The Czech Republic and Austrian Tourism in Scope of German Visitors

Lukáš Malec[1] | *Prague University of Economics and Business, Prague, Czech Republic*
Martina Strušková | *Prague University of Economics and Business, Prague, Czech Republic*

Received 16.6.2023, **Accepted** (reviewed) 18.7.2023, **Published** 15.9.2023

Abstract

Tourism demand modelling is one of the most studied areas in tourism economics, particularly focused on time series and econometric research. In this study, directly interpretable one-equation techniques are utilised, i.e. the autoregressive distributed lag model (ADLM) and the derived error correction model (ECM). To complement the sharing of information and habits in tourism, we apply regressors derived from wages, general prices, and dummies. For the Czech and Austrian data, short- as well as long-run sets of outputs act differently, regarding the specific situation. Such information can straightforwardly be applied to the effective planning of various activities covering the public and private sectors. The results are completed by the standard cointegration testing procedure and residual analysis.

Keywords	***DOI***	***JEL code***
Autoregressive Distributed Lag Model, Error Correction Model, cointegration, multipliers, tourism	*https://doi.org/10.54694/stat.2023.27*	*C01, Z31*

INTRODUCTION

In addition to its direct, indirect, and potentially induced effects, tourism plays a significant role in the economy of the country, both nationally and internationally. Indirect impacts result from the overall multilateral and mediated activity of tourism on economic development (Beránek, 2013). According to the Czech Statistical Office, the economic contribution of tourism is most often expressed by its share in the creation of the gross domestic product and by the share of tourism in overall employment. It contributes to the creation of new jobs and the growth of employment, with important areas including accommodation, catering and transport services, support of travel offices and agencies, tourist attractions, etc. Generally, many factors influence tourism, such as the economy, demography, geography, psychology, and ecology. Despite predominantly positive influences on people, the risks and negative impacts associated with tourism should be mentioned, e.g. the influence on the environment. In this study,

[1] Department of Statistics and Probability, Faculty of Informatics and Statistics, Prague University of Economics and Business, W. Churchill Sq. 4, 130 67 Prague 3, Czech Republic. E-mail: lukas.malec@vse.cz.

the economic view is selected to model supply and demand, for selected products or services in destinations classified as tourism products. Moreover, according to Palatková and Zichová (2014), tourism can be studied based on the platform of a certain product and various segments, as well as for territorial units. In the following, we have selected the scope of tourism destinations, which is the approach most often used in data processing studies.

The classification of tourism as an economic sector is the result of offices such as the United Nations World Tourism Organisation, which gathers and publishes data on tourism, organises thematic conferences, supports educational programmes, and maintains the sustainable development of tourism. Among others, the Organisation for Economic Co-operation and Development and the European Statistical Office ensure the methodology and standards of collecting, sorting, and processing data in the field of tourism. The outputs of the offices represent the fundamental core of successful data analysis (Palatková and Zichová, 2014). Individual methodologies for statistical surveys are presented, e.g. in the materials Methodological Manual for Tourism Statistics, International Recommendations for Tourism Statistics, and Tourism Satellite Account: Recommended Methodological Framework. Covering European Union, Regulation (EU) No 692/2011 of the European Parliament and of the Council of 6 July 2011 concerning European statistics on tourism and repealing Council Directive 95/57/EC is mandatory. This obliges member states to monitor and provide harmonised data on tourism in the specified time intervals, structure, and details.

The number of visitors to Europe had been almost increasing recently, up to 2020. For example, two drops in previous years, 2010 and 2014, were registered that especially influenced residents. In 2020, tourism became one of the sectors most affected by the Covid pandemic (Mrázková, 2020), as this also is the case in the Czech Republic and Austria we focus on. Despite the best accommodation result in history with a record 22 million people visiting the Czech Republic in 2019 (about 3.5% more than in 2018), a major decrease followed in 2020. The share of tourism in the total gross domestic product of around 3% fell from previous values to 1.48% (about CZK 84.3 billion). Tourism in Austria, which can be quantified by 41 million visitors in 2019, employed around 314 thousand people and the share of total employment in the national economy was about 7.9%. The largest number were employed by hotels and restaurants. Being more concentrated on non-residents (68%) in comparison to the Czech Republic, the drop in 2020 was severe.

In addition, both territories differ in tourist attractions and the structure of visitors (Palatková and Zichová, 2014; Jeřábek, 2018). While non-residents in the Czech Republic concentrate on historical monuments (specifically in Prague and other locations), culture and cities, it is more about natural wealth in Austria. Most visitors to the Czech Republic in 2019 came from Germany, Slovakia, Poland, the United Kingdom, and Italy. Meanwhile, the dominant number of visitors to Austria came from Germany, Holland, Switzerland, the United Kingdom, and Italy.

There exists a variety of models for tourism demand based on different variables describing economic theory, limited by a lack of available data (Lim, 2006). Although tourism is influenced by a range of factors that are economic, environmental, and political in nature, the large number of studies covering economic parameters is decisive (Song et al., 2010). For the quantitative and qualitative distribution of methods (Dwyer et al., 2012), note the use of artificial intelligence for forecasting in tourism research is currently overcoming the gap between both approaches. Quantitative methods are used the most, which Song and Li (2008) represent by time series and econometric models. The autoregressive integrated moving average techniques dominate the time series models, with an alternative seasonal component. The other branches are generalised autoregressive conditional heteroskedasticity methods, applied, e.g. by Chan et al. (2005), and a basic structural model with better forecasting performances than the univariate autoregressive moving average approaches (Turner et al., 1997). The basic structural model is also used by Greenidge (2001) for forecasting tourism arrivals to Barbados from the most significant source countries.

