally, for Italy and Spain, where there was a shutdown of non-essential economic activity, subsequent vertical dotted lines indicate the date of the beginning of the shutdown and the progressive re-opening of economic activity.

The stringency and scope of these measures differ widely across countries. For instance, Italy issued the first lockdown affecting 50,000 people already on February 21. It was extended to Lombardy and other 14 northern provinces on March 8 and finally to the whole country from March 10. Likewise, measures were implemented at different times and scales in the different German federal states. Other countries, such as France and Spain, implemented the lockdown homogeneously across the country.

Italy and Spain are particularly interesting as three phases are identifiable: (1) a first lockdown phase, (2) a second phase of non-essential economic activity shutdown, and (3) a subsequent progressive re-opening of economic activities. During the non-essential economic activity shutdown, daily electricity consumption declined on average 29% daily in Italy and 21% in Spain compared with the baseline. Electricity consumption started recovering in Italy and Spain with the progressive re-opening of economic activities and reached baseline levels by the end of July.

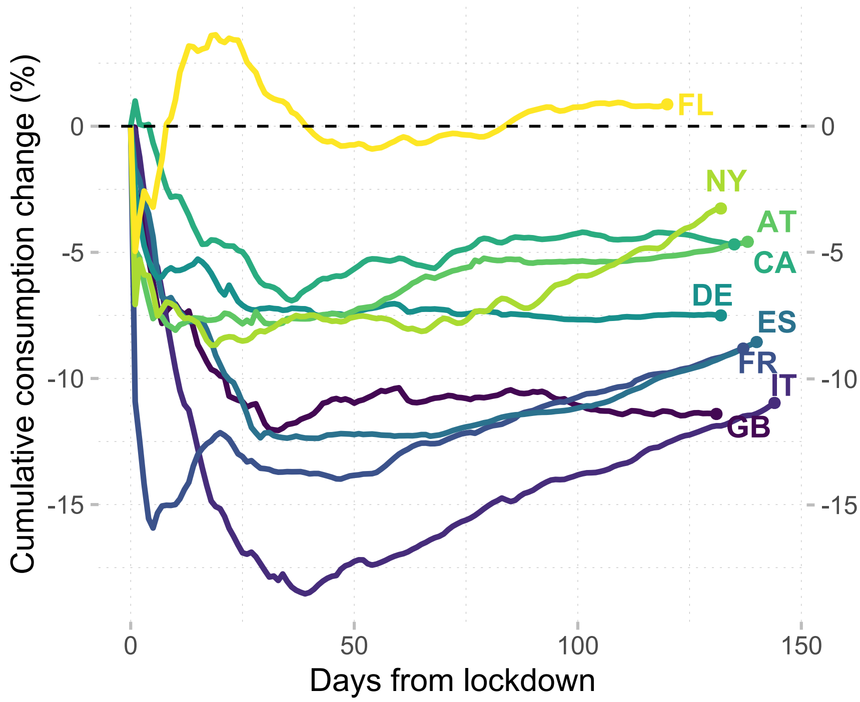

Figure 1. Impact Curve Flattens in Most Countries in About a Month After the Start of the Lockdown/Stay-Home Orders

Lines represent the cumulative change in electricity consumption compared with the forecast baseline levels. Country codes: FL, Florida; NY, New York; AT, Austria; CA, California; DE, Germany; ES, Spain; FR, France; IT, Italy; GB, Great Britain.

Great Britain experienced the strongest cumulative decline in electricity consumption of 11.4%. Whereas the initial impact was not as strong as in other countries such as Italy or France, electricity consumption in Great Britain has consistently remained below baseline levels and shows no sign of recovery. Conversely, France experienced an instant 20% decline with the beginning of the lockdown but has already recovered baseline electricity consumption. The European countries that experienced a stronger decline in the first weeks (Italy, France, and Spain) have recovered faster than those with lower initial declines (Germany and Great Britain). These results could suggest that stronger initial action reduces the duration of the shock. Austria lies between these two types of impacts, with an initial impact of −10% that recovers in 2 months, followed by a slight relapse in June that recovers again in July.

Generally, the impact of COVID-19 measures on electricity consumption has been lower and the recovery faster in the studied USA states than in the European countries. Variability in the estimates is also higher in the USA states, perhaps owing to the presence of confounding factors such as the protests at the end of May–beginning of June. Florida did not even experience a net negative impact.

Measures Stringency

The depth of the consumption decline is directly related to the stringency of the containment measures. The stringency index, estimated by the Coronavirus response tracker (Hale et al., 2020a, 2020b), is composed of nine policy response indicators ranging from information campaigns to movement restrictions (see Supplemental Information for full list). Each of these individual indicators is measured in an ordinal scale depending on stringency (e.g., whether a measure is only a recommendation or an obligation) and scope (i.e., whether the measure is general or targeted to a specific group or region). The stringency index aggregates each of these rescaled individual indicators to reach a score between 0 and 100 (see Figure S3).

Figure 3 shows the relationship between the daily drop in electricity consumption (Figure 2) and the stringency of the COVID-19 measures. The dots represent the drop in electricity consumption and the stringency index for each day and country/state during the study period, and the solid black line represents

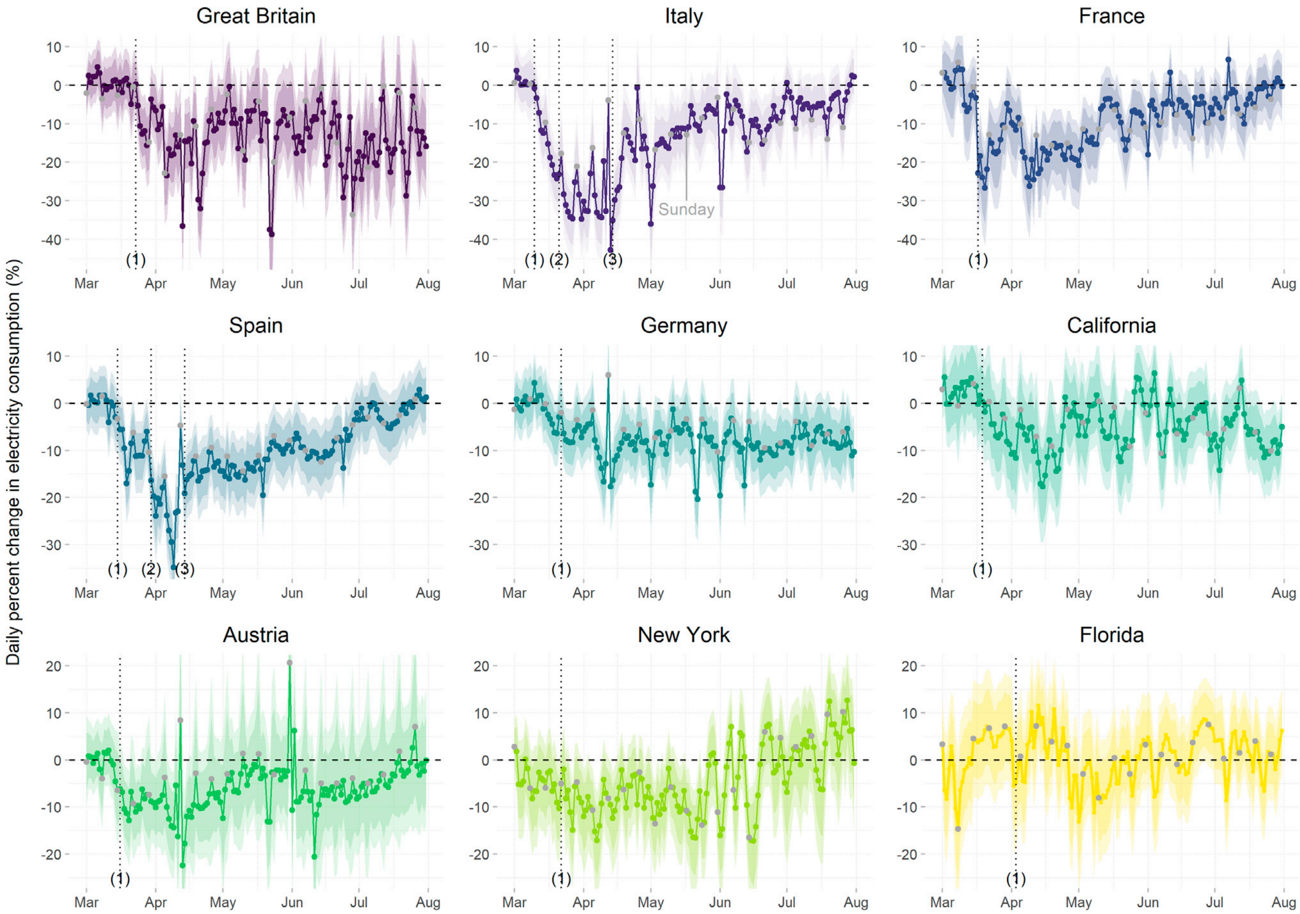

Figure 2. Different Containment Measures Across Countries Led to Different Impacts on electricity Consumption

