**Title:** Time series analysis of COVID-19’s impact on the European’s hospitality industry: estimates based on accommodation statistics from 18 countries[[1]](#footnote-1)

**Abstract**

In this study we quantitatively analyze adverse effects of the COVID-19 pandemic-related restrictions on a hospitality industry’s demand indicator dynamics in 18 European countries. We propose a unified approach for measuring COVID-related losses based on comparing actual outcomes with counterfactual outcomes obtained using the state-of-the-art Prophet procedure. We show that the algorithm is very competitive compared to some of the widely used automated forecasting procedures. Using data disaggregated to segments based on countries, accommodation types, tourists’ residence, and month, it has been shown that losses are heterogeneous across various segments of the hospitality market. The relative importance analysis using a decomposition of explained variance in regression models has shown that most of the explained variance can be attributed to time effects followed by country effects. The role of tourists’ residence and accommodation type is much smaller, but still significant. The most and the least impacted groups of countries are identified.

**Keywords:** forecasting, COVID-19, hotels, accommodation, demand, Shapley value

**JEL:** C53, L83

1. **Introduction**

On 17 March 2020, EU Member States agreed on coordinated action at the external borders to restrict non-essential travel due to the COVID-19 outbreak for a specific period which has been extended a number of times (European Comission, 2020). Other restrictions were applied by EU countries as well. All these restrictions dramatically affected people’s rights to participate in hospitality and tourism (Baum and Hai, 2020). To assess the impact of restrictions associated with the COVID-19 outbreak on any industry, including the hospitality industry, it is crucial to be able to obtain high-quality baseline forecasts of the industry’s key performance indicators. Such forecasts are necessary to figure out how close the industry is to having recovered from the downturn at any given point in time, as well as to give governments quantitative estimates for providing differentiated rather than unified support for each segment of the hospitality industry taking non-homogeneity of the lockdown’s effect across these segments. A relatively small lag of 1-2 months with which European tourism statistics becomes available, makes such targeted data-based decisions potentially possible.

Accommodation statistics are a key part of the system of tourism statistics in the EU and have a long history of data collection, but there have been no systematic research into the best methods for obtaining annual baseline forecasts for the hospitality industry’s performance indicators. The goal of the paper is to propose a framework for obtaining such counterfactual forecasts and for assessing losses of tourism industry caused by unusual events such as the COVID pandemic and to provide preliminary quantitative estimates by assessing incremental differences between the actual values of an important hospitality and tourism industry indicator and its baseline forecast. The topic is important not only now, when the industry is still far from full recovery and the threats of new waves of the outbreak remain, but also to make it possible for government agencies and professional associations to obtain such estimates quickly in case of any other influential events that may occur in the future.

This study uses time series data to identify the incremental effect of the COVID-19 by comparing observed values of a key hospitality industry indicator - nights spent at tourist accommodation establishments - to those predicted in the absence of COVID-19 based on data from 2012-2019. Many forecasting techniques were used for predicting tourism-related demand indicators, including ARIMA (Chang and Liao, 2010), ETS models (Athanasopoulos and Hyndman, 2008; Gunter and Önder, 2015), and neural networks (Claveria and Torra, 2014). The performance of all methods varied from study to study and there is no evidence that any single method outperforms all or most others. Prophet forecasting procedure (Taylor and Letham, 2018), used in this study, has not been applied to tourism data before, while being a promising tool for bulk forecasting without fine-tuning each model individually.

First, we compare four state-of-the art time series modeling techniques based on the quality of predictions obtained using them for the 12 months of 2019 using monthly data from 84 previous months. Second, we obtain forecasts for each month of 2020 based on all pre-COVID data from January 2012 to December 2019. This gives a baseline for all other comparisons that can be used over the whole year. By comparing the actual figures for March-May 2020 to the baseline forecast we get estimates of losses from COVID-related consequences. Finally, we meta-analyze our estimates across all time series to reveal which countries and segments suffered the most (in percentage terms) in which months based on the incremental decrease observed in March, April and May, after the borders were closed for tourists.

1. **Literature review**

There have been several important applications of causal impact analysis techniques to the hospitality and tourism research, including but not limited to the following topics:

* Impact of mega-sport events on tourist arrivals (Fourie and Santana-Gallego, 2011). Using a standard gravity model of bilateral tourism flows between 200 countries from 1995 to 2006, the authors have shown that mega-sport events promote tourism but the gain varies depending on the type of mega-event, the participating countries and whether the event is held during the peak season or off-season.
* Impact of terrorism on tourism. Arana and León (2008) studied short-run impacts of the September 11 attacks in New York on tourist preferences for competing destinations in the Mediterranean and the Canary Islands using a stated preference model based on two different samples taken at different points in time in relation to terrorist attacks. It was shown that the attacks caused a shock to tourists’ utility, and a change in the image profile of destinations.
* Impact of the sharing economy on the hotel industry. Zevras et al. (2015) identified Airbnb's causal impact on hotel room revenue in Texas by exploiting the significant spatiotemporal variation in the patterns of Airbnb adoption across city level markets, which allowed them to use a difference-in-differences empirical strategy.

