UPOTREBA ANALIZE I ANALITIČKOG ZNANJA U SVRHU OBRAZOVANJA: PRIMJER MAKROEKONOMSKE ANALIZE CENA U UGOSTITELJSTVU

APPLIED ANALYSIS AND USE OF ANALYTICAL KNOWLEDGE FOR THE PURPOSES OF EDUCATION: THE CASE OF MACROECONOMIC ANALYSIS OF PRICES IN HOSPITALITY INDUSTRY

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Rezime: *Ovaj rad istražuje koji ARIMA model koristiti za proučavanje indeksa cena za različite statističke i ekonometrijske pristupe, koristeći indekse vremenskih serija. U radu istražujemo tri različita ARIMA modela na osnovu mesečnih sezonskih neprilagođenih podataka. Detajli su dobijeni od Statističkog ureda Republike Slovenije, europskog statističkog ureda Eurostat i američke Nezavisne uprave za energetiku. Mod*

: (i) SPSS ARIMA model rezultira u najniži Bajsonov informacijski kriterijum (BIC) i sa srednjom prosečnom apsolutnom procentnom greškom MAPE (48,2%), (ii) inspekcijski ARIMA model ima najnižu MAPE (47,9 %) i najviši BIC, i (iii) avio ARIMA model ima srednji BIC međutim najviši MAPE (55 %). Sa upotrebom diferencijacije podatka smo izgubili najmanje dva zapažanja. S

cena u ugostiteljstvu u euro zoni (diffIHIPEA), indeks potrošačkih cena (diffCPI), indeks cena tečnih goriva (diffIFP) i D2 (dummy variabla koja naznačava period nakon uvođenja eura). Dobiveni rezultati su jak element stručnog i naučnog znanja koji se provodi za zemlje koje ulaze u Europsku uniju i za zemlje koje će uvest euro kao valutu. Dobivena iskustva na osnovi analize potrebno je razmotriti te jih iskoristiti u svrhu obrazovanja.

Ključne reči: *ugostiteljstvo, cene, inflacija, obrazovanje, ARIMA model, regresiona analiza, Slovenija.*

Abstract: *This paper investigates, which ARIMA model using of time series price indices for different statistical and econometric approaches is preferable. Three different ARIMA models for the Slovenia's indices based on monthly seasonally unadjusted data are considered. Data were obtained from Statistical Office of the Republic of Slovenia, Eurostat and the U.S. Energy Information Administration. Inspected ARIMA model, SPSS ARIMA model and airline ARIMA model are used. We find the following: (i) SPSS ARIMA model results are with the lowest Bayesian Information Criteria (BIC), but with middle Mean Absolute Percentage Error (MAPE) (48.2%), (ii) inspected ARIMA model has the lowest MAPE (47.9%) and the highest BIC, and (iii) airline ARIMA model has the middle BIC and the highest MAPE (55%). With the differencing time series variables we lost at least two observations. Yet, the time series has another meaning, but time series is stable. By using the regression analysis as the most statistically significant are proved the explanatory variables index of prices in hospitality industry in euro zone (diffIPHIEA), consumer price index (diffCPI), index of fuel prices (diffIFP) and D2 (dummy variable which captures time period after the euro adoption). These results represent a strong element of technical and scientific knowledge, which can be usefully implemented for the countries entering the European Union and the countries that will adopt the euro. The resulting applied-based analysis is necessary to consider for the use in education purposes.*

Keywords: *hospitality industry, prices, inflation, education, ARIMA specification, regression analysis, Slovenia.*

1. INTRODUCTION

When we refer to the field of tourism we are thinking of numerous sub sectors of tourism, like accommodation and lodging, food and beverage services, travel and transportation, event management and similar. As the tourism industry is growing, the need for labour employed in the field of tourism and thus the demand for higher education (HE) in the field of tourism is growing too [1].

There are some universal factors that impact the demand for HE in general as well as in the field of tourism. These are several economic factors, like perceived benefits from HE and cost of study [2], and other social and family related factors, like education and the social position of parents. The process of science is a way of building knowledge about the constructing new ideas that illuminate the world around us. Those ideas are inherently tentative, but as they cycle through the process of science, they are tested and retested in different ways to become increasingly confident in them. Furthermore, through iterative processes, ideas are modified, expanded, and combined into more powerful explanations.