On the other hand, econometric models based on fundamental econometric theory identify potential causal relations between exogenous and endogenous variables, covering errors in the exogenous ones, see, e.g. Malec and Žák (2021). These models analyse the impact of tourism but moreover help in planning various activities in the public and private sectors (Pech, 2010). Econometric models enable us to examine the relationships between tourism demand and the factors that influence it (Abdou et al., 2021). According to Dwyer (2022), ADLM and error correction approaches dominate here. In this study, we apply and demonstrate the power of the ECM derived from a fundamental autoregressive distributed lag, being a straightforwardly interpretable technique for tourism research. This method allows short-run relations with short memory knowledge, continuously arising and ceasing, to be studied separately from long memory in time series. Due to one approach being selected from the range of existing techniques, the outputs are supported by standard testing cointegration and other additional tests, thus contributing to the correctness of the application. The results can be used by airlines, travel offices and agencies, and accommodation and catering establishments to reach various business decisions or devise tourism policy strategies (Song and Turner, 2006).

1 EXPERIMENTAL

1.1 Data used

The combination of Czech, Austrian and European Statistical Offices are used to gather monthly and quarterly information from 2003 to 2022. For analysing the tourism industry, the periods of monthly data in the source are transformed into quarterly information. With Song et al. (2010), demand can be measured using the number of arrivals and overnight stays, presence, income from tourism, or the criterion of distance to the target destination. Although arrivals are the leading indicator, see, e.g. Lim et al. (2006), Song and Li (2008), and Jeřábek (2018), we concentrate on the endogenous variable number of nights spent (NTS). It is considered superior to arrivals because the length of stay is included (Bakkal and Scaperlanda, 1991). We focus on hotels, holiday and other short-stay accommodations, camping grounds, recreational vehicle parks and trailer parks. The ratio of German visitors to domestic tourism (NRR), gathered with the same methodology, is included as an optional parameter. Note that tourist expenditures are usually ascertained through visitor surveys (Song et al., 2010). On the other hand, the number of tourists is generally recorded at the borders of a given destination through border controls, surveys of visitors at the borders or close to it, and using questionnaires at accommodation facilities (Jeřábek, 2018).

Covering exogenous variables, the first factor is wages and salaries (WSA) in source Germany. Wages and salaries (D.11), together with social contributions for employees (D.12) selected for their eligibility, form the employee compensation item in the national accounts (D.1) that the employer has to pay the employee for the work performed in the given accounting period. We select current prices in millions of Euros as part of the gross domestic product. Generally, income is a subjective variable and some authors supply this by using real capita consumption, recreational expenditure, or the production index to estimate income elasticities (Dwyer and Forsyth, 2006). Next is the relative prices (RPR) indicator gathered by European Statistical Office. This is the harmonised indicator of consumer prices in the source country to the target one. This indicator, in the form of an index, measures the change in the prices of goods and services purchased by ordinary households over time. It is based in 2015 and focuses exclusively on segments covering tourism and related activities. Due to the monthly periodicity, its values are averaged. In the case of the Czech Republic, the exchange rate is included in the formula. Prices (PRI) in the target destination are included as well. It is also based on the harmonised indicator of consumer prices focused on tourism, but with it reciprocal to positively influence tourism in the country visited. In the case of the Czech Republic, again the exchange rate parameter is incorporated. We do not include the exchange rate directly, due to evidence that tourists react to exchange rate movements but not to any real relative change in inflation rates in the process of their decision to travel (Bekaert and Gray, 1998; Artus, 1978).

The consumer confidence indicator (CCI), reported on unadjusted data (i.e., neither seasonally adjusted nor calendar adjusted data), measures future developments in households, including consumption and saving. It is based on a questionnaire about their expected financial situation, opinion on the general economic situation, unemployment, and on their ability to save. If the indicator is greater than 100, it signals a boost in confidence towards the future economic situation, with consumers being less prone to save and more inclined to spend money on major purchases. Less than 100 demonstrates a pessimistic opinion on developments in the economy, less consumption and more saving. Visitor expectations, any information sharing, the word-of-mouth effect, and the persistence of habit, reflecting supply constraints in the form of the lagged endogenous variable, are also included. According to Song et al. (2003), this is one of the most important factors in tourism demand. Dummy variables then cover the economic crisis of 2008 with its consequential impact and the Covid pandemic with a value of 1 from the second quarter of 2020. Marketing, consumer expectations, habit persistence and population size in the origin country can serve other potential factors influencing tourism for the cross-elasticities of competing destinations. The transport cost variable is rarely used due to the lack of data (Lim, 2006), sometimes replaced by the price of oil.

In this study, the current version of the R software platform with RStudio contribution (R Core Team: Vienna, Austria, 2023) is selected for preprocessing the data and consequent analyses. All the variables were evaluated for the Kruskal-Wallis test using *isSeasonal* function from the seastests library. For those significant at 5%, the *seas* function from the seasonal library applies X-13ARIMA-SEATS for automatic seasonal adjustment. It is omitted, e.g. in some cases of PRI and CCI. Note that this method belongs to one of the most used covering statistical offices over Europe. The Augmented Dickey-Fuller test using *ur.df* with the critical values given by Dickey-Fuller tables, and the KPSS test (Kwiatkowski et al., 1992) from the urca library, are used to test the unit root in time series. The results of both tests, although the null is reversed, demonstrate very close conclusions, as the time series almost always (and in all cases for endogenous variables) are of I(1). There are some exceptional cases of prices (RPR and PRI) and CCI being rather stationary. To improve heteroskedasticity, the non-linearity and asymmetry of the data, the Box-Cox technique is applied with a typical parameter value of 0.3. Using the methodology in the MASS library, this is handled by the maximum likelihood estimation with usual values of 0 for logarithmic, and 0.5 for square root transformations.

1.2 Methods

The straightforward way in the case of a stationary time series is the application of vector autoregressive models for describing long-run dynamics. When the time series are non-stationary, the differencing approach can be used to apply the model for a stationary time series, however, long-run information is lost by this procedure. If the target is to analyse long- as well as short-run data, we can apply some of the approaches for a non-stationary series, such as ECM. It originates from the cointegration principle for a non-stationary time series with the long-lasting relation expressed by the error correction mechanism. As Engle and Granger (1987) stated, variables that are cointegrated can always be transformed into an error correction problem and *vice versa*. This covers an adjustment process preventing a time series from excessively drifting from the expected equilibrium time path. When we analyse the mixture of stationary and non-stationary time series, the majority (and always endogenous in this study) are non-stationary. Although such properties can influence inductive conclusions, the interpretation is more direct than in the case of procedures developed exclusively to analyse a mixture of various orders of integration. I(2) series, being rare in tourism, are not included either, as well as the oscillatory convergent, explosive, mean and fractionally integrated time series are excluded.

