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MODELLING DOMESTIC TOURISM IN CROATIA

Abstract: The aim of this paper is to use extrapolative modelsin the attempt to analyse and understand domestic tourism demand flows in Croatia. Such, more detailed and systematic studies should be considered as starting points of future tourism development strategies in Croatia, as a predominantly tourism oriented country. Croatian tourism is predominantly internationally oriented. Nevertheless, domestic tourism demand should be considered more exhaustively in quantitative tourism researches. The present study emphasizes the necessity of more systematic domestic tourism demand determinants quantitative analysis and researches. Econometric modelling and forecasting should be considered as a significant Croatia's tourism sector development tool. The objective of the study is therefore to examine the determinants and the functional form of domestic tourism demand in Croatia. As an approximation of domestic tourism demand, the monthly number of domestic tourist arrivals in Croatia is analysed from January 2005 to December 2017. Modelling and ex post forecasting is performed using some extrapolative models i.e. the seasonal naive model, the seasonal multiplicative Holt-Winters triple exponential smoothing model, the seasonal multiplicative exponential trend model and the seasonal multiplicative integrated autoregression moving average model. Modelling the actual number of monthly domestic tourist arrivals was done for the period from January 2005 to December 2017. Based on the selected forecast models, the ex post forecast of the future value of the monthly number of domestic arrivals was made for the period from January 2018 to September 2018. The statistical diagnostic performance tests of the used models and the analysis of their prognostic efficiency showed that all the models fit well the actual data throughout the entire estimation and forecasting period.

Key Words: tourism demand, domestic tourism, monthly number of domestic tourist arrivals, the seasonal naive model, the seasonal multiplicative Holt-Winters triple exponential smoothing model, the seasonal multiplicative exponential trend model and the seasonal multiplicative integrated autoregression moving average model.

INTRODUCTION

Tourism is the most important Croatian economic sector. Among the service industries, tourism, above all, contributes to the Croatian economic growth and development. It is a well-known fact that tourism is one of the world's leading economic activities accounting for 30% of the world's services consumption and 6% of total goods and services export (www.ira.lib.polyu.edu.hk). In Croatia, tourism is one of the most propulsive economic sectors and the driver of economic growth and development. It is common knowledge that international tourism demand in Croatia is predominant with respect to domestic flows. According to the Tourist Information Service (www.turizmoteka.hr) data, in August 2018, the commercial accommodation facilities generated 4.4 million arrivals and 27.1 million tourist nights. Compared to August 2017, tourist arrivals increased by 3.9% and a slight increase in overnight stays by 0.8%. Domestic tourists realized 284 thousand arrivals and 1.6 million overnight stays, an increase of 12.5%

in arrivals and an increase in overnight stays by 8.4% as compared to August 2017. Although, Croatian tourism is predominantly international oriented, domestic tourism should be considered more exhaustively in quantitative tourism researches. Starting from the importance of tourism in the world and Croatian economy, its detailed and efficient analysis requires the implementation of specific and adequate quantitative methods in modelling and forecasting future tourist market features trends and key determinants. The enhancement of Croatian tourism competitiveness is based on a set of policy goals postulated by official institutions and bodies, i.e. to profile Croatia as one of the high-quality tourist destinations in the Mediterranean and Europe, to increase earnings by rising the spending in tourism, to extend the tourist season as well as to develop a sustainable and competitive tourism. The achievement of such and other tourism development goals necessitates a synergic action of all counterparts and stakeholders involved in the tourism sector, but above all it necessitates an accurate and combined qualitative and quantitative analysis, modelling and forecasting. (Baldigara, Mamula, 2012). Based on these premises, the paper investigates the application of time-series based quantitative methods in Croatian domestic tourism demand modelling and forecasting. Tourism demand and its characteristics, as tourism market keys determinants, are the basis for business decision making, adoption and development of business strategies in all, for tourism related, business activities and sectors of the Croatian economy. The growing interest in quantitative research on tourism demand is motivated by the rapid expansion of tourism industry all over the world. The tourism demand modelling, the analysis of economic and non-economic impacts of its determinants and the creation of efficient forecasts are the main researching issues in a large number of recent numerous discussions and studies.

LITERATURE REVIEW

Along with the growing significance of the international tourism in Croatia, it should be a growing interest in modelling and forecasting tourism demand and its components: "Modelling tourism demand in order to analyse the effects of various determinants, and accurate forecasting of future tourism demand, are two of the major focuses of tourism demand studies" (Song & Witt, 2005). Accurate forecasts of tourism demand and its features can certainly improve planning and decision-making. Numerous studies on tourism demand modelling and forecasting have been published over the past decades. Still, according to Peng, Song and Crouch (Peng, Song, Crouch, 2014) no consensus has been reached in regards to which types of forecasting models tend to be more accurate and in which circumstances. In a comprehensive study Song and Li (2008) reviewed 121 papers on tourism demand modelling and forecasting published in the period between 2000 and 2007 and they found out that in 72 studies time-series models, were used to model or forecast tourism demand. Various versions of exponential smoothing models were used in tourism demand forecasting, but also as benchmarks in forecasting accuracy comparison. Buger, Dohnal, Katharda and Law in a study (2001) used, among others, the exponential smoothing technique in forecasting the US demand for travel to Durban, South Africa. Hue at al. (2004) used the Naïve 2 and the exponential smoothing techniques in forecasting the number of restaurants' daily customers. Law (2004) used the Naïve 2, the exponential smoothing and the trend extrapolation in forecasting hotel room occupancy rate. In the detailed outline of researches Song and Li (2008) listed 121 publications and among these there are 22 publications that used the Naïve 2, the double exponential smoothing, the moving average, the linear trend and the autoregressive method to compare forecasting accuracy. According to Song and Li (2008) "Naïve

2 (or constant-growth rate), exponential smoothing models and simple autoregressive models have frequently appeared in the post-2000 studies, but as in earlier tourism forecasting studies, they are usually used as benchmarks for forecasting accuracy evaluation." In researching the importance of quantitative modelling, Saroja and Brinda (Saroja, Brinda, 2009) analysed and modelled monthly tourist arrivals, a time-series with strong seasonal patterns, using univariate time-series model. Although, as mentioned before, there is an increasing interest in time-series modelling and forecasting, in Croatia, there are still a lack of systematic analysis of tourism demand determinants. Profoundly aware that, modelling and forecasting tourism determinants, is a demanding issue, tourism development and economic growth should rely on accurate quantitative models and forecasts.