Tourism has important impacts on the economies of both developing and industrialized countries, resulting in job creation, additional income creation for the private and public sectors, foreign currency receipts, potential for higher investment activities and economic growth. Indeed, tourism has acted as a catalyst to economic restructuring in many recipient countries, assisting a shift away from primary sector activities, towards greater reliance on services and manufacturing. Many tourism service organizations – such as hotels and credit card companies – provide services beyond their core services to attract customers. For example, many hotels offer a complimentary breakfast, transportation service, free access to a swimming pool and gym, and free internet access. Given the scale of tourism's contribution to the macroeconomic dimension over time, knowledge concerning the nature of the demand upon which it is based is of both theoretical and practical relevance. It is well known that tourism demand is responsive to variables such as income growth, relative prices and exchange rates. What is less known is how the responsiveness of demand to changes in these variables alters during a country's economic transition and integration into the wider world initial turmoil or subsequent years? Does the sensitivity of tourism demand to changes in its own prices, or those of its competitors, change between different periods? Further questions concern the degrees of complementarity or substitutability between tourism destinations and the extent to which these changed during periods of economic transition. Complementarity occurs if holidays in different destinations are purchased as a package. Alternatively, there may be an intense degree of competition between destinations. Relationships of complementarity or substitutability may change over economic development. Little information is available about these issues. It is not known, for example, whether lower income destinations tend to become more or less competitive over time, either relative to other developing countries or relative to more industrialized nations [3].

The task facing the modern time-series econometrics is to develop reasonably simple models capable of forecasting, interpreting, and testing hypotheses concerning economic data. The challenge issues have grown over time; the original use of time-series analysis was primarily as an aid to forecasting. As such, a methodology was developed to decompose a time series into a trend, a seasonal, a cyclical, and an irregular component. The trend component represented the long-term behaviour of the time series and the cyclical component represented the regular periodic movements. The irregular component was stochastic and the goal of the econometrician was to estimate and forecast this component [4]. Many empirical studies [5] on the ARIMA (Autoregressive (AR)/Integrated (I)/Moving Average (MA)) model either do not address the properties of the time series data used or simply assume their stationarity. However, nonstationarity can be pronounced in macroeconomic time-series data of emerging economies. The results for variables depend on the test used and on the assumption used about the deterministic components. Consequently, we test the autocorrelation and use regression analysis between dependent and explanatory variables.

Hospitality services are specific in its management. Customers' needs are often endogenous variable. Because services cannot be pre–produced and stored, synchronizing supply and demand is often difficult [6]. Furthermore, because in many situations, tourists and other customers are co–producers of the service, and specific tasks are assigned to them (in self–service restaurants, or automatic check–in/out machines in budget hotels and other hospitality industry services), providers have to facilitate customer involvement [7]. From the customers` perspectives they need to make a decision when choosing between alternatives. Consumers have to weight input factors such as time, effort, and money against outcome factors such as level of reliability, expertise, and the anticipated pleasantness of the service experience. Since in hospitality services clear–cut evaluation is usually available after purchase, consumer knowledge is typically based on expectations of service attributes. These expectations are derived from indirect attributes. For instance, brand names can be used for beliefs about the service: some brand names may be known for high quality standards and high price levels, while others are known for their cheap products and services. However, in many cases, restaurants, cafes, or hotels are not part of such well–known chains, or may be local brands in themselves, unknown to many guests. In those cases, consumers cannot use brand name information to infer important service attributes such as price and quality. In considering consumer decision–making, price is generally considered as a key variable to acquire these services. Therefore, the decision whether or not to accept a service offer is typically based on comparison of the required sacrifice (price) with the expected benefits of the service. As a consequence, price image is one of the key competitive tools in hospitality marketing. For many hotels and restaurants, price is one of the most important attributes in their positioning [7], [8], [9].

The dynamic analysis of wages, prices and other macroeconomic time series data is of policy relevance at macroeconomic and microeconomic levels [10], [11]. The interaction of wage- and price-dynamics is important for inflation prediction [12].

Our paper contributes to the empirical knowledge about the dynamics of time series data in two ways. First, we present evidence based on a multivariate time-series analysis for Slovenia, which is complementary with respect to results available in literature. We estimate three different ARIMA models for hospitality industry prices for the last decade. This period is important for Slovenia from at least two main reasons: firstly, to become a member state of European Union (EU), euro adoption, high level of food prices and recent economic and financial crises. The obtained evidence is new and complements other evidence on current nominal and real rigidities in the EU based on survey data. Secondly, departing from long tradition in macroeconomics, we do not impose a vertical long-run Phillips curve (PC), but test ARIMA model and use regression analysis with I (1) time series data. It [13] shows that only money was equilibrium correcting to the long-run demand relation and to the medium-run relation between the growth rate of money and inflation rate. None of the variables, i.e. wages, prices and exchange rates were affected by the two monetary equilibrium errors.

The rest of the paper is organized as follows. Section 2 presents the data used and methodology for ARIMA model. Section 3 discusses the results of ARIMA model. In Section 4 we expose regression analyses. Final section 5 concludes.

