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THE DETERMINANTS OF TOURISM DESTINATION COMPETITIVENESS IN 2006 – 2016: A PARTIAL LEAST SQUARES PATH MODELLING APPROACH

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Abstract *In this paper, we analyze the relationship between tourism destination competitiveness and its determinants at national level in the period 2006–2016, by applying partial least squares path models to biannual panel data. Our research is innovative because a long period (11 years) is considered, changes over time are assessed, and an overall evaluation is performed. Indicators, data sources and model specification are coherent with the ones in current applied researches on the topic, thus comparison with other recent empirical findings is possible. Results show that competitiveness does not significantly depend on demand conditions; the formative constructs have a constant composition throughout the considered period; the most important competitiveness determinants are infrastructures, followed by core resources and attractiveness and by communication technologies; the effect of competitiveness determinants is stable throughout the considered period. Our ranking indicates that Iceland, Austria, Cyprus and Qatar are the most competitive destinations.*

Keywords: *country-level; formative constructs; PLS; structural equation models; time series.*

1. INTRODUCTION

The tourism and travel sector has become an important driver of the contemporary economy, contributing significantly to social, technological and economic development (Dwyer and Kim, 2003). However, the full potential of the sector may be achieved only by enhancing its competitiveness in the complex world tourism market, where a multiplicity of actors are involved in the delivery of the service (Dwyer et al., 2000). The world tourism market is characterized by different goals of service providers (short or long term profit, exploiting or satisfying), by different goals of destination managers (economic or social return), and by the uniqueness

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of the tourists' interest, which all make it difficult to manage destination competitiveness (Crouch, 2011). Thus, the ongoing study of destination competitiveness has acquired increasing importance for tourism researchers and policy makers (Namhyun, 2012). Furthermore, in 2010, the EU Commission recognized the tourism industry as a key element in European growth and announced a new political framework for tourism in Europe (The European Commission, 2010).

Covariance-based structural equation models (CB-SEMs) have proved to be a powerful methodology for tourism research and analysis, with a large number of applications in the last decade, also specifically focused on the analysis of tourism destination competitiveness (TDC) (Alves and Nogueira, 2015; Assaker et al., 2014; Estevao et al., 2015; Mazanec and Ring, 2011; Mazanec et al., 2007; Weldearegay, 2017). The main advantage of CB-SEMs relies in the opportunity to empirically estimate the weights of each indicator and each determinant of competitiveness from data, overcoming the great limitation of constant weights underlying the Tourism and Travel Competitiveness Index (World Economic Forum, 2007).

In recent years, particular attention was paid to partial least squares path models (PLS-PMs), an alternative to CB-SEMs requiring weaker sample size requirements, making no assumptions on the distribution of data, and allowing not only reflective but also formative constructs (Howell et al., 2013). According to several authors, PLS-PMs have introduced a substantial improvement in the methodology for tourism research compared to CB-SEMs (see the review in do Valle and Assaker, 2016), especially because a formative specification appears more adequate than a reflective one for those constructs comprising indicators of different nature (Hardin et al., 2011; Law et al., 1998), like it is the case of TDC determinants. In fact, they are typically represented as formative constructs in current applied researches. However, existing applications focus on a single year, failing to understand the temporal evolution of the relationship between TDC and its determinants.

The present research addresses the analysis of TDC at national level in the period 2006–2016 using biannual panel data. Several partial least squares path models relating TDC to its determinants are estimated: one for each biannual time point and a pooled one. Our research is innovative because a long period (11 years) is considered, changes over time are assessed, and an overall evaluation is performed. Indicators, data sources and model specification are coherent with the ones in current applied researches on the topic, thus comparison with other recent empirical findings is possible.

This paper is structured as follows. In Section 2, the literature on the analysis of tourism destination competitiveness is reviewed, with particular focus on the use of structural equation models. Section 3 provides a description of the data, and the methodology of the research. In Section 4, results are presented and discussed.

Section 5 includes concluding remarks on the contribution.

2. LITERATURE REVIEW

Different theories, concepts and paradigms on how tourism destination competitiveness (TDC) should be explained and measured have emerged from the 90s, rooted on the theory of competitive advantage of Porter (1990). Over the last decade, several conceptual models for TDC have been proposed. Hassan (2000) builds on the theory of comparative advantage and the destination's ability to create a competitive market position out of comparative advantages. In particular, it is emphasized the importance of demand orientation and environmental commitment, from which depend not only the uniqueness of the environment and nature, but also the positioning in a market niche (Hassan, 2000).

