Impact of COVID-19 measures on electricity consumption

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Abstract

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 second pandemic waves. Here we show that the cumulative decline in electricity consumption within the four months following the stay-home orders ranges between 4-13% in the most affected EU countries and USA states, except Florida that shows no significant impact. Whereas the studied USA states have recovered baseline levels, electricity consumption remains lower in the European countries. These results illustrate the severity of the crisis across countries and can support further research on the effect of specific measures, evolution of economic activity or relationship with other high-frequency indicators.

Introduction

From social distancing guidelines to strict lockdowns and paralysation of non-essential economic activity, governments worldwide have taken a wide range of measures to halt the spread of the COVID-19 pandemic[1]. Global CO_2 emissions decreased by 17% during forced confinements[2] and global GDP is expected to decline by 3% in 2020 as a result of the pandemic[3]. 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%[4]. Given the unprecedented nature of this crisis, governments are uncertain about the economic impacts of the implemented measures[5]. The unfolding outbreaks in other countries[6] beyond the ones studied here and the potential emergence of second pandemic waves[7] reveal the urgency to improve our knowledge about the potential impacts of the containment measures.

Given the relationship between electricity consumption and GDP[8] and the real-time availability of electricity consumption data, analysing 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[9], that provides information on temperature-adjusted peak-hour electricity consumption in European countries compared to last year. The International Energy Agency provides a broader analysis of the impact of COVID-19 on the energy sector[10]. Several media outlets have also provided information on the fall of electricity consumption in different countries compared to previous years' weekly or monthly averages[11,12].

However, given that electricity consumption is determined by many factors such as temperature, trends, seasonal cycles, calendar effects and short-term dynamics[13], ignoring such factors will likely bias the results. 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[14]. This allows us to build a reliable counterfactual baseline scenario with test accuracy ranging between 2.7–4.3% mean average percentage error. 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 Methods section and Supplementary Information for more details).

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 June. 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 ~4–13% within the four months following the start of the crisis, except Florida that has not suffered a significant negative impact with respect to the baseline scenario.

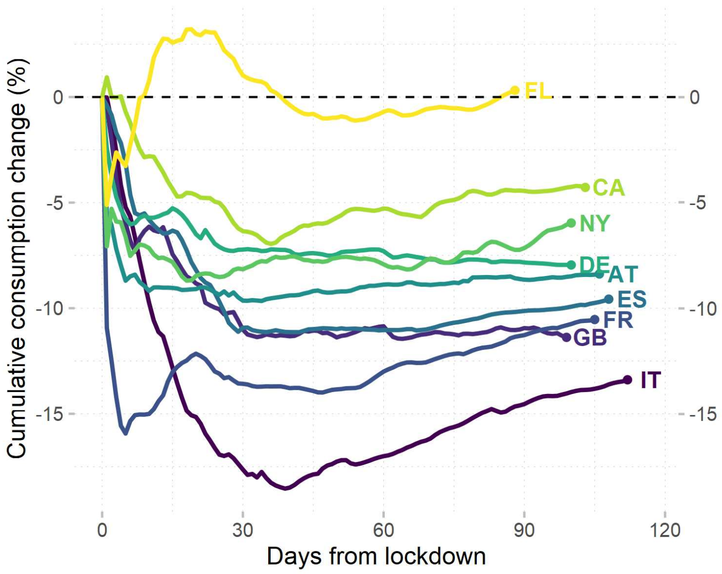

Figure 1. Impact curve flattens in most countries in about a month after the start of the lockdown/stay-home orders. Lines represent the cumulative change in electricity consumption compared to the forecast baseline levels.

Figure 2 provides greater detail for each particular country/state, presenting the daily percentage change in electricity consumption compared to the expected counterfactual baseline (see Supplementary Figure 4 for the actual and forecast electricity consumption in absolute terms). Countries are sorted and coloured (darker to lighter) according to the cumulative impact during the study period as shown in Fig. 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 reopening 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 clearly identifiable: (i) a first lockdown phase, (ii) a second phase of non-essential economic activity shutdown, and (iii) a subsequent progressive opening of economic activities. During the non-essential economic activity shutdown, daily electricity consumption declined ~30% in Italy and ~20% in Spain compared to the baseline. Electricity consumption started recovering in Italy and Spain with the progressive opening of economic activities, and is now the closest to baseline levels amongst the studied European countries.

After Italy, Great Britain and France experienced the strongest cumulative decline in electricity consumption of 11.4% and 10.5%, respectively. Whereas France experienced a sudden drop of about 20% the first week of the lockdown that has been recovering slowly since then, Great Britain experienced a lower initial drop but shows no signs of recovery. Both Germany and Austria experienced a cumulative decline of about 8% and show a similar consumption pattern with stable lower consumption during the studied period. The countries that experienced a stronger decline in the first weeks (Italy, France and Spain) have recovered faster than those with lower initial declines (Germany, Austria and Great Britain). These results could suggest that stronger initial action reduces the duration of the shock.

In contrast to the European countries, New York and California seem to have recovered baseline levels. The effect of COVID-19 measures is confounded with the effect of the Black Lives Matter protests in the USA, which could explain the high variability observed in New York during June. We cannot observe any significant negative impact in Florida. Overall, electricity consumption decline has been stronger in Europe than in the USA. Electricity consumption remains between -5% and -10% below the baseline levels in all of the studied European countries.

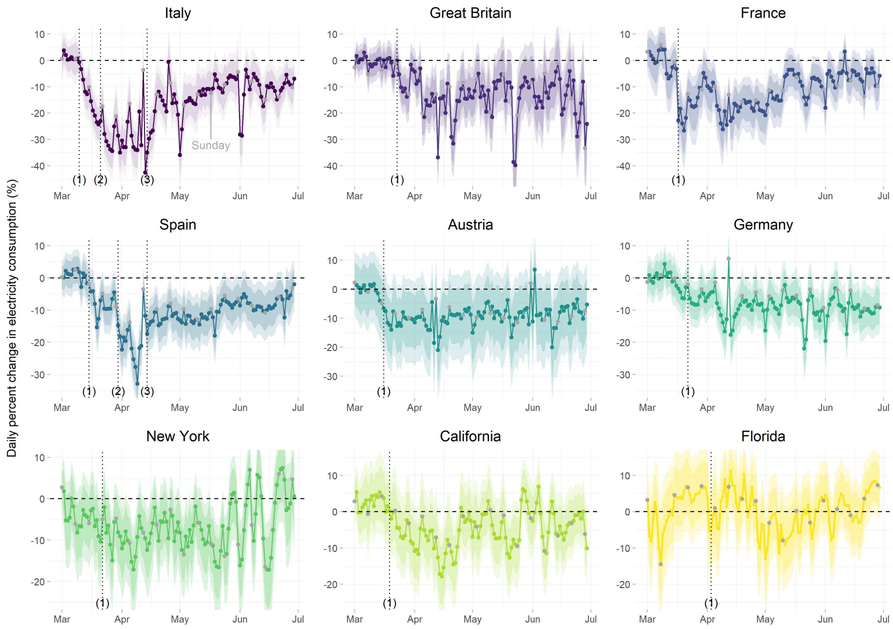

Figure 2. Different containment measures across countries led to different impacts on electricity consumption. Solid lines show the daily percentage change in electricity consumption. Dark and light shades indicate 80% and 95% prediction intervals, respectively. Sundays are coloured grey. Vertical dotted lines indicate the start of (1) lockdown/stay-home orders, (2) non-essential economic activity shutdown, and (3) progressively resuming economic activity. Note that vertical axis ranges are different for each row. See Methods for details and Supplementary Fig. 4 for absolute values.

