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Forecasting Croatian inbound tourism demand

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The aim of this paper is to present a forecasting model for the overnight stays of foreign tourists in Croatia. Tourism is one of the most important parts of the Croatian economy. It is particularly important in the context of the services sector. Regular and significant surpluses and the consumption of foreign guests are an important element of budget revenues, especially VAT. The ability to forecast the development of inbound tourism demand in a timely manner is crucial for both business decisions and policy-making. We combine the Granger causality test for identifying leading indicators with a grid search of the weights used to construct a composite indicator. An endogenous grid search for data driven weights was employed to minimise the mean absolute percentage error (MAPE) of the out-of-sample forecast. In total, we carried out 7.7 billion out-of-sample regressions in order to find the optimal combination of leading indicator weights. Results indicate that only four out of the 12 identified leading indicators are relevant in explaining variations in inbound tourism demand. The most important leading indicators are: real GDP and imports in Poland and gross wages in the Czech Republic and Slovakia.

Keywords: tourism demand; forecasting; leading indicators; composite indicator; Granger causality; weights optimisation

JEL classification: L83; C53; F17.

1. Introduction

The aim of this paper is to present a forecasting model for the number of overnight foreign tourist stays in Croatia. Having timely forecasts of inbound tourism demand in Croatia is very important. According to recent research, tourism accounts for 14.7% of the total gross value added of the Croatian economy (Šutalo, Ivandić, & Marušić, 2011). In addition, tourism has an impact on almost all segments of Croatian society and makes a huge contribution to overall national identity (Čavlek, Bartoluci, Prebežec, Kesar, & co-authors, 2011). Hence, any attempt to research the quantitative dimension of tourism in Croatia is welcome and useful.

In order to assess the model, we have employed the NBER methodology to identify the leading indicators combined with an endogenous weight selection process that minimises the mean absolute percentage error (MAPE) of the out-of-sample forecast of the leading composite index.

Forecasting tourism demand is a very progressive field of tourism research. Modern econometric models such as vector autoregression (VAR), the error correction model

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(ECM) and the time varying parameter model (TVP) are frequently used in forecasting tourism demand. However, the general impression of all these attempts is that they are only experiments with the main aim of answering the question of whether or not these methods can be useful in forecasting tourism demand.

Attempts at comprehensive research with the aim of modelling an accurate analytical tool for forecasting tourist arrivals, overnight stays or expenditure are very rare in the literature. One of the major reasons for this is the complexity of the phenomenon of tourism demand and the very large number of factors that should be taken into account when forecasting its dynamics.

Kožić's (2013) dissertation is one of the rare attempts to tackle the issue of forecasting overnight tourist stays in Croatia. The composite leading indicator methodology was used in order to forecast turning points in inbound tourism demand in Croatia. In order to build a leading composite indicator for forecasting turning points of foreign tourist overnight stays in Croatia, Kožić (2013) used economic indicators for the ten most important countries of origin of foreign tourists in Croatia (Germany, Slovenia, Austria, Italy, the Czech Republic, Slovakia, Hungary, the Netherlands, Poland and France), Croatia's five most important competitors (Greece, Spain, France, Italy and Turkey), and the dynamics of indicators related to extraordinary events such as terrorist attacks or geopolitical crises.

In this paper, we follow Kožić's (2013) approach in identifying potential leading indicators. However, we have built upon his work and developed an improved methodology for the purpose of minimising statistical errors in forecasting foreign tourist overnight stays in Croatia.

The paper is organised as follows. Section 2 provides a brief overview of the field of forecasting tourism demand with an accent on recent practice in empirical studies and the usage of leading indicators in forecasting tourism demand. Section 3 briefly describes the leading composite indicators and the methodology for their construction. In addition, Section 3 also describes the weights optimisation methodology used in this paper. Finally, the results and implications of this paper are briefly discussed in Section 4.

2. Literature review of forecasting tourism demand

Over the last 50 years, tourism demand has grown rapidly in many countries in the world. Along with the physical growth of tourism demand, a growing interest in tourism research has been recorded. The field of forecasting tourism demand is an especially progressive field in tourism research. Since the pioneering work by Guthrie (1961), followed by Gerakis (1965) and Gray (1966), more than 500 studies on forecasting tourism demand have been published. The general impression of these studies is that tourism demand forecasting practices have followed practices in macroeconomics and finance, which can be considered as paragons of economic forecasting. Novel forecasting techniques from macroeconomics and finance have been applied in studies that deal with tourism demand. This has been especially true in recent years. Comprehensive reviews of tourism demand forecasting have been made by Lim (1997a, 1997b, 1999), Li, Song, and Witt (2005), Song and Li (2008) and Kožić (2013). The conclusions drawn by these studies can be described as follows:

- The analytical skills of authors have grown through the years along with the contents of the reports that they have provided in their papers. For example, simple econometric techniques such as multiple regression and simple time series models were used in earlier studies, whereas more sophisticated techniques such as VAR, ECM and TVP have been used in more recent papers. In addition, in the past authors were not always aware that it is very important to provide diagnostic tests for the models in their studies. Recent studies usually contain all the information on parameters and diagnostic tests.

- The aim of earlier papers was mainly to identify the determinants of tourism demand by means of which its dynamics could be forecast. Recent papers have been more focused on the accuracy of forecasting models. Their major aim has mainly been to compare several competing models and to find the one with the best forecasting performance.
- In terms of forecasting accuracy, the general rule is the more complex and sophisticated the forecasting model, the better will be its forecasting performance. Hence, it is crucial to pay attention to many different characteristics of tourism demand such as seasonality and non-stationarity. It is also recommended to combine the outputs of several different models to obtain a better forecasting performance (Wong, Song, Witt, & Wu, 2007).
- The dependent variables in forecasting models are usually tourist arrivals or tourist overnight stays, while explanatory variables are income and prices, which are often combined with other economic and social factors influencing tourism demand.