2. DATA USED AND ARIMA MODEL

Many empirical studies on the ARIMA (Autoregressive (AR)/Integrated (I)/Moving Average (MA)) model either do not address the properties of the time series data used or simply assume their stationarity. However, nonstationarity can be pronounced in macroeconomic time-series data of transition and emerging market economies. The results for variables depend on the test used and on the assumption about the deterministic components. Consequently, we test the autocorrelation, and regression analysis between explanatory and dependent variables. Dependent variable is IPHI – index of prices in hospitality industry. Explanatory variables are: IPHIEA – index of prices in hospitality industry in euro zone, IFP – index of fuel prices, tourists – tourists arrivals, ISP – index of service prices, IPPP – index of product prices by producers, IGP – index of gas prices, NEER – nominal effective exchange rate, VR – value added tax rate, IWHI – index of wages in hospitality industry, IFB – index of food and non-alcoholic beverages [14], [15], dummy variable for the euro adoption (D1), and dummy variable for the period after the euro adoption (D2). Long-term comovement is the main precondition for the reasonability impact of regressor components on the dependent variable. We apply sample autocorrelation function (ACF) – test where degree and direction of dependence between time series of the same articles is measured by the autocorrelation (ρ_s), where is:

$$\rho_0 = 1,\ \rho_1 = a_1,\ \rho_2 = (a_1)^2,\ \rho_s = (a_1)^s \quad (1)$$

Its value in relation to the length of lag $(a_1)^s$ is usually displayed as a special chart called autocorrelogram [4]. If the residuals are stationary, it means that either variables are stationary I(0) or that they are nonstationary I(1) or higher.

Our time series dataset consists of monthly seasonally unadjusted data ranging from January 2000 to September 2010. This period is posterior to major transitional reforms in Slovenia when the monetary policy acted in a very discretional way and diverse administrative measures such as price liberalizations affected the inflation rates. The process of price convergence in Slovenia was smooth and timely, so that Slovenia could join the euro area at the beginning of 2007, at that time the only one among the EU new member states. Slovenian national strategy of the euro adoption was defined in November 2003, when the Program for joining the ERM II and adoption of the euro was prepared. The principal source of the data is Statistical Office of Republic of Slovenia (SORS) and Eurostat. Time-series data of some energy prices were obtained from additional sources such as US Energy Information Administration.

The basic tool for modelling the dependent observations is autoregression [16]. Price time series has a feature that the price at time *t* is associated with the price in the previous period. This time dependence violates the independence rule, which is a prerequisite in the regression models. The simplest way of describing the time dependence of the pattern of connections between today's value and the value of time series from the previous period is called autocorrelation. If the observed variables are indexed and denoted $Y_1,...,Y_T$, this yields:

$$r_{0,s} = \frac{\sum_{t=s+1}^{T}\left(Y_t-\overline{Y}_{1+s}^{T}\right)\left(Y_{t-s}-\overline{Y}_{1}^{T-s}\right)}{\sqrt{\sum_{t=s+1}^{T}\left(Y_t-\overline{Y}_{1+s}^{T}\right)^2 \sum_{t=s+1}^{T}\left(Y_{t-s}-\overline{Y}_{1}^{T-s}\right)^2}} \quad (2)$$

where are:

$\overline{Y}_{1+s}^{T}$ and $\overline{Y}_{1}^{T-s}$ – are the averages of the observations $Y_{1+s},...,Y_T$ and the lagged observations $Y_1,...,Y_{T-s}$, respectively. The sequence $(r_{0,0}, r_{0,1}, r_{0,2}, r_s)$ of sample autocorrelations is called the sample autocorrelation,

t – time, and

s – value of the lagged observations;

with the backward-looking term and with the represent of the residuals. Note that the residual can be autocorrelated for different reasons: (i) inflation shocks (e.g. cost-push shocks) are autocorrelated, (ii) the prediction error and the random, (iii) there are omitted variables (e.g. various external variables for small open economies).

Plotting the chart gives a graphical representation of correlation coefficients (ACF) in a rectangular coordinate system, where abscise axis is defined by a time lag, the ordinate axis is with a coefficient of correlation with a lag, which is called correlogram. Correlograms are simple to calculate, but the econometric software often calculated thumbnail autocovariance:

$$g_{0,s} = \frac{\sum_{t=s+1}^{T}\left(Y_t-\overline{Y}_{1}^{T}\right)\left(Y_{t-s}-\overline{Y}_{1}^{T}\right)}{\sum_{t-1}^{T}\left(Y_t-\overline{Y}_{1}^{T}\right)^2} \quad (3)$$

where is:

$\overline{Y}_{1}^{T}(r_{0,0}, r_{0,1}, r_{0,2}, r_s)$– average of all observations Y_1, ..., Y_T.

Correlogram for the time series data can be used to test the hypothesis of independence of the time series. This can be demonstrated, because the time independence $Tr_{0,s}^2 \approx \chi^2[1]$ in accordance with $\sqrt{T}g_{0,s} \approx N[0,1]$ and in the case of a 129 price observations (T = 129), then horizontal lines $\pm 2/\sqrt{T}$ show the critical values for testing independence at the 5% risk level [16].