Measures stringency

The depth of the consumption decline is directly related to the stringency of the containment measures. The stringency index[1] is calculated across nine dimensions (schools closures, events cancellations, movement restrictions, etc.–see Supplementary Information Section 1.3 for details) and weighted by stringency (e.g. whether a measure is only a recommendation or an obligation) and scope (i.e. whether the measure is regional or national). Figure 3 shows the relationship between the daily drop in electricity consumption (Fig. 2) and the stringency of the COVID-19 measures as estimated by the coronavirus response tracker[1]. The dots represent the drop of electricity consumption and the stringency index for each day and country (state-level stringency index data are not available) during the study period, and the solid grey line represents the relationship between both variables. The country codes represent the median value for each of the countries during this period, revealing that the stronger stringency, the higher electricity consumption decline. Whereas this is only a high-level illustration, as more data is 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.

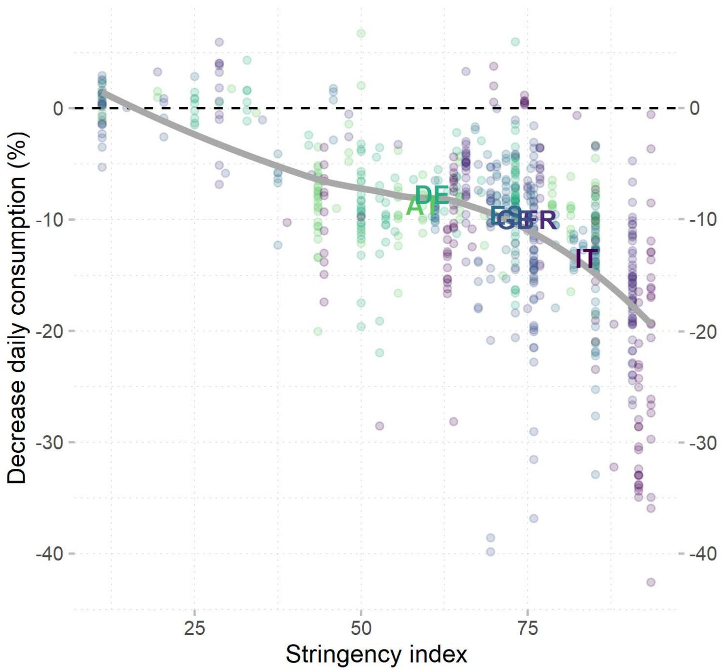

Figure 3. The stronger the government response, the greater the consumption decline. Each dot represents the daily electricity consumption change and stringency index for each country. The country codes indicate the median values for each country. The grey line represents the relationship between electricity consumption and stringency.

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 -13% in Italy to no net negative effect in Florida. Whereas USA states have recovered baseline consumption levels, European countries remain between -5% and -10% of that level. 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 businesses that rely on personal interaction[15]. From the supply side, halting non-essential activities may have propagation effects across the supply chain to other regions and sectors[16]. An increase in uncertainty, such as the one caused by this pandemic[17] affects both demand by lower consumer spending and supply by lower investment and capital formation. The labour market could also be a transmission mechanism as the crisis affects mostly workers that need a long time to be employable again[18]. Finally, a financial mechanism through which higher private and public indebtedness slows down potential long-term growth could also come into play[19,20].

If the economic contraction caused by the COVID-19 measures turns out to be L-shaped, this would contrast with all previous epidemics that have generally caused transient V-shaped shocks[21], 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[1], to assess the relationship with other real-time indicators, such as mobility[22] or electronic payments[23], or to nowcast economic activity[24].

Methods

Accuracy and method selection

We have compared forecast business as usual daily electricity consumption with actual consumption data from March to May 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 Supplementary Figure 2, 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 Supplementary tables 1-9 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.

ARIMA dynamic harmonic regression

Equation (1) indicates the regression specification

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

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 tacked 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 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.

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

1. The time series are transformed following Cox-Box[25] 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[26] 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 following 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 June 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.

Supplementary Table 10 summarises the model parameters of points 1-3 above. Supplementary Tables 11-19 present the regression results and Supplementary Figures 5-13 show the respective residual diagnostics.

Data

We use three different types of data: (i) Electricity consumption (actual load) 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 June 2020 both included; (ii) Maximum daily temperature from ASOS provided by Iowa University (https://mesonet.agron.iastate.edu/ASOS/); 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). See Supplementary Information for illustrations and further details.

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.

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Authors declare no competing interests.

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Author contribution

JLP conceived the research design, analysed the data and wrote the manuscript. SO collected data and contributed to analysing the data and writing the manuscript.

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Supplementary Information to
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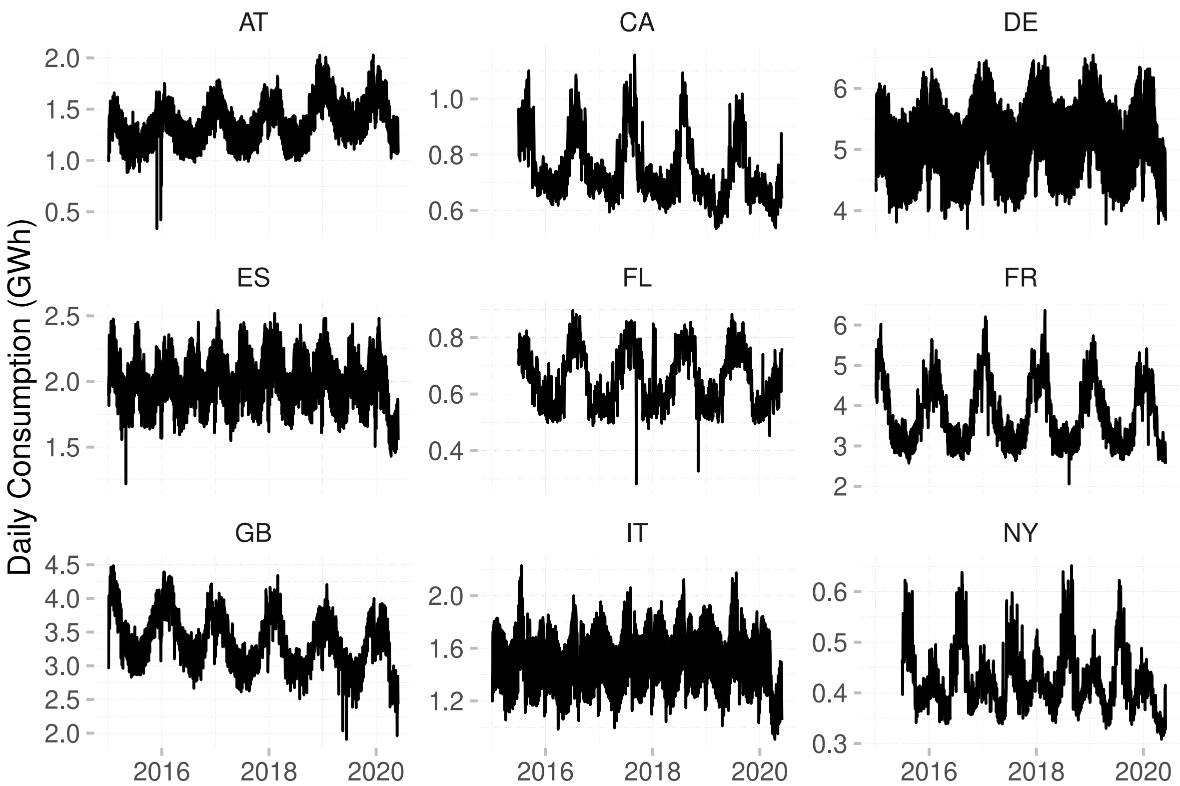
1 Data