Solid lines show the daily percentage change in electricity consumption. Dark and light shades indicate 80% and 95% prediction intervals, respectively. Sundays are colored gray. Vertical dotted lines indicate the start of (1) lockdown/stay-home orders, (2) non-essential economic activity shutdown, and (3) progressively resuming non-essential economic activity. Note that vertical axis ranges are different for each row. See Supplemental Information for details and Figure S4 for absolute values.

the relationship between both variables. The country codes represent the median value for each of the countries during this period, revealing that the stronger the stringency, the higher the electricity consumption decline. The non-linear shape of this relationship suggests that moderate measures may have a small impact on electricity consumption and thus economic activity. Although this is only a high-level illustration, as more data are generated on both the evolution of the stringency across countries and the evolution of electricity demand, these two measures will reveal the impact of the different COVID-19 measures on electricity consumption and therefore on economic activity.

DISCUSSION

We estimate the impact of COVID-19 containment measures on electricity consumption by comparing the counterfactual baseline "business as usual" consumption forecast with actual data. We have identified large differences across countries/states, from cumulative contraction beyond −10% in Great Britain and Italy to no net negative impact in Florida. Italy, France, Spain, California, Austria, and New York have recovered baseline consumption levels within 5 months since the first outbreak, whereas Great Britain and Germany remain below baseline levels. If this situation persists after all containment measures are lifted, this could reveal either a structural impact on economic activity or a structural change in the relationship between GDP and electricity consumption.

There are multiple mechanisms through which this short-term shock could have structural economic effects. From the demand side, the immediate effects of the social distancing measures may disrupt

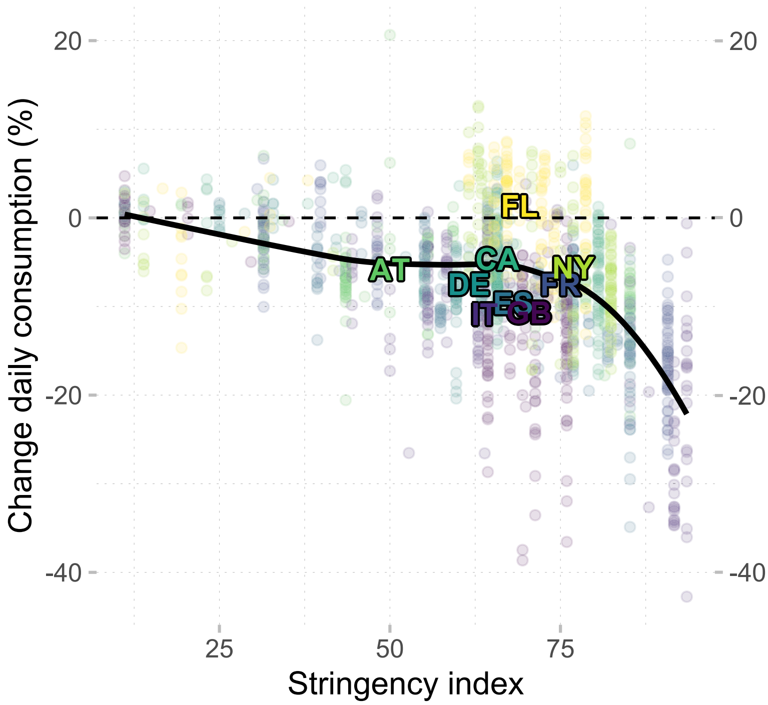

Figure 3. The Stronger the Measures Stringency, the Greater the Consumption Decline
Each dot represents the daily electricity consumption change and stringency index for each country. The country codes indicate the median values for each country. The black line represents the relationship between electricity consumption and stringency.

businesses that rely on personal interaction (Koren and Peto, 2020). From the supply side, halting non-essential activities may have propagation effects across the supply chain to other regions and sectors (Inoue and Todo, 2020). An increase in uncertainty, such as the one caused by this pandemic (Baker et al., 2020), affects both demand by lower consumer spending and supply by lower investment and capital formation. The labor market could also be a transmission mechanism as the crisis affects mostly workers that need a long time to be employable again (Gregory et al., 2020). Finally, a financial mechanism through which higher private and public indebtedness slows down potential long-term growth could also come into play (Dar and Amirkhalkhali, 2014; Cecchetti and Zampolli, 2011).

If the economic contraction caused by the COVID-19 measures turns out to be L-shaped for some countries, this would contrast with previous epidemics that have generally caused transient V-shaped shocks (Carlsson-Szlezak et al., 2020), revealing the unprecedented nature of this crisis and the urgent need for further research to understand the implications of the pandemic and the measures taken by governments to contain its spread. The counterfactual baseline electricity consumption data provided here are publicly available (see below repository link) and can thus help in that direction by providing an estimate of the drop in electricity consumption due to the crisis. Furthermore, our results can contribute to estimating the effects of specific policies (Hale et al., 2020a), to assess the relationship with other real-time indicators, such as mobility (Google, 2020) or electronic payments (Aprigliano et al., 2019), or to nowcast economic activity (Buono et al., 2017).

Limitations of the Study

As this is an evolving situation, these results will need to be updated periodically and could be extended to other countries and regions to obtain more comprehensive conclusions. Likewise, given the heterogeneity found across countries, more detailed studies at a higher resolution will be beneficial to better understand the impact of specific COVID-19 containment measures on particular sectors and economic activities. Other potential extensions relate to the relationship between electricity consumption and other high-frequency indicators to nowcast economic activity.

Our results can be further improved with newly updated data. Although we have used real-time electricity consumption data, these data are updated several times after the first release with increased quality. For this reason, later studies with newer versions of these data may provide results with a lower error. Additionally, it is hard to evaluate stringency data quality, as stringency has an inherently qualitative aspect. Likewise, actual enforcement might not be correlated with stringency and may vary across countries, which may increase the noise in our results.

Finally, in terms of methods, we have selected a forecast model that can make a compromise between accuracy and generalizability. More accurate modeling, including microdata or more detailed specifications, are likely possible but less able to make comparisons across countries.

Resource Availability

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Materials Availability

This study did not generate new unique reagents.

Data and Code Availability

Data and code are available on https://github.com/jlprol/covid. The document "replication.Rmd" provides the instructions and basic code for the replication of the main results. See https://jlprol.shinyapps.io/covid/ for interactive figures and easy data download. For further research, please use and cite the following dataset on Mendeley Data: http://dx.doi.org/10.17632/ffryvnskb9.1.

METHODS

All methods can be found in the accompanying Transparent Methods supplemental file.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.isci.2020.101639.

