DETUROPE – THE CENTRAL EUROPEAN JOURNAL OF REGIONAL DEVELOPMENT AND TOURISM
Vol. 16 Issue 2 2024 *ISSN 1821-2506*

Original scientific paper

DETERMINANTS OF THE CROATIAN PRE-PANDEMIC INBOUND TOURISM DEMAND: EVIDENCE FROM THE DYNAMIC PANEL APPROACH

Esmeralda MARIĆ[a]

[a] School of Economics and Business Sarajevo, Trg oslobođenja – Alija Izetbegović 1 71000 Sarajevo Bosnia and Herzegovina, 061/371-001, esmeralda.maric@efsa.unsa.ba

Cite this article: Marić, E. (2024). Determinants of the Croatian Pre-pandemic Inbound Tourism Demand. *Deturope*, 16(2), 22-35.

Abstract

Tourism is a vital sector for the Croatian economy. During the pre-pandemic period, Croatia reported increasing numbers of tourist arrivals and experienced a significant contribution of tourism to GDP and earnings. This research aims to investigate the impact of economic and supply-side determinants on inbound tourism demand. The analysis was conducted on panel data with a five-year long-time dimension and forty-seven incoming countries included in the cross-sectional dimension. In order to investigate determinants of Croatian inbound tourism demand, this research relies on the Two-step System Generalized Methods of Moments (GMM). The results suggest that supply-side determinants and tourist arrivals from the previous year positively affect inbound tourism demand. However, none of the economic determinants proved to have a significant effect on the number of tourist arrivals. Consequently, our findings suggest that infrastructural enhancements and quality services that could lead to an increased number of repeated visits and recommendations are crucial for Croatian inbound tourism demand.

Keywords: inbound tourism, tourism demand, tourism management, services marketing

INTRODUCTION

Croatia is a tourism-oriented country, with the contribution of tourism amounting to 39.8 billion Croatian Kunas in 2017 (Statista, 2023). Previous research suggests that the impact of tourism on economic growth is greater in smaller, tourism-specialised countries (Easterly & Kraay, 2000), such as Croatia. Specifically, research proves that the higher ratio of the number of tourists visiting the country and the country's population is associated with higher economic growth (Sequeira & Maçãs Nunes, 2008). The primary research question in this study pertains to the determinants of inbound tourism demand in Croatia. More precisely, this study aims to investigate whether economic and supply-side determinants influence inbound tourism demand in Croatia. The research focuses on the period before the pandemic, which has been a common procedure in some of the recent studies (e.g., Simundic, 2022). Studying inbound tourism in the pre-pandemic period separately from the post-pandemic period can be highly beneficial for making comparisons and drawing parallels, providing valuable insights for future tourism planning (Bhuiyan, Crovella, Paiano & Alves, 2021; Esquivias, Sugiharti, Rohmawati & Sethi, 2021). Specifically, concerning Croatian tourism, research on the determinants of tourism demand in the pre-pandemic period can hold a strategic value. Croatian tourism development strategy up to 2020 defined specific goals and specific measures for their achievements (Croatian Ministry of Tourism, 2013). Reflecting on what has happened in the period covered by tourism strategy can be beneficial for the goals achievements assessments and draw attention to the specific points of tourism planning success and failure, which have already been discussed in previous studies (Tica & Kožić, 2015). Additionally, according to our knowledge, this study is the first to explore the determinants of inbound tourism demand in Croatia, incorporating only data from the years following Croatia's entrance to the EU. The results may be of interest to decision-makers, especially in the context of understanding the economic and supply-side factors influencing tourist arrivals and consequently creating appropriate tourism development strategies. Apart from these obvious practical implications, our research enriches the current body of literature on inbound tourism demand by employing the dynamic panel approach in a new context.