Based on the Engle and Granger (1987) methodology, we study one cointegrating relationship among variables, a reasonable approximation in tourism (Song et al., 2008). Although there exist some alternatives (Johansen, 1988; Arlt and Arltová, 2007) where there are more such vectors possible, the average cointegrating vector over them is revealed herein. While the ADLM methodology is relatively unique, there are variant approaches to applying error correction. Song et al. (2008) introduce three fundamental methods for estimation, i.e. the two-step procedure of Engle and Granger (1987), the one-step approach given by Wickens and Breusch (1988), and the third method is based on the ADLM background published by Pesaran and Shin (1995). In this study, we process the data using the last procedure mentioned, applied in tourism research (Song and Turner, 2006). The technique starts with the autoregressive model specification to study any change in the endogenous variable for unit change in the lagged endogenous variable, and the current and delayed exogenous variables (*ceteris paribus*). Then, the model is transformed into ECM, connecting short-run dynamics with a long-run equilibrium in time series. This technique is in close connection to the cointegration analysis. We restrict error correction for the linear trend below.

The starting ADLM is selected as a combination of Akaike, Schwarz and Bayesian information criteria in this study, although the Bayesian approach is preferred to annual data (Pesaran and Shin, 1998). Due to the collinearity issue, the maximum lag of 4 is accepted for NTS modelling. The *auto_ardl* function in R is used to select the best model, supplemented by criteria such as autocorrelation tests, and more. The one-equation ADLM(p, q_1, …, q_k) without the deterministic trend (Natsiopoulos and Tzeremes, 2022) can be stated

$$y_t = c + \sum_{i=1}^{p} b_{y,i} y_{t-i} + \sum_{j=1}^{k} \sum_{l=0}^{q_j} b_{j,l} x_{j,t-l} + \varepsilon_t \,, \tag{1}$$

for $t = 1, 2, \ldots, T$. Then, the corresponding ECM has the form

$$\Delta y_t = c + \sum_{i=1}^{p-1} \psi_{y,i} \Delta y_{t-i} + \sum_{j=1}^{k} \sum_{l=1}^{q_j-1} \psi_{j,l} \Delta x_{j,t-l} + \sum_{j=1}^{k} \omega_j \Delta x_{j,t} + \pi_y y_{t-1} + \sum_{j=1}^{k} \pi_j x_{j,t-1} + \varepsilon_t \,. \tag{2}$$

The equation can be reformulated using the error correction term $ect = y_{t-1} - \sum_{j=1}^{k} \theta_j x_{j,t-1}$ in the formula, stated with the corresponding coefficient. There, short- and long-run multipliers exist, where the short-run ones are expressed by ω_j. Above that, the long-run multipliers are given by the term

$$\frac{\partial y_{t+\infty}}{\partial x_{j,t}} = \frac{\pi_j}{-\pi_y} \,. \tag{3}$$

We apply tests for no cointegration in ECM, i.e. Wald bounds F-test with H_0: $\pi_y = \pi_1 = \cdots = \pi_k = 0$ and bounds t-test for H_0: $\pi_y = 0$.

If the endogenous variable is I(1), the ADLM methodology allows a mixture of I(1) and I(0) variables (Grant and Lebo, 2016; Pesaran and Shin, 1998) to be studied. Moreover, the value of *ect* depends also on the order of integration, sample size and the number of variables. This is remarkable, especially using the traditional t-test. Note that in covering macroeconomics analyses the *ect* coefficients are often relatively small, due to the intervention of governments, actions of external factors, etc. If the coefficient is high, close to 1, it means the error correction takes place in almost the time one period only. Although the range of exclusion and exogeneity tests are not utilised due to background economic theory, an analysis of residues evaluates the nature of the time series. The tests used cover autocorrelation, heteroskedasticity and normality, concentrating on the efficiency of estimates and inductive conclusions.

Cointegration is also tested by a standard procedure using residue from the static regression model, for which the function *lm* from the stats library is applied. We use the Augmented Dickey-Fuller test discussed by Song et al. (2008) for critical values given by the formula $\beta_\infty + \beta_1/T + \beta_2/T^2$. Here, the parameters

β_∞, β_1 and β_2 are given by the work of MacKinnon (2010) and T is the number of observations. From the results of analyses and 5% significancy is detected, there exists at least one cointegrating relationship in all the cases considered.

2 RESULTS AND DISCUSSION

Although there are many interpretational aspects, we initially apply the ADLM, and then the ECM with short- and long-run multipliers. Some original variables multiplied by 10 in the case of modelling NTS are used for clarity in the interpretation. In all the cases, the influence of the Covid pandemic is significant and negative. The effect of the event of a crisis is diverse, and it can be concluded that it does not play a significant role globally. Covering Table 1, both bounds F- and t-tests for no cointegration with the values of test statistics about 22.811 and –9.970, respectively, are significant with p-values < 1e-06.