The methods frequently used in studies of tourism demand forecasting are presented in Table 1. Although some examples can be found of the application of qualitative methods in forecasting tourism demand, quantitative methods predominate, especially in recent years. Among the quantitative methods, the leading indicators approach can be considered a novel approach in the field of forecasting tourism demand. It is a rare example of a methodology used heavily in macroeconomic forecasting but which has

Table 1. Frequently used methods in studies on forecasting tourism demand.

Qualitative	Quantitative Extrapolative methods	Causal methods
Survey	Linear extrapolation	Linear regression
Delphi method	Moving average (MA)	Regression with binary dependent variable (LOGIT/PROBIT)
Jury of experts opinion	Autoregression (AR)	Autoregressive distributed lag model (ARDL)
	Autoregressive integrated moving average (ARIMA)	Error correction model (ECM)
	Seasonal autoregressive integrated moving average (SARIMA)	Vector autoregression (VAR)
	General autoregressive conditional heteroscedasticity (GARCH)	Time varying parameter model (TVP)
	Basic structural model of time series (BSM)	Linear almost ideal system of demand model (LAIDS)
	Neural networks	Structural equation models (SEM)
		Leading indicators approach

Source: Fernando (2010).

not yet been extensively used in forecasting tourism demand. Papers that apply leading indicators in forecasting tourism demand have only emerged over the past ten years.

The most cited example of the application of leading indicators in forecasting tourism demand is the study by Rossello-Nadal (2001) in which the author applied leading indicators to forecast international visitor arrivals in the Balearic Islands in Spain. The author selected a group of macroeconomic indicators from the tourists' countries of origin and applied the method of cross-correlation coefficients to calculate their possible correlation with the dependent variable, i.e. international tourist arrivals in the Balearic Islands. After selecting the macroeconomic indicators which show an ability to influence the dynamics of the dependent variable, the author composed them into a linear regression model, which he tested and then used to successfully forecast turning points in inbound tourism demand in the Balearic Islands.

Cho (2001) compares the forecasting performance of several models. Using the sample of the top five countries of origin of tourists visiting Hong Kong, the author compares the forecasting accuracy of the exponential smoothing model, ARIMA, and the adapted ARIMA model, supplemented with leading indicators. In this manner, the author transforms the classic univariate ARIMA model into the so-called multivariate ARIMAX model with exogenous variables. The author concludes that the multivariate ARIMAX model with leading indicators is the most accurate one, especially in the case of geographically closer countries of origin of tourists. It should be mentioned that the ARIMAX model is actually an autoregressive distributed lag model (ARDL) frequently applied in macroeconomic forecasting.

The ARDL model is also used by Kulendran and Witt (2003). The authors create an ARDL model using the leading indicators of six countries, which represent the top tourist destinations for British tourists. Among all the potential leading indicators, the authors take into consideration those variables that are most frequently used in the econometric modelling of tourism demand. The authors conclude that the forecasting ability of the ARDL model is not stronger than the control model (ARIMA). However, the former is more precise in short-term forecasting compared with another control model (ECM).

Kulendran and Wong (2009) use cross-correlation coefficients in order to identify leading indicators among selected economic variables, which are frequently used in econometric modelling of tourism demand. They arrange the leading indicators into a composite leading indicator, which is then used for the construction of an ARDL model. The authors conclude that the ARDL model with a composite leading indicator enhances the forecasting of tourism demand.

Composite leading indicators, i.e. synthetic indices, are frequently used in forecasting tourism demand. For example, Choi (2003) develops a leading indicator system for the US hotel industry to predict the industry's growth. The author applies the method of cross-correlation coefficients to identify the leading, coincident and lagging indicators of US hotel industry growth. He then uses the NBER methodology in order to form three composite indices: leading, coincident and lagging. The author identifies forecasting accuracy at a satisfactory level for all of three composite indices and concludes that together they can be a valuable forecasting tool in the hotel industry.

Fernando (2010) criticises the frequent application of linear models in forecasting turning points in tourism demand, and proposes the use of non-linear models such as composite indicators, and LOGIT and PROBIT models. Using the case of Australian inbound tourism demand, the author confirms that LOGIT and PROBIT econometric models are the most accurate. The author argues that composite leading indicators also represent a good option in forecasting turning points in tourism demand.

Kulendran and Wong (2011) apply LOGIT and PROBIT models in order to forecast turning points in international tourism demand in Hong Kong. The authors use these models in a comparative analysis of the forecasting ability of basic determinants of tourism demand, such as disposable income, tourism product prices, substitute prices and transportation prices, in relation to ready-made composite leading indicators such as the national composite leading indicator and the OECD composite leading indicator. The authors conclude that the LOGIT and PROBIT models can forecast equally well. However, these models prove to be more superior in forecasting if they incorporate ready-made composite leading indicators rather than individual determinants of tourism demand.

Tourism demand forecasting articles are usually published in the most prominent journals promoting tourism research, such as *Annals of Tourism Research*, *Tourism Economics*, *Tourism Management* and *Journal of Travel Research*. However, some papers have recently been published in economic and management journals (Song & Li, 2008). On average, between one and three articles on tourism demand forecasting are published every year in the aforementioned journals.

3. Leading composite indicator and methodology

We used the number of tourist overnight stays as a dependent variable in the analysis. Such approximation is common in the literature (Song, Li, Witt, & Fei, 2010) and very reasonable in a situation where the data series for total tourism revenue is not available for the entire analysis.

We used the Granger causality test in order to investigate statistical significance and the leading time of 118 potential leading indicators. The variables used as regressors were selected based on microeconomic theory: (i) variables used as proxies for income effects in the countries of origin of tourists; and (ii) variables used as proxies for substitution effects in countries that are competitors of Croatia. The list of all variables and sources of data are presented in Table 2, while Figures 1–2 present the original data series used in the analysis.

The Granger causality test was employed on log-difference regressors. The results indicate that there are 12 statistically significant variables that Granger-cause Croatian inbound tourism demand.