Crouch and Ritchie (1999) developed a complex model embracing a broad area of influencing factors that: (i) lie within the destination (qualifying and amplifying determinants, destination policy, planning and development, destination management, core resources and attractiveness, supporting factors and resources); (ii) originate from the main area of a destination's tourism activities (competitive micro-environment); or (iii) stem from outside the tourism industry (global macro-environment). The model considers comparative and competitive advantages, and has the main objective to explicate TDC. The authors underline that the focus of TDC is the destination experience, rather than the competition between enterprises (Crouch and Ritchie, 1999; Ritchie and Croutch, 2000), and their main concern is the link between TDC and sustainability, as "*competitiveness is illusory without sustainability*" (Ritchie and Croutch, 2000, page 2).

Dwyer and Kim (2003) developed a model with four general attributes: core resources, destination management, demand conditions, situational conditions. In this model, demand, which seems to be neglected by Crouch and Ritchie (1999), is acknowledged as an important determinant of TDC.

The World Travel and Tourism Council (WTTC) initiated a data collection in 2004, called Competitiveness Monitor, aimed at developing a composite index measuring TDC. The index relies on the theory of comparative advantage and is composed of 23 indicators concerning price competitiveness, infrastructure development, environmental quality, technology advancement, human resources, level of openness, social development and human tourism. These indicators are derived from data from the World Bank and the United Nations Development Programme and, therefore, are readily available and comparable (Gooroochurn and Sugiyarto, 2005).

The World Economic Forum (WEF) developed a composite index called Travel and Tourism Competitiveness Index (TTCI), which was first proposed in the Travel and Tourism Competitiveness Report (TTCR, World Economic Forum, 2007). The TTCR was published yearly from 2007 to 2009, then every two years from 2011 to 2017, with the objective to provide a periodical ranking of several tourism destinations (125 in 2007, 136 in 2017) at country level. The TTCI is composed by three sub-indexes representing three determinants of TDC: regulatory framework, business environment and infrastructure, cultural and natural resources. The TTCI is the best existing index in terms of comprehensiveness and methodological development at international level, so that there is often anonymous acceptance of the proposed indicators by many tourism management scientists around the world. However, it has several serious limitations. The first is that the value of a sub-index is computed as a unweighted mean of its indicators, and TDC is measured by summing up the values of all the three sub-indices. In doing so, it is assumed that indicators of the same sub-index, as well as sub-indices themselves, have the same weight. Such assumption may produce inconsistent results when hard data and survey data appear in the same sub-index, or when the value of several indicators in the same sub-index is missing. A further problem of the TTCI is that, when the datum for the target period is unavailable, the most recent datum is taken from the past. Typically, indicators in a certain edition of the TTCI may refer from one to three years in the past, posing problem of comparability.

A solution to the main limitations of the TTCI is represented by structural equation models (SEMs, see for example Hoyle, 2012). In a SEM, TDC and its determinants are represented as latent variables (constructs), each measured by a set of indicators, and each other related by a causal structure. Thus, the weight of each indicator and TDC determinant is estimated from data, and the validity of the model can be criticized empirically. In covariance-based (CB) SEMs, constructs have a reflective specification, data are assumed to follow the Multivariate Gaussian distribution, and parameter estimation is performed by minimizing the distance between the empirical and the theoretical covariance matrix. Partial least square path models (PLS-PMs, see for example Esposito Vinzi et al., 2010) are an alternative to CB-SEMs not requiring assumptions on the distribution of data, where parameter estimation is performed by maximizing the explained variance. PLS-PMs represent an improvement in the methodology for tourism research not only for their higher robustness to small sample size and non-normality of data, but also because they allow not only reflective, but also formative constructs.

The first important application of SEMs to the evaluation of TDC is provided by Mazanec et al. (2007). WTTC data were used to develop a PLS-PM with the following TDC determinants: heritage and culture, communication facilities, openness, education, social competitiveness, environmental preservation, infrastructure and tourism price competitiveness. The considered outcomes of tourism activity were: unweighted share of arrivals, share weighted by distance to the population centers in the generating countries, market growth rate. These Authors paid great attention in the selection of destinations in order to have no more than 15% of missing values, leading to 169 destinations out of 197. Missing values were replaced by their mean within predefined groups of destinations. Results indicate that the major driver of TDC is heritage and culture, followed by social competitiveness and communication facilities. Instead, education resulted in a negative effect on TDC.

In Mazanec and Ring (2011), the 2007 and 2008 TTCI is transformed into a PLS-PM and a CB-SEM, and its predictive power is examined. Results show a negative effect of core resources on TDC for both the two years. By applying an automated clustering procedure, the Authors verified to be due to unobserved heterogeneity among the considered destinations. A further model highlighted a significant negative interaction between resources and business environment.

Some scholars explicitly support the assumption of a performance-based indicator of TDC. For example, Croes (2011) and Croes and Kubickova (2013) state that TDC should express the competitive level (outcome) of a tourism destination. More recently, even Hanafiah et al. (2016) state that a performance measurement of TDC directly responds to the needs of tourism policy makers, and is consistent with the definition and meaning of TDC (see, for example, Mazanec et al., 2007).