Table 1 The Czech Republic ADLM and ECM for nights spent

ADLM(4,2,2,3,1)				ECM			
Parameter in model	Estimate	Std error	*p*-value	Parameter in model	Estimate	Std error	*p*-value
Intercept	–22.818	41.275	0.5827	Intercept	–22.818***	1.995	0.0000
L(NTS, 1)	0.507***	0.105	0.0000	d(L(NTS, 1))	0.480***	0.091	0.0000
L(NTS, 2)	0.371***	0.105	0.0009	d(L(NTS, 2))	0.852***	0.119	0.0000
L(NTS, 3)	–0.467***	0.074	0.0000	d(L(NTS, 3))	0.385***	0.098	0.0002
L(NTS, 4)	–0.385**	0.113	0.0012	d(WSA)	16.036***	2.124	0.0000
WSA	16.036***	2.740	0.0000	d(L(WSA, 1))	–14.632***	2.364	0.0000
L(WSA, 1)	–28.985***	3.435	0.0000	d(RPR)	–0.367	1.280	0.7753
L(WSA, 2)	14.632***	3.126	0.0000	d(L(RPR, 1))	–4.474**	1.593	0.0068
RPR	–0.367	1.588	0.8181	d(PRI)	2.082	3.102	0.5048
L(RPR, 1)	1.622	2.133	0.4506	d(L(PRI, 1))	–4.037	3.023	0.1871
L(RPR, 2)	4.474*	1.738	0.0130	d(L(PRI, 2))	–7.879**	2.694	0.0050
PRI	2.082	3.531	0.5580	d(CCI)	1.660.	0.940	0.0829
L(PRI, 1)	–6.321	5.305	0.2389	D_cri	1.335***	0.271	0.0000
L(PRI, 2)	–3.842	4.917	0.4381	D_cov	–3.526***	0.696	0.0000
L(PRI, 3)	7.879*	3.065	0.0131	*ect*	–0.974***	0.088	0.0000
CCI	1.660	1.069	0.1264				
L(CCI, 1)	–2.169*	1.067	0.0473				
D_cri	1.335***	0.348	0.0003				
D_cov	–3.526***	0.868	0.0002				

Notes: ADLM: Residual standard error: 5.050 on 52 degrees of freedom, Multiple R-squared: 0.9687, Adjusted R-squared: 0.9579, F-statistic: 89.38 on 18 and 52 DF, *p*-value: < 2.2e-16. ECM: Residual standard error: 4.866 on 56 degrees of freedom, Multiple R-squared: 0.9297, Adjusted R-squared: 0.9121, F-statistic: 52.86 on 14 and 56 DF, *p*-value: < 2.2e-16. Here, L(variable, order) states lag with corresponding order, and d is differencing. Significance codes: < 0.001 as ***, < 0.01 as **, < 0.05 as * and < 0.1 as .
Source: Own construction

The significant sharing of information and habit in tourism is evident (see Table 1), covering the first and second lagged quarters positive and the rest of negative action. The negative signs probably mean the turning effect from preceding periods. German wages and salaries are also important, depending positively on the current quarter, to make a prompt decision. Relative prices and prices are almost insignificant and cover only the last lag considered. For the error correction model in the short run, the sharing of information and habit is also evidently decisive, as well as wages and salaries for the given quarter. Partially, the positive action of the consumer confidence indicator is visible. The coefficient estimated at *ect* means a prompt return to equilibrium about one period in turn. For Table 2, wages and salaries and relative prices are decisive in the long run, both positively influencing NTS.

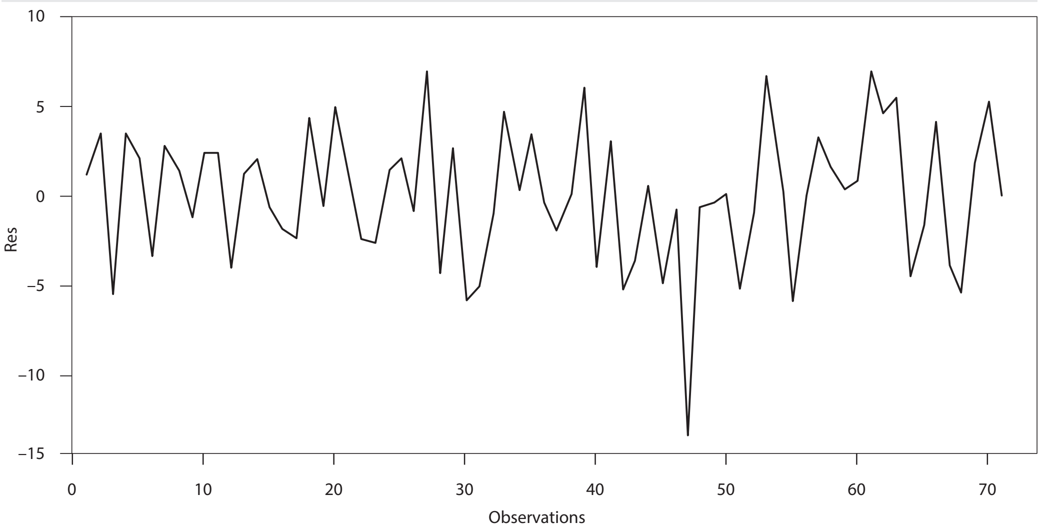
Analysing the residual part, the graphical representation contributed to selected hypothesis testing is demonstrated in Figure 1. No issues are evident in the scope of the statistics used.

Table 2 The Czech Republic long-run multipliers for nights spent

Parameter in model	Estimate	Std error	*p*-value
Intercept	–23.433	42.815	0.5865
WSA	1.728	0.316	0.0000
RPR	5.883	1.393	0.0001
PRI	–0.207	1.791	0.9084
CCI	–0.522	0.755	0.4926

Source: Own construction

Figure 1 ECM residual diagnostics for nights spent



Durbin-Watson test for autocorrelation by *durbinWatsonTest* with the value of test statistic 2.08779 and *p*-value 0.6523; Breusch-Godfrey test for serial correlation of order up to 1 by *bgtest* with the value of test statistic 0.39516 and *p*-value 0.5296; Breusch-Godfrey test for serial correlation of order up to 3 by *bgtest* with the value of test statistic 0.65231 and *p*-value 0.8844; Studentized Breusch-Pagan test for homoskedasticity by *bptest* with the value of test statistic 11.05342 and *p*-value 0.9221; Jarque Bera test for normality by *jarque.bera.test* with the value of test statistic 4.44014 and *p*-value 0.1086.
Source: Own construction

Covering Table 3, both bounds *F*- and *t*-tests for no cointegration with the values of test statistics about 12.155 (*p*-value < 1e-06) and –5.673 (*p*-value < 1e-03), respectively, are significant.