Table 3 shows results for 12 significant variables. Five variables are negatively correlated with Croatian inbound tourism demand, and the time lags of leading indicators are mostly 1 year, with the exception of real exchange rates and the Slovenian gross monthly wage with 2-year lags.

In the second step, 12 variables that were significant in the Granger causality test (also called leading indicators) were used to construct the leading composite indicator of Croatian inbound tourism demand. The leading composite indicator was constructed according to the OECD methodology (2012) combined with the NBER methodology clearly presented by Bačić and Vizek (2008).

A simplified overview of the composite indicator construction procedure is as follows:

(1) standardisation of amplitudes of leading indicators;
(2) inversion of leading indicators;
(3) lag-shifting (synchronisation of leading indicators);
(4) weighting of leading indicators;

Table 2. List of variables used in the analysis together with abbreviations and data sources.

Description	Variable	Source
Overnight stays of foreign tourists in Croatia	*Y*	Croatian Bureau of Stat.
Austrian real GDP at constant prices from 2005	GDP_Aut	UNCTAD Statistics
Austrian CPI (rate of change)	CPI_Aut	World Bank Statistics
Austrian gross monthly wage in industry	Wage_Aut	LABORSTA (ILO)
Austrian total unemployment	Unmp_Aut	LABORSTA (ILO)
Austrian imports of goods	Imp_Aut	UNCTAD Statistics
Austrian exports of goods	Exp_Aut	UNCTAD Statistics
ATX – index of Vienna stock exchange (2005=100)	Sex_Aut	EUROSTAT
Czech real GDP at constant prices from 2005	GDP_Cze	UNCTAD Statistics
Czech gross monthly wage in industry	Wage_Cze	LABORSTA (ILO)
Czech imports of goods	Imp_Cze	UNCTAD Statistics
Czech exports of goods	Exp_Cze	UNCTAD Statistics
French real GDP (2005=100)	GDP_Fra	EUROSTAT
French CPI (rate of change)	CPI_Fra	World Bank Statistics
French net minimal wage	Wage_Fra	INSEE France
French total unemployment	Unmp_Fra	LABORSTA (ILO)
French imports of goods	Imp_Fra	UNCTAD Statistics
French exports of goods	Exp_Fra	UNCTAD Statistics
CAC40 – index of French stock exchange (2005=100)	Sex_Fra	EUROSTAT
Italian real GDP at constant prices from 2005	GDP_Ita	UNCTAD Statistics
Italian CPI (rate of change)	CPI_Ita	World Bank Statistics
Italian total unemployment	Unmp_Ita	LABORSTA (ILO)
Italian imports of goods	Imp_Ita	UNCTAD Statistics
Italian exports of goods	Exp_Ita	UNCTAD Statistics
Italian total term deposits in commercial banks	Dep_Ita	Banca d'Italia
Hungarian real GDP (1960=100)	GDP_Hun	KSH Magyarorszag
Hungarian CPI (1960=100)	CPI_Hun	KSH Magyarorszag
Hungarian gross monthly wage	Wage_Hun	KSH Magyarorszag
Hungarian retail turnover (1960=100)	Rtt_Hun	KSH Magyarorszag
Hungarian industrial production (1960=100)	Ind_Hun	KSH Magyarorszag
Hungarian imports of goods	Imp_Hun	UNCTAD Statistics
Hungarian exports of goods	Exp_Hun	UNCTAD Statistics
Dutch real GDP (2005=100)	GDP_Hol	UNCTAD Statistics
Dutch CPI (rate of change)	CPI_Hol	CBS Nederland
Dutch gross weekly wage in industry	Wage_Hol	LABORSTA (ILO)
Dutch total unemployment	Unmp_Hol	CBS Nederland
Dutch imports of goods	Imp_Hol	UNCTAD Statistics
Dutch exports of goods	Exp_Hol	UNCTAD Statistics
AEX – index of Amsterdam stock exchange (2005=100)	Sex_Hol	EUROSTAT
German real GDP (2005=100)	GDP_Ger	Deutsche Bundesbank
German CPI (2005=100)	CPI_Ger	Deutsche Bundesbank
German gross monthly wage in industry	Wage_Ger	LABORSTA (ILO)
German retail turnover (2005=100)	Rtt_Ger	Deutsche Bundesbank
German industrial production (2005=100)	Ind_Ger	Deutsche Bundesbank
German imports of goods	Imp_Ger	UNCTAD Statistics
German exports of goods	Exp_Ger	UNCTAD Statistics
DAX30 – index of Frankfurt stock exchange (2005=100)	Sex_Ger	EUROSTAT
German total term deposits in commercial banks	Dep_Ger	Deutsche Bundesbank
German total lending to domestic employees and other individuals	Crd_Ger	Deutsche Bundesbank

(*Continued*)

Table 2. (*Continued*).