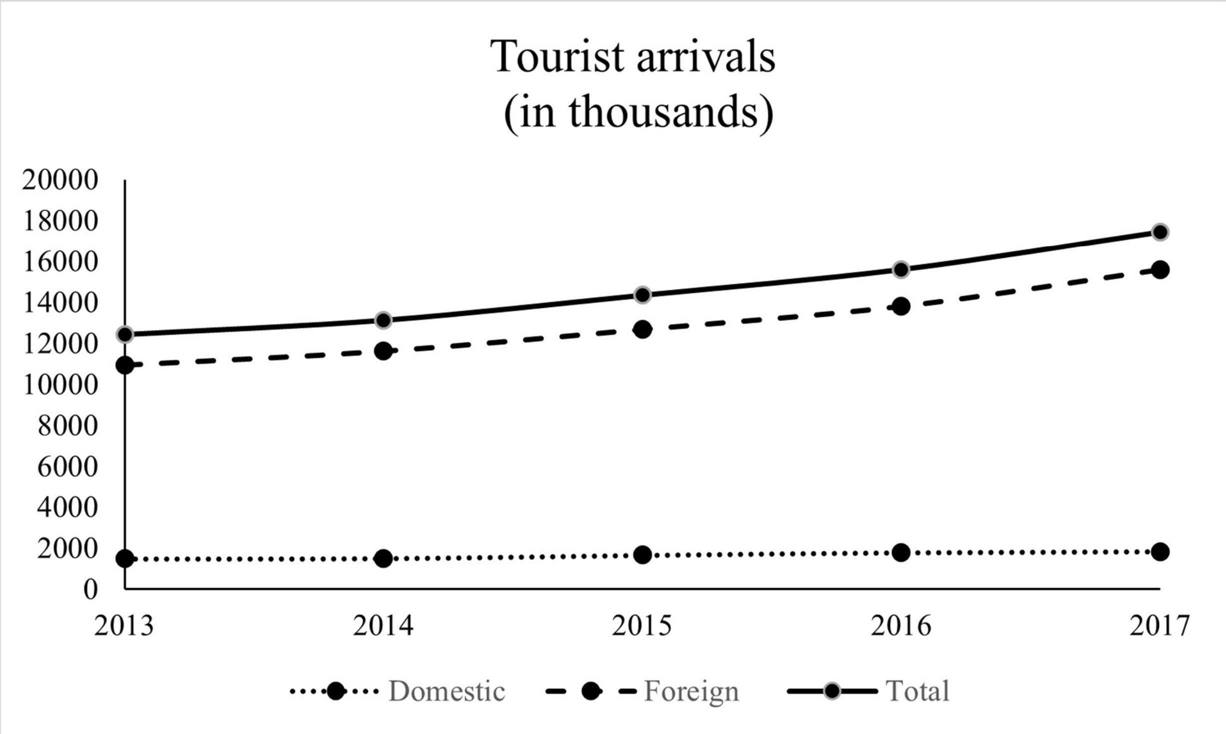
In the following text, we will provide a literature review on the topic, explain our methodological approach and procedures, present the main findings, provide discussion, and make conclusions by putting our findings in the context of previous empirical studies.

THEORETICAL BACKGROUND

Tourism in Croatia

Croatia is one of the most popular European summer destinations (Holidu, 2023). Figure 1 represents how total arrivals changed during the observed period. It is apparent that international tourist arrivals had a predominant share in tourism demand during all the observed years. The number of international tourist arrivals ranged from 10.948.000 in 2013. to 15.593.000 in 2017. The number of tourist arrivals performed steady growth, indicating no shock that would change the trend and lead to significant decreases. Furthermore, Table 1 shows that almost all of the countries holding top positions among international visitors were European countries, as expected due to geographical distance, cultural similarities, and the huge base of Croatian immigrants in some of these countries. Together, these ten countries held above 50% of the overall market share in 2013. 2015. and 2017. Finally, with the share in GDP above 10%, as well as the share in exports of goods and services above 30%, tourism proved a significant contributor to the Croatian economy (Table 2). This short review of Croatian tourism demand and the contribution of the tourism sector to the Croatian economy indicates the high importance of this sector and points to the particular importance of inbound tourism and related analyses.

Figure 1 Tourism demand in Croatia between 2013. and 2017



Source: Croatian Bureau of Statistics (2018)

Table 1 Top ten tourist arrivals to Croatia 2013-2017.

Country	**Arrivals in 2011**	**Market share %**	**Country**	**Arrivals in 2015**	**Market share %**	**Country**	**Arrivals in 2017**	**Market share %**
Germany	1.932	15.54	Germany	2.124	14.81	Germany	2.616	15.01
Slovenia	1.067	8.58	Slovenia	1.192	8.31	Austria	1.331	7.64
Italia	1.017	8.18	Austria	1.120	7.81	Slovenia	1.298	7.45
Austria	969	7.79	Italia	1.111	7.75	Italia	1.110	6.37
Czechia	652	5.24	Chechia	696	4.85	Poland	934	5.36
Poland	636	5.12	Poland	675	4.71	UK	751	4.31
France	449	3.61	UK	491	3.42	Czechia	742	4.26
UK	389	3.20	France	466	3.25	Hungary	546	3.13
Slovakia	337	2.71	Hungary	436	3.04	France	536	3.07
Hungary	326	2.70	Slovakia	381	2.66	USA	452	2.59