1.1 Electricity consumption

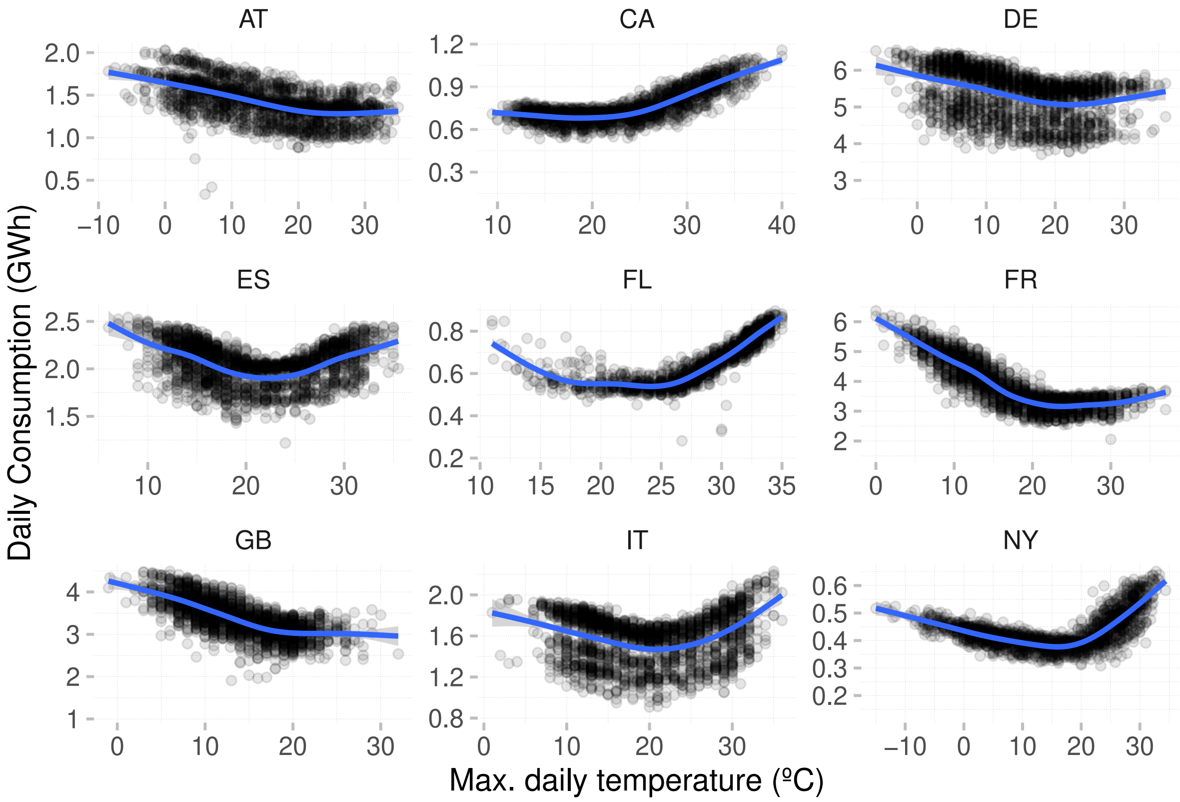
Electricity consumption has been obtained from the ENTSO-E transparency platform for the European countries since January 2015 and from the USA Energy Information Administration for the American states since July 2015, both until June 2020 included. ENTSO-E data corresponds to the country's actual load 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 excludes 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. Supplementary Figure 1 shows the daily electricity consumption data for each country/state.



Supplementary Figure 1. Electricity consumption data

1.2 Temperature

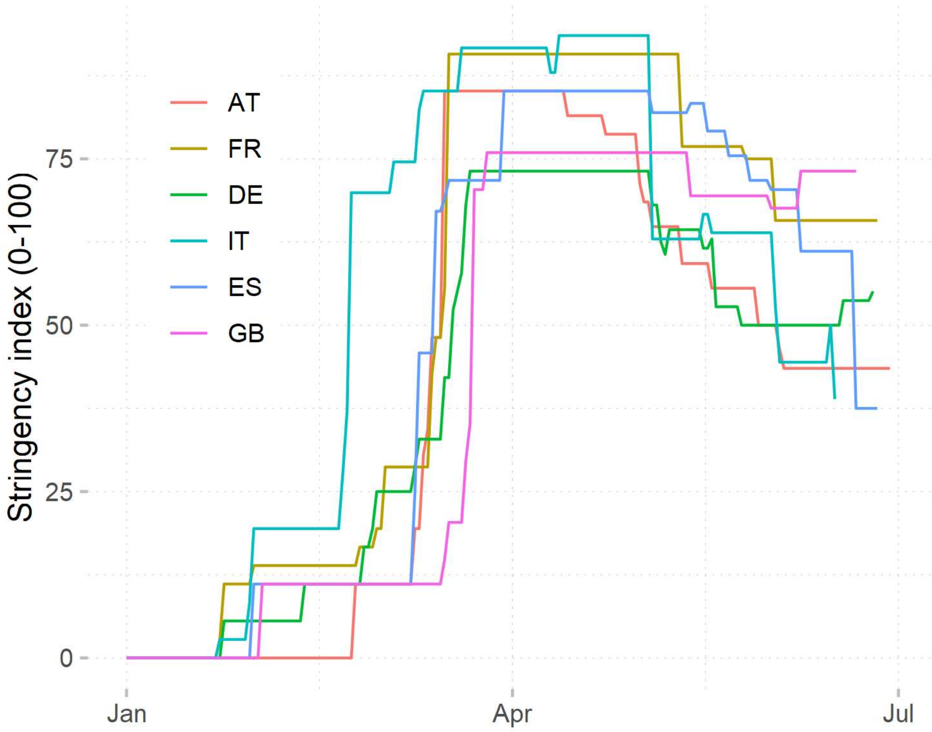
We tested our models with both mean and maximum daily temperature. Since maximum temperature shows a slightly better predictive performance, we use the maximum rather than the mean. Daily maximum temperature data from January 2015 to June 2020 have been obtained from the Automated Surface Observing System provided by Iowa State University. 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 country/state. Temperature and electricity consumption have a quadratic relationship, as can be seen in Supplementary Figure 2. For this reason, we control for quadratic temperature in the dynamic harmonic ARIMA regression.