DATA AND METHODOLOGY

According to Song, Witt and Li (Song, Witt and Li, 2012) tourism demand is considered as the foundation on which the most of the tourism-related business decisions rest. Because of such a key role, tourism demand is considered as a determinant of business profitability, and its estimating, modelling and forecasting constitute a significant element in all planning and development strategies. In the literature traditionally, there emerge two categories of quantitative methods, the time-series models and the econometric approaches which analyse the casual relationship between the dependent and the explanatory variables. The paper researches the potentials of time-series models in analysing and researching domestic tourism demand in Croatia. Several extrapolative methods are used in the attempt to model and forecast domestic tourism demand in Croatia. In this paper, domestic tourism demand is measured in terms of the number of domestic tourists.Data are monthly, collected form the Croatian national statistical bureau and cover the period from January 2005 to September 2018.In the attempt to model and forecast domestic tourism in Croatia several extrapolative models are estimated and used for *ex post* tourism demand forecasting. Figure 1 shows the estimating and forecasting time horizon.

Figure 1: Estimating and ex post forecasting time horizon
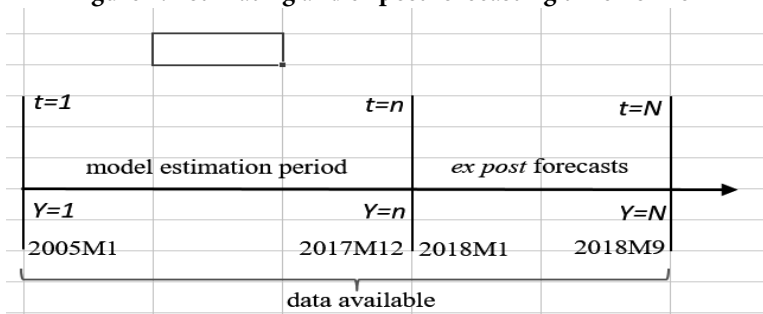
Source: Adapted from Song, H., Witt, S.F., Li, G. (2012), *The Advanced Econometrics of Tourism Demand*, New York, Routledge, p.183.

In Figure 1 *t* represents the time-span and *Y* the monthly number of domestic tourist arrivals. As shown in Figure, historical data are available from January 2005 to September 2018. Tourism demand model will be estimated based on data from January 2005 to December 2017 (the sample data). Based on the estimated models, *ex post* forecasted will be generated from January 2018 to September 2018. For all the estimating

and the forecast time-span all the values of the explanatory's variable and the dependent variable are known. Figure 2 shows the ac- tual data of the number of domestic tourist arrivals in the analysed period.

Figure 2: The Number of Domestic Tourist Arrivals: Time-span January 2005 to September 2018
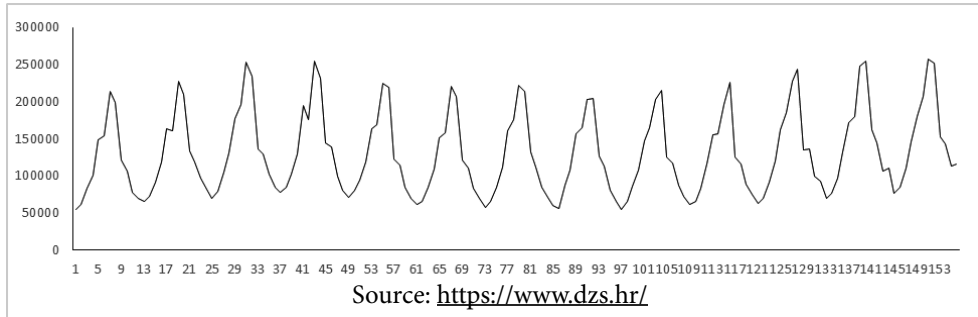

Source: https://www.dzs.hr/

Figure 2 reveals that the time-series pre- sents strong, seasonal influences and a slight upward trend. It is well known that tourism in Croatia is pronouncedly seasonal sensi- tive. In fact, the number of domestic tour- ists' presences is at its maximum levels in the summer period from July until August, with a drastic fall in the period from October to May. The observed time series consists of 165 observations with a mean of 130 256, 6 and a standard deviation of 55 402, 3 of domestic tourist arrivals. The maximum number of domestic arrivals was 257 617 in July 2017, while the lowest number of 53 683 arrivals was realised in January 2005.It is clearly shown that the seasonal patterns are rather consistent over the analysed pe- riod. In analysing and modelling tourism demand, it is therefore important to consid- er its seasonal character. In literature, there are different approaches for dealing with seasonality. In this study, the-ratio-to-mov- ing-average method, as one of the seasonal adjustment methods, is used to decompose the empirical time-series. The main purpose of the-ratio-to-moving-average method is to decompose the time-series and isolate, among the trend, the cyclical and the irreg- ular components, the seasonal influences. In this study the multiplicative model is used (Frechtling, 2008):