Note: Source: Croatian Bureau of Statistics; Tourist arrivals are in thousands

Table 2 Contribution of tourism to Croatian GDP and export earnings

Year	Tourism receipts (billion US$)	GDP (billion US$)	Exports of goods and services (billion US$)	Tourism receipts % of GDP	Tourism receipts % of exports of goods and services
2013	9.72	59.36	23.60	16.37	41.19
2014	10.08	59.21	25.28	17.02	39.87
2015	8.21	50.74	23.18	16.18	35.42
2016	9.22	52.39	24.55	17.60	37.56
2017	10.53	55.94	27.47	18.82	38.33

Source: World Bank

Inbound tourism demand

Tourism scholars have been showing considerable interest in examining the impact of economic and non-economic determinants on inbound tourism demand across numerous countries for over two decades now. Commonly considered determinants include the Gross Domestic Product (GDP) of the origin country (e.g., Habibi, 2017; Tang & Tan, 2015), tourism price in the destination country (TP) (e.g., Garín-Munoz, 2006), tourism price in alternative countries (TPS) (Dogru, Sirakaya-Turk & Crouch, 2017; Tang, Yuan, Ramos & Sriboonchitta, 2019), and tourism capacities measured, for instance, by the number of hotel rooms (e.g., Habibi, 2017).

Typically, the GDP of the origin country has a positive effect on tourist arrivals, given that demand for tourism services generally increases as income levels increase (Choyakh, 2008; Habibi, 2017; Kim & Song, 1998). Regarding tourism prices, economic theory suggests that an increase in prices leads to a decrease in tourist arrivals, as demonstrated in previous research studies (e.g., Ibrahim, 2011; Phakdisoth & Kim, 2007). The theory of consumer behaviour, along with several empirical studies on tourism demand (Dogru et al., 2017; Seetanah, Durbarry & Ragodoo, 2010; Tang et al., 2019), suggests that tourism demand depends not only on tourism prices in the destination country but also on prices in alternative destinations. The expected impact of this variable differs based on whether the alternative country serves as a complementary or substitute destination (Habibi, 2017; Kim & Song, 1998). Finally, variables expressing a country's tourism capacity are often taken as predictors of inbound demand, with empirical research indicating that an increase in capacity positively affects the international tourism demand (Habibi, 2017).

Most previous studies conducted on Croatian data aimed to forecast tourist demand using various methods such as ARIMA (Baldigara & Mamula, 2015), ARAR (Apergis, Mervar & Payne, 2017), ARDL methods (Mervar & Payne, 2007), VAR, and GARCH models (Tica & Kožić, 2015). Several studies are grounded in panel methodology (Erjavec & Devčić, 2022;

Škrinjarić, 2011; Škuflić & Štoković, 2011). Some of these studies were concerned with forecasting demand and explaining the effects of seasonality (Baldigara & Mamula, 2015; Apergis, Mervar & Payne, 2017). However, in available studies focused on identifying factors affecting Croatian inbound tourism demand, GDP of the origin country and gross wages (Tica & Kožić, 2015), accommodation capacity and relative prices represented in exchange rates (Erjavec & Devčić, 2022), capital investments and tourists contentment (Škrinjarić, 2011), as well as accommodation ratings (Škuflić & Štoković, 2011), emerged as significant determinants of Croatian international tourism demand. However, these studies were often limited by the number of origin countries and demand factors that they considered. Additionally, upon a thorough review of the available literature, we can conclude that limited effort has been invested in analysing Croatian inbound tourism demand after the entrance to the EU. Focus on the pre-pandemic period, i.e., the period after the entrance of Croatia to the EU, the inclusion of available origin countries and the examination of the impact of both economic and supply-side determinants using a dynamic panel approach, make this study unique and ads to its scientific and practical contributions.

Dynamic panel analysis has proven to be the most commonly employed method for analysing determinants of inbound tourism demand (Chiu, Zhang & Ding, 2021; Garín-Munoz, 2006; Garin-Munoz & Montero-Martin, 2007; Habibi, 2017; Habibi & Abbasianejad, 2011; Habibi, Rahim, Ramchandran & Chin, 2009; Tang, 2018). Particularly intriguing is that estimating dynamic panels enables researchers to measure the effects of lagged dependent variables (usually the number of tourist arrivals). Researchers interpret this variable as the influence of word-of-mouth communication (WOM) (e.g., Garín-Munoz, 2006; Habibi, 2017) or repeated tourist visits (Garin-Munoz & Montero-Martin, 2007).