Supplementary Figure 2. Relationship between daily load and maximum temperature

1.3 Stringency index

The stringency index is a composite measure created by the Blavatnik School of Government of Oxford University and publicly available on the Coronavirus government response tracking website. It is composed of 9 subindices ranging between 0-100: (1) School closing, (2) Workplace closing, (3) Cancel public events, (4) Restrictions on gatherings, (5) Close public transport, (6) Stay at home requirements, (7) Restrictions on internal movement, (8) International travel controls, and (9) Public info campaigns. See Halle et al. (2020) for details.



Supplementary Figure 3. Stringency index

2 Methods

2.1 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. Supplementary tables 1-9 present the accuracy results for each country and method:

- Accuracy indicators:
  - ME: mean error.
  - RMSE: root mean squared error.
  - MAE: mean average squared error.
  - MPE: mean percentage error.
  - MAPE: mean average 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: dynamic harmonic regression with Fourier terms for seasonality and ARIMA errors.

Table 1: Austria

	ARIMA	NNAR	TBATS	STLF
ME	-0.03	0.15	0.01	0.01
RMSE	0.09	0.22	0.09	0.21
MAE	0.07	0.17	0.07	0.18
MPE	-1.64	8.87	0.50	-0.55
MAPE	4.34	10.64	4.21	12.01

Table 2: California

	ARIMA	NNAR	TBATS	STLF
ME	-0.01	-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	-1.63	-5.92	-4.14	-7.72
MAPE	4.13	6.99	6.67	9.70

Table 3: Germany

	ARIMA	NNAR	TBATS	STLF
ME	-0.13	-0.04	-0.03	-0.09
RMSE	0.24	0.54	0.33	0.70
MAE	0.18	0.40	0.21	0.59
MPE	-2.72	-1.53	-0.99	-3.12
MAPE	3.50	7.84	4.08	11.65

Table 4: Spain

	ARIMA	NNAR	TBATS	STLF
ME	-0.02	-0.10	0.90	-0.01
RMSE	0.07	0.24	0.95	0.20
MAE	0.05	0.19	0.90	0.17
MPE	-1.27	-5.75	44.30	-1.09
MAPE	2.65	9.80	44.49	8.39

Table 5: Florida

	ARIMA	NNAR	TBATS	STLF
ME	-0.01	0.00	-0.07	-0.01
RMSE	0.03	0.04	0.10	0.06
MAE	0.03	0.03	0.08	0.05
MPE	-1.35	-0.84	-10.45	-2.13
MAPE	4.33	4.09	11.94	7.86

Table 6: France

	ARIMA	NNAR	TBATS	STLF
ME	-0.05	-0.03	-0.03	-0.13
RMSE	0.22	0.26	0.28	0.42
MAE	0.17	0.20	0.22	0.33
MPE	-1.48	-1.36	-1.48	-4.27
MAPE	4.43	5.57	5.49	8.81

Table 7: Great Britain

	ARIMA	NNAR	TBATS	STLF
ME	0.01	-0.07	1.97	0.02
RMSE	0.16	0.20	2.07	0.27
MAE	0.11	0.14	1.98	0.21

	ARIMA	NNAR	TBATS	STLF
MPE	0.01	-2.50	62.77	-0.24
MAPE	3.57	4.44	62.82	6.87

Table 8: Italy

	ARIMA	NNAR	TBATS	STLF
ME	0.01	0.00	0.00	-0.01
RMSE	0.07	0.11	0.12	0.25
MAE	0.05	0.08	0.08	0.21
MPE	0.21	-0.31	-0.97	-2.32
MAPE	3.57	5.24	5.38	13.63

Table 9: New York

	ARIMA	NNAR	TBATS	STLF
ME	-0.01	0.00	0.08	0.00
RMSE	0.03	0.02	0.08	0.04
MAE	0.02	0.02	0.08	0.03
MPE	-1.86	-1.19	17.37	0.19
MAPE	4.31	3.93	17.42	6.87

2.2 ARIMA parametrisation

Table 10 presents the parameters chosen for each of the regressions.

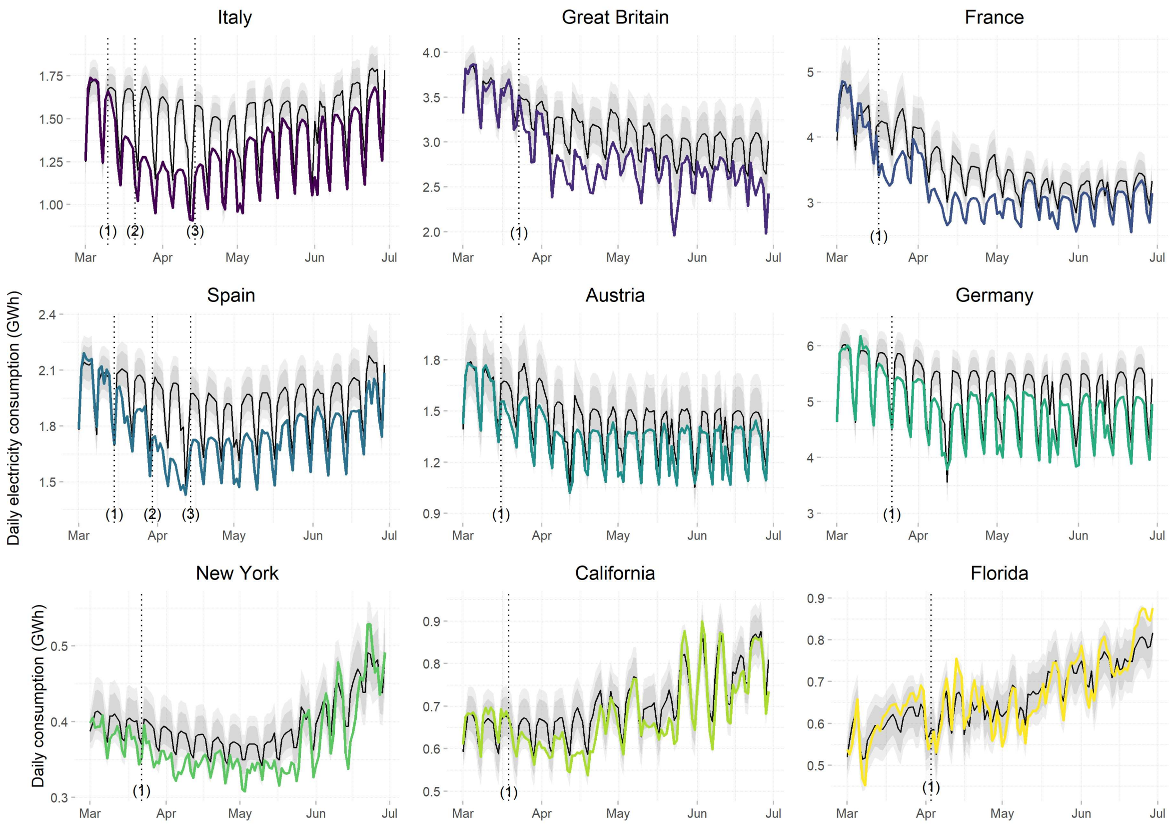
Table 10: Model parameters

Country	Lambda	Fourier.j.k.	ARIMA.p.d.q.
Austria	0.15	(3,4)	(5,1,1)
California	1.11	(3,3)	(4,1,3)
Germany	0.81	(3,11)	(4,1,1)
Spain	-0.06	(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	(3,19)	(2,1,3)
Italy	0.98	(3,21)	(2,1,1)
New York	-1.00	(3,5)	(3,1,1)

3 Additional results

3.1 Actual vs. forecast (baseline) daily electricity consumption

Supplementary Figure 4 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.