So far there have been relatively few studies on consequences of COVID-19 for the hospitality industry. Nicola et al. (2020)reviewed socio-economic implications of the COVID-19 pandemic. A paper by Gössling et al. (2020) presents an overview of challenges faced specifically by the tourism industry and discusses why COVID-19 is an analogue to the ongoing climate crisis, and why there is a need to reconsider the volume growth tourism model advocated by various tourism organizations. Baum and Hai (2020) provide a comprehensive list of rights to participate in hospitality and tourism that were affected on a scale unprecedented before the coronavirus outbreak. These papers have structured and discussed some scattered information that was published by mass media and consulting companies. Duarte Alonso et al. (2020) explored key concerns, ways of coping, and the changes and adjustments undertaken by these firms’ owners and managers during the COVID-19 outbreak using an international sample of 45 hospitality businesses.

The impact of COVID-19 on the hospitality industry has not been empirically modeled in academic research using any official statistics yet. Accommodation statistics for the EU is made available earlier than in many other regions of the World, which has made our preliminary estimates of the COVID-related losses possible. The hospitality industry’s reopening is going to be a slow process, especially taking into account that recent research has shown that most customers (over 50%) are not willing to travel to a destination and stay at a hotel any time soon (Baum and Hai, 2020).

1. **Data**

We collected monthly data on nights spent at tourist accommodation establishments of 18 European countries for which data for March-May 2020 was already available from Eurostat (<https://ec.europa.eu/eurostat/web/tourism/data/database>) as of September, 1 2020. All time series span over the maximum time range provided by Eurostat: from January 2012 to March 2020. For each country, the following set of time series obtained from table *tour\_occ\_nim* was used:

* Nights spent in hotels and similar accommodation (I551), residents of foreign countries (FOR)
* Nights spent in hotels and similar accommodation (I551), residents of the reporting country (NAT)
* Nights spent in holiday and other short-stay accommodation (I552), residents of foreign countries (FOR)
* Nights spent in holiday and other short-stay accommodation (I552), residents of the reporting country (NAT)
* Nights spent in camping grounds, recreational vehicle parks and trailer parks (I553), residents of foreign countries (FOR)
* Nights spent in camping grounds, recreational vehicle parks and trailer parks (I553), residents of the reporting country (NAT)

The data has been downloaded as a wide format table with 114 columns corresponding to nights spent at tourist accommodations. All series were given short descriptive names containing the country’s name (*denmark*/*germany*/etc.), the type of accommodation establishment (*hotel*/*holiday*/*camping*) and the group of visitors (*foreign*/*national*).

1. **Methods**
   1. **Counterfactual framework for COVID impact estimation**

The approach to assessing losses from COVID-19 adopted in this study is based on the counterfactual framework of causal inference (Morgan and Winship, 2015) and on the idea of potential outcomes in particular (Rubin, 2005). A potential outcome is the outcome under a potential treatment. The causal effect of the treatment is the difference between the potential outcome if the treatment is received and the potential outcome if it is not. A univariate time series analysis without regressors was used to obtain potential outcomes in the absence of COVID-19 by projecting 2012-2019 series to 2020. The use of univariate time series modeling may seem an oversimplification at first. However, as overall pre-epidemics economic conditions were favorable in the world, we can expect that all the recent trends could have been projected to 2020 in the absence of the pandemics. In addition, we are interested in 12 month ahead forecasting, and reliable forecasts of influential indicators (currency exchange rate, weather, etc.) are not available many months ahead. Therefore, the choice of the univariate analysis approach seems to be reasonable, especially due to high predictability of tourism flows, which will be demonstrated in the results section. Using the forecasting algorithm that performed the best on 2019 data, we obtained point estimates for the percentage difference between actual value of the dependent variable and the baseline forecast. 80% uncertainty intervals, commonly used in forecasting (e.g. Hyndman and Athanasopoulos (2018)) were obtained as well.

One of the main requirements to forecasting methods applied to our data is that they should have some built-in parameter tuning functionality as the problem involves forecasting hundreds of time series and they cannot be fine-tuned individually. We compare the performance of several state-of-the-art time series modeling techniques using monthly data from 2012 to 2018 as the training sample and 2019 – as the testing sample. Methods are briefly described in the next section of the paper and references to more extensive descriptions are provided.