$$A_t = T_t \cdot C_t \cdot S_t \cdot I_t \qquad (1)$$

where

A – the actual value in time series
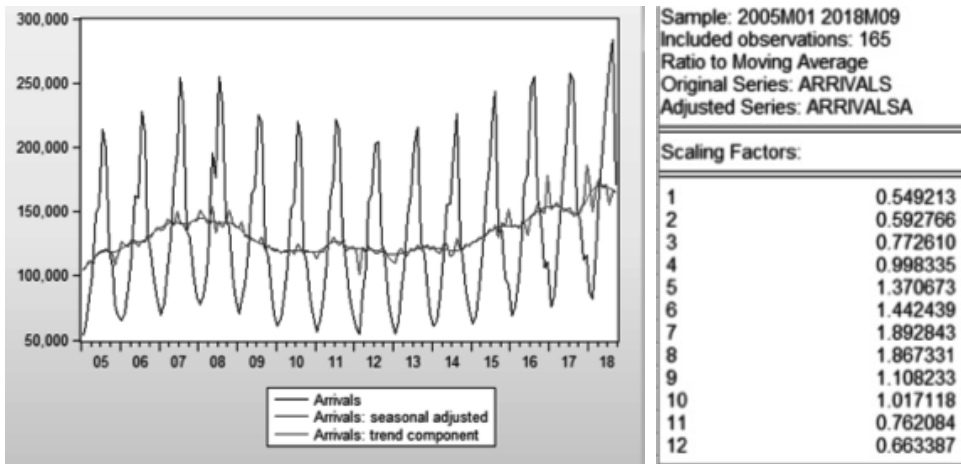
T – the trend component

C – the cyclical component

S – the seasonal component

I – the irregular component

T – some time periods less than one year[1]

Figure 3 shows the actual values, the seasonal adjusted values and the trend component.

1

Figure 3: Domestic Tourist Arrivals: Actual Values, Adjusted Time-series, Trend Component and Seasonal Factors

Source: *EViews output*

Seasonal factors show a pronounced seasonality in July and August. It is noticeable that the number of domestic tourist arrivals in July is on average higher by 89% and in August by 87% due to seasonal influences. In analysing and modelling domestic tourism demand, it is therefore important to consider its seasonal character. Therefore, specific quantitative methods that take into account this pronounced seasonal component, should be used to model the empirical time-series values. In literature, there are different approaches in dealing with seasonality. Among the different models, built to capture the seasonal component, the Seasonal Naïve, the Holt-Winters, the exponential trend and the Seasonal ARIMA modelling are used in this study. The following describes the theoretical concepts of the modelling techniques adopted in this study and the essentials of the selected forecasting error to be used in evaluating the forecasting accuracy.

The Seasonal Naïve Model

The seasonal naive model is used with seasonal data and postulates that the next period's value is equal to the value of the same period in the previous year. The seasonal naive model is expressed as follows:

$$\hat{Y}_t = Y_{t-m} \tag{2}$$

where

$\hat{Y}$ = forecast value

Y = actual value

t = some period time

m = number of periods in a year

The Naïve concepts are usually used as a benchmark forecast, namely for comparison with the forecast generated by other more sophisticated forecasting methods.

The Multiplicative Seasonal Holt-Winters Model

The Holt-Winters' trend and seasonality method employs triple exponential smoothing: one equation for the level, one for the trend and one for the seasonality. The following equations are associated with all the named elements[2]:

Level:
$$L_t = \alpha \cdot \frac{Y_t}{S_{t-s}} + (1 - \alpha)(L_{t-1} + b_{t-1}) \tag{3}$$

Trend:
$$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1} \tag{4}$$

Seasonal:
$$S_t = \gamma \frac{Y_t}{L_t} + (1 - \gamma)S_{t-s} \tag{5}$$

Forecast:
$$F_{t+h} = (L_t + hb_t)S_{t-s+h} \tag{6}$$

where

L = level of the series
α = level smoothing constant between 0 and 1
Y_t = actual value
s = number of seasonal periods in a year
b = trend of the series
β = seasonal smoothing constant between 0 and 1
S = seasonal component
γ = seasonal smoothing constant between 0 and 1
t = some period time
h = number of time periods ahead to be forecast

The initialization, as the process of providing a forecast value for the first period, can be approached using the following equations:

Initial level:
$$L_s = \frac{Y_1 + Y_2 + \cdots + Y_s}{s} \tag{7}$$

Initial trend:
$$b_s = \frac{1}{S}\left(\frac{Y_{s+1} - Y_1}{S} + \frac{Y_{s+2} - Y_2}{S} + \cdots + \frac{Y_{s+s} - Y_s}{S}\right) \tag{8}$$

Seasonal indices for the first year:
$$S_1 = \frac{Y_1}{L_s}, S_2 = \frac{Y_2}{L_s}, \dots, S_s \frac{Y_s}{L_s} \tag{9}$$

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2 Adapted from Frechtling, D. C. (2008), Forecasting Tourism Demand: Methods and Strategies, Butterworth Heinemann, Oxford, pp. 95-97.

Alternatively, the initial level, initial trend and the seasonal factors can be obtained by fitting a least squares trend line of the historical data.