The basic tool for the description of time series, as the price p_t is autoregression. Partial autocorrelation can give first-order dependence, which can be seen from correlogram. It has a high initial value of the correlation $r_{0,1}$, and low the next, a second value of correlation $r_{0,2.1}$. Partial autocorrelation can be demonstrated by the following equation:

$$r_{0,2.1} = \frac{r_{0,2} - r_{0,1}r_{1,2}}{(1 - r_{0,1}^2)^{1/2}(1 - r_{1,2}^2)^{1/2}} \quad (4)$$

Through this equation we analyse whether Y_{t-2} and Y_{t-2} are in the correlation or not. Analysis of the partial autocorrelation displays whether Y_t and Y_{t-1} are correlated while analysing them. The sequence of partial correlations is marked with ($r_{0,1}$, $r_{0,2.1}$, $r_{0,3.1,2}$,...), which is called partial autocorrelation function and this function chart is a partial autcorrelogram (PACF).

Layout of the autoregression model is similar to the regression model for cross-sectional data. The time series random variables Y_t are indexed $t = 0,...,T$ such that the total number of observations is $T + 1$. Statistical model is formulated in terms of normal distribution. The model has conditional independence

$$(Y_t|Y_0, \dots, Y_{t-1}) =^D (Y_t|Y_{t-1}) \quad (5)$$

normal distributions

$$(Y_t|Y_{t-1}) =^D N[\beta_1 + \beta_2 Y_{t-1}, \sigma^2] \quad (6)$$

where ≥ 1 and the range of variables are: $\beta_1, \beta_2, \sigma^2 \in \mathbb{R}^2 \times \mathbb{R}_+$. There are two differences from the usual two-variable regression model. First, the distribution of the original variables Y_0 is not given, so the model enters a contingent variable Y_0. Second, independent variable is a backward time series-variable, also called lagged dependent variable. A similar and equivalent formulation is given in terms of equations:

$$Y_t = \beta_1 + \beta_2 Y_{t-1} + \epsilon_t, \text{ for } t = 1,\dots, T \quad (7)$$

where are:

β_1 – constant,

β_2 – regression coefficient of the first difference,

Y_t – dependent variable,

Y_{t-1} – lagged dependent as independent or explanatory time series variable and

ε_t – disturbance-stochastic variable.

The problem of non-stationarity in the variance model is often present in time series. Econometric and economic theory gives an explanation that the variables, which are a subject to change by more than 100% from the baseline, are non-stationary and their modification could also be negative. In most cases, they become stationary in first difference I (1)

$$(Y_t = \beta_1 + \beta_2 Y_{t-1} + \epsilon_t, \text{ for } t = 1,\dots,T) \quad (8)$$

such as macroeconomic variables: prices, gross domestic product (GDP) and the exchange rate; rare there are examples of the higher differential. Some variables are already fixed with I (0), such as value added tax rate and unemployment.

In order to mitigate or even eliminate this problem, it is possible to use several approaches. Database (usually prices) can be in a logarithm form, but the homogeneity of variance is not granted, the problem is just watered down. In the presence of heteroscedasticity, which means that the variance is different over time, we can use another way through explicit inclusion in the model, e.g. ARMA specification (Autoregressive (AR)/Moving Average (MA)) for y_t.

The autoregressive part of the model is the difference equation given by the homogeneous portion of equitation and the moving average part is the x_t sequence:

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-1} + x_t \quad (9)$$

If the homogeneous part of the difference equitation p lags and the model for x_t contains q lags, the model is called ARMA(p, q) model. If q=0, the process is called a pure autoregressive process denoted by AR(p) and if p=0, the process is a pure moving-average process denoted by MA(q). If one or more characteristic roots of x_t are greater or equal to unity, the y_t sequence is said to be an integrated process and y_t is called an ARIMA model. The equitation of x_t is as follows:

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{i=0}^{q} \beta_i \varepsilon_{t-1} \quad (10)$$

where are:

a_0 – locations variable

$\sum_{i=1}^{p} a_i y_{t-1}$ – AR (p) part of the equitation,

$\sum_{i=0}^{q} \beta_i \epsilon_{t-1}$ – MA (q) part of the equitation.

If any portion of the homogeneous equitation is present, the mean, variance, and all covariances will be time-dependent. Hence, for any ARMA(p, q) model, stationarity necessitates that the homogeneous solution be zero. A common example of non stationarity is random walk. Random walk series is stationary differential series, at the first difference stationary series y_t. Differenced stationary series is called integrated series and denoted by I (d) where d is the order of integration. Order of integrating is a root of the number of units or the number of operations needed for the differentiation, that the series has become stationary. For example, the random walk is one order of integration; since it contains only one unit root I (1). Similarly, a stationary series are marked with I (0).