In Assaker et al. (2014), a PLS-PM including TDC determinants like economy, natural environment and infrastructures was developed from a cross-sectional sample of 154 destinations. An original point of this research consists in the postulation of both a direct and an indirect effect (through infrastructures) of economy on TDC. Results indicate that economy has a positive indirect impact on TDC mediated through the infrastructure and the environment, which in turn have a direct positive impact on TDC.

In Estevao et al. (2015), TDC in Portugal was investigated by applying a CB-SEM on data from a questionnaire based upon the variables put forward by the model of Dwyer and Kim (2003). The results show a significant positive effect of resources, supply and tourism destination management on TDC.

In Alves and Nogueira (2015), a CB-SEM was developed on secondary indicators for 5565 Brazilian municipalities. The following TDC determinant factors were postulated: tourism infrastructure, information and communication technology, education, heritage and culture, socio-economic development, environmental preservation. Tourism flow, jobs, wages and revenue were considered as outcomes of tourism activity. Results showed that tourism infrastructure has the greatest impact on TDC, followed by heritage and culture, communication technology and socio-economic development.

In Weldearegay (2017), a CB-SEM was applied to 78 countries in 2013, using TTCI and World Bank data. The following TDC determinants were considered: core resources and attractiveness, complementary conditions, destination management, demand conditions, urbanization. Market share based on international arrivals, market share based on international tourism receipts and tourism revenue/ spending per arrival were considered as outcomes of tourism activity. The Authors found urbanization to have a strong positive effect on TDC, and complementary conditions to be the greatest explanation of TDC. Also, a significant negative relationship between demand conditions and TDC was detected.

3. MATERIALS AND METHODS

In this research, five constructs are considered: TDC and four among its determinants, i.e., core resources and attractiveness (CRA), communication technology (ICT), infrastructures (INF), demand conditions (DEM). TDC is assumed as reflective, while CRA, ICT, INF and DEM as formative constructs. In a reflective specification, the construct is hypothesized as cause of the indicators, whereas in a formative specification, the indicators are hypothesized as causes of the construct. Thus, indicators should be highly correlated in the reflective case, and little correlated in the formative case. The considered constructs and their specification are coherent with the ones in current applied researches on the topic.

In our analysis, TDC is specified as a reflective construct because it is intended as a scale giving rise to the performance indicators being observed: international arrivals, international tourism receipts and international tourism expenditure, which are consequences of competitiveness. This view is theoretically consistent with the definition of TDC, as it is a destination's ability to attract increasing numbers of visitors by reaching stable or increasing market shares and tourist revenue, and to improve visitor satisfaction and resident well-being in a sustainable perspective (Hassan, 2000; Ritchie and Croutch, 2000).

The use of a formative scheme for the determinants of TDC can be justified on a theoretical basis. We believe that multiple sources of variability, and not a unique latent variate, underlie the proposed indicators, as they are not interchangeable (Borsboon et al., 2003; Diamantopoulos and Siguaw, 2006).

We focused on the period 2006–2016, biannual data. The following subsections describe the data and the methodology.

3.1 DATA

This research is based on 123 countries in the period 2006–2016. We used data from UNESCO, World Bank, World Economic Forum and World Tourism and Travel Council. The data have biannual frequency, and specifically we considered the years 2006, 2008, 2010, 2012, 2014 and 2016. The indicators considered and the data sources, detailed in Table 1, are coherent with the ones in current applied researches on the topic. Descriptive statistics are shown in Table 2.

Tourism destinations were selected in a two-stage procedure. Firstly, the ones with a surface area less than 2000 squared kilometers and less than one million population were excluded. Whenever possible, destinations excluded in this way were merged together with a contiguous one, like it was the case of Belgium and Luxembourg. Secondly, the remaining destinations were selected to obtain a dataset with no more than 5% of missing values in overall. The selection procedure led to a total of 123 tourism destinations. All the indicators have less than 5% of missing values, excepting the ones for the INF construct, for which the percentage of missing values ranges from 10% to 20% in 2006, from 8% to 14% in 2008, and from 5% to 7% in 2016.

We performed missing data imputation by assuming that each missing value depends on all the observed ones (missing at random assumption, Rubin, 1976), and by exploiting the longitudinal structure of the data. According to our procedure, for each missing datum x_i for the *i*-th statistical unit in indicator *X*:

- a linear regression (logarithmic scale) is fitted with *X* as response variable and, as explanatory variables, all the indicators without missing value for the *i*-th statistical unit, plus the first-order auto-regressive term (if not missing);
- x_i is replaced by the value predicted by such regression.

3.2 METHODOLOGY

One PLS-PM was estimated at each biannual time point in the period 2006–2016.