Description	Variable	Source
Polish real GDP at constant prices from 2005	GDP_Pol	UNCTAD Statistics
Polish CPI (chain index)	CPI_Pol	GUS Polska
Polish gross monthly wage	Wage_Pol	GUS Polska
Polish imports of goods	Imp_Pol	UNCTAD Statistics
Polish exports of goods	Exp_Pol	UNCTAD Statistics
Slovakian real GDP at constant prices from 2005	GDP_Svk	UNCTAD Statistics
Slovakian GDP deflator (rate of change)	CPI_Svk	World Bank Statistics
Slovakian gross monthly wage in industry	Wage_Svk	LABORSTA (ILO)
Slovakian imports of goods	Imp_Svk	UNCTAD Statistics
Slovakian exports of goods	Exp_Svk	UNCTAD Statistics
Slovenian gross monthly wage	Wage_Slo	LABORSTA (ILO)
Croatian rate of inflation according to index of cost of living	CPI_Cro	Croatian Bureau of Stat.
Greek CPI (2009=100)	CPI_Gre	El.STAT Ellada
Spanish CPI (rate of change)	CPI_Esp	World Bank Statistics
Turkish CPI (rate of change)	CPI_Tur	World Bank Statistics
Nominal exchange rate of official Croatian currency to Austrian schilling/euro	Nxr_Cro_Aut	Croatian National Bank
Nominal exchange rate of official Croatian currency to Czech koruna	Nxr_Cro_Cze	UNCTAD Statistics
Nominal exchange rate of official Croatian currency to French franc/euro	Nxr_Cro_Fra	Croatian National Bank
Nominal exchange rate of official Croatian currency to Italian lira/euro	Nxr_Cro_Ita	UNCTAD Statistics
Nominal exchange rate of official Croatian currency to Hungarian forint	Nxr_Cro_Hun	UNCTAD Statistics
Nominal exchange rate of official Croatian currency to Dutch guilder/euro	Nxr_Cro_Hol	UNCTAD Statistics
Nominal exchange rate of official Croatian currency to German mark/euro	Nxr_Cro_Ger	Croatian National Bank
Nominal exchange rate of official Croatian currency to Polish zloty	Nxr_Cro_Pol	UNCTAD Statistics
Nominal exchange rate of official Croatian currency to official Slovakian currency	Nxr_Cro_Svk	UNCTAD Statistics
Real exchange rate of official Croatian currency to Austrian schilling/euro	Rxr_Cro_Aut	Authors' calculation
Real exchange rate of official Croatian currency to French franc/euro	Rxr_Cro_Fra	Authors' calculation
Real exchange rate of official Croatian currency to Italian lira/euro	Rxr_Cro_Ita	Authors' calculation
Real exchange rate of official Croatian currency to Hungarian forint	Rxr_Cro_Hun	Authors' calculation
Real exchange rate of official Croatian currency to Dutch guilder/euro	Rxr_Cro_Hol	Authors' calculation
Real exchange rate of official Croatian currency to German mark/euro	Rxr_Cro_Ger	Authors' calculation
Real exchange rate of official Croatian currency to Polish zloty	Rxr_Cro_Pol	Authors' calculation
Nominal exchange rate of official French currency to Czech koruna	Nxr_Fra_Cze	UNCTAD Statistics
Nominal exchange rate of official French currency to Hungarian forint	Nxr_Fra_Hun	UNCTAD Statistics

(*Continued*)

Table 2. (*Continued*).

Description	Variable	Source
Nominal exchange rate of official French currency to Polish zloty	Nxr_Fra_Pol	UNCTAD Statistics
Real exchange rate of official French currency to Hungarian forint	Rxr_Fra_Hun	Authors' calculation
Real exchange rate of official French currency to Polish zloty	Rxr_Fra_Pol	Authors' calculation
Nominal exchange rate of official Greek currency to Czech koruna	Nxr_Gre_Cze	UNCTAD Statistics
Nominal exchange rate of official Greek currency to Hungarian forint	Nxr_Gre_Hun	UNCTAD Statistics
Nominal exchange rate of official Greek currency to Polish zloty	Nxr_Gre_Pol	UNCTAD Statistics
Real exchange rate of official Greek currency to Hungarian forint	Rxr_Gre_Hun	Authors' calculation
Real exchange rate of official Greek currency to Polish zloty	Rxr_Gre_Pol	Authors' calculation
Nominal exchange rate of official Italian currency to Czech koruna	Nxr_Ita_Cze	UNCTAD Statistics
Nominal exchange rate of official Italian currency to Hungarian forint	Nxr_Ita_Hun	UNCTAD Statistics
Nominal exchange rate of official Italian currency to Polish zloty	Nxr_Ita_Pol	UNCTAD Statistics
Real exchange rate of official Italian currency to Hungarian forint	Rxr_Ita_Hun	Authors' calculation
Real exchange rate of official Italian currency to Polish zloty	Rxr_Ita_Pol	Authors' calculation
Nominal exchange rate of official Spanish currency to Czech koruna	Nxr_Esp_Cze	UNCTAD Statistics
Nominal exchange rate of official Spanish currency to Hungarian forint	Nxr_Esp_Hun	UNCTAD Statistics
Nominal exchange rate of official Spanish currency to Polish zloty	Nxr_Esp_Pol	UNCTAD Statistics
Real exchange rate of official Spanish currency to Hungarian forint	Rxr_Esp_Hun	Authors' calculation
Real exchange rate of official Spanish currency to Polish zloty	Rxr_Esp_Pol	Authors' calculation
Nominal exchange rate of official Turkish currency to Austrian schilling/euro	Nxr_Tur_Aut	UNCTAD Statistics
Nominal exchange rate of official Turkish currency to Czech koruna	Nxr_Tur_Cze	UNCTAD Statistics
Nominal exchange rate of official Turkish currency to French franc/euro	Nxr_Tur_Fra	UNCTAD Statistics
Nominal exchange rate of official Turkish currency to Italian lira/euro	Nxr_Tur_Ita	UNCTAD Statistics
Nominal exchange rate of official Turkish currency to Hungarian forint	Nxr_Tur_Hun	UNCTAD Statistics
Nominal exchange rate of official Turkish currency to Dutch guilder/euro	Nxr_Tur_Hol	UNCTAD Statistics
Nominal exchange rate of official Turkish currency to German mark/euro	Nxr_Tur_Ger	UNCTAD Statistics
Nominal exchange rate of official Turkish currency to Polish zloty	Nxr_Tur_Pol	UNCTAD Statistics

(*Continued*)

Table 2. (*Continued*).