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AUTHOR CONTRIBUTIONS

J.L.P. conceived the research design, analyzed the data, and wrote the manuscript. S.O. collected data and contributed to analyzing the data and writing the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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Supplemental Information

Impact of COVID-19 Measures on Short-Term Electricity Consumption in the Most Affected EU Countries and USA States

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1 Transparent methods

1.1 Accuracy and method selection

We have compared forecast business as usual daily electricity consumption with actual consumption data from March to July 2020 to estimate the effect of the COVID-19 measures on electricity consumption. Before deciding to use dynamic harmonic regression to estimate the baseline, we tried four different methods:

(i) Seasonal and trend decomposition using loess forecasting (STLF) is a univariate method that consists in decomposing the time series into three structural components: a trend capturing the long-term evolution of the time series, a seasonal pattern of constant frequency and a remaining error capturing the randomness of the data. This is a relatively simple model that works well when there is no more information available than the time series and there are clear seasonal and trend patterns in the data, but fails to capture complex dynamics as those present in our long-term daily time series.

(ii) Trigonometric seasonality with Box-Cox transformation, ARMA errors, trend and seasonal components (TBATS). This model is more complex than the previous, as it allows for autoregressive and moving average components (ARMA) to capture short-term dynamics, Box-Cox transformation for variance stabilisation and Fourier terms for complex seasonality, in addition to the seasonal and trend components common to the STLF.

(iii) Neural network autoregression $NNAR(p, P, k)_m$ where p is the order of the time series lags that are included as predictors of the network and k is the number of nodes that form the network. P is the order of the seasonal lags with frequency m. We run a feed-forward network with one hidden layer where all the parameters are automatically learned from the data. Seasonality is set to 365 (yearly) and weekly seasonality is modelled with a weekday categorical variable. Two more predictors are included: maximum temperature and a holiday dummy. Neural networks are very flexible and perform well when there are many variables which relationship with the outcome is unknown ex-ante.

(iv) $ARIMA(p, d, q)$ dynamic harmonic regression, where p indicates the order of the autoregressive terms, d is the order of integration and q denotes the moving average component, with Fourier terms for complex seasonality. The dynamic regression performs well when the relationship between predictors and outcomes is known. As shown in Figure S2, we include maximum temperature in quadratic form as the main driver of electricity demand. We also include a holiday dummy to control for moving calendar effects such as Easter. Complex seasonality (weekly and annual) is captured by Fourier terms of order (j, k) respectively. Fourier terms capture seasonality through (j, k) pairs of sines and cosines. Finally, short-term dynamics are captured by the ARMA components.

To compare the accuracy of these methods, we split the data into training set (years 2015–2018 both included) and test set (2019) and evaluate their accuracy with five different metrics. TBATS perform best for Austria but shows high accuracy differentials across countries, which makes it unsuitable for our purposes. NNAR performs best in countries that have the most irregular consumption patterns but is outperformed by the dynamic harmonic regression in most countries. Finally, dynamic harmonic regression performs best in most countries and shows the lowest spread across accuracy estimates, such that the differences with NNAR accuracy is low when the latter performs better, and the results are comparable across countries (see Tables S1-9 for detailed accuracy results). Finally, the selected model is trained with all the data until February 2020, and the forecast is predicted from March using actual temperature data. We use maximum daily temperature data as it shows better prediction accuracy than the average. Temperature data is collected from Automated Surface Observing System (ASOS) stations, which are spatially distributed throughout the countries, and take the median of the maximum temperature across all available stations in each country/state.

1.2 ARIMA dynamic harmonic regression

Equation (1) indicates the regression specification

$$
\begin{aligned}
y_t = \alpha + \beta_1 T_t + \beta_2 T_t^2 + \beta_3 H_t + \\
\sum_{j=1}^{J} \big(\gamma_{1,j} s_j(t) + \gamma_{2,j} c_j(t)\big) + \\
\sum_{k=1}^{K} \big(\gamma_{3,k} s_k(t) + \gamma_{4,k} c_k(t)\big) + \\
\sum_{p=1}^{P} \phi y_{t-p} + \sum_{q=1}^{Q} \theta \varepsilon_{t-q} + \epsilon_t \quad (1)
\end{aligned}
$$

where electricity consumption in day t y_t is modelled as a function of a constant α, temperature in a quadratic form ($\beta_1 T_t + \beta_2 T_t^2$) and a dummy variable of state-specific holidays H_t. Complex seasonality is captured by Fourier terms of the form:

$$
\begin{aligned}
s_j(t) = \sin(\frac{2\pi jt}{7}) \quad ; \quad c_j(t) = \cos(\frac{2\pi jt}{7}) \\
s_k(t) = \sin(\frac{2\pi kt}{365.25}) \quad ; \quad c_k(t) = \cos(\frac{2\pi kt}{365.25})
\end{aligned}
$$

where 7 and 365.25 denote the weekly and annual seasonal levels respectively, and (j, k) represent the number of sine/cosine elements for each of the seasonal levels. The last two elements of equation (1) represent the $ARMA(p, q)$ structure that captures short-term dynamics, allowing the error term of the model to approach as much as possible a normally distributed white noise. Since all time series are integrated of order one, the model is run in first differences and the constant is thus removed. We tried including economic variables such as GDP and unemployment as predictors. However, since they did not improve prediction accuracy (partially due to their lower temporal resolution than our daily prediction), we exclude them from the final specification. Although such economic variables are relevant for long-term forecasts, they do not significantly influence short-term estimations (Jun and Ergün 2011).

The data analysis process can be summarised in the following steps:

1. The time series are transformed following Cox-Box (Box and Cox 1964) to stabilise the variance.
2. The time series are tested for stationarity and differenced if necessary.
3. The optimal $ARMA(p, q)$ structure and Fourier(j, k) order is automatically determined by the Hyndman and Khandakar algorithm (Hyndman and Khandakar 2008) to minimise the corrected Akaike information criteria (AICc).
4. Residuals are studied for signs of remaining signals and the ARMA and Fourier parameters are manually fine-tuned to achieve optimal results according to the following criteria: having the simplest possible model with the lowest possible AICc that shows the closest possible residuals to a normally distributed white noise.
5. Forecast the baseline electricity consumption from March to July 2020 and compare it with the actual values. The point forecast is back-transformed, such that it represents the median, rather than the mean of the forecast distribution. All results are provided with 80% and 95% prediction intervals.

Section 3 provides the results of the process described above: accuracy (3.1), model parameters of points 1-3 (3.2), forecast compared with actual consumption (3.3), regression results (3.4) and their respective residual diagnostics (3.5).

2 Data

We use three different types of data that we describe below in more detail: (i) Electricity consumption (defined as actual load excluding self-consumption) data acquired from the Energy Information Administration of the USA (https://www.eia.gov/) and ENTSO-E (https://transparency.entsoe.eu/) between January (July for the USA) 2015 and July 2020 both included; (ii) Maximum daily temperature from ASOS provided by Iowa Environmental Mesonet (IEM) (https://mesonet.agron.iastate.edu/ASOS/) and defined as the median of the maximum temperature across all available stations within each country/state (excluding islands); and (iii) Stringency index provided by the Blavatnik School of Government of Oxford University (https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker).

2.1 Electricity consumption

Electricity consumption has been obtained from the ENTSO-E transparency platform for the European countries since January 2015 and from the USA Energy Information Administration for the American states since July 2015, both until July 2020 included. ENTSO-E data corresponds to the country's actual load defined as the sum of power generated by plants on both TSO/DSO networks minus the balance (export-import) of exchanges on interconnections and minus the power absorbed by energy storage resources. EIA demand data comes from the U.S. Electric System Operating Data (EIA-930). In both cases, the data exclude self-consumed electricity. All the data have been collected in UTC and then transformed to local times. Likewise, the original data are in sub-daily resolution and we have aggregated to daily after transforming to their respective local time. Figure S1 shows the daily electricity consumption data for each country/state.