Table 3 The Czech Republic ADLM and ECM for the German and domestic tourism ratio

ADLM(3,3,1,2,1)				ECM			
Parameter in model	**Estimate**	**Std error**	***p*-value**	**Parameter in model**	**Estimate**	**Std error**	***p*-value**
Intercept	–0.179	0.676	0.7932	Intercept	–0.179***	0.023	0.0000
L(NRR, 1)	0.699***	0.099	0.0000	d(L(NRR, 1))	0.421***	0.063	0.0000
L(NRR, 2)	–0.441***	0.084	0.0000	d(L(NRR, 2))	–0.020	0.075	0.7918
L(NRR, 3)	0.020	0.086	0.8163	d(WSA)	–0.042	0.029	0.1484
WSA	–0.042	0.038	0.2807	d(L(WSA, 1))	–0.183***	0.030	0.0000
L(WSA, 1)	–0.146**	0.042	0.0012	d(L(WSA, 2))	0.293***	0.033	0.0000
L(WSA, 2)	0.477***	0.043	0.0000	d(RPR)	1.255	2.230	0.5759
L(WSA, 3)	–0.293***	0.051	0.0000	d(PRI)	–0.301	0.544	0.5816
RPR	1.255	2.665	0.6402	d(L(PRI, 1))	–0.598	0.484	0.2216
L(RPR, 1)	2.592	2.601	0.3234	d(CCI)	0.026	0.016	0.1016
PRI	–0.301	0.606	0.6206	D_cri	0.079.	0.045	0.0843
L(PRI, 1)	–0.639	0.879	0.4703	D_cov	–0.454***	0.071	0.0000
L(PRI, 2)	0.598	0.539	0.2718	*ect*	–0.721***	0.089	0.0000
CCI	0.026	0.017	0.1401				
L(CCI, 1)	–0.024	0.018	0.1959				
D_cri	0.079	0.063	0.2164				
D_cov	–0.454***	0.131	0.0006				

Notes: ADLM: Residual standard error: 0.088 on 55 degrees of freedom, Multiple R-squared: 0.9506, Adjusted R-squared: 0.9362, F-statistic: 66.13 on 16 and 55 DF, *p*-value: < 2.2e-16. ECM: Residual standard error: 0.085 on 59 degrees of freedom, Multiple R-squared: 0.8781, Adjusted R-squared: 0.8533, F-statistic: 35.42 on 12 and 59 DF, *p*-value: < 2.2e-16. Here, L(variable, order) states lag with corresponding order, and d is differencing. Significance codes: < 0.001 as ***, < 0.01 as **, < 0.05 as * and < 0.1 as .
Source: Own construction

For the ratio of German to domestic visitors, the significant sharing of information and habit is evident (see Table 3), covering the first lag for positive and the second lag for negative relation. Wages and salaries in Germany are important, especially covering historical values with first and third lags opposite to second. The rest of the parameters are not significant to a great extent. In the short run, sharing information and habit covers the first lag. Wages and salaries are important, covering the negative value in the first and positive value in the second lag, similarly as in ADLM. The error correction term means returning to equilibrium for one period of 72.1%, approximately. For Table 4, the significance of the coefficients is lower in the long run. Possibly, the most influencing parameter is relative prices with a positive effect. Our case of a strong significant *ect* and insignificant long-run multipliers could be caused by partial collinearity reasons in regressors. It can be handled simply by reducing the order of some variables, keeping *ect* and cointegration tests significant. However, we apply the criterion for minimum information criteria due to the fact, that the interpretation of the reduced model is almost the same.

Covering Table 5, both bounds F- and t-tests for no cointegration with the values of test statistics about 24.775 and –9.060, respectively, are significant with p-values < 1e-06.

Note the similar results to analysing the NTS parameter in the Czech Republic and Austria (see Table 5). The significant sharing of information and habit in tourism is evident, covering the first and

Table 4 The Czech Republic long-run multipliers for the German and domestic tourism ratio

Parameter in model	Estimate	Std error	*p*-value
Intercept	−0.247	0.945	0.7943
WSA	−0.007	0.007	0.3497
RPR	5.332	3.025	0.0835
PRI	−0.475	0.382	0.2194
CCI	0.003	0.017	0.8432

Source: Own construction

Table 5 Austrian ADLM and ECM for nights spent

ADLM(4,3,1,3,2)				ECM			
Parameter in model	Estimate	Std error	*p*-value	Parameter in model	Estimate	Std error	*p*-value
Intercept	2.569	77.740	0.9738	Intercept	2.569	1.829	0.1658
L(NTS, 1)	0.285**	0.089	0.0024	d(L(NTS, 1))	0.112	0.088	0.2085
L(NTS, 2)	0.867***	0.108	0.0000	d(L(NTS, 2))	0.979***	0.134	0.0000
L(NTS, 3)	−0.240**	0.090	0.0099	d(L(NTS, 3))	0.739***	0.094	0.0000
L(NTS, 4)	−0.739***	0.099	0.0000	d(WSA)	8.079***	1.402	0.0000
WSA	8.079***	2.001	0.0002	d(L(WSA, 1))	−0.508	1.609	0.7536
L(WSA, 1)	−6.059*	2.475	0.0178	d(L(WSA, 2))	−5.423**	1.640	0.0017
L(WSA, 2)	−4.916.	2.585	0.0629	d(RPR)	−6.274*	2.407	0.0118
L(WSA, 3)	5.423*	2.281	0.0212	d(PRI)	5.450**	1.695	0.0022
RPR	−6.274*	2.944	0.0379	d(L(PRI, 1))	0.093	1.857	0.9601
L(RPR, 1)	5.590.	2.908	0.0602	d(L(PRI, 2))	−4.628*	1.809	0.0133
PRI	5.450**	1.977	0.0081	d(CCI)	−0.616	0.940	0.5154
L(PRI, 1)	−3.565	2.968	0.2352	d(L(CCI, 1))	2.510**	0.856	0.0049
L(PRI, 2)	−4.722	2.998	0.1214	D_cri	−0.152	0.210	0.4733
L(PRI, 3)	4.628*	1.973	0.0229	D_cov	−3.936***	0.462	0.0000
CCI	−0.616	0.999	0.5406	*ect*	−0.827***	0.072	0.0000
L(CCI, 1)	2.527.	1.267	0.0514				
L(CCI, 2)	−2.510*	1.225	0.0456				
D_cri	−0.152	0.342	0.6599				
D_cov	−3.936***	0.716	0.0000				