Supplementary Figure 4. Actual and Forecast daily electricity consumption.

3.2 Regression results

Supplementary Tables 11-20 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 11: Austria summary regression results

Variable	Coefficient	SE	z-value	p-value
AR1	0.309	0.024	13.100	0.000
AR2	0.093	0.024	3.799	0.000
AR3	0.009	0.024	0.356	0.722
AR4	0.149	0.024	6.158	0.000
AR5	0.017	0.023	0.744	0.457
MA1	-0.979	0.005	-180.179	0.000
Temperature	-0.010	0.001	-18.939	0.000
Temperature2	0.000	0.000	8.080	0.000
Holiday	-0.135	0.004	-36.988	0.000

Table 12: California summary regression results

Variable	Coefficient	SE	z-value	p-value
AR1	0.043	0.202	0.214	0.831
AR2	-0.119	0.262	-0.455	0.649
AR3	0.639	0.148	4.325	0.000
AR4	-0.112	0.043	-2.609	0.009
MA1	-0.059	0.199	-0.297	0.767
MA2	-0.087	0.254	-0.342	0.732
MA3	-0.824	0.119	-6.919	0.000
Temperature	-0.017	0.000	-109.216	0.000
Temperature2	0.000	0.000	41.578	0.000
Holiday	-0.021	0.002	-13.329	0.000

Table 13: Germany summary regression results

Variable	Coefficient	SE	z-value	p-value
AR1	0.528	0.045	11.772	0.000
AR2	-0.071	0.037	-1.891	0.059
AR3	0.085	0.032	2.634	0.008
AR4	-0.050	0.024	-2.090	0.037
MA1	-0.987	0.004	-274.733	0.000
Temperature	-0.015	0.011	-1.284	0.199
Temperature2	0.000	0.000	4.217	0.000
Holiday	-0.509	0.072	-7.074	0.000

Table 14: Spain summary regression results

Variable	Coefficient	SE	z-value	p-value
AR1	0.008	0.398	0.021	0.983
AR2	0.302	0.228	1.325	0.185
AR3	-0.028	0.026	-1.091	0.275
MA1	-0.404	0.398	-1.014	0.311
MA2	-0.544	0.387	-1.405	0.160
Temperature	-0.015	0.000	-57.411	0.000
Temperature2	0.000	0.000	20.472	0.000
Holiday	-0.113	0.003	-36.401	0.000

Table 15: Florida summary regression results

Variable	Coefficient	SE	z-value	p-value
AR1	0.309	0.024	13.100	0.000
MA1	0.093	0.024	3.799	0.000
MA2	0.009	0.024	0.356	0.722
Temperature	0.149	0.024	6.158	0.000
Temperature2	0.017	0.023	0.744	0.457
Holiday	-0.979	0.005	-180.179	0.000

Table 16: France summary regression results

Variable	Coefficient	SE	z-value	p-value
AR1	0.416	0.062	6.666	0.000
AR2	-0.531	0.080	-6.650	0.000
AR3	0.085	0.101	0.840	0.401
AR4	-0.066	0.089	-0.742	0.458
AR5	-0.403	0.076	-5.334	0.000
AR6	0.362	0.038	9.545	0.000
AR7	0.240	0.026	9.378	0.000
MA1	-0.879	0.061	-14.352	0.000
MA2	0.556	0.102	5.441	0.000
MA3	-0.342	0.121	-2.839	0.005
MA4	-0.071	0.118	-0.603	0.547
MA5	0.367	0.090	4.082	0.000
MA6	-0.622	0.053	-11.817	0.000
Temperature	-0.005	0.000	-47.774	0.000
Temperature2	0.000	0.000	22.010	0.000
Holiday	-0.021	0.001	-20.506	0.000

Table 17: Great Britain summary regression results

Variable	Coefficient	SE	z-value	p-value
AR1	0.780	0.148	5.274	0.000
AR2	-0.314	0.098	-3.220	0.001
MA1	-1.245	0.151	-8.263	0.000
MA2	0.434	0.174	2.502	0.012
MA3	-0.109	0.065	-1.687	0.092
Temperature	-0.067	0.004	-14.925	0.000
Temperature2	0.002	0.000	12.323	0.000
Holiday	-0.298	0.021	-13.918	0.000

Table 18: Italy summary regression results

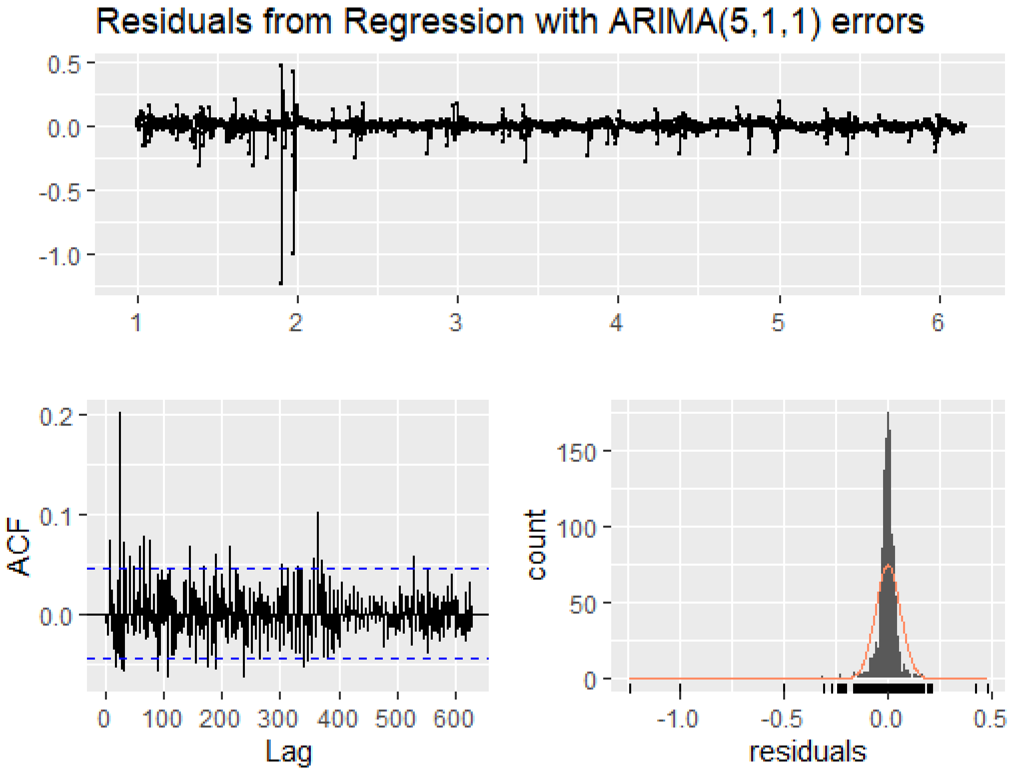
Variable	Coefficient	SE	z-value	p-value
AR1	0.512	0.025	20.688	0
AR2	-0.123	0.025	-4.937	0
MA1	-0.971	0.007	-143.581	0
Temperature	-0.031	0.001	-47.987	0
Temperature2	0.001	0.000	21.697	0
Holiday	-0.209	0.006	-32.589	0