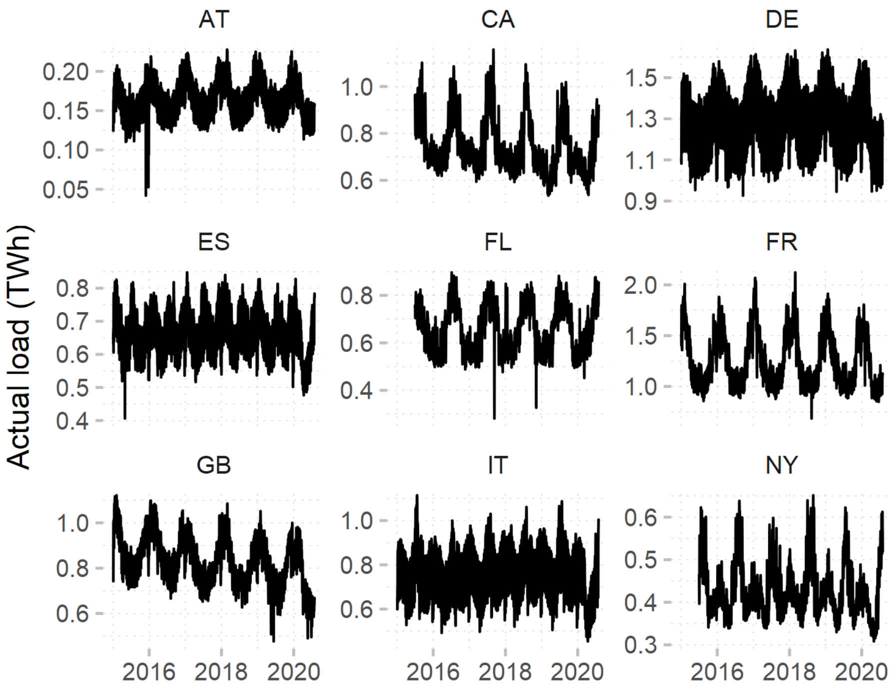

Figure S1. Daily electricity consumption data. Related to Figures 1 and 2.

2.2 Temperature

We tested our models with both mean and maximum daily temperature. Since maximum temperature shows a slightly better predictive performance, we use the maximum rather than the mean. Daily maximum temperature observational data from January 2015 to July 2020 have been obtained from the Automated Surface Observing System provided by Iowa Environmental Mesonet (IEM). ASOS stations are spatially distributed throughout countries and have wide coverage. We first collected daily maximum temperature from all available stations within each country/state excluding islands. We then calculated the median of the maximum temperature across the stations for each day and country/state. Temperature and electricity consumption have a quadratic relationship, as can be seen in Figure S2. For this reason, we control for quadratic temperature in the dynamic harmonic ARIMA regression.

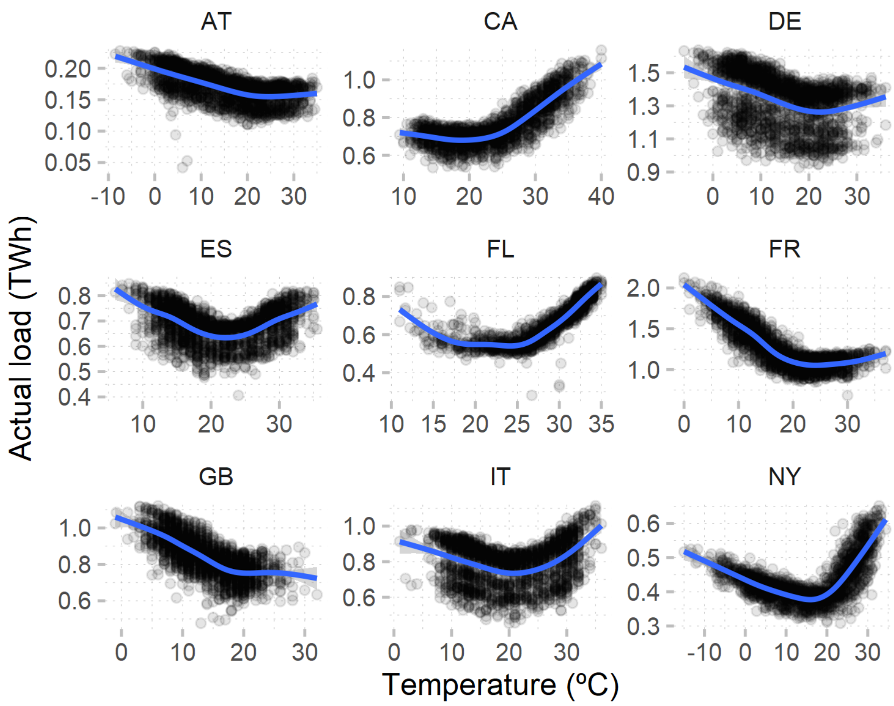

Figure S2. Relationship between daily load and maximum temperature. Related to Figures 1 and 2.

2.3 Stringency index

The stringency index, created by the Blavatnik School of Government of Oxford University and publicly available on the Coronavirus government response tracking website, is composed of nine policy response indicators:

1. School closing
2. Workplace closing
3. Cancel public events
4. Restrictions on gathering size
5. Close public transport
6. Stay at home requirements
7. Restrictions on internal movement
8. International travel controls
9. Public info campaigns

Each of these individual indicators are measured in an ordinal scale depending on stringency (e.g. whether a measure is only a recommendation or an obligation) and scope (i.e. whether the measure is general or targeted to a specific group or region). The stringency index aggregates each of these rescaled individual indicators to reach a score between 0 and 100. Figure S3 shows the evolution of the stringency index for each country/state.

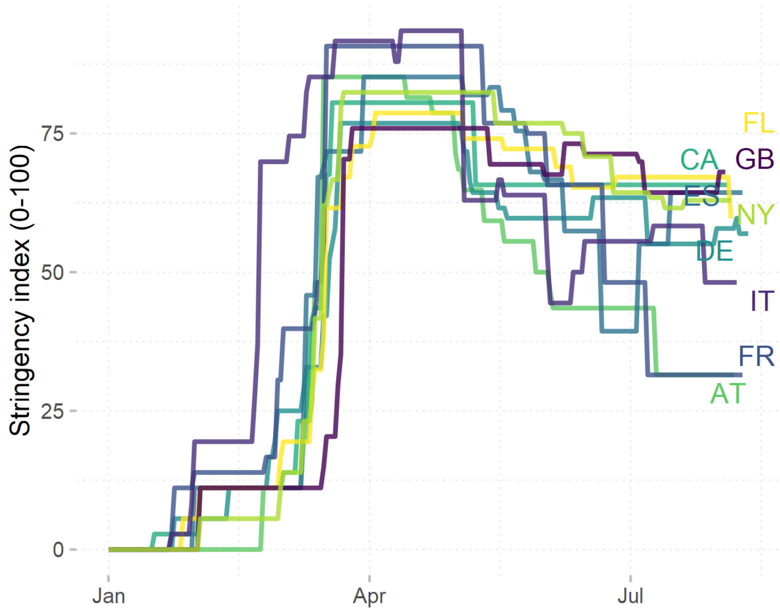

Figure S3. Stringency index. Related to Figure 3.

3 Intermediate results

3.1 Accuracy comparison between different methods.

To test the accuracy of the different methods to forecast daily electricity demand we split the data into training (years 2015-2018) and test (year 2019) sets and evaluate the test set forecast with the actual load data. We present five different accuracy indicators to provide a comprehensive overview of the error of each model and country. Each indicator measures bias and precision differently. The mean error shows the bias of the estimation. The mean absolute error measures precision, but since errors are considered in absolute terms, it does not capture bias. Similarly, the root mean squared error indicates precision penalizing large errors and ignoring its sigh by squaring them. These three indicators are scale-dependent. Both the mean percentage error and the mean absolute percentage error are on the contrary expressed in percent terms, so they are more suitable for comparisons across different consumption levels. Tables S1-9 present the accuracy results for each country and method:

- Accuracy indicators:
  - ME: mean error.
  - RMSE: root mean squared error.
  - MAE: mean absolute error.
  - MPE: mean percentage error.
  - MAPE: mean absolute percentage error.
- Methods
  - STLF: seasonal and trend decomposition using loess forecasting.
  - TBATS: trigonometric seasonality with Box-Cox transformation, ARMA errors, trend and seasonal components.
  - NNAR: neural network autocorrelation.
  - ARIMA: integrated dynamic harmonic regression with Fourier terms for seasonality and ARMA errors.

Table S1. Accuracy indicators Austria. Related to Figures 1 and 2.