* 1. **Forecasting methods**

One of the main requirements to forecasting methods applied to our data is that they should have some built-in parameter tuning functionality as the problem involves forecasting hundreds of time series and it is hardly possible to manually fine-tune each model. We compare the performance of several state-of-the-art time series modeling techniques: Automated Seasonal ARIMA, Neural Network Autoregression (NNETAR), State space models of exponential smoothing (ETS), and the Prophet algorithm. Data from 2012 to 2018 was used as the training sample and 2019 – as the testing sample.

All models were fitted on 84 months of training data (January 2012 – December 2018). A comparison of methods was done based on their performance in terms of their mean absolute percentage error (MAPE) on the testing sample containing all 12 months of 2019. In addition, a few cases were scrutinized to make sure that the winning methods make sensible forecasts from a judgmental point of view. Each of the time series forecasting methods compared in our study is briefly described below.

**Automated Seasonal ARIMA**

Seasonal ARIMA*(p,d,q)(P,D,Q)m* models use *p* past values of the forecast variables, as well as *q* past forecast errors in regression-like model. The original series is differenced *d* times if it is non-stationary. The seasonal part of the model (*P,D,Q*) consists of terms that are similar to the non-seasonal components of the model but involve backshifts of the seasonal period (*m*). In the case of monthly data *m*=12. We used a variation of the Hyndman-Khandakar algorithm (Hyndman and Khandakar, 2008), implemented in the *auto.arima* function of the *forecast* package for R. The automated ARIMA procedure combines unit root tests, minimization of the AICc (AIC with a correction for small sample sizes) and MLE to obtain an ARIMA model:

1. The number of differences 0≤d≤2 is determined using KPSS tests of stationarity.
2. The values of *p* and *q* are then chosen by minimizing the AICc after differencing the data *d* times. The algorithm uses a stepwise search to traverse the model space.
3. Four initial models are fitted:

* ARIMA (0, *d*, 0),
* ARIMA (2, *d*, 2),
* ARIMA (1, *d*, 0),
* ARIMA (0, *d*, 1)

1. A constant is included unless *d*=2.
2. If *d*≤1, an additional model is also fitted: ARIMA (0,*d*,0) without a constant.
3. The best model (with the smallest AICc value) is set to be the “current model”.
4. Variations on the current model are considered by changing *p* and/or *q*. The best model considered so far (either the current model or one of these variations) becomes the new current model. The process is repeated until no lower AICc can be found.

**State space models of exponential smoothing (ETS)**

The state space forecasting framework is an automated approach to selecting models from the exponential smoothing family. Each model from the so-called ETS (Error-Trend-Seasonality) family consists of a measurement equation that describes the observed data, and some state equations that describe how the unobserved components or states (level, trend, seasonal) change over time. The framework was proposed in Hyndman et al. (2002) and later developed in Hyndman et al. (2008). Each state space model is referred to as ETSwhere the possibilities for each component cover all traditional, as well as more intricate exponential smoothing models. The error component can be either additive or multiplicative (*A* or *M*). The trend component can take 3 values (None (*N*), Additive (*A*), or damped additive (*Ad*)). The Seasonal component can take 3 values as well (None (N), Additive (A), or Multiplicative). For example, ETS(*M*,*N*,*N*) is simple exponential smoothing with multiplicative errors, ETS(*A*,*A*,*N*) is Holt’s linear method with additive errors, while ETS(*M*,*A*,*N*) is Holt’s linear method with multiplicative errors. As a result, a total of 18 models are estimated within the ETS framework, and the best one is selected based on AICc. The methodology is fully automatic. The only required argument for ETS is the time series. This methodology performed extremely well on the M3-competition data (Hyndman *et al.*, 2002).

**Neural Network Autoregression (NNETAR)**

A neural network can be thought of as a network of “neurons” which are organized in layers. The predictors (or inputs) form the bottom layer, and the forecasts (or outputs) form the top layer, while the hidden layer contains a few neurons as well that make the model nonlinear. We use an automated procedure *NNETAR* which fits a feed-forward neural network (Svozil, Kvasnicka and Pospichal, 1997) with a single hidden layer and lagged inputs for forecasting univariate time series (Hyndman and Athanasopoulos, 2018). The specification is NNAR(*p*,*P*,*k*)*m* , where *p* is the order of autoregression, *P* is the differencing parameters, *m* specifies the periodicity (*m*=12 for monthly data), and *k* is the number of neurons at the hidden layer. If the values of *p* and *P* are not specified, they are selected automatically. For non-seasonal time series, the default is the optimal number of lags (according to the AIC) for a linear AR(*p*) model. For seasonal time series, the default values are *P*=1 and *p* is chosen from the optimal linear model fitted to the seasonally adjusted data. If *k* is not specified, it is set to *k*=(*p*+*P*+1)/2 (rounded to the nearest integer). In the case of forecasting, the network is applied iteratively. For forecasting one step ahead, we simply use the available historical inputs. For forecasting two steps ahead, we use the one-step forecast as an input, along with the historical data. This process proceeds until we have computed all the required forecasts (Hyndman and Athanasopoulos, 2018).