Multiplicative Seasonal Exponential Trend Model

In the attempt to model time-series with a pronounced seasonal pattern the exponential trend model is usually used:

$$Y_t = \beta_0 \cdot \beta_1{}^{x_t} \cdot \varepsilon_t \tag{10}$$

where

Y_t = actual value of the series in period t

x_t = assigned time value in period t

ε_t = term error in period t

The multiplicative model is suitable for modelling when the amplitude of seasonal variations decreases or increases proportionally over time, which is the characteristic of many economic time-series. If the seasonal component is constant through the whole period, seasonality can be removed by adding seasonal dummy variables. When analysing seasonal time-series with monthly data, equation (9) is modified and adjusted to fit the actual data pattern:

$$Y_t = \beta_0 \beta_1{}^{x_t} \beta_2{}^{M_1} \beta_3{}^{M_2} \beta_4{}^{M_3} \beta_5{}^{M_4} \beta_6{}^{M_5} \beta_7{}^{M_6} \beta_8{}^{M_7} \beta_9{}^{M_8} \beta_{10}{}^{M_9} \beta_{11}{}^{M_{10}} \beta_{12}{}^{M_{11}} \tag{11}$$

where

Y_t	= actual value of the series in period t
x_t	= time
β_0	= constant
$(\beta_1 - 1) \cdot 100$	= average monthly growth rate
$\beta_{2,...,}\beta_{12}$	= monthly multiplier compared to base month
$M_{2,...,}M_{12}$	= seasonal dummy variables taking a value of 1 in the relevant month and 0 otherwise

In model (11) the intercept term is included and the number of dummy variables is once smaller than the number of unit time intervals. The lack of modelling tourism demand with this model is reflected in its very assumptions, namely the deterministic character of the trend and seasonal variations. Namely, the seasonal component is usually not deterministic and independent of other non-seasonal components. It is most commonly stochastic and correlates with other non-seasonal components present in the time series. Models that describe such processes are defined as ARIMA models.

The Multiplicative Seasonal Autoregressive Integrated Moving Average Model

Seasonal Autoregressive Integrated Moving Average (SARIMA) processes are used in modelling time series with trend components and seasonal patterns. They have been developed from the standard model of Box and Jenkins (1970) and incorporate both

seasonal autoregressive and moving average factors into the modelling process. In order to deal with seasonality, ARIMA processes have been modified and adjusted and SARIMA models have then been formulated. The seasonal ARIMA (the SARIMA) models incorporate both non-seasonal and seasonal factors in a multiplicative model as follows (Baldigara, Mamula, 2012):

$$ARIMA(p, d, q) \times (P, D, Q)S \qquad (12)$$

where:

p = non-seasonal AR order
d = non-seasonal differencing
q = non-seasonal MA order
P = seasonal AR order
D = seasonal differencing
Q = seasonal MA order
S = time span of repeating seasonal pattern

The seasonal autoregressive integrated moving average model of Box and Jenkins (1970) is given by

$$\phi(B)\Phi(B^s)(1 - B)^d(1 - B^s)^D Y_t = \Theta_0 + \theta(B)\Theta(B^s)\varepsilon_t \qquad (13)$$

where

$\phi(B)$ $= 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p$ is the p-order non seasonal AR model

$\theta(B)$ $= 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ is the q-order non seasonal MA model

$\Phi(B^s)$ $= 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots - \Phi_p B^{Ps}$ is the P-order seasonal AR model

$\Theta(B^s)$ $= 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \cdots - \Phi_Q B^{Qs}$ is the Q-order seasonal MA model

$(1 - B)^d$ denotes the non-seasonal differencing of order d

$(1 - B^s)^D$ denotes the seasonal differencing of order D

ε_t is the error term ~IID ($0, \sigma^2$)

B is the backward shift

S is the seasonal order

Model Performance and Forecast Accuracy

Forecast model performances and accuracy is evaluated using some chosen prognostic errors as forecast accuracy measures. According to Frechling (Frechtling, 2001) "the most familiar concept of forecasting accuracy is called "error magnitude accuracy", and relates to forecast error associated with a particular forecasting model." The error magnitude is defined as:

$$e_t = A_t - F_t \qquad (14)$$

where

t = some time period
e = forecast error
A = actual value of the variable being forecast
F = forecast value

Among the different methods developed to measure the error magnitude accuracy this paper will consider the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE). The following describes the basic concepts of the different forecast accuracy measures used in this paper.

The Absolute Error (MAE) is the most popular and simplest to use measure of forecasting accuracy. It is the average of the difference between the forecast and the actual value and it is measured in the same units as the original data. The expression to calculate MAE is:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|(A_t - F_t)| \tag{15}$$

The smaller the value of MAE is, the more accurate is the forecast.

The Root Mean Square Error (RMSE) is computed by the following expression:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \tag{16}$$

For purpose of communicating results, it is usually best to report the Root Mean Square Error (RMSE) rather than MSE, because the RMSE is measured in the same units as the data, rather than in squared units, and is representative of a "typical" error (Nau, 2013). The RMSE is usually more sensitive than other forecast accuracy measures. RMSE and MAE can only be compared between models whose errors are measured in the same units.

The Mean Absolute Percentage Error (MAPE) is expressed in generic percentage terms and it is computed by the following formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|(A_t - F_t)|}{A_t} \cdot 100 \tag{17}$$

MAPE is a simple measure that permits to compare the accuracy of different models, with different time periods and numbers of observations.

EMPIRICAL RESULTS AND ANALYSIS

The following reports the results of the estimated extrapolative models and the *ex post* forecasting results.

Seasonal Naïve Model

The Seasonal Naive model was defined under the assumption that the number of monthly domestic tourist arrivals at time *t* was the same as the value at time *t-12*. The model was estimated using actual data from January 2005 to December 2017. The ex post forecast was generated using data from January 2018 to September 2018. Results are show in the nest figure.