DATA AND METHODS

The models estimated in this research build upon previous studies. The study encompasses 47 origin countries and a period of 5 years (2013-2017). The countries included are those for which there is data available within tourism reports provided by the Croatian Bureau of Statistics. The period of 5 years (2013-2017) was chosen because it fits into the timeframe of the Croatian tourism development strategy up until 2020 and covers inbound tourism data upon the entrance to the EU. An overview of the variables, their descriptions, calculation methods, and data sources is provided in Table 3. Descriptive statistics are presented in Table 4.

Table 3 Variable descriptions

Variable	Variable mark	Variable description	Calculation methods	Data source
Tourist arrivals	TA	The number of tourists arriving from the country of origin to Croatia in a specific year		Croatian Bureau of Statistics (2018)
Income	GDP	Real GDP per capita in the origin country		WDI (2023)
Tourism price	TP	Croatian CPI divided by the CPI of the origin country, adjusted for the exchange rate (calculation according to Habibi, 2017)	$TP_{i,t} = \left(\frac{CPI_{h,t}}{CPI_{i,t}}\right) \times \left(\frac{ER_{h,t}}{ER_{i,t}}\right)$	WDI (2023)
Tourism prices in alternative destinations	TPS	Pondered consumer price index in alternative countries (calculation according to Habibi, 2017; Kumar, Kumar, Patel, Hussain Shahzad & Stauvermann, 2020)	$TPS = \sum_{j=1}^{6}\left(\frac{CPI_j}{EX_j}\right) w_j$	WDI (2023)
Number of rooms	RN	Number of rooms in all accommodation types available in Croatia		Croatian Bureau of Statistics (2018)

Source: Authors' work

Notes: In the TPi,t equation, CPIh,t represents the consumer price index in Croatia during period t, CPIi,t is the consumer price index in the origin country, ERh,t represents the exchange rate of Croatian currency and US dollar, ERi,t is the exchange rate of the origin country's currency and US dollar; in the TPSj equation j = 1, 2, 3, 4 and 5 represent Spain, Italy, France, Greece, Albania and Montenegro (alternative countries were selected based on geographical proximity and the significance of maritime tourism); wj is the share of the origin county in the overall number of international tourist arrivals to selected countries and is calculated $w_j = (TTA_j / \sum_{j=1}^{6} TTA_j)$, where TTA represents the number of international tourists arriving in the alternative country.

Table 4 Descriptive statistics

Variables	Mean	Minimum	Maximum	Standard deviation	Within groups standard deviation	Between groups standard deviation
lnTA	11.40	7.60	14.78	1.65	0.21	1.65
lnGDP	10.06	7.66	11.73	0.87	0.09	0.87
lnTP	0.66	-5.25	2.39	1.85	0.32	1.84
lnTPS	4.84	5.03	5.22	0.09	0.09	0.00
lnRN	12.78	12.68	12.91	0.08	0.08	0.00

Source: Authors' work

The log-log model is the most common functional form used to measure tourism demand. Its utilisation is primarily rooted in the ease of thinking in terms of elasticity, as well as empirical findings that have demonstrated its superiority over the linear form (Song & Witt, 2006; Witt & Witt, 1995). Therefore, the log-log functional form is employed in this study.

Since we estimated two different models, the one without and the one with year dummies included, the equations for our models are:

$\ln TA_{i,t} = \beta_1 \ln TA_{i,t-1} + \beta_2 \ln TPS_t + \beta_4 \ln TP_{i,t} + \beta_5 \ln GDP_{i,t} + \beta_6 \ln RN_t + \varepsilon_{i,t} + \eta_{i,t}$ (Model 1)

$\ln TA_{i,t} = \beta_1 \ln TA_{i,t-1} + \beta_2 \ln TPS_t + \beta_4 \ln TP_{i,t} + \beta_5 \ln GDP_{i,t} + \beta_6 \ln RN_t + d_t + \varepsilon_{i,t} + \eta_{i,t}$ (Model 2)

When the model includes a lagged dependent variable as a predictor and independent variables are not strictly exogenous, Ordinary Least Squares (OLS) cannot be applied. In such situations, scholars often utilise the Generalized Method of Moments (GMM), where lagged values of the dependent variable and independent variables serve as instruments (Biagi, Brandano & Detotto, 2012). The Arellano-Bond GMM procedure is considered suitable for analysing two-dimensional panel data characterised by a short time dimension and a larger cross-sectional dimension, as is the case with this study. In this procedure, lagged values of the dependent variable for two or more periods are considered valid instruments (Albaladejo, González-Martínez & Martínez-García, 2016; Rey, Myro & Galera, 2011; Habibi, 2017). However, a short time dimension and not a very large cross-sectional dimension can lead to overfitting biases due to a large number of instruments (Roodman, 2009b). Therefore, the number of lags in the instruments is limited to a maximum of two per variable, following previous practices (e.g., Albaladejo et al., 2016; Sequeira & Maçãs Nunes, 2008). The lagged dependent variable, the number of rooms, and GDP are treated not as strictly exogenous but as predetermined variables, meaning they are considered correlated with past error terms. Tourism price and the price of tourism in alternative destinations are treated as endogenous variables. Treating these variables as endogenous implies that they are correlated with the idiosyncratic error term from the current and previous periods. Since it is expected that prices in alternative countries and tourism prices in Croatia can be affected by tourism demand from current and previous periods, treating these variables as endogenous and specifying instruments seems a valid approach.