	ARIMA	NNAR	TBATS	STLF
ME	-0.01	0.00	0.00	0.00
RMSE	0.01	0.01	0.01	0.02
MAE	0.01	0.01	0.01	0.02
MPE	-3.45	-0.16	-1.61	-2.54
MAPE	4.60	2.97	3.94	11.54

Table S2. Accuracy indicators California. Related to Figures 1 and 2.

	ARIMA	NNAR	TBATS	STLF
ME	0.02	-0.04	-0.03	-0.05
RMSE	0.04	0.06	0.06	0.09
MAE	0.03	0.05	0.05	0.07
MPE	2.56	-5.77	-4.14	-7.72
MAPE	4.64	6.75	6.67	9.70

Table S3. Accuracy indicators Germany. Related to Figures 1 and 2.

	ARIMA	NNAR	TBATS	STLF
ME	-0.01	-0.02	-0.01	-0.02
RMSE	0.06	0.06	0.08	0.17
MAE	0.04	0.04	0.05	0.15
MPE	-1.33	-1.35	-1.01	-3.06
MAPE	2.92	3.06	4.11	11.66

Table S4. Accuracy indicators Spain. Related to Figures 1 and 2.

	ARIMA	NNAR	TBATS	STLF
ME	-0.01	-0.02	0.04	0.00
RMSE	0.02	0.08	0.06	0.07
MAE	0.02	0.06	0.05	0.06
MPE	-1.26	-4.17	5.87	-1.10
MAPE	2.65	9.37	7.25	8.39

Table S5. Accuracy indicators Florida. Related to Figures 1 and 2.

	ARIMA	NNAR	TBATS	STLF
ME	-0.01	0.00	-0.07	-0.01
RMSE	0.03	0.03	0.10	0.06
MAE	0.03	0.03	0.08	0.05
MPE	-1.36	-0.83	-10.45	-2.13
MAPE	4.38	3.92	11.94	7.86

Table S6. Accuracy indicators France. Related to Figures 1 and 2.

	ARIMA	NNAR	TBATS	STLF
ME	-0.02	-0.01	0.01	-0.04
RMSE	0.07	0.06	0.10	0.14
MAE	0.06	0.05	0.07	0.11
MPE	-1.50	-0.97	0.06	-4.27
MAPE	4.42	3.79	5.37	8.81

Table S7. Accuracy indicators Great Britain. Related to Figures 1 and 2.

	ARIMA	NNAR	TBATS	STLF
ME	0.01	-0.01	0.02	0.00
RMSE	0.04	0.05	0.05	0.07
MAE	0.03	0.03	0.04	0.05
MPE	0.31	-1.78	2.49	-0.42
MAPE	3.93	4.06	4.85	6.85

Table S8. Accuracy indicators Italy. Related to Figures 1 and 2.

	ARIMA	NNAR	TBATS	STLF
ME	0.00	0.01	0.01	0.00
RMSE	0.04	0.06	0.07	0.12
MAE	0.03	0.04	0.05	0.10
MPE	0.20	0.82	0.06	-2.33
MAPE	3.55	4.82	6.26	13.63

Table S9. Accuracy indicators New York. Related to Figures 1 and 2.

	ARIMA	NNAR	TBATS	STLF
ME	-0.01	-0.01	-0.01	0.00
RMSE	0.03	0.02	0.03	0.04
MAE	0.02	0.02	0.02	0.03
MPE	-1.86	-1.59	-2.19	0.19
MAPE	4.31	3.91	5.62	6.87

3.2 ARIMA parametrisation

Table S10 presents the regression parameters for each country/state.

Table S10. Model parameters. Related to Figures 1 and 2.

Country	Lambda	Fourier.j.k.	ARIMA.p.d.q.
Austria	1.95	(3,9)	(0,1,4)
California	1.12	(3,3)	(4,1,3)
Germany	0.81	(3,11)	(4,1,1)
Spain	-0.07	(3,23)	(3,1,2)
Florida	1.03	(3,3)	(1,1,2)
France	-1.00	(3,19)	(7,1,6)
Great Britain	1.20	(3,3)	(2,1,1)
Italy	0.98	(3,20)	(3,1,1)
New York	-1.00	(3,5)	(3,1,1)

3.3 Actual vs. forecast (baseline) daily electricity consumption

Figure S4 shows the forecast (black line) produced by each of the country-specific dynamic harmonic ARIMA regression with 80% (dark shade) and 95% (light) prediction intervals. The coloured lines represent the actual electricity consumption.

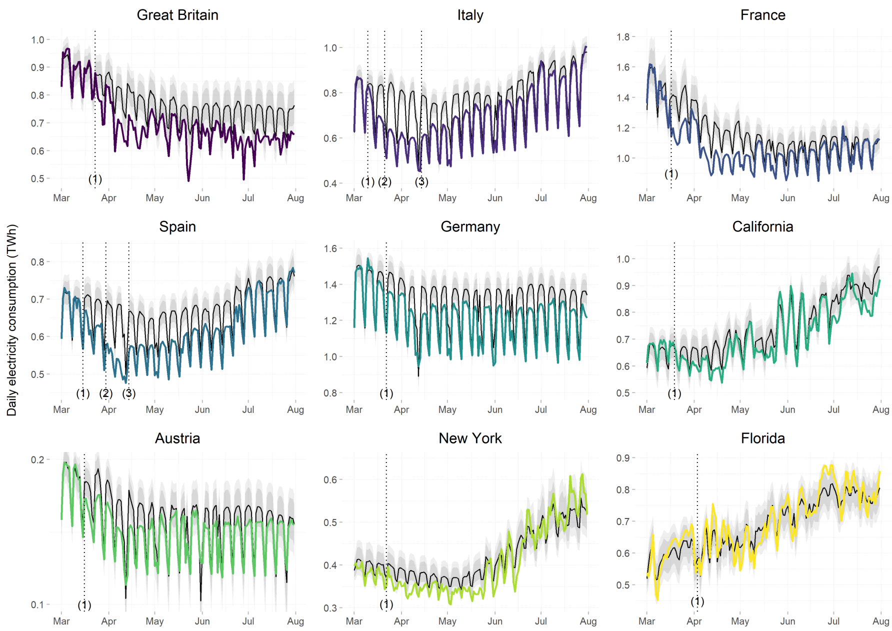

Figure S4. Actual and Forecast daily electricity consumption. Related to Figures 1 and 2.

3.4 Regression results

Tables S11-20 present the regression results for the dynamic harmonic regression of each country. Only the ARMA terms and the external regressors (quadratic temperature and holiday dummy) are included in the tables. Fourier terms have been omitted for simplicity.

Table S11. Austria summary regression results. Related to Figures 1 and 2.

Variable	Coefficient	SE	z-value	p-value
MA1	-0.510	0.279	-1.829	0.067
MA2	-0.213	0.051	-4.178	0.000
MA3	-0.162	0.089	-1.819	0.069
MA4	-0.040	0.160	-0.248	0.804
Temperature	0.000	0.003	-0.127	0.899
Temperature2	0.000	0.000	0.097	0.923
Holiday	-0.003	0.006	-0.538	0.590

Table S12. California summary regression results. Related to Figures 1 and 2.

Variable	Coefficient	SE	z-value	p-value
AR1	0.120	0.087	1.378	0.168
AR2	-0.239	0.154	-1.555	0.120
AR3	0.701	0.126	5.581	0.000
AR4	-0.123	0.046	-2.689	0.007
MA1	-0.132	0.081	-1.622	0.105
MA2	0.031	0.152	0.205	0.837
MA3	-0.870	0.111	-7.867	0.000
Temperature	-0.017	0.000	-111.322	0.000
Temperature2	0.000	0.000	41.394	0.000
Holiday	-0.021	0.002	-13.308	0.000

Table S13. Germany summary regression results. Related to Figures 1 and 2.