Figure4: Actual andEstimated Number of Monthly Domestic Tourist Arrivals: Time Span: 2005M1-2017M12 and Forecast 2018M1-2018M9
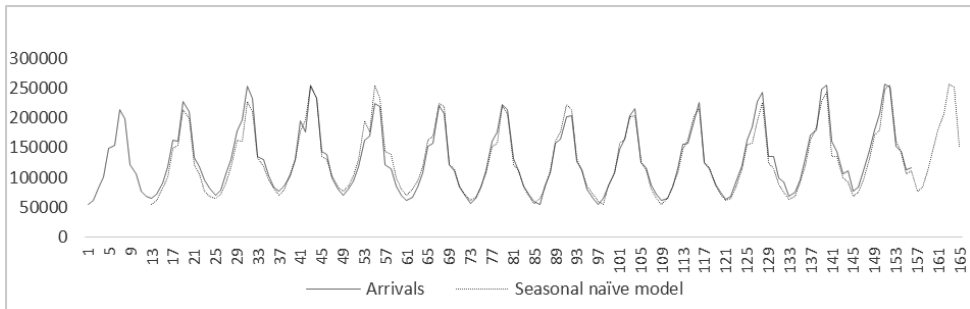
Source: Author's elaboration

As shown in figure 4 the estimated seasonal naïve model fits the data reasonably well throughout the entire estimating time period.

Triple Exponential Holt-Winters Model

The multiplicative seasonal Holt-Winters model was used in modelling and forecasting the number of monthly domestic tourist arrivals. In the multiplicative model, it is assumed that each observation is the product of a non-seasonal value and a seasonal index for that particular period.Analysis results are given bellow.

Figure 5: Holt-Winters Model Estimating Results


```
Sample: 2005M01 2017M12
Included observations: 156
Method: Holt-Winters Additive Seasonal
Original Series: ARRIVALS
Forecast Series: ARRIVASM

Parameters:   Alpha                    0.3700
              Beta                     0.0000
              Gamma                    0.0000
Sum of Squared Residuals              7.97E+09
Root Mean Squared Error               7149.079

End of Period Levels:   Mean             158417.4
                        Trend            260.5729
                        Seasonals: 2017M01   -64413.12
                                   2017M02   -58223.47
                                   2017M03   -37370.58
                                   2017M04   -10811.46
                                   2017M05    33966.12
                                   2017M06    42510.63
                                   2017M07    96589.21
                                   2017M08    93376.71
                                   2017M09     2344.984
                                   2017M10    -8366.973
                                   2017M11   -39069.78
                                   2017M12   -50532.27
```

Source: Eviewsoutput

The smoothing process resulted in three smoothing constants: α = 0, 37, β = 0, 0 and γ = 0, 0. Values of zero for the level and trend component smoothing constant indicate that the trend and seasonal component are estimated as fixed for the entire period, and not changing. According to Lee, Song and Mjelde (Lee, Song, Mjelde, 2008) a value of 0,5 for the smoothing constant α indicates that the current single smoothed values were

predicted based on the moderate weight on both current values adjusted for seasonality and previous values smoothed and trend values. The smoothing constant $\beta=0$ implies that the current trend values are a function of the previous trend values without considering the difference in the smoothed values. The smoothing constant $\gamma=0$ denotes that the current seasonal component is a function of the previous seasonal without considering the current values to be adjusted by the smoothed values. The following picture shows the original series of monthly domestic tourist arrivals and the forecast obtained with the seasonal multiplicative Holt-Winters model.

Figure6: Actual and Estimated Number of Monthly Domestic Tourist Arrivals: Time Span: 2005M1-2017M12 and Forecast 2018M1-2018M9
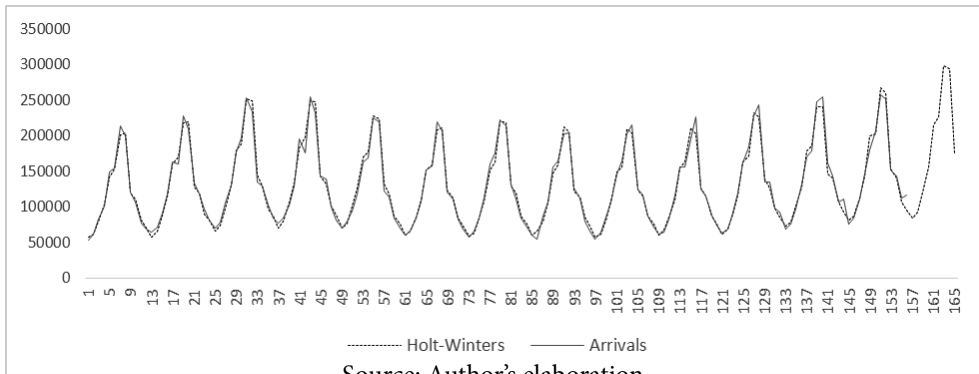
Source: Author's elaboration

Seasonal Multiplicative Exponential Trend Model

The regression model of the monthly series of domestic tourist arrivals with exponential trend and seasonal dummy variables given in equation (11) is linearized (using logarithms) and estimated using the least squares method. December 2017is selected as the benchmark month. The linearized model is given by the following expression:

$$ln\hat{Y} = ln\beta_o + X_t ln\beta_1 + M_{1t} ln\beta_2 + M_{2t} ln\beta_3 + M_{3t} ln\beta_4 + M_{4t} ln\beta_5 + M_{5t} ln\beta_6 + M_{6t} ln\beta_7 + M_{7t} ln\beta_8 + M_{8t} ln\beta_9 + M_{9t} ln\beta_{10} + M_{10t} ln\beta_{11} + M_{11t} ln\beta_{12} \tag{18}$$

Regression analysis results are given in the following output.