A review of available literature has found that, when applying GMM to the analysis of inbound tourism demand, some authors do not use dummy variables for years (e.g., Brida & Risso, 2009; Leitão, 2015), while others use them to control for the effects of specific events (e.g., Garín-Munoz, 2006). The third group of scholars tends to estimate both models with and without time dummies (e.g., Lio, Liu & Ou, 2011). Considering the practice in this field, as well as the recommendation of Roodman (2009a) regarding the inclusion of dummy variables for years, both model specifications were estimated in this study.

The models were estimated using the "Two-step system" GMM and the xtabond2 command following Roodman's instructions (2009a). The "Two-system" GMM is suitable for the analysis of dynamic panels with a lagged dependent variable as one of the predictors (Arellano & Bover, 1995; Blundell & Bond, 1998). "System GMM" is often preferred when there is a short time dimension because the "Difference GMM" model performs poorly under such circumstances (Blundell & Bond, 1998), which corresponds to the characteristics of this research. Regardless of evidence in favour of System GMM in the available literature, we conducted a formal test to decide between the "System GMM" and "Difference GMM" following the widely exploited rule of Bond, Hoeffler & Temple (2001) (Table 5). It should be noted that due to downward bias in standard errors in the "Two-step system" GMM, the "Windmeijer correction" was applied (Windmeijer, 2005).

Diagnostic tests for both of our models were appropriate, and the results obtained from these two models were not significantly different, leading to consistent conclusions (Table 6).

Table 5 Comparison of "Difference GMM" and "System GMM" models

Model	**Variables**	**Pooled OLS model**	**Fixed Effects model**	**One-step Difference GMM model**	**Two-step Difference GMM model**
Model 1	L.lnTA	0.99	0.24	0.17	0.21
Model 2	L.lnTA	0.99	0.24	0.12	0.17
Conclusion	Since the coefficients for the lagged dependent variable in the models estimated using the "Difference GMM" estimators are lower than the coefficients from the models estimated using the "Fixed Effects," the coefficients in the "Difference GMM" models are biased, and the "System GMM" is employed (Bond, Hoeffler & Temple, 2001).				

Source: Authors' work

RESULTS

Data analysis was conducted in STATA 13. The results are in Table 6.

Table 6 Comparison of the GMM results for estimated models

Variables	**Model 1**	**Model 2**	**Expected sign**
L.lnTA	0.96 [0.02]***	0.96 [0.03]***	+
lnGDP	0.02 [0.04]	0.01 [0.04]	+
lnTP	-0.01 [0.02]	-0.01 [0.02]	-
lnTPS	-0.13 [0.13]	-0.11 [0.14]	-/+
lnRN	0.38 [0.12]**	0.39 [0.12]**	+
Diagnostic tests			
Year dummies	NO	YES	
Wald test	1.22e+06 (0.000)	1.36e+06 (0.000)	
Hansen test	26.35 (0.237)	26.18 (0.199)	
AR (1) test	-1.77 (0.077)	-1.76 (0.078)	
AR (2) test	0.48 (0.628)	0.49 (0.628)	
No. of observations	188	188	

Source: Authors' work

Note: * represents a significance at a 10% level, ** represents a significance at a 5% level, *** represents a significance at a 1% level; Standard errors (SE) are placed in square brackets below the regression coefficients; p-values for diagnostic tests are in parentheses; dummy variables for years are included in model 2, but the program excluded some due to collinearity, which is a practice in the xtabond2 command in STATA; the values for the remaining dummy variable for the year 2016 in the model are non-significant and not reported.