A formal method for testing the stationarity is unit root test, examples of which are Augmented Dickey-Fuller test (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) [4]. In the ADF test with the help of tau (T) statistics, which is like a t-statistic, we find the validity of the null hypothesis. To illustrate, assume the presence of ADF test of first-order autocorrelation AR (1) in a time series:

$$y_t = \mu + \rho y_{t-1} + u_t \qquad (11)$$

where μ and ρ are parameters and ρ is a stochastic component or white noise. Time series is stationary if holds $-1 < \rho < 1$. When the value is $\rho = 1$, then y is non-stationary time series of random walk, which means that when the time series starts at a certain moment, the variance of variable y increases with time and goes to infinity. If the absolute value of the coefficient ρ is greater than 1, the time series is explosive. A hypothesis of stationary time series can be assessed by testing and the absolute value of the coefficient ρ is strictly less than one. The null hypothesis of ADF test of unit root is: $H_0 \equiv \rho \geq 1$. Explosive time series have no economic sense, so this hypothesis is tested with a combination with one-sided alternative hypothesis: $H_1 \equiv \rho < 1$. ADF test is conducted by assessing the coefficient γ, which is obtained from the deducted equitation above y_{t-1}:

$$\Delta y_t = \mu + \gamma y_{t-1} + u_t \qquad (12)$$

3. EMPIRICAL RESULTS OF ARIMA MODEL(S)

Combining the two types of differencing yields $(\Delta^d \Delta_s^D)$. Multiplicative models are written in the ARIMA form $(p,d,q)(P,D,Q)_s$, where:

p and *q* – the nonseasonal ARMA coefficients,
d – number of non seasonal differences,
P – number of multiplicative autoregressive coefficients,
D – number of seasonal differences,
Q – number of multiplicative moving average coefficients, and
s – seasonal period.

Using the notations, we can say that the fitted model is so called airline [17] ARIMA model. Moreover, the value of m_t can be written as ARIMA (0,1,1)(0,1,1). This type of model may be worth considering for analysis even if typical unit root tests do not support double differencing [5].

Our first model, which is presented in Table 1, is inspected model. This model is derived and made out of the theory. It [17] shows the inspection of the model in three steps: (i) visual model inspection, (ii) selection of the model and choose the model, which captures to the normal distribution, and (iii) results control. Table 1 presents ARIMA inspected model with all our analysed time series variables. This new and stable time series are also used for regression analysis. This new variables gives us the most appropriate results. With the differencing we lost at least two observations, while the time series has another meaning, but time series is stable.

Table 1: ARIMA inspected model with R^2, BIC and Q(18)

$\alpha + \rho(L)y_t = \theta(L)e_t$ and $(\Delta^d \Delta_s^D)$ for $\lvert\alpha\rvert < 1$				
	1			
time series	ARIMA	parameters		
	(p,d,q) $(P,D,Q)_s$	R^2	BIC	Q(18)
CPI	(1,1,0) $(0,0,0)_{12}$	0.06	-0.582	34.52 (0.006)
CPIEA	(1,1,0) $(0,0,0)_{12}$	0.10	-1.491	112.80 (0.000)
IHIP	(1,1,0) $(0,0,0)_{12}$	0.02	1.685	2.470 (1.000)
IHIPEA	(1,1,0) $(0,1,0)_{12}$	0.13	-0.565	158.24 (0.000)
IFB	(1,1,0) $(0,1,0)_{1}$	0.03	0.551	87.770 (0.000)
IWHI	(1,1,0) $(0,0,0)_{12}$	0.31	6.190	12.857 (0.746)
tourists	(1,0,0) $(0,1,0)_{12}$	0.17	4.822	29.873 (0.027)
IPPP	(1,1,0) $(0,0,0)_{12}$	0.17	-1.634	25.154 (0.091)
ISP	(1,1,0) $(0,1,0)_{12}$	0.11	0.419	127.407 (0.000)
IGP	(1,1,1) $(0,0,0)_{12}$	0.196	5.952	22.816 (0.119)
NEER	(1,1,0) $(0,1,0)_{12}$	0.06	-2.931	50.902 (0.000)
VR	(0,0,0) $(0,0,0)_{12}$	0.48	0.957	25.613 (0.060)
IFP	(1,1,1) $(0,0,0)_{12}$	0.12	4.704	25.613 (0.060)
K1	(1,1,0) $(0,0,0)_{12}$	0.25	-5.032	34.872 (0.006)
K2	(1,1,0) $(0,0,0)_{12}$	0.12	-1.949	68.871 (0.000)
Y=IHIP	(1,1,0) $(0,0,1)_{12}$	0.36	2.036	10.409 (0.844)