Figure 7: Regression analysis output

Dependent Variable: LNARRIVALS
Method: Least Squares
Date: 11/21/18   Time: 12:02
Sample: 2005M01 2017M12
Included observations: 156

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	11.22503	0.033424	335.8343	0.0000
TIME	0.000745	0.000189	3.941203	0.0001
M1	-0.212780	0.041643	-5.109595	0.0000
M2	-0.119637	0.041634	-2.873533	0.0047
M3	0.143977	0.041626	3.458825	0.0007
M4	0.398347	0.041619	9.571341	0.0000
M5	0.721000	0.041612	17.32659	0.0000
M6	0.771951	0.041607	18.55350	0.0000
M7	1.044773	0.041602	25.11352	0.0000
M8	1.031833	0.041598	24.80478	0.0000
M9	0.510761	0.041595	12.27935	0.0000
M10	0.426799	0.041593	10.26131	0.0000
M11	0.140135	0.041592	3.369307	0.0010

R-squared	0.942503	Mean dependent var		11.68829
Adjusted R-squared	0.937678	S.D. dependent var		0.424755
S.E. of regression	0.106037	Akaike info criterion		-1.570395
Sum squared resid	1.607881	Schwarz criterion		-1.316241
Log likelihood	135.4908	Hannan-Quinn criter.		-1.467169
F-statistic	195.3408	Durbin-Watson stat		0.359609
Prob(F-statistic)	0.000000			

Source: EViews output

According to Šošić (Šošić, 2004) the seasonal effect of the first month is contained in the constant. The value of the adjusted R-squared coefficient (93.7%) indicates a high accuracy of the trend, as can be seen from the results of the F-test. All estimated regression coefficients are significant at the level of 5%. In table 1, the original values of the estimated regression coefficients are given.

Table 1: Values of the Estimated Regression Coefficients

Regression coefficients	$ln\beta_i$	$\beta_i = e^{ln\beta_i}$
β_0: constant	11,19591	72831,74
β_1: the slope for the time interval (month)	0,001092	1,001093
β_2:January	-0,19279	0,824652
β_3:February	-0,11172	0,894298
β_4: March	0,159088	1,172441
β_5: April	0,419364	1,520993
β_6: May	0,731194	2,07756
β_7: June	0,789446	2,202175
β_8: July	1,050642	2,859485
β_9: August	1,043748	2,839841
β_{10}: September	0,522946	1,68699
β_{11}: October	0,427492	1,533407
β_{12}: November	0,140482	1,150828

Source: Elaborated by author

The constant β_0 = 74 984 represents the value of the monthly number of domestic tourist arrivals in the first month (January 2017). The actual number of monthly domestic arrivals in January 2017 was 53,683. The difference shows a residual of 21,301 monthly domestic arrivals. Since the trend presents covariation in terms of average, its accuracy can be evaluated using the standard deviation and the coefficient of variation. The standard deviation of the trend is 0.415020, that is, the average deviation of the actual monthly number of domestic arrivals from the trend values. The relative amount is 3.54%, which indicates good fit of the trend. The values of the estimated seasonal *dummy* variables for each month indicate the average change in the number of domestic arrivals for the unit time change. The average monthly growth rate of the observed time series is derived from the value of the regression coefficient

$$\beta_1: \quad (\beta_1 - 1) \cdot 100 = (1,001093 - 1) \cdot 100 = 0,1093\%$$

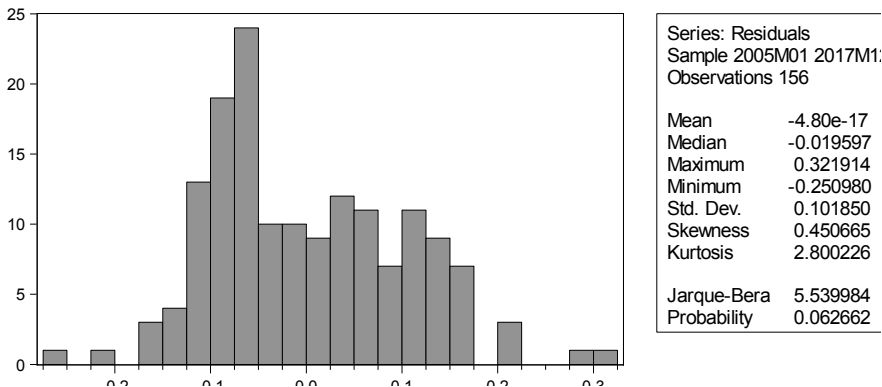The number of domestic tourist arrivals in the observed period grew by 0.1% on average. The obtained values of estimated coefficients represent monthly growth rates relative to the benchmark month and point to the conclusions that, due to seasonal influences, during:

- January there are on average 17.53% less domestic tourist arrivals than in December;
- February there are on average 10.57% of domestic tourist arrivals less than in December;
- March there are on average 17.24% of domestic tourist arrivals more than in December;
- April there are on average 52.09% of domestic tourist arrivals more than in December;
- May there are on average 107.76% of domestic tourist arrivals more than in December;
- June there are on average 120.22% of domestic tourist arrivals more than in December;
- July there are on average 185.95% of domestic tourist arrivals more than in December;
- August there are on average 183.98% of domestic tourist arrivals more than in December;
- September there are on average 68.69% of domestic tourist arrivals more than in December;
- October there are on average 53.34% of domestic tourist arrivals more than in December and
- November there are on average 15.08% of domestic tourist arrivals more than in December.

Diagnostic tests of the estimated model showed good results. The analysis of residuals indicates that they are normally distributed (Figure 8).

Figure 8: Distribution of the Residuals

| Series: Residuals	
Sample 2005M01 2017M1:	
Observations 156	
Mean	-4.80e-17
Median	-0.019597
Maximum	0.321914
Minimum	-0.250980
Std. Dev.	0.101850
Skewness	0.450665
Kurtosis	2.800226
Jarque-Bera	5.539984
Probability	0.062662

Source: EViews output

The next Figure shows the actual number of domestic tourist arrivals, the estimated number and the ex post forecast generated using the seasonal multiplicative exponential trend model.