Notes: ADLM: Residual standard error: 3.701 on 51 degrees of freedom, Multiple R-squared: 0.9808, Adjusted R-squared: 0.9736, F-statistic: 136.80 on 19 and 51 DF, *p*-value: < 2.2e-16. ECM: Residual standard error: 3.564 on 55 degrees of freedom, Multiple R-squared: 0.9230, Adjusted R-squared: 0.9020, F-statistic: 43.95 on 15 and 55 DF, *p*-value: < 2.2e-16. Here, L(variable, order) states lag with corresponding order, and d is differencing. Significance codes: < 0.001 as ***, < 0.01 as **, < 0.05 as * and < 0.1 as .
Source: Own construction

second quarters positive and the rest negative action. Wages and salaries in Germany are both significant parameters, depending positively on the given period, for making a prompt decision. The other periods are with various signs, but less significant. Although not so significant, the relative prices in a given period influence the NTS negatively and prices positively. The consumer confidence indicator is small significant in the first lag, with the turning point in the lag following. For the error correction model, in the short run, the word-of-mouth effect is significant with lags 2 and 3. This means a delay in covering response. Decisive are also wages and salaries and prices in the current period. The consumer confidence indicator acts positively but with a delay. The error correction term means returning to equilibrium for one period of 82.7%, approximately. For Table 6, wages and salaries and prices are important, as both positively influence the NTS in the long run.

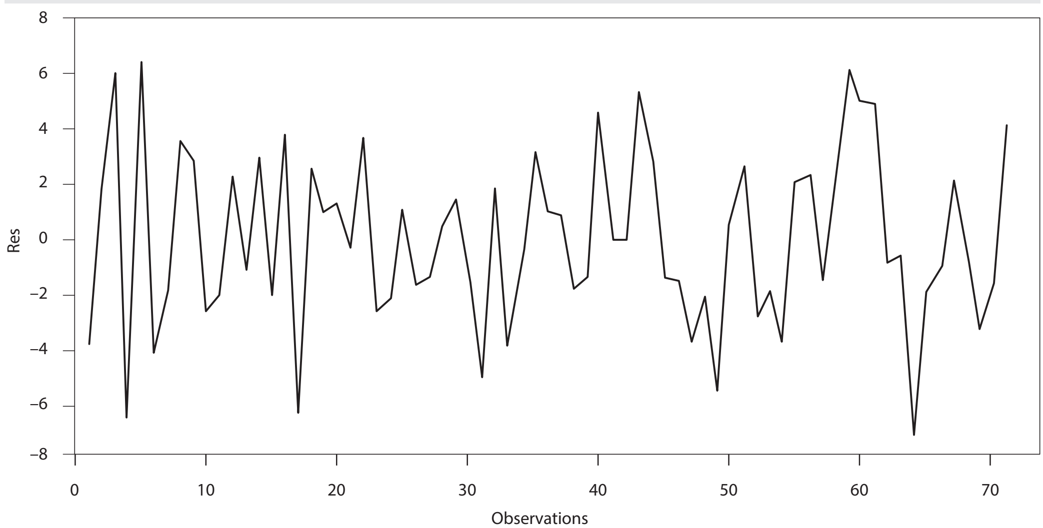
Table 6 Austrian long-run multipliers for nights spent

Parameter in model	Estimate	Std error	*p*-value
Intercept	3.107	93.880	0.9737
WSA	3.056	0.656	0.0000
RPR	–0.827	2.153	0.7025
PRI	2.166	0.420	0.0000
CCI	–0.724	1.244	0.5632

Source: Own construction

Analysing the residual part, the graphical representation contributed to selected hypothesis testing is demonstrated in Figure 2. No issues are evident in the scope of the statistics used.

Figure 2 ECM residual diagnostics for nights spent



Durbin-Watson test for autocorrelation by *durbinWatsonTest* with the value of test statistic 2.12725 and *p*-value 0.8722; Breusch-Godfrey test for serial correlation of order up to 1 by *bgtest* with the value of test statistic 0.94268 and *p*-value 0.3316; Breusch-Godfrey test for serial correlation of order up to 3 by *bgtest* with the value of test statistic 1.43285 and *p*-value 0.6978; Studentized Breusch-Pagan test for homoskedasticity by *bptest* with the value of test statistic 22.47086 and *p*-value 0.2614; Jarque Bera test for normality by *jarque.bera.test* with the value of test statistic 0.89051 and *p*-value 0.6407.
Source: Own construction

Covering Table 7, both bounds *F*- and *t*-tests for no cointegration with the values of test statistics about 5.220 (*p*-value = 0.0078) and –4.445 (*p*-value = 0.0151), respectively, are significant.

Table 7 Austrian ADLM and ECM for the German and domestic tourism ratio

ADLM(3,1,3,2,1)				ECM			
Parameter in model	**Estimate**	**Std error**	***p*-value**	**Parameter in model**	**Estimate**	**Std error**	***p*-value**
Intercept	0.877	1.077	0.4188	Intercept	0.877***	0.172	0.0000
L(NRR, 1)	0.041	0.119	0.7324	d(L(NRR, 1))	−0.494***	0.108	0.0000
L(NRR, 2)	0.272*	0.110	0.0166	d(L(NRR, 2))	−0.221	0.136	0.1080
L(NRR, 3)	0.221	0.151	0.1497	d(WSA)	0.005	0.021	0.8044
WSA	0.005	0.024	0.8301	d(RPR)	−12.096***	3.280	0.0005
L(WSA, 1)	−0.010	0.024	0.6668	d(L(RPR, 1))	8.464*	3.310	0.0132
RPR	−12.096**	3.510	0.0011	d(L(RPR, 2))	9.835**	3.358	0.0048
L(RPR, 1)	15.190**	5.017	0.0038	d(PRI)	5.995**	2.203	0.0085
L(RPR, 2)	1.371	5.469	0.8030	d(L(PRI, 1))	−2.886	2.358	0.2260
L(RPR, 3)	−9.835*	3.745	0.0112	d(CCI)	−0.024.	0.012	0.0567
PRI	5.995*	2.718	0.0316	D_cri	0.038	0.027	0.1634
L(PRI, 1)	−7.886*	3.809	0.0431	D_cov	−0.507***	0.057	0.0000
L(PRI, 2)	2.886	2.612	0.2741	*ect*	−0.465***	0.088	0.0000
CCI	−0.024.	0.013	0.0746				
L(CCI, 1)	0.027.	0.015	0.0830				
D_cri	0.038	0.039	0.3453				
D_cov	−0.507***	0.063	0.0000				