Note: $(\Delta^d \Delta_s^D)$ – d differencing, ARIMA model, where are ρ lag y_t, L lag operator, θ value, e_t random errors $\alpha + \rho(L)y_t = \theta(L)e_t \equiv Y_t = a_0 + \sum_{i=1}^{p} a\, y_{t-1} + \sum_{i=0}^{q} \beta_i\, \epsilon_{t-1}$
$\lvert\alpha\rvert < 1$ – stationary time series, CPIEA – consumer price index in euro zone, IPHIEA – index of prices in hospitality industry in euro zone, CPI – consumer price index, IFP – index of fuel prices, tourists – tourists arrivals, ISP – index of service prices, IPPP – index of product prices by producers, IGP – index of gas prices, NEER – nominal effective exchange rate, VR – value added tax rate, IWHI – index of wages in hospitality

industry, IFB – index of prices for food and non-alcoholic beverages, *q* – the nonseasonal ARMA coefficients, *d* – number of nonseasonal differences, *P* – number of multiplicative autoregressive coefficients, *D* – number of seasonal differences, *Q* – number of multiplicative moving average coefficients, *s* – seasonal period, R^2 – adjusted determination coefficient, N – number of observations of time series, BIC – Bayes information criteria, Q(18) – Ljung Box Q-statistic of residuals, the significance level is in brackets; 1 – ARIMA inspected model.

All models will be integrated with each other and compared on the basis of statistical significance with the residuals of Ljung-Box Q-statistic, the BIC information criterion and the adjusted determination coefficient.

Information criteria are the statistical parameters, which assessed benefits and costs from the integration of additional lag in the regression model. Whenever are added explanatory variables in the model, they are improving model fit. Additional lag in the ARIMA model are able to capture any information provided by the lower class missed deferral. However, with lags are caused the additional costs. Models with lower information criterion take precedence over models with higher-value information criterion. BIC criterion is used to select the model in the classical frequency econometrics. In addition to standard tests, the analysis of time series has a particular focus on the residuals. Q statistic for the residuals has χ^2 distribution with m degrees of freedom, which are equal to the number of lags. If the calculated Q exceeds a critical value Q reject a null hypothesis, which states that all autocorrelation coefficients are equal to zero simultaneously. Accept the alternative hypothesis, which states that at least one autocorrelation coefficient is significantly different from zero.

Three models were developed inspection like above, SPSS proposed model, and airline model. All three models are compared with each other. The first inspection, visual model:

$$y_t = a_1 y_{t-1} + \epsilon_t \tag{13}$$

Second model:

$$y_t = a_1 y_{t-1} + \epsilon_t + \beta_{12}\epsilon_{t-12} \tag{14}$$

and third airline model

$$\Delta_{12}^2 y_t = y_t - 2y_{t-12} + y_{t-24} \tag{15}$$

are based on monthly data, all with a lag of 12 to the MA coefficient. The first factor in all models is less than 1, which provides for stability $|a_1| < 1$. Last four columns in Tables 1 to 3 give us a rating. The lowest BIC has the second model (Table 2), then airline model (Table 3), and then the last inspection model (Table 1). Comparison of BIC between models shows that the estimated effects of these parameters overloaded. Therefore, benefits from the reduced squared residuals are high. Plotting residuals is useful inspection of the model. Q statistics for these residuals indicate that autocorrelation coefficients are less than two standard deviations from zero. Q statistics for residuals indicate that all autocorrelation coefficients are equal to zero, and thus we reject the null hypothesis.

Table 2: ARIMA SPSS model with R^2, BIC and Q(18)

$\alpha + \rho(L)y_t = \theta(L)e_t$ and $(\Delta^d \Delta_s^D)$ for $|\alpha| < 1$

time series	2			
	SPSS ARIMA	parameters		
		R^2	BIC	Q(18)
CPI	WA	0.31	-0.783	14.924 (0.457)
CPIEA	WA	0.51	-2.415	0.072 (0.004)
IHIP	(0,1,0) $(1,0,0)_{12}$	0.04	1.594	2.670 (1.000)
IHIPEA	WA	0.29	-2.995	46.632 (0.000)
IFB	WA	0.46	0.100	14.292 (0.504)
IWHI	SS	0.55	6.093	25.114 (0.068)
tourists	WM	0.57	4.590	37.735 (0.002)
IPPP	(1,1,0) $(0,0,0)_{12}$	0.17	-1.634	25.154 (0.091)
ISP	(0,1,0) $(0,1,1)_{12}$	0.08	-0.764	18.099 (0.383)
IGP	DT	0.21	5.924	21.656 (0.117)
NEER	(0,2,7) $(0,0,0)_{12}$	0.36	-3.636	15.326 (0.428)
IFP	(0,1,1) $(0,0,0)_{12}$	0.05	4.661	21.635 (0.199)
K1	(1,1,0) $(0,1,1)_{12}$	0.58	-5.221	14.836 (0.537)
K2	SS	0.50	-2.743	29.347 (0.022)
Y=IHIP	(0,1,0) $(0,0,0)_{12}$	0.45	1.151	10.005 (0.932)