Variable	Coefficient	SE	z-value	p-value
AR1	0.528	0.024	22.156	0.000
AR2	-0.071	0.026	-2.668	0.008
AR3	0.085	0.026	3.278	0.001
AR4	-0.050	0.023	-2.136	0.033
MA1	-0.987	0.004	-276.402	0.000
Temperature	-0.005	0.000	-9.491	0.000
Temperature2	0.000	0.000	6.319	0.000
Holiday	-0.166	0.004	-43.530	0.000

Table S14. Spain summary regression results. Related to Figures 1 and 2.

Variable	Coefficient	SE	z-value	p-value
AR1	1.367	0.055	24.954	0.000
AR2	-0.512	0.047	-10.890	0.000
AR3	0.072	0.025	2.847	0.004
MA1	-1.751	0.049	-35.491	0.000
MA2	0.753	0.049	15.275	0.000
Temperature	-0.015	0.000	-45.087	0.000
Temperature2	0.000	0.000	19.427	0.000
Holiday	-0.124	0.003	-37.383	0.000

Table S15. Florida summary regression results. Related to Figures 1 and 2.

Variable	Coefficient	SE	z-value	p-value
AR1	-0.510	0.279	-1.829	0.067
MA1	-0.213	0.051	-4.178	0.000
MA2	-0.162	0.089	-1.819	0.069
Temperature	-0.040	0.160	-0.248	0.804
Temperature2	0.000	0.003	-0.127	0.899
Holiday	0.000	0.000	0.097	0.923

Table S16. France summary regression results. Related to Figures 1 and 2.

Variable	Coefficient	SE	z-value	p-value
AR1	0.416	0.062	6.698	0.000
AR2	-0.532	0.079	-6.698	0.000
AR3	0.085	0.100	0.853	0.394
AR4	-0.068	0.089	-0.766	0.444
AR5	-0.402	0.075	-5.360	0.000
AR6	0.362	0.038	9.584	0.000
AR7	0.240	0.026	9.403	0.000
MA1	-0.878	0.061	-14.434	0.000
MA2	0.557	0.102	5.478	0.000
MA3	-0.343	0.120	-2.865	0.004
MA4	-0.070	0.118	-0.596	0.551
MA5	0.367	0.089	4.101	0.000
MA6	-0.622	0.052	-11.875	0.000
Temperature	-0.016	0.000	-51.697	0.000
Temperature2	0.000	0.000	22.272	0.000
Holiday	-0.062	0.003	-20.543	0.000

Table S17. Great Britain summary regression results. Related to Figures 1 and 2.

Variable	Coefficient	SE	z-value	p-value
AR1	0.605	0.029	20.827	0.000
AR2	0.040	0.028	1.433	0.152
MA1	-0.967	0.017	-55.485	0.000
Temperature	-0.012	0.000	-32.393	0.000
Temperature2	0.000	0.000	13.408	0.000
Holiday	-0.058	0.003	-17.751	0.000

Table S18. Italy summary regression results. Related to Figures 1 and 2.

Variable	Coefficient	SE	z-value	p-value
AR1	0.496	0.025	19.575	0.000
AR2	-0.089	0.027	-3.294	0.001
AR3	-0.074	0.024	-3.050	0.002
MA1	-0.965	0.008	-114.172	0.000
Temperature	-0.016	0.000	-36.334	0.000
Temperature2	0.000	0.000	22.053	0.000
Holiday	-0.107	0.003	-32.977	0.000

Table S19. New York summary regression results. Related to Figures 1 and 2.

Variable	Coefficient	SE	z-value	p-value
AR1	0.894	0.029	31.025	0
AR2	-0.305	0.033	-9.180	0
AR3	0.091	0.025	3.703	0
MA1	-0.990	0.004	-225.978	0
Temperature	-0.015	0.001	-13.980	0
Temperature2	0.001	0.000	14.042	0
Holiday	-0.075	0.008	-8.882	0

3.5 Residuals

Figures S5-13 present the residuals of the dynamic harmonic ARIMA regressions. The consumption data (Figure S1) have some outliers that can be observed in the residuals but do not significantly influence the accuracy of the forecast. All the residuals are close to a normally distributed white noise.

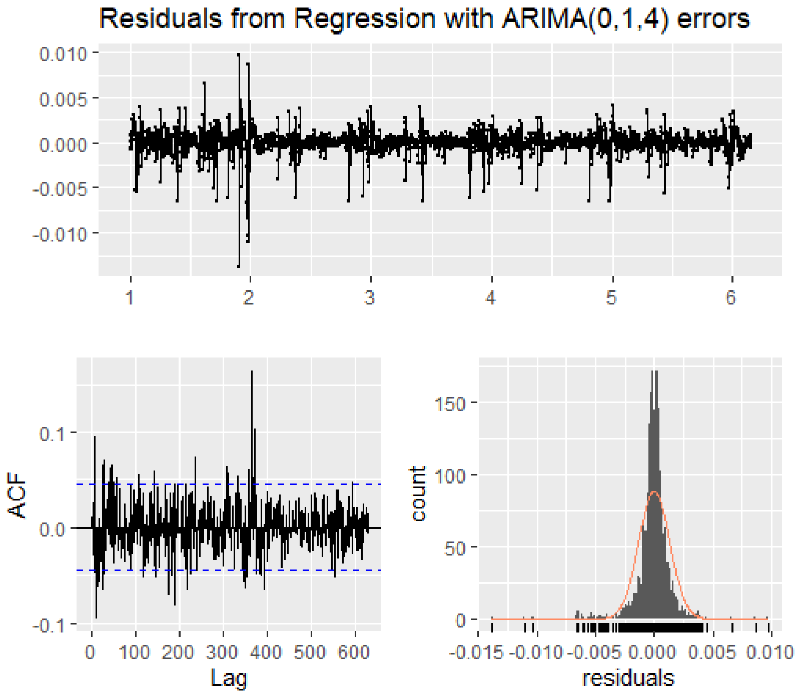

Figure S5. Austria residuals. Related to Figures 1 and 2.

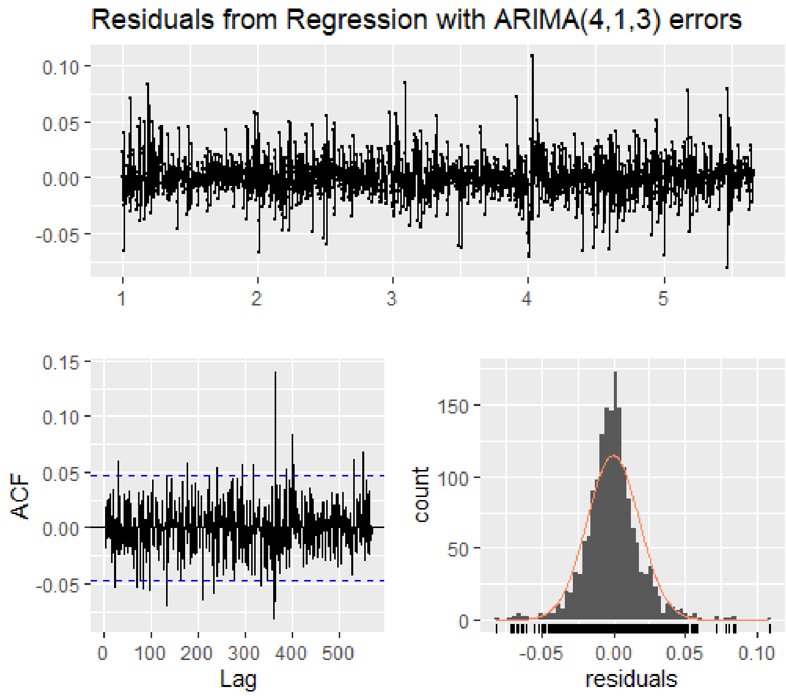

Figure S6. California residuals. Related to Figures 1 and 2.