Notes: ADLM: Residual standard error: 0.051 on 55 degrees of freedom, Multiple R-squared: 0.9646, Adjusted R-squared: 0.9543, F-statistic: 93.57 on 16 and 55 DF, *p*-value: < 2.2e-16. ECM: Residual standard error: 0.049 on 59 degrees of freedom, Multiple R-squared: 0.8410, Adjusted R-squared: 0.8086, F-statistic: 26.07 on 12 and 59 DF, *p*-value: < 2.2e-16. Here, L(variable, order) states lag with corresponding order, and d is differencing. Significance codes: < 0.001 as ***, < 0.01 as **, < 0.05 as * and < 0.1 as .
Source: Own construction

Table 8 Austrian long-run multipliers for the German and domestic tourism ratio

Parameter in model	Estimate	Std error	*p*-value
Intercept	1.885	2.454	0.4457
WSA	−0.011	0.017	0.5325
RPR	−11.541	6.056	0.0619
PRI	2.137	0.769	0.0075
CCI	0.007	0.020	0.7423

Source: Own construction

For the ratio of German to domestic visitors, sharing information and habit is not so significant, probably due to Austria being historically connected to Germany (see Table 7). Here significant relative prices are also in one lag, with a negative current effect revealed. Prices act without the lag positively and including the lag negatively, but both are less significant, and consumer confidence indicator as well. For the error correction model in the short run, the negative sharing of information and habit covers the first lag, again due to the typical destination to visit. This is also the case of the negative influence of relative prices without lag. Then, prices have a positive effect in the current period, with the small action of the consumer confidence indicator. The error correction term means returning to equilibrium for one period of 46.5%, approximately. For Table 8, decisive are prices with a positive relation in the long run.

CONCLUSION

Although the results depend partially on the frequency of the given data, time series length and type of processing, there have been many practical outcomes detected in this study. We perceive the importance of long-run relationships especially for policy-makers and planners, while short-run dynamics target business forecasting. Tourism modelling also enables government institutions to formulate and implement the right tourism policy strategies. This is related, e.g. to price regulation, the control of environmental quality and planning of suitable infrastructure. According to expectations, the *ect* parameter in the case of Austria achieves a lower value due to the long memory of the time series variable. The reason is the stable structure of visitors from Germany, which suppresses any response to changes in economic parameters.

For the Czech Republic and Austria in the case of modelling nights spent, a similar pattern of relationships is revealed, although we discuss some differences here. In the case of nights spent, the significant sharing of information and habit are evident in the first and second lag positive and then negative action. But in the short run, this relation is delayed in Austria, probably given by the historical connection of source and target countries. Current wages and salaries are decisive in both travel destinations, complemented in Austria by significant prices. This relationship pattern also holds for the short run. Moreover, the positive influence of the consumer confidence indicator is delayed opposite to the Czech Republic. While in both target destinations, for long-run relationships wages and salaries are important and positively related to nights spent; in the case of the Czech Republic, relative prices are decisive, and in Austria, prices are the most important. It seems that the Czech Republic is perceived in the long run as a destination with alternatives noticed to considerations. In Austria, both target and source countries are in close historical connection. So, a delay in the change of word-of-mouth effects and confidence is evident, supported by the inclination to price in short- and long-run actions, rather than to a mutual comparison of both territories. However, wages and salaries are significant in all the cases considered, a key parameter in the decision to travel.

In the case of studying the ratio of German visitors and residents, sharing information and habit is significant for the Czech Republic, whereas in Austria this is suppressed. The reasons are evident and mentioned above, as some destinations are complementary. But in Austria, the short-run influence is more significant. Wages and salaries are decisive in the Czech Republic, but in the case of Austria relative prices and prices are in play, although less significantly. This also holds in the case of short-run dependencies. For the long run, relative prices are important in the Czech Republic, whereas it is prices in Austria. In the short run, wages and salaries are decisive for the Czech Republic, but the comparison of source and target countries in price dominates the longer horizon. In Austria, prices seem decisive for the share of non-residents as well as nights spent.

References

ABDOU, M., MUSABANGANJI, E., MUSAHARA, H. (2021). Tourism demand modelling and forecasting: a review literature [online]. *African Journal of Hospitality, Tourism and Leisure*, 10(4): 1370–1393. <https://doi.org/10.46222/ajhtl.19770720-168>.

ARLT, J., ARLTOVÁ, M. (2007). *Ekonomické časové řady.* Prague: Grada Publishing.

ARTUS, J. R. (1978). Methods of assessing the long-run equilibrium value of an exchange rate [online]. *Journal of International Economics*, 8(2): 277–299. <https://doi.org/10.1016/0022-1996(78)90024-7>.

BAKKAL, I., SCAPERLANDA, A. (1991). Characteristics of US demand for European tourism: a translog approach [online]. *Review of World Economics*, 127: 119–137. <https://doi.org/10.1007/BF02707314>.

BEKAERT, G., GRAY, S. F. (1998). Target zones and exchange rates: an empirical investigation [online]. *Journal of International Economics*, 45(1): 1–35. <https://doi.org/10.1016/S0022-1996(97)00034-2>.

BERÁNEK, J. (ed.) (2013). *Ekonomika cestovního ruchu.* Prague: Mag Consulting.

CHAN, F., LIM, C., MCALEER, M. (2005). Modelling multivariate international tourism demand and volatility [online]. *Tourism Management*, 26(3): 459–471. <https://doi.org/10.1016/j.tourman.2004.02.013>.