**Prophet**

The Prophet procedure was developed by Taylor and Letham (2018) originally as a forecasting procedure for business forecasting at Facebook. It is a procedure for forecasting time series data based on an additive model flexibly accounting for even non-linear trends and any type of seasonality and holiday effects (relevant for daily data). It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well. What differentiates it from the exponential smoothing ETS models and other decomposable models is a different approach to modeling each component. Some of the key features are that the underlying algorithms rely on Fourier series to provide a flexible model of periodic effects (Harvey and Shephard, 1993), and on a piece-wise constant rate of growth model of the trend component. While both additive and multiplicative seasonality modes are allowed, the multiplicative mode was chosen as the more adequately describing demand for accommodation in most European countries in recent years.

* 1. **Evaluation and meta-analysis of the COVID-19 effect**

The method that worked best most often for the 108 time series was eventually used to obtain point estimates of the percentage differences between actual values of the dependent variable and the baseline forecasts, as well as 80% uncertainty intervals commonly used in forecasting (Makridakis, Wheelwright and Hyndman, 2008). Estimated losses were visualized using boxplots and heatmaps with hierarchical clustering which allowed to reveal groupings of subsectors and countries. Additional meta-analysis was aimed at explaining the heterogeneity of estimated percentage losses for 108 country-sector-guest combinations using the characteristics of the series (meta-data). All 4 explanatory variables were categorical (country/sector/guest’s residence/month), which is why an effective method for handling categorical data and revealing interactions was needed. We used OLS regressions with heteroscedasticity robust standard errors to explain heterogeneity of loss estimates and binary logistic regressions (Hosmer Jr, Lemeshow and Sturdivant, 2013) to explain the probability of being in the lowest quartile by losses. Based on the results of a series of models with different dependent variables (both continuous (% losses) and discrete (losses exceeding the median)) conclusions were made based on the most stable empirical facts. Shapley value decomposition was applied to decompose R2 (in the case of the OLS regression) and McFadden’s R2 (in the case of the binary logistic regression) into the contributions of individual factors. The decomposition is based on averaging relative importance over all orderings of the independent variables (Azen and Budescu, 2003; Azen and Traxel, 2009; Shorrocks, 2013).

1. **Results**

**5.1 Comparison of forecasting algorithms**

Table 1 reports the number of time series for which each model gave the lowest MAPE and MAE.

Table 1. Benchmarking of methods based on the number of time series where they outperformed competing methods (January – December, 2019)

|  |  |  |
| --- | --- | --- |
| **Method** | **Number of wins (by MAE)** | **Number of wins (by MAPE)** |
| **Automates Seasonal ARIMA** | 27 | 25 |
| **NNETAR** | 21 | 23 |
| **ETS** | 27 | **30** |
| **Prophet** | **33** | **30** |
| **Total number of time series** | 108 | 108 |

It turned out that, while all models are competitive, Prophet and ETS were the winners in terms of MAPE more often than others. The similarity of MAPEs between the Prophet and the ETS procedures were also observed in Taylor and Letham (2018). It has also been checked that the percentage of time series, where the MAPE is less than 5% and less than 10% is the highest for Prophet (31% and 57% of series, respectively).

Besides using the formal model selection criteria presented above, our final choice of the method was based on taking a closer look at several cases. ETS turned out to be not particularly well-suited for automated forecasting because of its revealed propensity to bias predictions because of overfitting weak non-linear trends. While having performed well in forecasting for 2019, it gave a clearly unrealistic 2020 baseline forecast for some series, such as *croatia\_camping\_for* (Figure 1). Even though it is possible to tweak the ETS algorithm manually to fix the identified problem by using the additive rather than the automatically selected multiplicative seasonality or by changing some model parameters, Prophet’s default settings consistently ensured sensible forecasts, making it a preferable method for large-scale forecasting of many time series.