Table 19: New York summary regression results

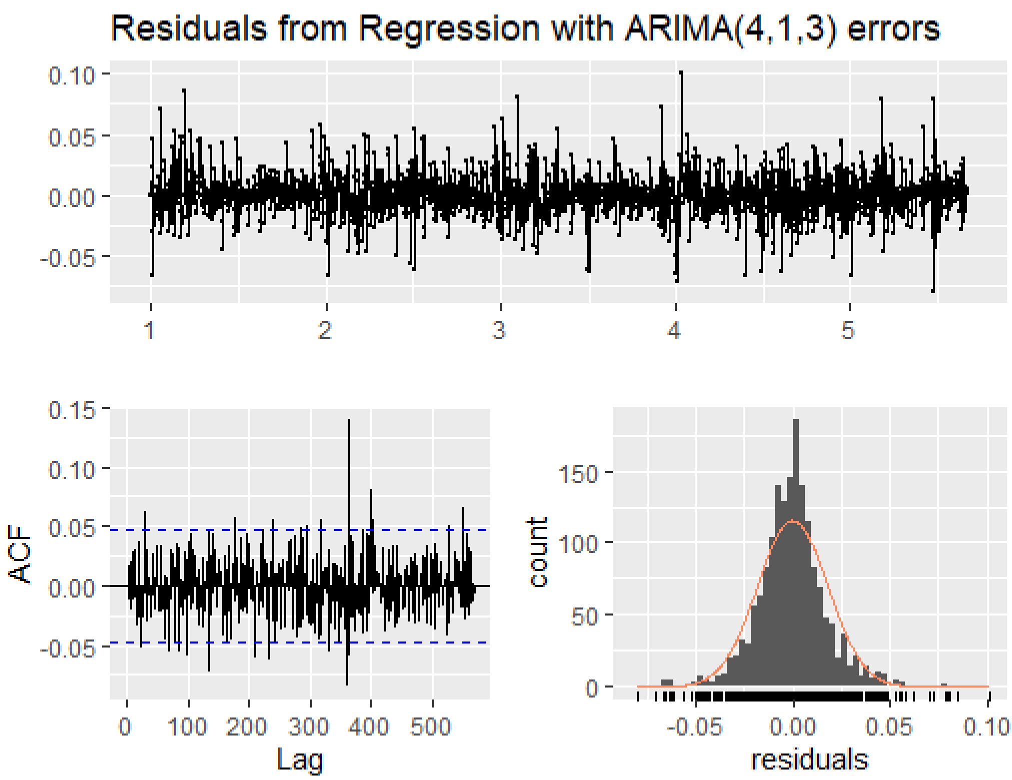
Variable	Coefficient	SE	z-value	p-value
AR1	0.893	0.029	30.999	0
AR2	-0.305	0.033	-9.172	0
AR3	0.091	0.025	3.714	0
MA1	-0.990	0.004	-225.969	0
Temperature	-0.015	0.001	-13.992	0
Temperature2	0.001	0.000	14.070	0
Holiday	-0.075	0.009	-8.870	0

3.3 Residuals

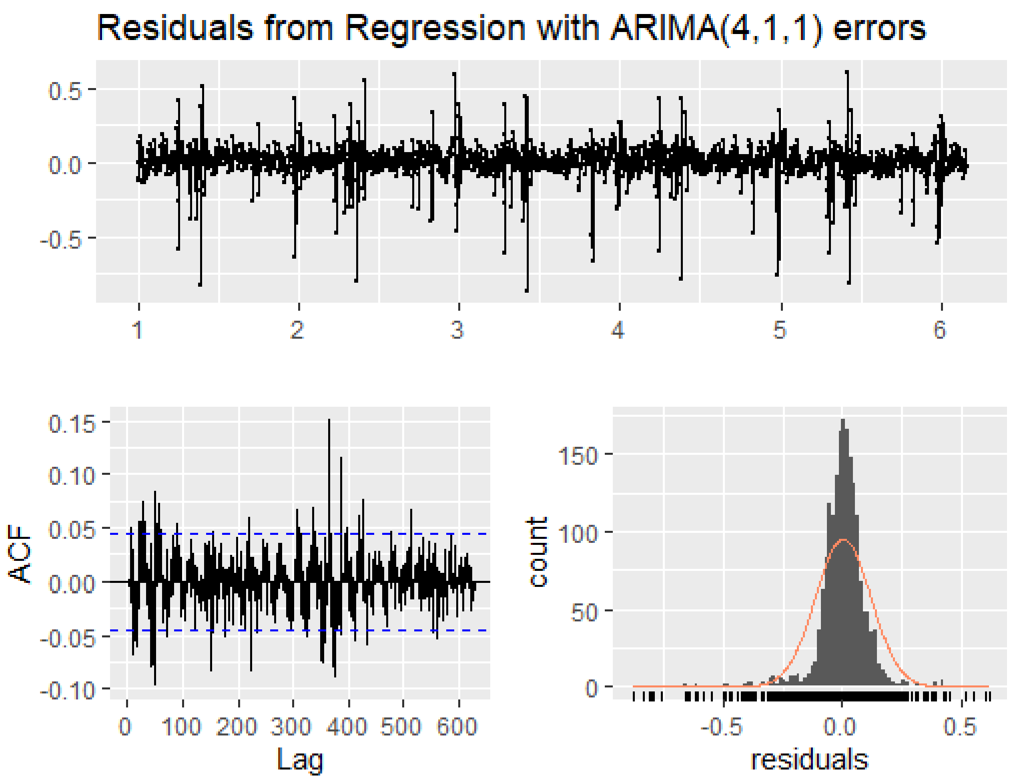
Supplementary Figures 5-13 present the residuals of the dynamic harmonic ARIMA regressions. The consumption data (Supplementary Figure 1) have some outliers that can be observed in the residuals but do not significantly influence the accuracy of the forecast. All the residuals are close to a normally distributed white noise.