DWYER, L. (2022). Tourism economics and policy. In: BUHALIS, D. (eds.) *Encyclopedia of Tourism Management and Marketing*, Cheltenham: Edward Elgar Publishing, 421–424.

DWYER, L., FORSYTH, P. (eds.) (2006). *International handbook on the economics of tourism.* Glouchester: Edward Elgar Publishing.

DWYER, L., GILL, A., SEETARAM, N. (eds.) (2012). *Handbook of research methods in tourism: quantitative and qualitative approaches.* UK: Edward Elgar Publishing.

ENGLE, R. F., GRANGER, C. W. J. (1987). Co-integration and error correction: representation, estimation, and testing [online]. *Econometrica*, 55(2): 251–276. <https://doi.org/10.2307/1913236>.

GRANT, T., LEBO, M. J. (2016). Error correction methods with political time series [online]. *Political Analysis*, 24(1): 3–30. <https://doi.org/10.1093/pan/mpv027>.

GREENIDGE, K. (2001). Forecasting tourism demand: an STM approach [online]. *Annals of Tourism Research*, 28(1): 98–112. <https://doi.org/10.1016/S0160-7383(00)00010-4>.

JEŘÁBEK, T. (2018). Analýza poptávky po cestovním ruchu v České republice z vybraných zemí eurozóny – VECM přístup. *Economics, Management, and Innovation*, 10(3): 87–97.

JOHANSEN, S. (1988). Statistical analysis of cointegration vectors [online]. *Journal of Economic Dynamics and Control*, 12(2–3): 231–254. <https://doi.org/10.1016/0165-1889(88)90041-3>.

KWIATKOWSKI, D., PHILLIPS, P. C., SCHMIDT, P., SHIN, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root? [online]. *Journal of Econometrics*, 54(1–3): 159–178. <https://doi.org/10.1016/0304-4076(92)90104-Y>.

LIM, C. (2006). A survey of tourism demand modelling practice: issue and implications. In: DWYER, L., FORSYTH, P. (eds.) *International handbook on the economics of tourism*, Cheltenham: Edward Elgar Publishing, 495.

MACKINNON, J. G. (2010). *Critical values for cointegration tests* [online]. Ontario, Canada: Queen's Economics Department, Working paper. <https://www.econstor.eu/bitstream/10419/67744/1/616664753.pdf>.

MALEC, L., ŽÁK, V. (2021). Modelling structural relations for tourism demand: the Central European cases [online]. *Statistika: Statistics and Economy Journal*, 101(2): 203–217. <https://www.czso.cz/documents/10180/143550797/32019721q2_malec.pdf/4fd33bc5-4ebc-497e-9186-ec800ba7f316?version=1.1>.

MRÁZKOVÁ, N. (2020). *Cestovní ruch v Rakousku* [online]. Prague, Czech Republic: University College Prague, final thesis. <https://is.ucp.cz/th/wjm8u>.

NATSIOPOULOS, K., TZEREMES, N. G. (2022). ARDL: an R package for the analysis of level relationships [online]. *Journal of Open Source Software*, 7(79): 3496. <https://doi.org/10.21105/joss.03496>.

PALATKOVÁ, M., ZICHOVÁ, J. (2014). *Ekonomika turismu.* Prague: Grada Publishing.

PECH, M. (2010). *Politika cestovního ruchu v Rakousku* [online]. Brno, Czech Republic: Masaryk University, Final thesis. <https://is.muni.cz/th/qs1ws>.

PESARAN, H. H., SHIN, Y. (1995). *An autoregressive distributed lag modelling approach to cointegration analysis* [online]. Cambridge, UK: Department of Applied Economics, Working paper. <https://www.cambridge.org/core/books/abs/econometrics-and-economic-theory-in-the-20th-century/an-autoregressive-distributedlag-modelling-approach-to-cointegration-analysis/0A3624D5C624BED6E2A963190403653A>.

PESARAN, H. H., SHIN, Y. (1998). Generalized impulse response analysis in linear multivariate models [online]. *Economics Letters*, 58(1): 17–29. <https://doi.org/10.1016/S0165-1765(97)00214-0>.

SONG, H., LI, G. (2008). Tourism demand modelling and forecasting – a review of recent research [online]. *Tourism Management*, 29(2): 203–220. <https://doi.org/10.1016/j.tourman.2007.07.016>.

SONG, H., LI, G., WITT, S. F., FEI, B. (2010). Tourism demand modelling and forecasting: how should demand be measured? [online]. *Tourism Economics*, 16(1): 63–81. <https://doi.org/10.5367/000000010790872213>.

SONG, H., TURNER, L. (2006). Tourism demand forecasting. In: DWYER, L., FORSYTH, P. (eds.) *International Handbook on the Economics of Tourism*, Cheltenham: Edward Elgar Publishing.

SONG, H., WITT, S. F., LI, G. (2003). Modelling and forecasting the demand for Thai tourism [online]. *Tourism Economics*, 9(4): 363–387. <https://doi.org/10.5367/000000003322663186>.

SONG, H., WITT, S. F., LI, G. (2008). *The advanced econometrics of tourism demand.* NY: Routledge.

STRUŠKOVÁ, M. (2022). *Využitie ECM prístupu v cestovnom ruchu* [online]. Prague, Czech Republic: University of Economics and Business, Final thesis. <https://vskp.vse.cz/87759_vyuziti-ecm-pristupu-v-cestovnim-ruchu?title=V&order=author&page=1058>.

TURNER, L. W., KULDERAN, N., FERNANDO, H. (1997). Univariate modelling using periodic and non-periodic analysis: inbound tourism to Japan, Australia and New Zealand compared [online]. *Tourism Economics*, 3(1): 39–56. <https://doi.org/10.1177/135481669700300103>.
WICKENS, M. R., BREUSCH, T. S. (1988). Dynamic specification, the long-run and the estimation of transformed regression models [online]. *The Economic Journal*, 98(390): 189–205. <https://doi.org/10.2307/2233314>.