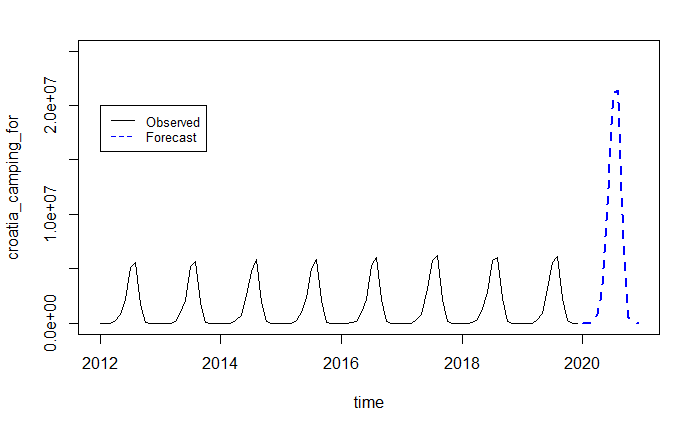


Figure 1. Nights spent by foreign visitors in Croatian camping grounds, recreational vehicle parks and trailer parks: observed (Jan 2012-Dec 2020) and incorrectly forecasted (Jan 2020-Dec 2020) using the ETS procedure

The largest unweighted average MAPE was observed for camping demand, especially from foreigners (MAPE=40%). Holiday accommodations are more predictable and the demand for hotels is, on average, almost perfectly predictable (Prophet’s MAPE=4.99% for foreign demand and 4.60% for internal demand). The difference in the magnitude of percentage errors is explained primarily by a relatively modest and intermittent demand in the camping sector. As a result, even a small absolute error can result in a huge percentage error when the percentage is found relative to a small number.

For example, if we take a look at *croatia\_ camping\_nat* series (Figure 2) we will see that there has been a growing trend in the last 4 years, but there was no steady growth before 2017, which causes uncertainty in the estimates. It is also worth mentioning that the demand for campings in the winter is typically close to zero, which explains large estimates of the percentage losses. At the same time, if we look at confidence bands the year 2020, there is some uncertainty mostly about the beginning and the end of the year, but, overall, the uncertainty intervals are narrow.

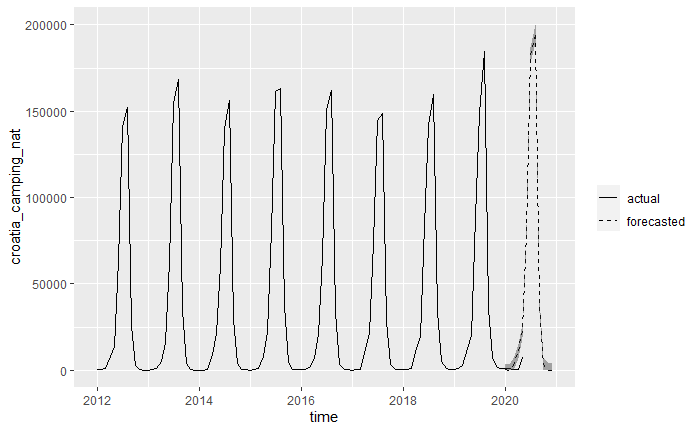


Figure 2. Nights spent by the country residents in Croatian camping grounds, recreational vehicle parks and trailer parks: observed (Jan 2012-May 2020) and forecasted (Jan 2020-Dec 2020) using the Prophet procedure

A plot representing forecasts for Germany is presented below for illustrative purposes (Figure 3). It shows that forecasted values almost perfectly match observed values in January and February of 2020 even though they were not included into the training sample. There is little uncertainty associated with 2020 forecasts made for Germany as there was a stable trend and seasonality over the years.

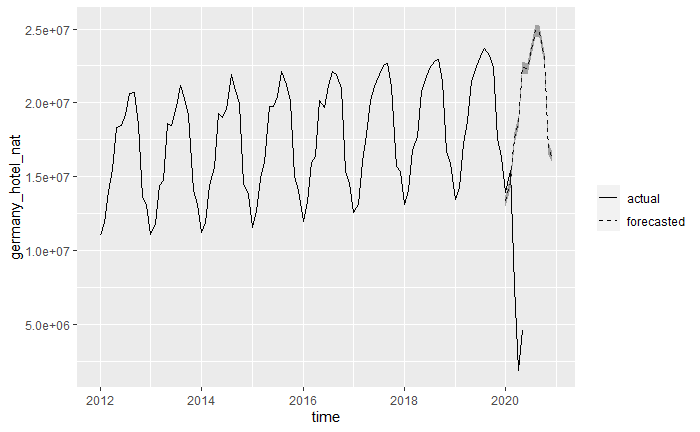


Figure 3. Nights spent by the country residents in German hotels:

observed (Jan 2012-Dec 2020) and forecasted (Jan 2020-Dec 2020) using the Prophet procedure

**5.2 Evaluation and meta-analysis of the COVID-19 effect**

Using all data points from January 2012 to December 2019 (the last month when Europe has not been influenced by COVID-19 in any way) a forecast for the next 12 months was generated using the Prophet algorithm, which was shown to perform better than others. First, a new training set was created so that it contains all time periods up to December 2019. Then the Prophet algorithm was applied to the new training dataset and a 12-month ahead forecast was obtained.