Description	Variable	Source
Nominal exchange rate of official Turkish currency to Slovakian koruna/euro	Nxr_Tur_Svk	UNCTAD Statistics
Nominal exchange rate of official Turkish currency to official Slovenian currency	Nxr_Tur_Slo	UNCTAD Statistics
Real exchange rate of official Turkish currency to Austrian schilling/euro	Rxr_Tur_Aut	Authors' calculation
Real exchange rate of official Turkish currency to French franc/euro	Rxr_Tur_Fra	Authors' calculation
Real exchange rate of official Turkish currency to Italian lira/euro	Rxr_Tur_Ita	Authors' calculation
Real exchange rate of official Turkish currency to Hungarian forint	Rxr_Tur_Hun	Authors' calculation
Real exchange rate of official Turkish currency to Dutch guilder/euro	Rxr_Tur_Hol	Authors' calculation
Real exchange rate of official Turkish currency to German mark/euro	Rxr_Tur_Ger	Authors' calculation
Real exchange rate of official Turkish currency to Polish zloty	Rxr_Tur_Pol	Authors' calculation
Nominal exchange rate of official Croatian currency to official Slovakian currency	Rxr_Tur_Svk	Authors' calculation
Oil price	Oil_Wrd	European Central Bank

Source: Created by authors

(5) aggregation of leading indicators into a leading composite indicator;
(6) amplitude adjustment of the leading composite indicator with regard to matching the amplitude of the reference series, i.e. Croatian inbound tourism demand.

Figure 3 shows the data for the 12 leading variables, which were standardised, inverted and lag-shifted in line with NBER methodology. In the construction of the weighted average of the 12 leading indicators, Kožić (2013) used the shares of countries of origin of tourists in foreign overnight stays in Croatia as weights. Although such an approach yielded satisfactory results in the case of forecasting turning points in Croatian inbound tourism demand, the major problem with such an exogenous selection of weights is the fact that it is completely theoretical without empirical corroboration.

Therefore, in this paper we employ endogenous weights selection. Instead of selecting 12 weights based on theory, we are looking for the 12 weights that will minimise the mean absolute percentage error (MAPE) of the out-of-sample forecast of magnitude of Croatian inbound tourism demand, i.e. the rate of change of overnight stays of foreign tourists in Croatia.

The leading composite indicator (Ω) is defined as the weighted average of the 12 leading indicators:

$$\Omega = \omega_1 Y_{POL} + \omega_2 ATX_{AUS} + \omega_3 P_{Hol} + \omega_4 P_{SVK} + \omega_5 E_{TUR/GER} + \omega_6 E_{TUR/ITA} + \omega_7 W_{CZE} + \omega_8 W_{SLO} + \omega_9 W_{SVK} + \omega_{10} \varepsilon_{HRV/GER} + \omega_{11} \varepsilon_{HRV/POL} + \omega_{12} IM_{POL}$$

with the constraint that the sum of all weights ω_i for i going from 1 to 12 should be equal to 1:

$$\sum_{i=1}^{12} \omega_i = 1$$

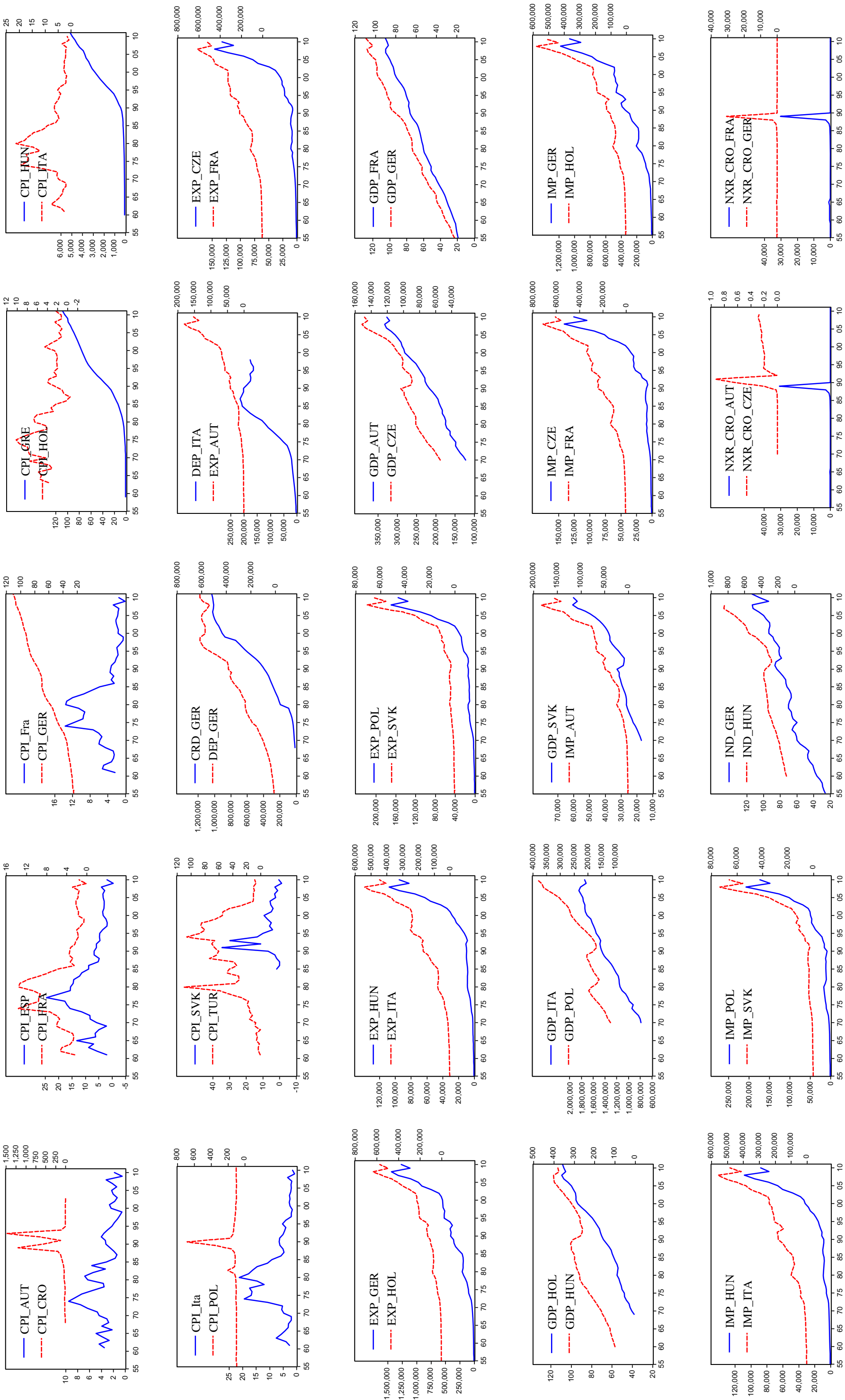

Figure 1. Original data series used in the analysis.
Source: Authors' calculation.