Prior to interpreting the coefficients, we examined the models' diagnostics. First-order autocorrelation exists at a significance level of 5%, while it is not present at a significance level of 10% (p=0.077 and p=0.078). More importantly, second-order autocorrelation isn't observed in any of our models (p=0.628 and p=0.628), indicating insufficient evidence to reject the null hypothesis of the absence of second-order serial autocorrelation (Arellano & Bond, 1991). Concerning the report of subsequent diagnostic tests, there is usually no consensus among authors. Some employ the practice of the Sargan test reporting only (e.g., Habibi, 2017), others rely on the values of the Hansen test (e.g., Uddin, Ali & Masih, 2017), while the third group of scholars report values for both tests (Permatasari & Esquivias, 2020). However, the Hansen test is considered superior to the Sargan test because the Sargan test, although not affected by the proliferation of instruments, requires homoskedastic errors, which is rare in practice (Roodman, 2009b).

Regarding the Hansen test for the assessment of the instrument's validity, Roodman (2009a,b) warns that scholars should not settle for values just above the significance thresholds (0.05 and 0.1) but also points out that values of 0.250 and above can be a reason for concern. The p-values of the Hansen test for our models are 0.237 and 0.199. Both values are in the appropriate range (0.1-0.25), indicating the validity of the instruments used. Although there is no clear rule regarding the appropriate number of instruments, the number of instruments in our models is way below the number of groups (28 vs. 47), which is a requirement that must be satisfied. The Wald test is significant at a 1% level.

The effects of the lnTPS1 and L.lnTA variables are significant in both models. A 1% increase in tourist arrivals from the previous year is associated with a 0.96% (models 1 and 2) increase in tourist arrivals in the current year in the short term, with a significance level of 1% and other conditions unchanged. Additionally, a 1% increase in the number of rooms is associated with a 0.38% (model 1) and 0.39% (model 2) increase in tourist arrivals in the short term, with significance at a 5% level and other conditions unchanged. Other valuables, although having expected signs, didn't show significant effects on tourist arrivals in our study.

DISCUSSION

Our findings regarding the tourism capacity measured by the number of available rooms align with previous empirical studies that proved the positive effect of such capacity on the inbound tourism demand (e.g., Ghosh, 2022; Habibi, 2017). The GDP coefficient has the expected sign, but the effect isn't significant. While most studies proved a significant impact of the origin country's income on tourist arrivals, some scholars warn that the results could vary based on what is taken as a proxy for income (Dogru et al., 2017). In the study by Habibi et al. (2009), the GDP coefficient is positive but non-significant as well. Since the research is conducted on tourism data for Malaysia, in the interpretation of their results, the authors conclude that Malaysia isn't perceived as a luxurious vacation destination. Therefore, the number of tourist arrivals does not increase significantly with the increase in income in origin countries. This could be the case with Croatia as well. Although the effect of tourism prices has a negative sign, it is non-significant, which is in line with the results of some other studies (Naudé & Saayaman, 2005; Deluna & Jeon, 2014). This could be due to tourists visiting Croatia not willing to sacrifice their holiday quality due to price increases. Additionally, even with price increases, tourists might perceive Croatia as not as expensive as some other holiday destinations. Consequently, the growth of tourism prices does not significantly affect tourists' decisions.

Furthermore, the coefficient for the tourism price in alternative destinations is negative but non-significant. Generally, depending on whether countries are substitutes or complementary destinations, coefficients for this variable can be positive (e.g., Seetaram, 2012) or negative (e.g., Habibi, 2017). However, since the coefficient is not significant, one cannot point at a strictly complementary character of alternative destinations.

CONCLUSION

Our research indicates that a short-term inbound tourism demand in Croatia depends on the number of arrivals from the previous year, indicating a significant number of repeated visits and recommendations (Garín-Munoz, 2006; Garin-Munoz & Montero-Martin, 2007). The number of international tourists arriving in Croatia is under the influence of tourism capacity. Therefore, we can conclude that the supply side positively affects tourist demand in Croatia, with the variable representing it not necessarily meaning just a higher number of accommodations available but better tourism infrastructure in general (Habibi & Abbasianejad, 2011). The results align with previous findings that suggest that increased investments in tourism and infrastructure enhance the destination's reputation (Albaladejo et al., 2016), leading to a higher number of visits. Insights derived from non-significant coefficients are also important. For example, the non-significant coefficient for the GDP of the origin country aligns with findings from previous research that draw attention to the dependence of tourism demand in Croatia on the development of Eastern Europe and the middle class, making it challenging to target high-income tourists in the short term (Tica & Kožić, 2015). All of this implies that, in the short term, Croatian tourism must invest in attractive facilities and overall infrastructure. Additionally, providing quality service and memorable experiences is vital to encourage tourist returns and increase recommendations.

The main limitations of this study are the short time dimension and some of the potentially interesting variables that may influence tourism demand not being included in our models. Recommendations for future research include adding data from a broader time period and additional determinants of tourist demand to the model, as well as considering alternative ways of expressing tourism prices or costs.