Figure 9: Actual and Estimated Number of Monthly Domestic Tourist Arrivals: Time Span: 2005M1-2017M12 and Forecast 2018M1-2018M9
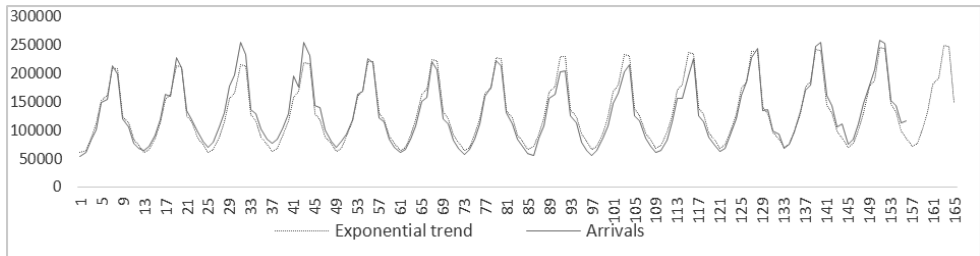
Source: Author's elaboration

Seasonal multiplicative ARIMA model

The plotting of the empirical time-series of the monthly number of domestic tourist arrivals indicates a slight and continuous upward trend after 2011. Stationarity ADF testing (Figure 10) has shown that the time series is seasonally integrated (1, 12).

Figure 10: ADF Test Results

Source: EViews output

Various models were generated and among them the seasonal (0,1,1)(0,1,1)$_{12}$ARIMA model was selected. In fact, this model presented the smallest AIC, SBC and HQ Information criterion and the smallest mean absolute percentage error. In the model the constant term was not included since the mean of the differentiated time series with the standard deviation of 10194, 99 results in the standard error of $se(\bar{z}) = \frac{\hat{\sigma}}{\sqrt{n}} = \frac{10194,99}{\sqrt{152}} = 833,68$ and the ratio $\bar{z} = 45,32237$ $se(\bar{z}) = \frac{\hat{\sigma}}{\sqrt{n}} = \frac{10194,99}{\sqrt{152}} = 833,68$ indicating that the constant term is not statistically significant and does not need to be included in the model. The estimation results of the selected model are reported in the next table.

Figure 11: Parameter Estimation Results for the Selected Seasonal (0,1,1) (0,1,1)$_{x12}$ARIMA Model

```
Dependent Variable: D(ARRIVALS,1,12)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/21/18   Time: 13:45
Sample: 2006M02 2017M12
Included observations: 143
Convergence achieved after 21 iterations
Coefficient covariance computed using outer product of gradients
```

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	-0.586806	0.066571	-8.814733	0.0000
SMA(12)	-0.498686	0.071410	-6.983429	0.0000
SIGMASQ	55520576	5851471.	9.488311	0.0000

R-squared	0.423001	Mean dependent var		-39.06294
Adjusted R-squared	0.414758	S.D. dependent var		9843.809
S.E. of regression	7530.624	Akaike info criterion		20.73906
Sum squared resid	7.94E+09	Schwarz criterion		20.80121
Log likelihood	-1479.843	Hannan-Quinn criter.		20.76432
Durbin-Watson stat	2.030540			

Inverted MA Roots	.94	.82-.47i	.82+.47i	.59
	.47-.82i	.47+.82i	.00+.94i	.00-.94i
	-.47+.82i	-.47-.82i	-.82+.47i	-.82-.47i
	-.94			

Source: EViews output

The parameter of the estimated model are all significant at 5% level and the adjusted R^2 of 0, 42 shows a quite good model fit.

The selected model is tested for invertibility by using the inverted AR/MA roots. The results are shown in the figure below.

Figure 12:Invertibility Results Testing

Inverse Roots of AR/MA Polynomial(s)
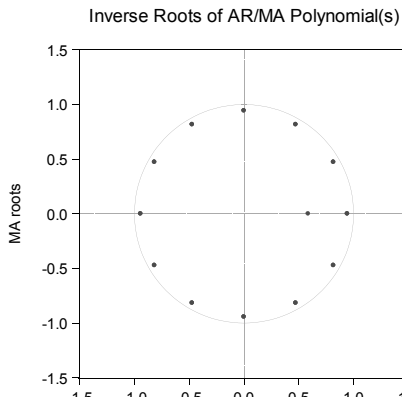
```
Inverse Roots of AR/MA Polynomial(s)
Specification: D(ARRIVALS, 1,12) MA(1)SMA(12)
Date: 11/21/18   Time: 13:50
Sample: 2005M01 2017M12
Included observations: 143
```

MA Root(s)	Modulus	Cycle
-2.50e-16 ± 0.943667i	0.943667	4.000000
-0.817240 ± 0.471834i	0.943667	2.400000
0.817240 ± 0.471834i	0.943667	12.00000
0.943667	0.943667	
-0.471834 ± 0.817240i	0.943667	3.000000
-0.943667	0.943667	
0.471834 ± 0.817240i	0.943667	6.000000
0.586806	0.586806	

No root lies outside the unit circle.
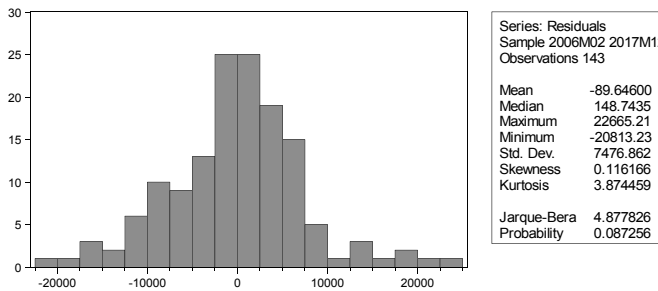ARMA model is invertible.

Source: EViews output

As reported in *Figure 12* all the absolute values of the inverted MA roots are smaller than one, the estimated model is therefore invertible. The selected multiplicative seasonal integrated autoregressive moving av-erage model passes all the diagnostic tests. In fact, testing results showed that the residuals are normally distributed and not correlated (figure 13).