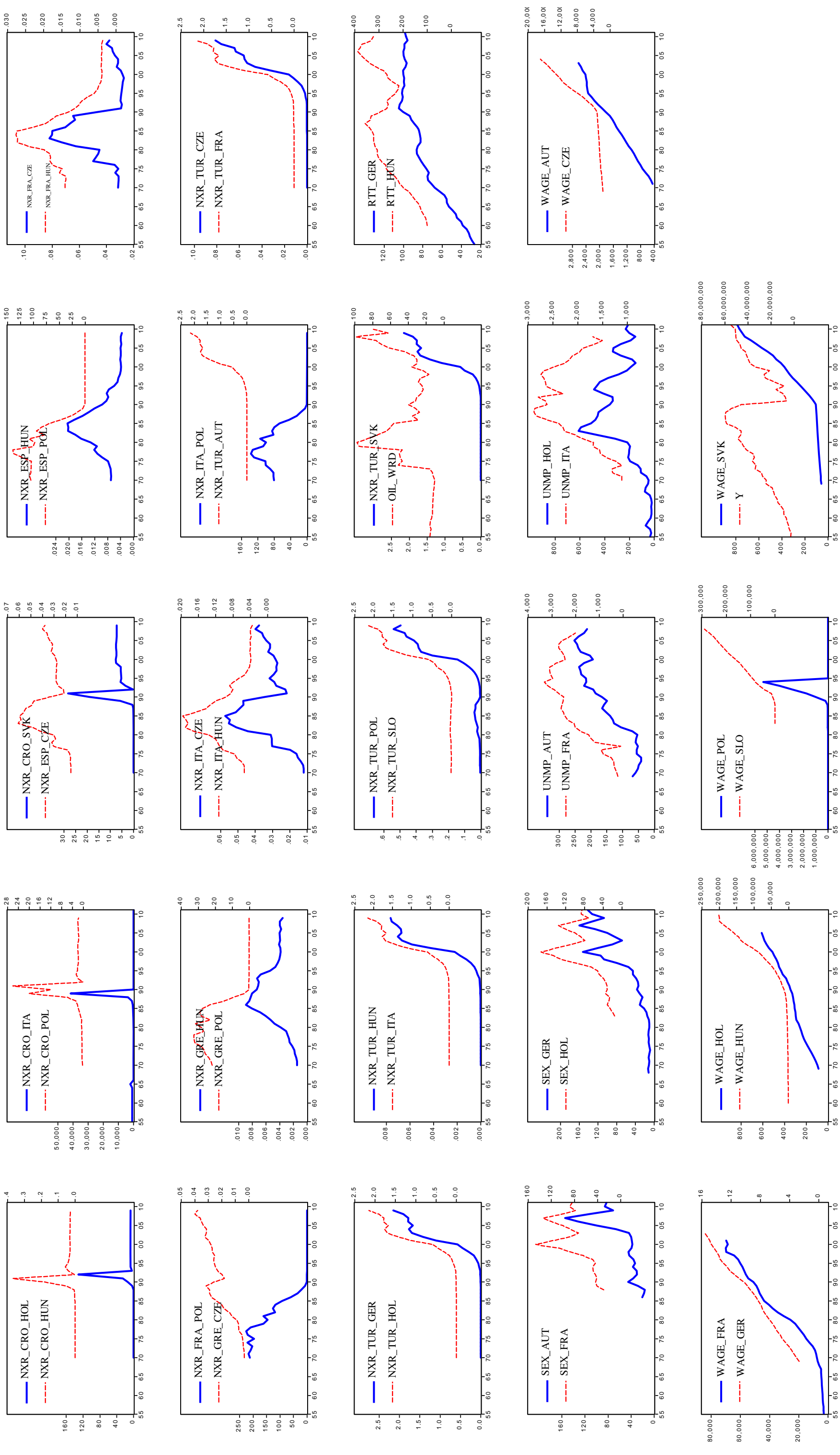

Figure 2. Original data series used in the analysis – continued.
Source: Authors' calculation.

Table 3. Leading indicators of Croatian inbound tourism demand.

Indicator	Data source	Direction of correlation	Leading time in years	Results of Granger causality test (*p*-value)
Polish real GDP in constant prices from 2005	UNCTAD Statistics	(+)	1	0.017
Dutch CPI	CBS Nederland	(-)	1	0.019
Slovakian GDP deflator	World Bank Statistics	(+)	1	0.000
Czech gross monthly wage in industry	LABORSTA (ILO)	(+)	1	0.000
Slovakian gross monthly wage in industry	LABORSTA (ILO)	(+)	1	0.000
Slovenian gross monthly wage in industry	LABORSTA (ILO)	(-)	2	0.001
Polish imports of goods	UNCTAD Statistics	(+)	1	0.044
ATX – index of Vienna stock exchange	EUROSTAT	(-)	1	0.013
Nominal exchange rate of Turkish lira to Italian lira/euro	UNCTAD Statistics	(-)	1	0.031
Nominal exchange rate of Turkish lira to German mark/euro	UNCTAD Statistics	(-)	1	0.001
Real exchange rate of Croatian kuna to German mark/euro	Calculation (data provided by central banks of Croatia and Slovenia, Deutsche Bundesbank and Croatian Bureau of Statistics)	(+)	2	0.007
Real exchange rate of Croatian kuna to Polish zloty	Calculation (data provided by UNCTAD Statistics, GUS Poland and Croatian Bureau of Statistics))	(+)	2	0.017

Source: Authors' calculation and Kožić (2013).