Some positive or very small negative point estimates of the percentage difference between the actual and forecasted values (implying no losses) were caused by the presence of highly uncertain estimates (mostly for camping grounds in countries with small intermittent demand for them). Such outliers were eliminated by excluding all loss estimates with a prediction interval wider than 20 percentage points. After that, the distribution of the remaining estimates was summarized using boxplots grouped by month and sector (Figure 4). Across all countries holiday and other short-stay accommodation experienced smaller median losses than hotels and camping grounds.

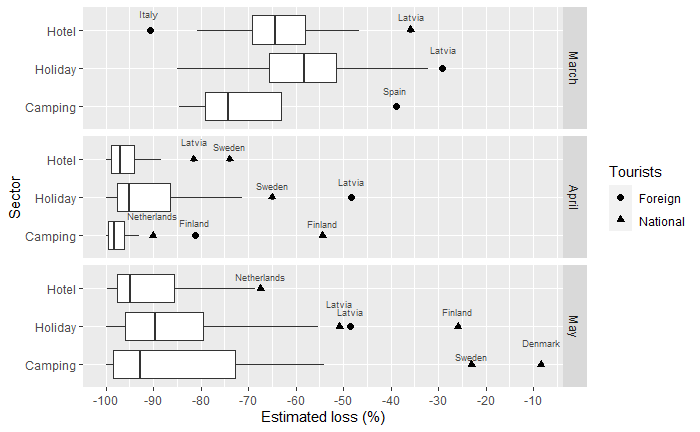


Figure 4. Boxplots of estimated losses by month and sector

A clustered heatmap was constructed with rows and columns ordered to highlight patterns and are accompanied by dendrograms (Figure 5). The heatmap clearly shows the clustering of 18 countries and 18 indicators by estimated percentage losses. First, most camping segments loss estimates has wide uncertainty intervals and are not reported. March losses were consistently the lowest, because all major restrictions were introduced only in the second half of the month.

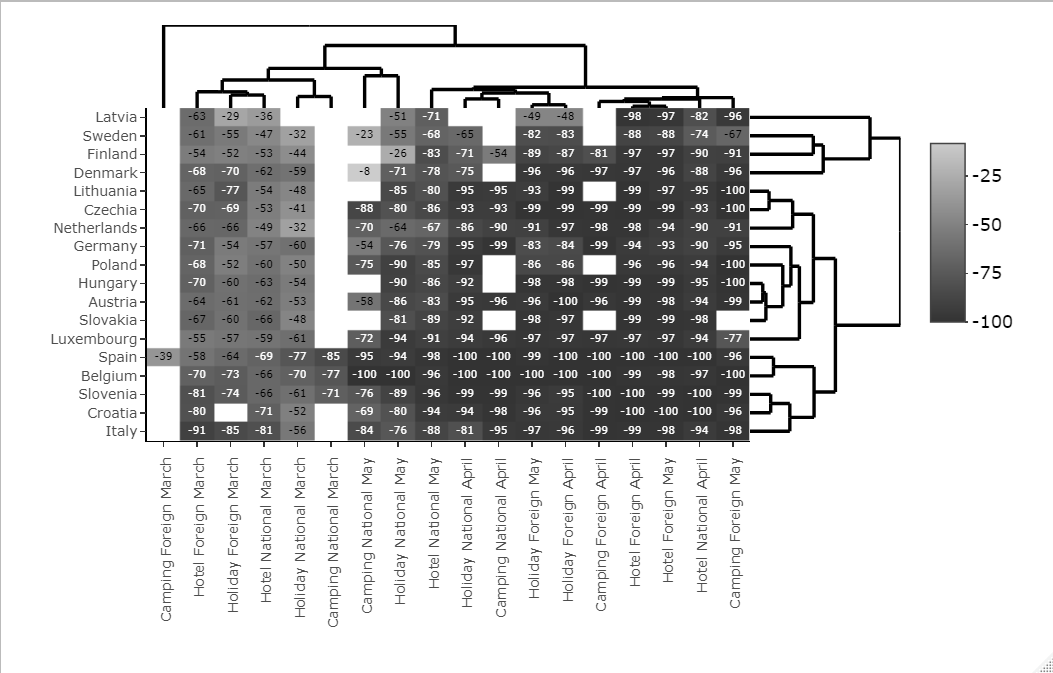


Figure 5. Clustered heatmap of estimated losses (%)

Even though all countries experienced serious losses during restrictions associated with COVID-19, there is a cluster of countries where percentage losses in the number of nights spent at tourist accommodations were smaller: Latvia, Sweden, Finland, and Denmark. The most impacted group of countries includes Italy, Croatia, Slovenia, Belgium, and Spain. The rest of the 9 countries are in the medium segment mainly due to smaller losses during the first month of the all-European lockdown.