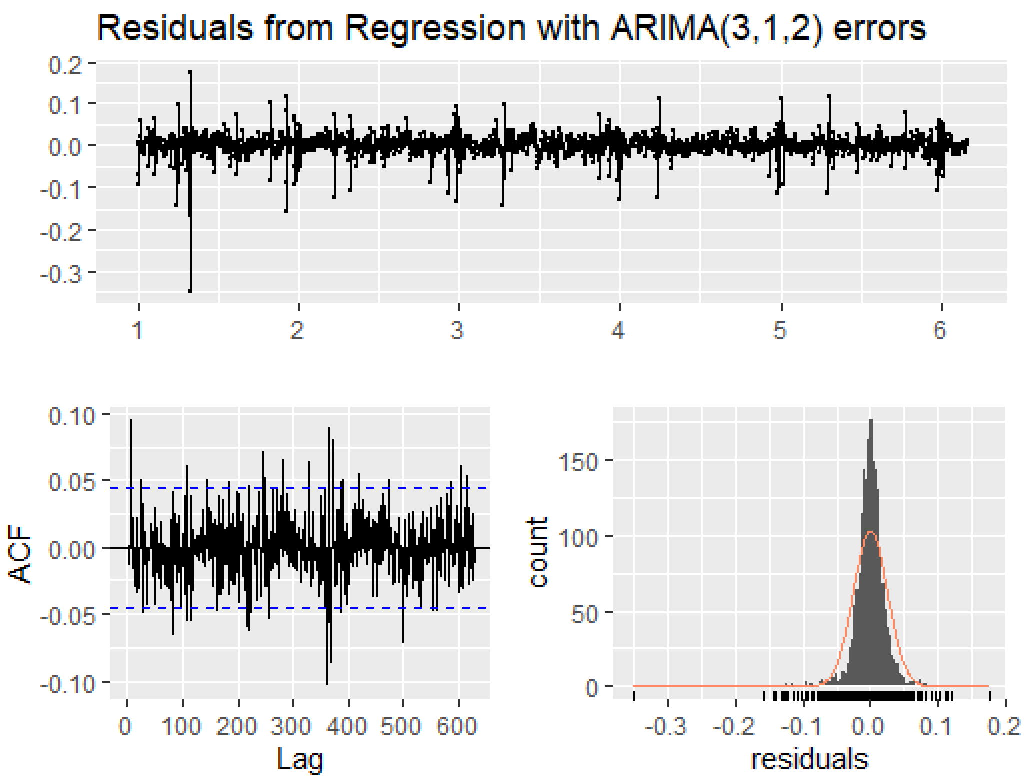
Supplementary Figure 5. Austria



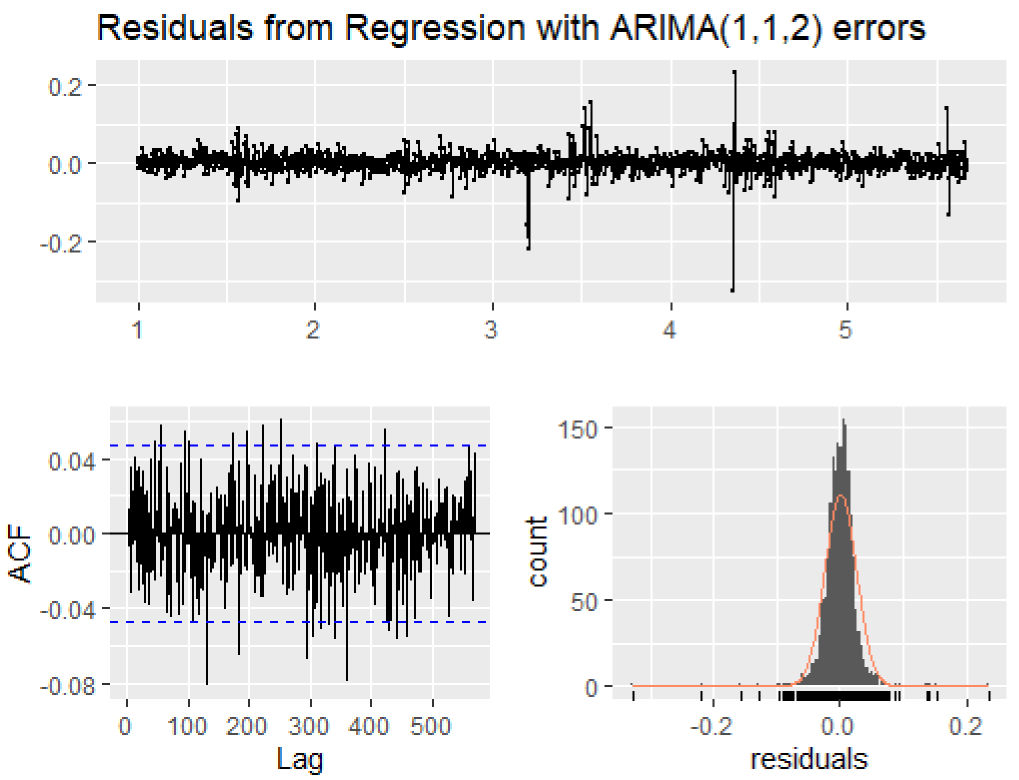
Supplementary Figure 6. California



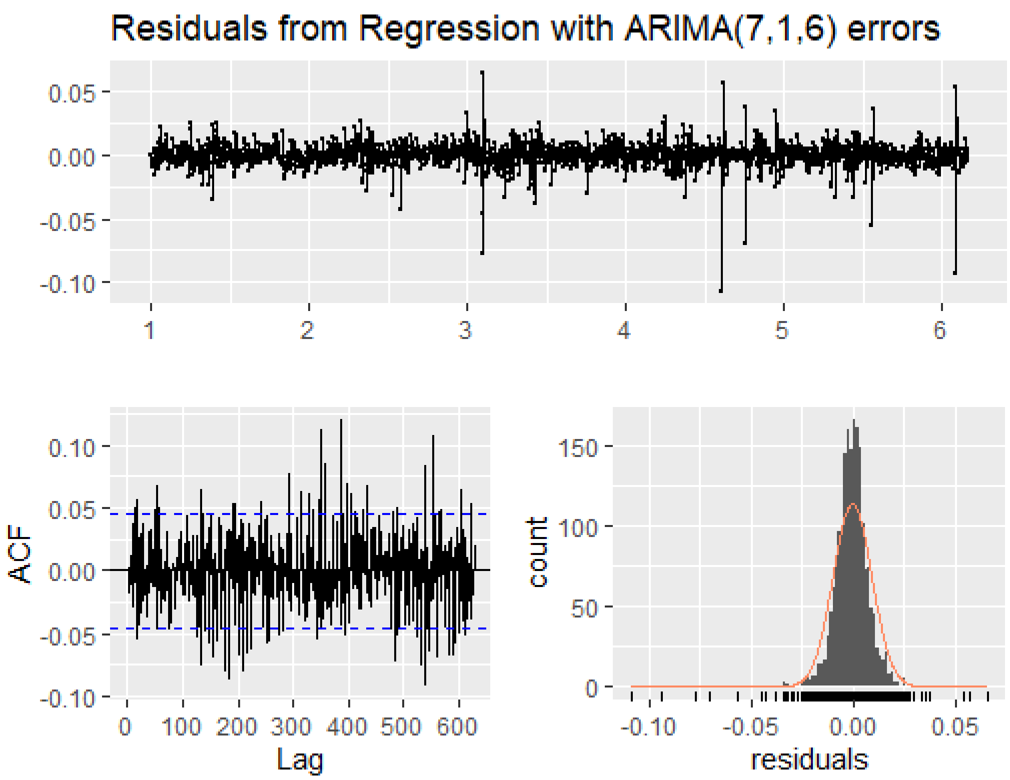
Supplementary Figure 7. Germany



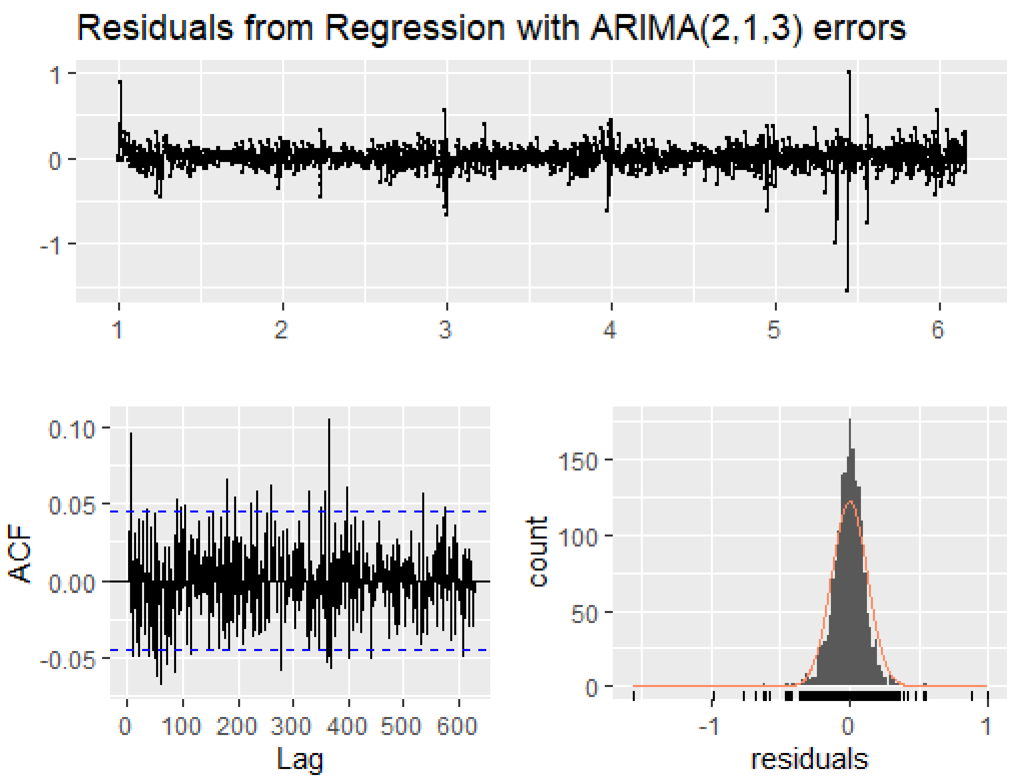