REFERENCES

Albaladejo, I. P., González-Martínez, M. I., & Martínez-García, M. P. (2016). Nonconstant reputation effect in a dynamic tourism demand model for Spain. *Tourism Management*, *53*, 132-139.

Apergis, N., Mervar, A., & Payne, J. E. (2017). Forecasting disaggregated tourist arrivals in Croatia: Evidence from seasonal univariate time series models. *Tourism Economics*, *23*(1), 78-98.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, *58*(2), 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, *68*(1), 29-51.

Baldigara, T., & Mamula, M. (2015). Modelling international tourism demand using seasonal ARIMA models. *Tourism and hospitality management*, *21*(1), 19-31.

Bhuiyan, M.A., Crovella, T., Paiano, A., & Alves, H. (2021). A review of research on tourism industry, economic crisis and mitigation process of the loss: Analysis on pre, during and post pandemic situation. *Sustainability*, *13*(18), p.10314.

Biagi, B., Brandano, M. G., & Detotto, C. (2012). The effect of tourism on crime in Italy: A dynamic panel approach. *Economics*, *6*(1), 20120025.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, *87*(1), 115-143.

Bond, S. R., Hoeffler, A., & Temple, J. R. (2001). GMM estimation of empirical growth models. *Available at SSRN 290522*.

Brida, J. G., & Risso, W. A. (2009). A dynamic panel data study of the German demand for tourism in South Tyrol. *Tourism and Hospitality Research*, *9*(4), 305-313.

Chiu, Y. B., Zhang, W., & Ding, K. (2021). Does globalisation influence inbound tourism? Evidence from a dynamic panel threshold analysis. *Journal of Travel Research*, *60*(5), 1074-1084.

Choyakh, H. (2008). A model of tourism demand for Tunisia: inclusion of the tourism investment variable. *Tourism Economics*, *14*(4), 819-838.

Croatian Bureau of Statistics. (2018). Statistical Yearbook of the Republic of Croatia 2018**.** Retrieved August 8, 2023, from https://www.dzs.hr/Hrv_Eng/publication/2022/SGRH_2022.pdf

Croatian Ministry of Tourism. (2013). Croatian tourism development strategy. Retrieved August 8, 2023, from https://mint.gov.hr/UserDocsImages/arhiva/130426-Strategija-turizam-2020.pdf

Deluna Jr, R., & Jeon, N. (2014). Determinants of international tourism demand for the Philippines: an augmented gravity model approach. *MPRA Paper 55294*, University Library of Munich, Germany.

Dogru, T., Sirakaya-Turk, E., & Crouch, G. I. (2017). Remodeling international tourism demand: Old theory and new evidence. *Tourism management*, *60*, 47-55.

Easterly, W., & Kraay, A. (2000). Small states, small problems? Income, growth, and volatility in small states. *World development*, *28*(11), 2013-2027.

Erjavec, N., & Devčić, K. (2022). Accommodation Capacity, Trade Openness and International Tourism Demand in Croatia: Evidence From a Dynamic Panel Model. *Tourism: An International Interdisciplinary Journal*, *70*(1), 43-52.

Esquivias, M.A., Sugiharti, L., Rohmawati, H., & Sethi, N. (2021). Impacts and implications of a pandemic on tourism demand in Indonesia. *Economics & Sociology*, *14*(4), 133-150.

Garín-Munoz, T. (2006). Inbound international tourism to Canary Islands: a dynamic panel data model. *Tourism management*, *27*(2), 281-291.

Garin-Munoz, T., & Montero-Martín, L. F. (2007). Tourism in the Balearic Islands: A dynamic model for international demand using panel data. *Tourism management*, *28*(5), 1224-1235.

Ghosh, S. (2022). Modelling inbound international tourism demand in Australia: Lessons from the pandemics. *International Journal of Tourism Research, 24(1),* 71-81.

Habibi, F. (2017). The determinants of inbound tourism to Malaysia: A panel data analysis. *Current Issues in Tourism*, *20*(9), 909-930.

Habibi, F., & Abbasianejad, H. (2011). Dynamic panel data analysis of European tourism demand in Malaysia. *Iranian Economic Review*, *15*(29), 27-41.

Habibi, F., Rahim, K. A., Ramchandran, S., & Chin, L. (2009). Dynamic model for international tourism demand for Malaysia: Panel data evidence. *International Research Journal of Finance and Economics*, *33*(1), 208-217.

Holidu. (2023). *The European cities most overloaded with tourists*. Retrieved September 23, 2023, from https://www.holidu.co.uk/magazine/european-cities-overtourism-index

Ibrahim, M. A. M. A. (2011). The determinants of international tourism demand for Egypt: Panel data evidence. European Journal of Economics, Finance and Administrative Sciences, 30, 50–58.