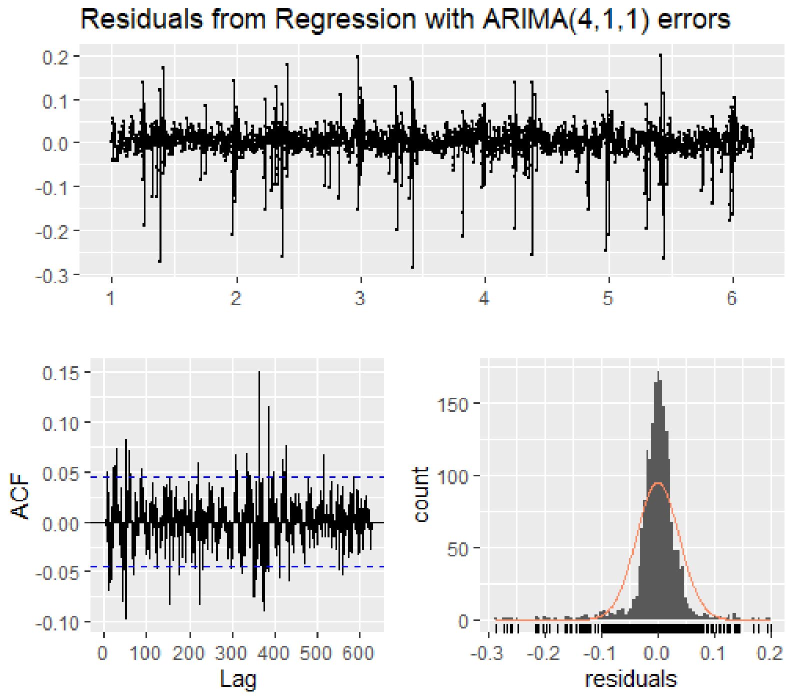

Figure S7. Germany residuals. Related to Figures 1 and 2.

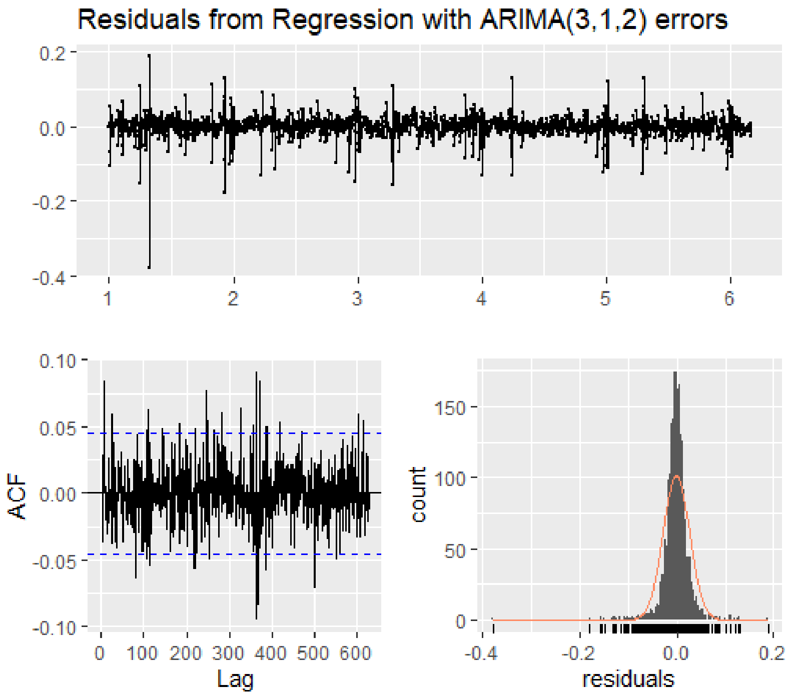

Figure S8. Spain residuals. Related to Figures 1 and 2.

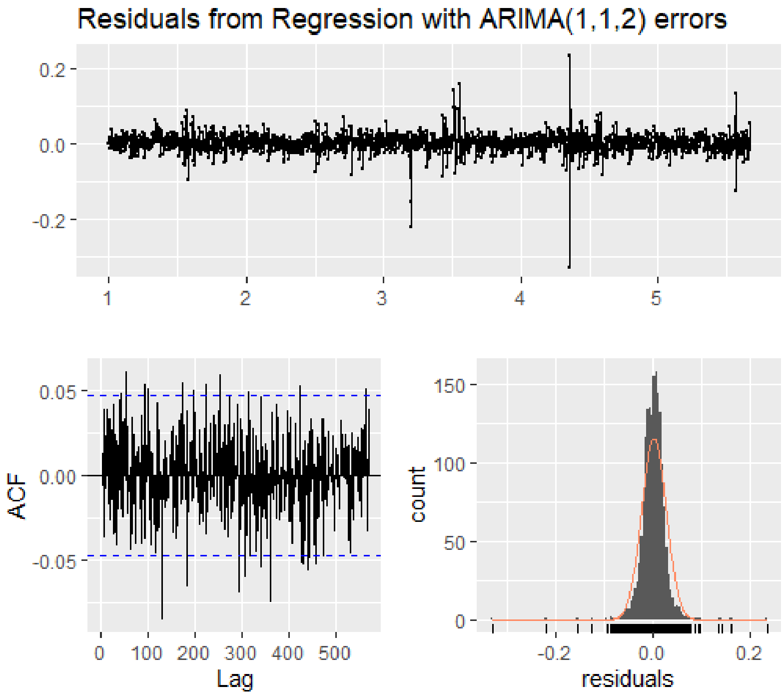

Figure S9. Florida residuals. Related to Figures 1 and 2.

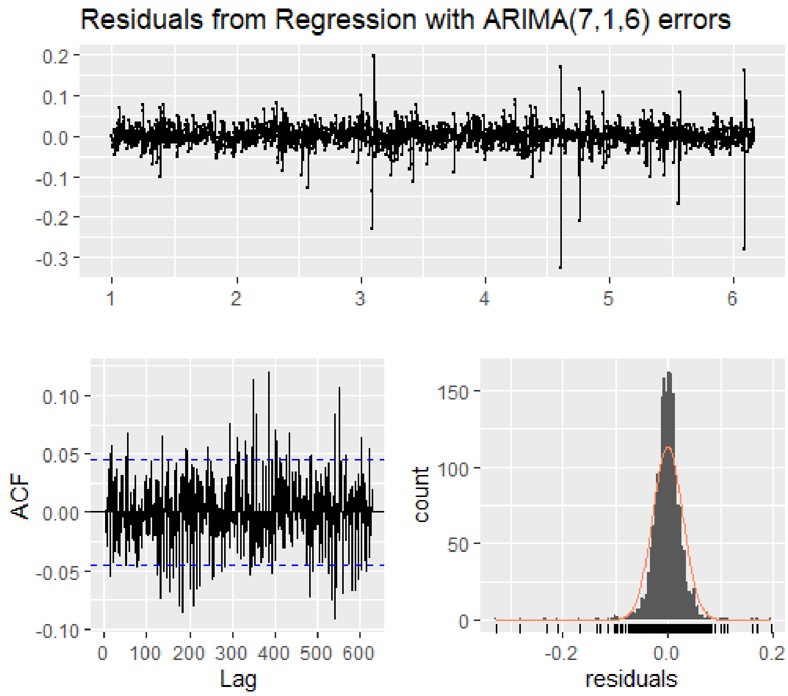

Figure S10. France residuals. Related to Figures 1 and 2.

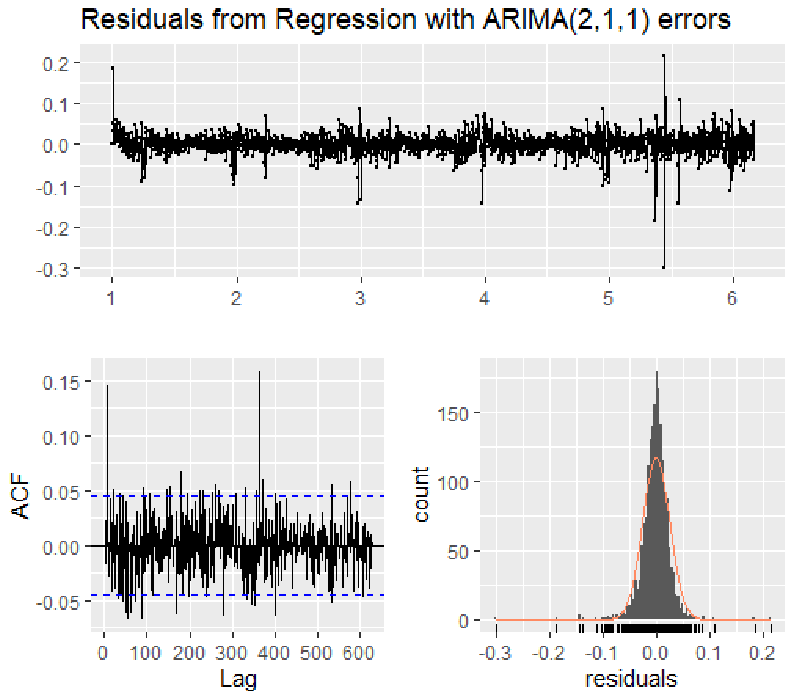

Figure S11. Great Britain residuals. Related to Figures 1 and 2.