Figure 13: Residuals Results Testing for the Selected Seasonal ARIMA Mode l
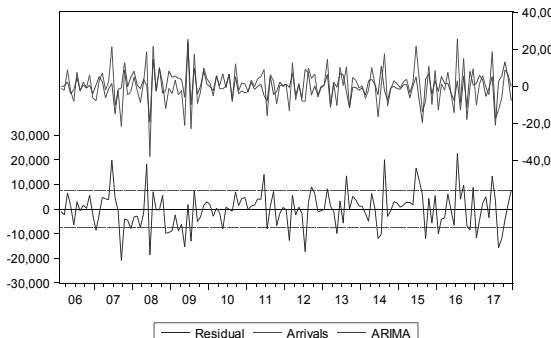

Source: EViews output

All the autocorrelation coefficients do not differ significantly from zero and they are within the 2–sigma limits ($\pm 2 \cdot \frac{1}{\sqrt{n}}$) and there is no evidence of autocorrelation of residuals. Moreover, the residuals are normally distributed. The actual time series of the monthly number of domestic arrivals, the estimated value obtained using the seasonal multiplicative ARIMA model (0, 1, 1) (2, 1, 2)12, and the series of residual deviations, are shown below.

Figure 14: Actual, Estimated Number of Monthly Domestic Tourist Arrivals

Source: EViews output

The results confirm the correct specification of the model.

Forecast Accuracy of the Estimated Extrapolative Models

The models used to analyse the monthly number of domestic tourist arrivals fit the general movement of the analysed series during the entire sample period. The empirical results are reasonably good. The forecasted values, in fact, are quite close to the actual values. The actual number of monthly domestic tourist arrivals and the forecasted values are shown in the following table.

Table2: Actual and Forecasted Values

	Actual number	Seasonal Naïve model	Holt-Winters model	Exponential trend model	ARIMA model
2018MI	87 973	76 040	84 630,93	71 292,04	86 197,24
2018M2	82 011	84 378	92 986,29	77 397,52	93 331,5
2018M3	118 715	110 553	120 838,7	101 580,8	114 221,6
2018M4	167 231	146 113	155 832,6	131 923,8	149 915,6
2018M5	199 562	179 948	215 364,8	180 394,2	188 399,9
2018M6	233 896	207 001	226 694	191 422,8	195 829,5
2018M7	262 573	257 617	297 811,8	248 831,2	263 506,3
2018M8	283 678	252 217	294 047,3	247 392,1	265 534,9
2018M9	170 058	151 809	174 688,2	147 122,4	174 915,6

Source: Elaborated by author

The forecasting results are plotted as showed in *Figure 15.*

Figure 15: Actual and Forecasted Values of the Number of Monthly Domestic Tourist Arrivals from 2018M01 to 2018M09
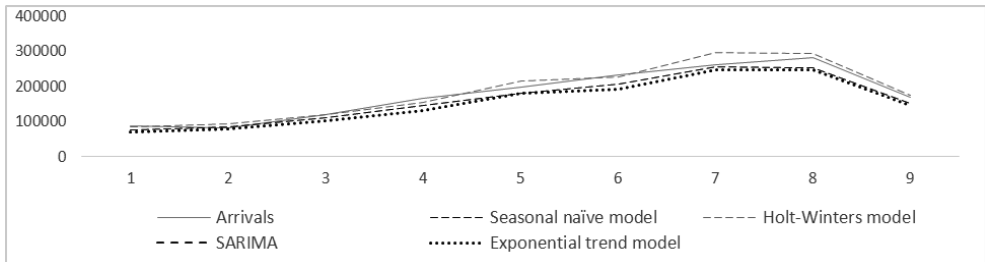
Source: Elaborated by author

The conducted diagnostic tests showed that all selected models describe and forecast the time series of monthly domestic tourist arrivals reasonably well. The forecasting accuracy is evaluated using the previously mentioned forecast errors.

Table 16: Forecasting Accuracy Evaluation

Model	MAE	MAPE	RMSE
Seasonal Naïve Model	9264,23	7,35	11892,42
Holt-Winters Model	5257,24	4,08	4832,93
Exponential Trend Model	1,09513	2,18	1,114944
SARIMA Model	13069,16	6,94	16953,52

Source: Elaborated by author

The results indicate that the Holt-Winters Model and the Exponential Trend Model generated the most accurate forecasts, although all the estimated models present a reasonably good forecasting accuracy.

CONCLUSIONS

The aim of the paper was to model and forecast domestic tourist demand in Croatia. Although Croatia's tourism is primarily of international character, in recent years, domestic tourism has become an increasingly important andsignificant source of income. As an approximation of the domestic tourism demand, the monthly number of domestic tourist arrivals in Croatia is analysed in the period from January 2005 to September 2018. Modelling and ex post forecasting was performed using extrapolative models, i.e. the seasonal naive model, the seasonal multiplicative Holt-Winters model, the seasonal multiplicative exponential trend model and the seasonal multiplicative integrated autoregressionmoving average model. The estimation span-time referred to the period from January 2005 to December 2017 and ex post forecasts were generated for the period from January 2018 to September 2018. The statistical diagnostic performance tests and the forecast accuracy evaluation confirmed that models well describe the actual data throughout the entire estimation period, but also over the forecasting time period. Profoundly aware that modelling tourism demand is a challenging and controversial issue, that the adequacy of a forecasting model is valued according to its out-of-sample forecasts as well as that it is still difficult to indicate which model or class of models is more adequate for tourism demand modelling, the author of this study wished to highlight the necessity of more systematic quantitative analysis of Croatia's tourism demand in all its determinants.

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