Note: $(\Delta^d \Delta_s^D)$ – d differencing, ARIMA model, where are ρ lag y_t, L lag operator, θ value, e_t random errors $\alpha + \rho(L)y_t = \theta(L)e_t \equiv Y_t = a_0 + \sum_{i=1}^{p} a\, y_{t-1} + \sum_{i=0}^{q} \beta_i\, \epsilon_{t-1}$
$|\alpha| < 1$ – stationary time series, CPIEA – consumer price index in euro zone, IPHIEA – index of prices in hospitality industry in euro zone, CPI – consumer price index, IFP – index of fuel prices, tourists – tourists arrivals, ISP – index of service prices, IPPP – index of product prices by producers, IGP – index of gas prices, NEER – nominal effective exchange rate, IWHI – index of wages in hospitality industry, IFB – index of prices for food and non-alcoholic beverages, SPSS calculated models: WA – winter additive, SS – simple seasonal, DT – damped trend, *q* – the nonseasonal ARMA coefficients, *d* – number of nonseasonal differences, *P* – number of multiplicative autoregressive coefficients, *D* – number of seasonal differences, *Q* – number of multiplicative moving average coefficients, *s* – seasonal period, R^2 – adjusted determination coefficient, N – number of observations of time series, BIC – Bayes information criteria, Q(18) – Ljung Box Q-statistic of residuals, the significance level is in brackets; 2 – ARIMA SPSS model.

Table 3: ARIMA airline model with R^2, BIC and Q(18)

$\alpha + \rho(L)y_t = \theta(L)e_t$ and $(\Delta^d \Delta_s^D)$ for $\lvert\alpha\rvert < 1$				
	3			
time series	ARIMA	parameters		
	$(0,1,1)$ $(0,1,1)_s$	R^2	BIC	Q(18)
CPI	(0,1,1) $(0,1,1)_{12}$	0.27	-0.665	18.453 (0.298)
CPIEA	(0,1,1) $(0,1,1)_{12}$	0.35	-2.175	24.533 (0.078)
IHIP	(0,1,1) $(0,1,1)_{12}$	0.01	1.779	1.982 (1.000)
IHIPEA	(0,1,1) $(0,1,1)_{12}$	0.18	-2.791	32.277 (0.009)
IFB	(0,1,1) $(0,1,1)_{12}$	0.34	0.390	14.451 (0.565)
IWHI	(0,1,1) $(0,1,1)_{12}$	0.52	6.329	15.425 (0.494
tourists	(0,1,1) $(0,1,1)_{12}$	0.49	4.820	16.045 (0.450)
IPPP	(0,1,1) $(0,1,1)_{12}$	0.46	-1.383	17.006 (0.385)
ISP	(0,1,1) $(0,1,1)_{12}$	0.05	-0.722	14.097 (0.591)
IGP	(0,1,1) $(0,1,1)_{12}$	0.56	6.200	33.223 (0.007)
NEER	(0,1,1) $(0,1,1)_{12}$	0.27	-3.132	28.749 (0.026)
IFP	(0,1,1) $(0,1,1)_{12}$	0.51	4.937	27.121 (0.040)
K1	(0,1,1) $(0,1,1)_{12}$	0.55	-5.114	22.524 (0.127)
K2	(0,1,1) $(0,1,1)_{12}$	0.46	-2.536	14.373 (0.571)
Y=IHIP	(0,1,1) $(0,1,1)_{12}$	0.40	2.084	6.655 (0.979)

Note: $(\Delta^d \Delta_s^D)$ – d differencing, ARIMA model, where are ρ lag y_t, L lag operator, θ value e_t random errors $\alpha + \rho(L)y_t = \theta(L)e_t \equiv Y_t = a_0 + \sum_{i=1}^{p} a\, y_{t-1} + \sum_{i=0}^{q} \beta_i\, \epsilon_{t-1}$
$\lvert\alpha\rvert < 1$ – stationary time series, CPIEA – consumer price index in euro zone, IPHIEA – index of prices in hospitality industry in euro zone, CPI – consumer price index, IFP – index of fuel prices, tourists – tourists arrivals, ISP – index of service prices, IPPP – index of product prices by producers, IGP – index of gas prices, NEER – nominal effective exchange rate, VR – value added tax rate, IWHI – index of wages in hospitality industry, IFB – index of prices for food and non-alcoholic beverages, *q* – the nonseasonal ARMA coefficients, *d* – number of nonseasonal differences, *P* – number of multiplicative autoregressive coefficients, *D* – number of seasonal differences, *Q* – number of multiplicative moving average coefficients, *s* – seasonal period, R^2 – adjusted determination coefficient, N – number of observations of time series, BIC – Bayes information criteria, Q(18) – Ljung Box Q-statistic of residuals, the significance level is in brackets; 3 – ARIMA airline model.