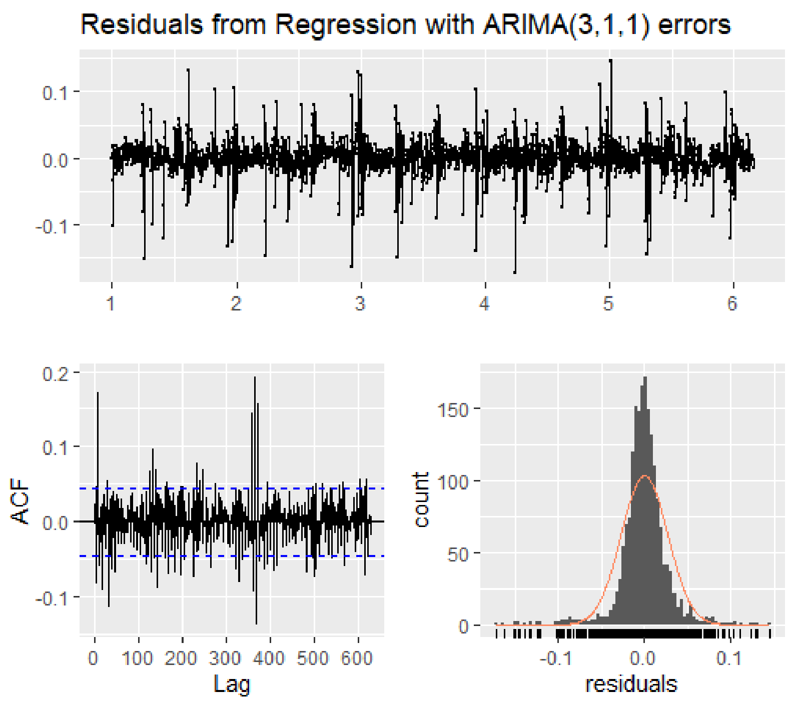

Figure S12. Italy residuals. Related to Figures 1 and 2.

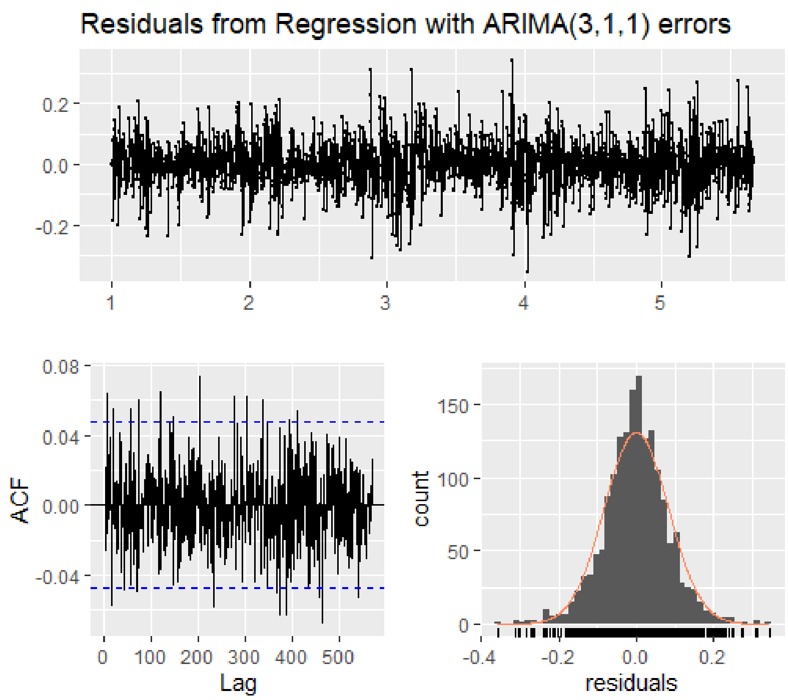

Figure S13. New York residuals. Related to Figures 1 and 2.

3.6 Bias of a naive comparison with last year data

Here we show the bias that would occur if instead of using the dynamic harmonic ARIMA regression to estimate the baseline electricity consumption we had simply taken 2019 electricity consumption. For this purpose, we first calculate the weekly (weeks 12 to 30) change in electricity consumption between 2019 and 2020 (naive estimation) and compare it with the weekly-aggregated results from our method using the dynamic harmonic ARIMA regression (see Figure 2 in the main text). Figure S14 shows the difference between the naive comparison and our main results. Whereas aggregating to weekly already reduces the error by removing weekly seasonality and short-term dynamics, we can see that a naive comparison would overestimate the drop in electricity consumption for most countries/states (except California where it would underestimate it) up to 10 percentage points in some weeks.

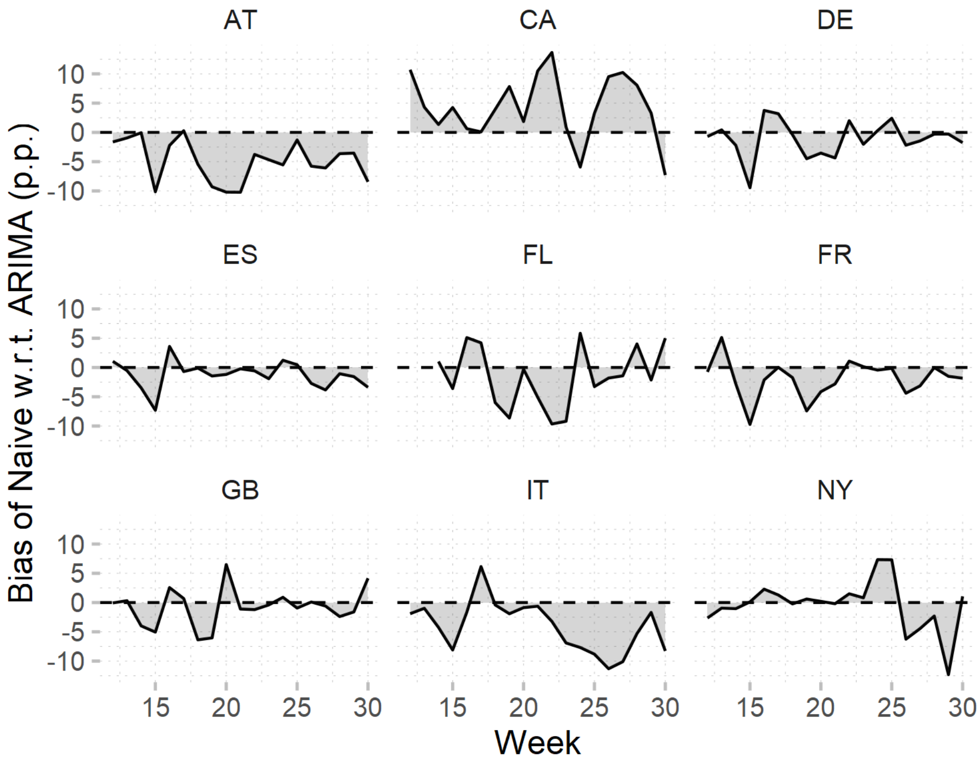

Figure S14. Difference in the change of electricity consumption between the naive estimation and the dynamic harmonic ARIMA regression. Negative means that the simple comparison overestimates the drop in electricity consumption. Related to Figures 1 and 2.

Supplemental references

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