Negative linear regression coefficients indicate on average larger losses, while negative logistic regression coefficients - lower probabilities of smaller than 2/3 decrease compared to the baseline forecast (Table 2). The estimates of linear and logistic regressions presented in Table 2 confirm that controlling for other factors Sweden, Latvia and Finland were significantly less damaged compared to Austria (the reference country representing the medium damage segment). Parameter estimates are consistently negative for Belgium, Italy, and Slovenia with some evidence of similarly unfavorable situation in Croatia, Czechia, and Spain. Therefore, regression analysis results agree with the clustering results presented previously. According to a series of linear hypothesis tests, compared to April, in May the situation improved unsubstantially, but statistically significantly (at the 1% level according to specifications 1 and 2 and at the 10% level according to specifications 3 and 4). Percentage losses in the number of nights spent by a country’s residents were, on average, around 10% smaller compared to those in the number of nights spent by foreign visitors. The hotel sector experienced around 5-7% larger losses than holiday and camping accommodations.

Table 2. Parameter estimates of OLS and logistic regressions

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | | | |
|  | ***Dependent variable:*** | | | |
|  |  | | | |
|  | **Estimated loss**  **(continuous, <0 for all observations)** | | **Estimated loss smaller**  **than 67% (=1 if yes, =0 if no)**  **Logistic regression** | |
|  | ***OLS*** | |
|  | **(1)**  **All observations** | **(2)**  **Subsample: uncertainty**  **interval width≤20**  **percentage points** | **(3)**  **All**  **observations** | **(4)**  **Subsample: uncertainty**  **interval width≤20**  **percentage points** |
|  | | | | |
| ***Country (reference category: Austria)*** | | | | |
| Belgium | -7.87\*\*\* | -8.96\*\*\* | -3.24\* | -6.56\*\*\* |
| Croatia | -4.61 | -3.21 | -3.24\*\* | -5.22\*\*\* |
| Czechia | -3.16 | -1.31 | -2.16\* | -3.95\*\*\* |
| Denmark | 8.30 | 6.27 | -0.00 | -2.51 |
| Finland | 20.38\*\*\* | 12.73\*\*\* | 2.13\* | 1.34 |
| Germany | 2.52 | 3.54 | -0.65 | -1.12 |
| Hungary | -1.33 | -2.66 | -1.36 | -2.44\*\* |
| Italy | -6.31\*\* | -4.94\* | -3.24\*\* | -5.53\*\*\* |
| Latvia | 18.48\*\*\* | 19.27\*\*\* | 2.58\*\* | 2.96\*\* |
| Lithuania | 15.37 | -1.44 | -0.00 | -2.44 |
| Luxembourg | -1.57 | 0.69 | -0.65 | -1.13 |
| Netherlands | 6.14\*\* | 5.55\*\* | 0.60 | 0.00 |
| Poland | 2.73 | 1.38 | -0.00 | -2.50\*\* |
| Slovakia | -0.78 | -1.00 | -0.00 | -2.41\*\* |
| Slovenia | -5.92\*\* | -6.37\*\*\* | -2.16\* | -5.14\*\*\* |
| Spain | -5.17 | -6.37\* | -1.36 | -4.37\*\* |
| Sweden | 23.97\*\*\* | 19.02\*\*\* | 3.44\*\*\* | 2.56\*\* |
| ***Sector (reference category: Camping)*** | | | | |
| Holiday | -1.01 | 0.20 | 1.08\* | -0.34 |
| Hotel | -7.04\*\*\* | -5.83\*\*\* | -0.24 | -2.27\*\* |
| ***Guest type (reference category: Foreign)*** | | | | |
| National | 11.87\*\*\* | 10.12\*\*\* | 1.99\*\*\* | 2.46\*\*\* |
| ***Month (reference category: March)*** | | | | |
| April | -31.50\*\*\* | -32.96\*\*\* | -5.08\*\*\* | -8.28\*\*\* |
| May | -24.13\*\*\* | -25.88\*\*\* | -4.04\*\*\* | -6.78\*\*\* |
| Constant | -66.92\*\*\* | -64.58\*\*\* | -0.10 | 3.98\*\*\* |
|  | | | | |
| Observations | 324 | 272 | 324 | 272 |
| R2 | 0.56 | 0.74 |  |  |
| Adjusted R2 | 0.53 | 0.71 |  |  |
| Log Likelihood |  |  | -86.10 | -49.12 |
| Akaike Inf. Crit. |  |  | 218.21 | 144.23 |
| Residual Std. Error | 16.38  (df = 301) | 10.06  (df = 249) |  |  |
| F Statistic | 17.53\*\*\*   (df = 22; 301) | 31.56\*\*\*  (df = 22; 249) |  |  |
|  | | | | |
| *Note:* | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | | | |

According to the Shapley value decomposition of each variable’s contribution to the overall explanatory power of these models, we inferred the relative importance of country, sector, guest type and month in explaining the heterogeneity of losses (Table 3). Month played by far the largest role, yet country-differences’ contribution was also substantial - around 20-30%. While being less important, the combined influence of the sector and the guest type is also quite substantial (10-15%).

Table 3. Percentage contributions of independent variables to the explanatory power of regression models (based on Shapley value decomposition)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Factor** | **Regression specification from Table 2** | | | |
| **(1)** | **(2)** | **(3)** | **(4)** |
| **Country** | 29.2 | 21.5 | 32.6 | 24.6 |
| **Sector** | 3.0 | 3.7 | 3.0 | 4.7 |
| **Guest type** | 11.1 | 9.5 | 9.0 | 5.9 |
| **Month** | 56.7 | 65.4 | 55.3 | 64.9 |

**Conclusion**

In this study we proposed a framework based on time series forecasting for obtaining baseline forecasts of tourism demand that serve as counterfactual outcomes. It turned out that the Prophet forecasting procedure is a very competitive algorithm that has not been widely used in the hospitality industry but allows avoiding some of the ETS framework's fallacies. By comparing actual tourism demand observed in March, April, and May 2020 we obtain first statistically sound estimates of hospitality industry losses for each tourist accommodation market segment of 18 European countries. The framework makes it possible to estimate losses experienced by a particular segment of the hospitality market of a particular country in any given month as soon as tourism statistics becomes available from European statistical agencies. The comparison of observed demand dynamics with counterfactual (baseline) estimates will remain important for revealing signs of recovery/deterioration and figuring out how far the demand levels are from those that would be expected in the absence of COVID-19.

Our meta-analysis of the heterogeneity in loss estimates has shown that countries that were systematically identified as having been exposed to the smallest damage of the hospitality industry are Finland, Latvia and Sweden. Belgium, Italy, and Slovenia were systematically identified among those with the most severe damage for the industry. Differences across sectors (“hotels and similar accommodation”, “holiday and other short-stay accommodation”, and “camping grounds, recreational vehicle parks and trailer parks”) were not as substantial as differences across months and countries, but still worth accounting for – the hotels sector suffered significantly more than the two other sectors.

Some methodological improvements are worth considering in future research. In our study we selected a single method that would fit all time series reasonably well, and, taking into account that we had a substantial number of time series for model testing (108), it was sufficient to have a single testing sample per series as eventually we chose the method that performed well across a large number of series from the same domain. We also used a single testing sample to evaluate forecasting accuracy due to the relative shortness of our time series and due to prohibitively high computational intensity of so-called nested cross-validation, which can generally be recommended (Bergmeir, Hyndman and Koo, 2018).bThe method requires creating multiple training samples such as January 2012 - December 2017, January 2012 - January 2018, January 2012 - February 2018, etc. and testing forecasting performance by generating forecasts *n* steps ahead (in our case, *n*=12). As a result, nested cross-validation gives multiple estimates of the testing period's error, which should lead to more robust estimates of the testing sample performance of each method. This method is especially useful when working with a single time-series because it gives more data points to assess a method's performance.

The benchmarking of time series forecasting models can be further complemented by the analysis of statistical properties associated with good/bad performance of each model. Such meta-analysis can contribute to understanding the correspondence between data features and the best method. Such modeling can potentially lead to a data-driven framework for selecting the most appropriate class of models based on time series characteristics, at least for a particular type of time series such as those related to the demand for various accommodation establishments.

In addition to providing insights into the effect of COVID-19 on one of the hospitality industry’s key metric, our paper is supplemented with an R language-based implementation for automated forecasting of many time series using multiple methods and for model comparison. This part of our work can serve as a practitioner’s guide for people working with many time series, ranging from revenue managers of hotel chains working with demand planning for multiple properties to retail sales analysts making forecasts for thousands of SKU-level forecasts on a daily basis.

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