The third estimate is the Mean Absolute Percentage Error: ror the first model is expressed as a percentage (MAPE) 47.9%, 48.2% for the second model and 55% for the third model.

We find that an appropriate inspected ARIMA model is for the variables IWHI, IPPP and IGP, since all autocorrelation coefficients are equal to zero simultaneously. SPSS gives the appropriate models, considering the Q statistics in all cases, except for the variable tourists, IHIPEA and K2 since at least one autocorrelation coefficient is different from zero. We find that SPSS predicts the most appropriate model based on BIC and MAPE. SPSS gives models as the winter additive, simple seasonal and damped trend. These methods are not used in our study. So, we try on the basis of previous empirical research [17], [18] taking in mind that we get the best results with airline ARIMA model.

In regression analysis inspected model is used. Inspected ARIMA model has almost all variables in one differencing, so we lost only two observations. Five variables are also seasonal differencing: IHIPEA, IFB, ISP, NEER, and tourists. The adjusted determination coefficient of the model Y=IHIP shows the degree of the regression explanation by the independent variables. Degree of explained variance of the model is 36%. Another 64% are unknown and specific factors.
It is worth citing [19] that the long-lasting struggle to understand inflatory mechanisms has not only influenced the empirical discussion, but also shaped the view that empirical modelling should not just be about testing pre-specified hypotheses and estimating parameters, but also about generating new hypothesis to be subsequently tested on new data.

5. REGRESSION ANALYSIS

In order to rebut the spurious regression, we checked the reliability of regression estimates in a way that we evaluate the regression of transformed variables with the first difference (without logarithms) [18]. We apply ACF test where degree and direction of dependence between time series of the same articles is measured by the autocorrelation. Its value in relation to the length of lag is usually display as a special chart called autocorrelogram [4]. If the residuals are stationary, it means that either variables are stationary I (0) or that they are nonstationary I (1) or higher.

At this point we are giving briefly summary of the regression analysis for the analysed period. As the most statistically significant, in the whole period, the following explanatory variables are proved: diffIHIPEA, diffCPI, diffIFP and D2. These results indicate that the price behaviour in the hospitality industry in Slovenia is determined: first, by the hospitality industry prices in the euro area. This finding is inherent in the idea of creating a monetary union contributing to the convergence of prices in the member states towards a common European price level. Second, by the fuel prices as input costs, which play an important role on the output prices in the hospitality industry, which for many hotels and restaurants is one of the most important attributes of market competition. Price is the only marketing mix element that produces revenue. All others represent costs. Third, the results also show that the general price level have a significant effect on international tourism (hospitality industry prices) for Slovenia. Fourth, after the euro adoption, in March 2007, price in hospitality industry in Slovenia declined significantly. This evidence confirms some of the anticipated effects of EMU and of globalization [20]. The patterns in real price developments are important for marketers and managers for understanding of price competitiveness. Charging too much chases away potential customers.

Our regression analysis findings are consistent with findings of some previous analysis. Relative prices and exchange rates have significant effects on international tourist demand [3]. Consumers felt price increases, while statistics did not detect them on the time of euro adoption in Slovenia. Price increases were in fact concentrated only in certain groups of expenses, particularly some goods and services which are more visible in the everyday life [21].

More, hospitality industry prices have had statistically significantly declined after the euro adoption in Slovenia [22]. Additional results of regression analysis can be seen in [22].

5. CONCLUSION

Given the importance of macroeconomic evidence and its implications in everyday life various proposals have been made in the recent literature, which is pointed out to improve the hospitality industry prices. In this study we have focussed on the question whether ARIMA inspected, SPSS ARIMA or airline ARIMA model should be used. Our times series data is based on different monthly seasonal unadjusted series, for the country of Slovenia, for the period January 2000 to September 2010. Slovenia is a member state of the EU since 1st May 2004 and has adopted euro on 1st January 2007. The empirical results clearly show how important is analytical knowledge for the academic research, which is captured from models in literature to estimated models with use of econometric software and academic model. In fact, our modelling results obtained suggest inspected model rather than SPSS model. Yet, our results suggest that using inspection model for further research should be default.

In practice it is difficult to decide which studied model is the best. We show for all variables used the most relevant models, and they are stationary. When using differenced variables for further analysis we recommended inspection model, which is more time demanded using a lot of tests and being experience with the empirical knowledge.

As an issue for the future research, this is, first to investigate when the time series has a stochastic or deterministic trend, and second, to use GARCH model for the same or different time series. In addition to the hospitality industry prices, this methodology can be used also for investigation of similar economic questions in other areas of market price analysis and other time series data analysis.

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