Supplementary Figure 8. Spain



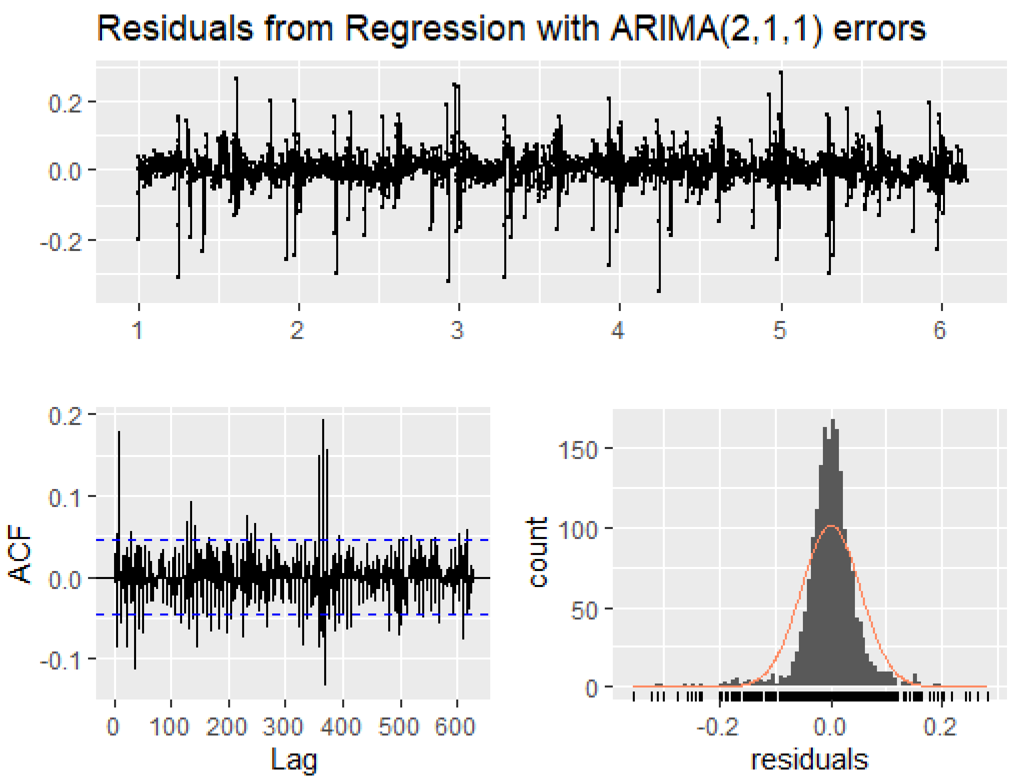
Supplementary Figure 9. Florida



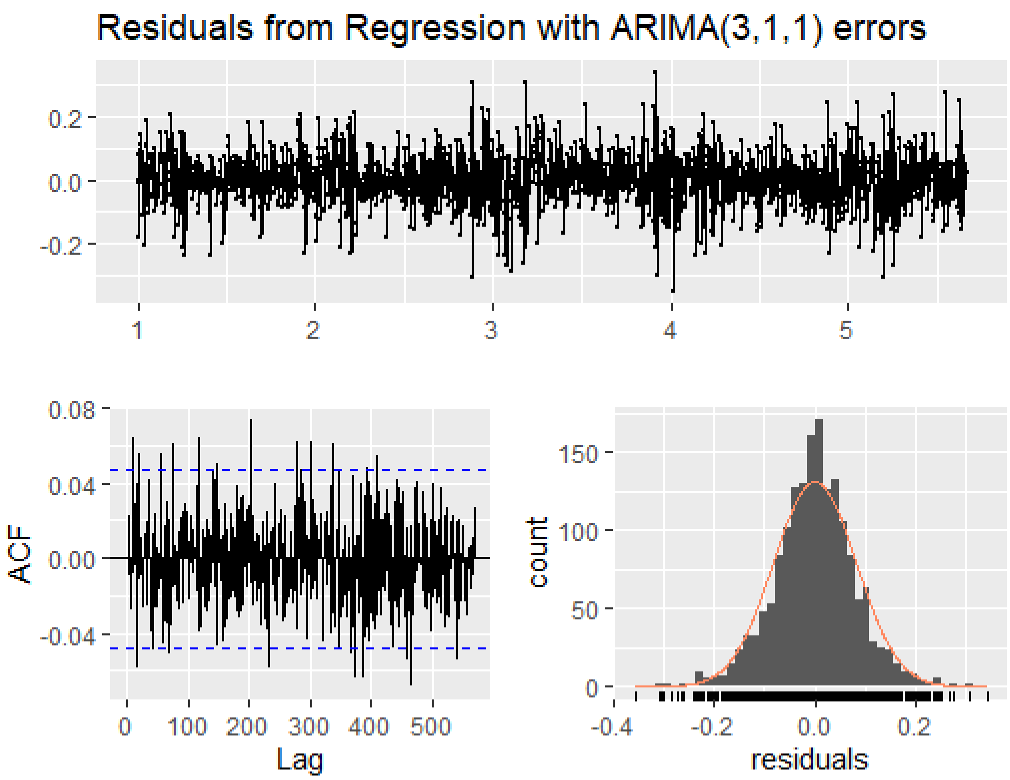
Supplementary Figure 10. France



Supplementary Figure 11. Great Britain



Supplementary Figure 12. Italy



Supplementary Figure 13. New York