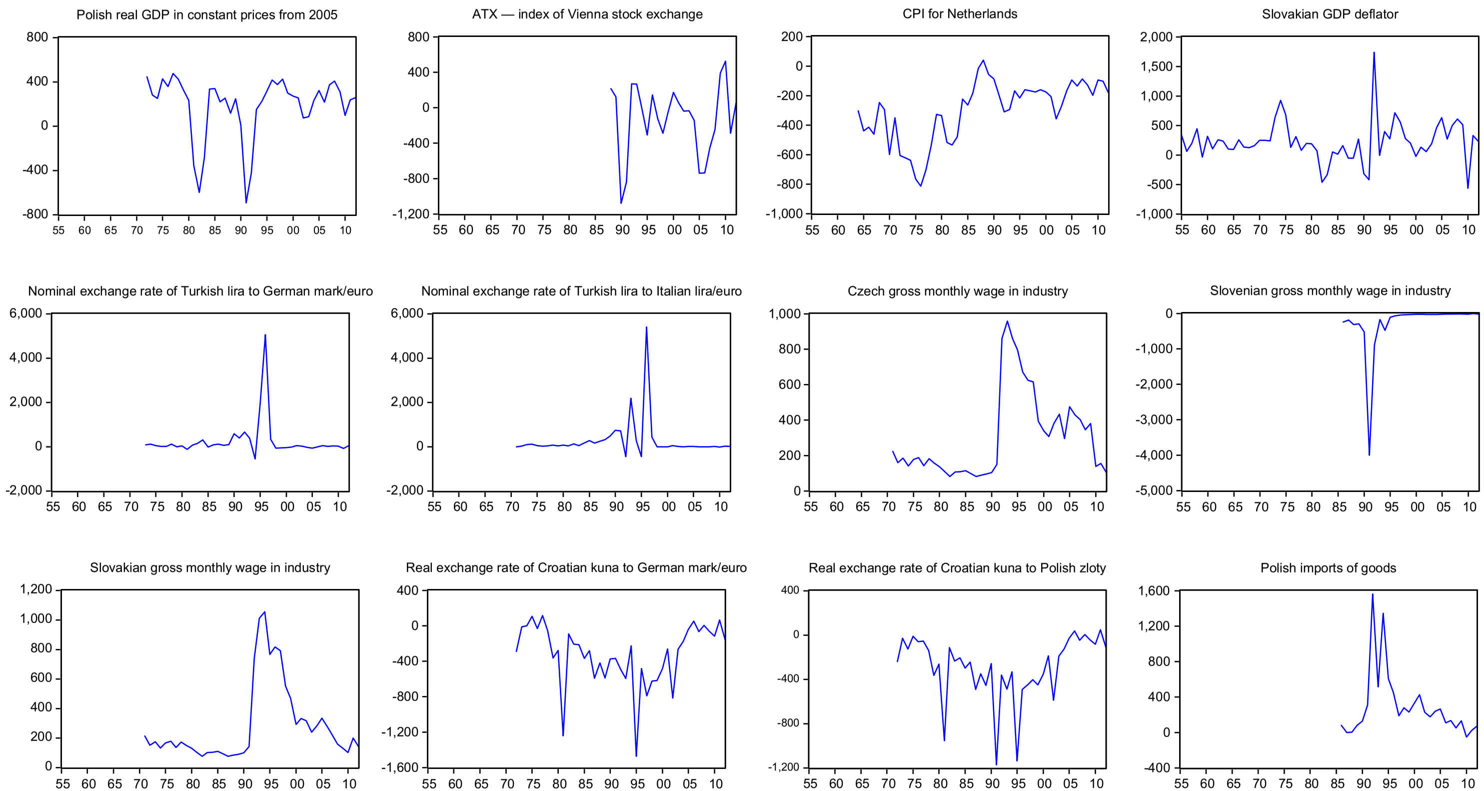

Figure 3. Leading indicators after standardisation of amplitudes, inversion and lag-shifting (Step 3 of the methodology).
Source: Authors' calculation.

Table 4. Results of weights optimisation procedure (grid search).

Indicator	Weight
Polish real GDP in constant prices from 2005	0.270
Dutch CPI	0.000
Slovakian GDP deflator	0.000
Czech gross monthly wage in industry	0.600
Slovakian gross monthly wage in industry	0.030
Slovenian gross monthly wage in industry	0.000
Polish imports of goods	0.100
ATX – index of Vienna stock exchange	0.000
Nominal exchange rate of Turkish lira to Italian lira/euro	0.000
Nominal exchange rate of Turkish lira to German mark/euro	0.000
Real exchange rate of Croatian kuna to German mark/euro	0.000
Real exchange rate of Croatian kuna to Polish zloty	0.000
MAPE	5.1%
Number of regression estimated	7.67E+09

Source: Authors' calculation.

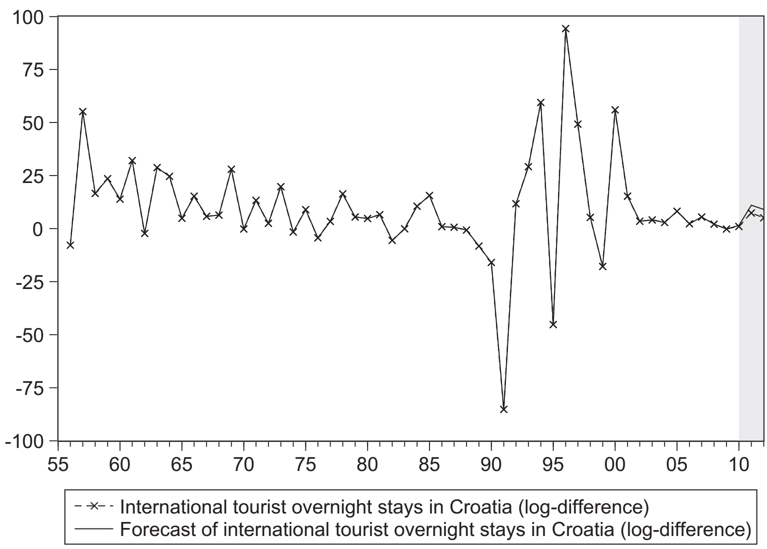

Figure 4. Out of sample forecast of composite leading indicator.
Note: Shaded area represents period of the out of sample forecast.
Source: Authors' calculation.