Kim, S., & Song, H. (1998). Analysis of inbound tourism demand in South Korea: a cointegration and error correction approach. *Tourism Analysis*, *3*(1), 25-41.

Kumar, N., Kumar, R. R., Patel, A., Hussain Shahzad, S. J., & Stauvermann, P. J. (2020). Modelling inbound international tourism demand in small Pacific Island countries. *Applied Economics*, *52*(10), 1031-1047.

Leitão, N. C. (2015). Portuguese tourism demand: a dynamic panel data analysis. *International journal of economics and financial issues*, *5*(3), 673-677.

Lio, M. C., Liu, M. C., & Ou, Y. P. (2011). Can the internet reduce corruption? A cross-country study based on dynamic panel data models. *Government Information Quarterly*, *28*(1), 47-53.

Mervar, A., & Payne, J. E. (2007). An analysis of foreign tourism demand for Croatian destinations: long-run elasticity estimates. *Radni materijali EIZ-a*, (1), 5-21.

Naudé, W. A., & Saayman, A. (2005). Determinants of tourist arrivals in Africa: a panel data regression analysis. *Tourism economics*, *11*(3), 365-391.

Permatasari, M. F., & Esquivias, M. A. (2020). Determinants of tourism demand in Indonesia: A panel data analysis. *Tourism Analysis*, *25*(1), 77-89.

Phakdisoth, L., & Kim, D. (2007). The determinants of inbound tourism in Laos. *ASEAN economic bulletin*, 225-237.

Rey, B., Myro, R. L., & Galera, A. (2011). Effect of low-cost airlines on tourism in Spain. A dynamic panel data model. *Journal of Air Transport Management*, *17*(3), 163-167.

Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system GMM in Stata. *The stata journal*, *9*(1), 86-136.

Roodman, D. (2009b). A note on the theme of too many instruments. *Oxford Bulletin of Economics and statistics*, *71*(1), 135-158.

Seetanah, B., Durbarry, R., & Ragodoo, J. N. (2010). Using the panel cointegration approach to analyse the determinants of tourism demand in South Africa. *Tourism Economics*, *16*(3), 715-729.

Seetaram, N. (2012). Estimating demand elasticities for Australia's international outbound tourism. *Tourism Economics*, *18*(5), 999-1017.

Sequeira, T. N., & Maçãs Nunes, P. (2008). Does tourism influence economic growth? A dynamic panel data approach. *Applied economics*, *40*(18), 2431-2441.

Simundic, B. (2022). Evidence on pre-pandemic outbound tourism demend determinants in OECD countries. *Economic and Social Development: Book of Proceedings*, 75-85.

Škrinjarić, T. (2011). Investigation of foreign tourism demand in Croatia using panel data analysis. *Acta turistica*, *23*(2), 145-173.

Škuflić, L., & Štoković, I. (2011). Demand function for croatian tourist product: A panel data approach. *Modern economy*, *2*(1), 49-53.

Song, H., & Witt, S.F., 2006. Forecasting international tourist flows to Macau. *Tourism management*, *27*(2), 214-224.

Statista. (2023). Retrieved September 8, 2023, from https://www.statista.com/

Tang, C. F. (2018). The impacts of governance and institutions on inbound tourism demand: evidence from a dynamic panel data study. *Asia Pacific Journal of Tourism Research*, *23*(10), 1000-1007.

Tang, C. F., & Tan, E. C. (2015). The determinants of inbound tourism demand in Malaysia: another visit with non-stationary panel data approach. *Anatolia*, *27*(2), 189-200.

Tang, J., Yuan, X., Ramos, V., & Sriboonchitta, S. (2019). Does air pollution decrease inbound tourist arrivals? The case of Beijing. *Asia Pacific Journal of Tourism Research*, *24*(6), 597-605.

Tica, J., & Kožić, I. (2015). Forecasting Croatian inbound tourism demand. *Economic research-Ekonomska istraživanja*, *28*(1), 1046-1062.

Uddin, M. A., Ali, M. H., & Masih, M. (2017). Political stability and growth: An application of dynamic GMM and quantile regression. *Economic Modelling*, *64*, 610-625.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of econometrics*, *126*(1), 25-51.

Witt, S. F., & Witt, C. A. (1995). Forecasting tourism demand: A review of empirical research. *International Journal of forecasting*, *11*(3), 447-475.

World Bank. (2023). *World Development Indicators (WDI).* Retrieved August 8, 2023, from https://databank.worldbank.org/source/world-development-indicators