The mean absolute percentage error (MAPE) is defined as:

$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|1 - \frac{Y_f}{Y}\right|$$

where Y_f is the out-of-sample forecast of Croatian inbound tourism demand, Y is the actual Croatian inbound tourism demand and n is the number of observations in the out-of-sample forecast. In other words, Y_f is the fitted value of Y for the out-of-sample period 2010–2012 forecast using the coefficient vector $\hat{\beta}$ estimated in the in-sample data for 1955–2009 using:

$$\hat{\beta} = (\Omega'\Omega)^{-1}\Omega'Y$$

In order to find the combination of weights ω_i that minimise the MAPE statistics, we employed a grid search and estimated the coefficient vector $\hat{\beta}$ for all possible combinations of weights ω_i that satisfy the condition that the sum of all weights is equal to 1. We tried all the combinations between 0.01 and 1.00 for all weights, bearing in mind the constraint. In order to save computer time, we used steps of 0.03, meaning that we tried values 0.01, 0.04, 0.07, etc. for each weight.

4. Results

The weights optimisation procedure was conducted in several steps. It aimed to find the lowest possible rate of change of weights, i.e. the parameters of the regression model, which is feasible in the context of constraints regarding the computer hardware. Since the running of the weights optimisation procedure on PCs is extremely CPU-consuming, as has already been pointed out, the lowest reasonable rate of change of weights was 0.03. In total, 7.7 billion regression models were estimated. A single PC was used to run the computer algorithm for the weights optimisation procedure and the whole calculation process lasted continuously for two months.

The final results are shown in Table 4. The lowest MAPE is 5.1%, which can be considered as highly accurate forecasting (Frechtling, 2001, p. 26). Only four of the 12 initial leading indicators are included in the final leading composite indicator of Croatian inbound tourism demand. Two of them are related to wages (in the Czech Republic and Slovakia) and two (real GDP and the import of goods) are related to the macroeconomic situation in Poland.

Figure 4 shows the comparison of the out-of-sample forecast and the actual data during the out-of-sample period (the shaded area in Figure 4). The implications of the final results are briefly discussed in the conclusion.

5. Conclusion

The weights determination process is highly important in modelling composite indicators. It is not only important for the proper setting of the parameter values in the model but also because the weights reflect the relative importance of each variable in the forecasting model. The method of weights optimisation should be considered in accordance with the main purpose of the forecasting model.

Unlike the example presented in Kožić (2013), where the main purpose of the forecasting model was to predict tourism demand cycle stages and turning points, the main purpose of the analysis presented in this paper was to improve the model developed by Kožić (2013) for accurate forecasting of the magnitude of the annual rate of change of Croatian inbound tourism demand.

Therefore, a more sophisticated and mathematically more rigid method was needed to accomplish the task. Thus, the grid search was used as a data driven (endogenous) weights determination technique. Using a grid search, we managed to minimise the MAPE of forecasting to 5.1%, which can be considered as highly accurate forecasting. In addition, the list of relevant leading indicators of the annual rate of change of overnight stays of foreign tourists in Croatia was reduced. We found that only four out of the 12 identified leading indicators of Croatian inbound tourism demand are relevant in forecasting the magnitude of its annual rate of change. They are 'Czech gross monthly wages', 'Slovakian gross monthly wages', 'Polish real GDP', and 'Imports of goods in Poland'.

It is not surprising that the four relevant leading indicators are related to Eastern European countries. It is very likely that, on the basis of standard of living and travel habits, tourists from these countries are representative foreign visitors to Croatia. Moreover, it is also very likely that even those tourists in Croatia from Western European countries, Germany for example, have a standard of living and travel habits similar to those tourists from Eastern European countries.

Such a conclusion is supported by the TOMAS survey on the attitudes and expenditure of tourists in Croatia that is frequently conducted by the Croatian Institute for Tourism. According to the latest available data, the average daily expenditure of tourists in Croatia is €58, and nearly half (47%) of tourists come from households with a monthly income of €2000 or less (Marušić, Čorak, Sever, & Ivandić, 2011). Likewise, it is not surprising that two of the four relevant leading indicators for forecasting the magnitude of Croatian inbound tourism demand are related to Poland. Poland is a relatively large European economy. It has very close trade links with the rest of Europe, especially with the rest of Eastern Europe, and thus it could be expected that its economic indicators reflect economic developments in other countries.

Such practical implications of the study suggest that Croatian inbound tourism demand is mainly driven and can be explained by economic developments in Eastern Europe. This could serve as very practical input for tourism policymakers, especially those that make decisions on tourism marketing strategies. Business cycle marketing measures should depend in the first place on the Eastern European economic outlook. The measures should be designed to have an impact on middle class tourists. On the other hand, although the current long-term national strategy of attracting tourists with higher incomes might be considered as welcome, based on the current state of overall Croatian inbound tourism demand, such a goal could be very hard to achieve in the short-run.

Finally, future work on this topic should include the frequent revision of leading indicators and consequently the revision of their weights. The major limitation of this study is the fact that the leading indicators are not stable over a longer period of time. Prognostic models that are based on leading indicators tend to lose their prognostic qualities. An economic indicator that is a highly important leading indicator can lose its leading character very fast. On the other hand, certain other economic indicators can increase in importance as leading indicators. Therefore, it is very important to repeat the whole procedure of identifying leading indicators and determining their relative importance, reflected by their weights, every couple of years.

Another limitation of the study can be found in the relatively short data series for the out-of-sample forecasting. Since it was determined by the overall length of the data series, it can be expected that this problem will be less significant in the future, as the number of observations will naturally rise. It is also worth mentioning that the whole procedure should be conducted with tourism revenues as a dependent variable. A deeper insight could be also provided by the construction of a single model for every country of origin of tourists.

Disclosure statement

No potential conflict of interest was reported by the authors.

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