In addition, we estimated a pooled PLS-PM where all the data in 2006–2016 are considered after subtracting the destination-specific mean from each indicator.

Tab. 1: Indicators considered and data sources. UNESCO: United Nations Educational, Scientific and Cultural Organization. WEF: World Economic Forum. WTTC: World Tourism and Travel Council.

Indicator	Description	Source	Construct
$X_{\mathrm{CRA},1}$	Number of natural world heritage sites per 10,000 people	UNESCO	CRA
$X_{\mathrm{CRA},2}$	Number of cultural world heritage sites per10,000 people	UNESCO	CRA
$X_{\mathrm{ICT},1}$	Number of mobile cellular subscriptions per100 people	World Bank	ICT
$X_{\mathrm{ICT},2}$	Number of fixed broadband subscriptions per100 people	World Bank	ICT
$X_{\mathrm{INF},1}$	Number of aircraft departures per 1,000 peo-ple	World Bank	INF
$X_{\mathrm{INF},2}$	Number of airports per million people	WEF	INF
$X_{\mathrm{INF},3}$	Number of hotel rooms per 10,000 people	WEF	INF
$X_{\mathrm{INF},4}$	Number of automated teller machines per 100,000 adult people	World Bank	INF
$X_{\mathrm{INF},5}$	Presence of seven major car rental companies(%)	WEF	INF
$X_{\mathrm{DEM},1}$	Price level ratio of power purchasing parityconversion factor to market exchange rate	World Bank	DEM
$X_{\mathrm{DEM},2}$	Consumer price annual inflation	World Bank	DEM
$X_{\mathrm{TDC},1}$	Number of international arrivals per million people	WTTC	TDC
$X_{\mathrm{TDC},2}$	International tourism receipts per million people (US dollars, 2006 prices)	WTTC	TDC
$X_{\mathrm{TDC},3}$	International tourism expenditure per millionpeople (US dollars, 2006 prices)	WTTC	TDC

Tab. 2: Descriptive statistics.

Indicator	Mean	Minimum	First quartile	Median	Third quartile	Maximum
$X_{\mathrm{CRA},1}$	0.001	0.0000	0.0000	0.0001	0.0007	0.0315
$X_{\mathrm{CRA},2}$	0.004	0.0000	0.0005	0.0018	0.0061	0.0321
$X_{\mathrm{ICT},1}$	97.875	3.242	73.719	103.629	122.866	218.430
$X_{\mathrm{ICT},2}$	10.657	0.001	0.693	5.243	18.942	46.275
$X_{\mathrm{INF},1}$	8.852	0.001	0.797	3.147	9.572	163.428
$X_{\mathrm{INF},2}$	1.735	0.050	0.400	0.800	1.500	30.000
$X_{\mathrm{INF},3}$	183.350	0.638	14.072	41.417	122.231	5170.040
$X_{\mathrm{INF},4}$	49.271	0.046	13.354	38.037	65.597	369.223
$X_{\mathrm{INF},5}$	67.932	0.000	42.857	71.429	100.000	100.000
$X_{\mathrm{DEM},1}$	257.173	0.111	0.905	5.684	69.253	8239.113
$X_{\mathrm{DEM},2}$	105.647	86.954	101.950	104.086	107.857	162.169
$X_{\mathrm{TDC},1}$	470.206	0.784	65.605	245.591	642.866	5361.224
$X_{\mathrm{TDC},2}$	506.580	0.170	40.634	166.601	699.416	7452.081
$X_{\mathrm{TDC},3}$	424.295	2.353	40.124	115.777	438.417	5982.087

Our approach removes the destination-specific level from each indicator, thus accounting for the panel structure of the data and making the values of the indicators comparable across all the destinations.

Each PLS-PM consisted of three parts: a *formative part,* representing the relationships between each TDC determinant and the respective indicators, with the latter causing the former; a *reflective part*, representing the relationships between TDC and the outcomes of tourism activity, with the former causing the latter; and a *structural part* representing the relationship between TDC and its determinants. The path diagram of each PLS-PM is shown in Figure 1. Parameters in a PLS-PM are represented by the correlation between each indicator and the corresponding construct, and by the standardized regression coefficients linking the constructs in the structural part (path coefficients). Technical details on PLS-PMs can be found in Esposito Vinzi et al. (2010).

Bootstrap *p*-values were computed for each PLS-PM to test the equality to 0 for each parameter at each time point.

Multiple group analysis (MGA) was performed to assess whether each path coefficient is constant across all the biannual models, that is whether it is stable in the considered period (time invariance), thus allowing the use of the pooled model to perform an overall evaluation of the relationships between TDC and its determinants. At this purpose, pairwise comparisons among biannual models were made using bootstrap *t*-test with Bonferroni adjustment.

The ranking of the destinations by biennium was computed from TDC scores in the biannual models.

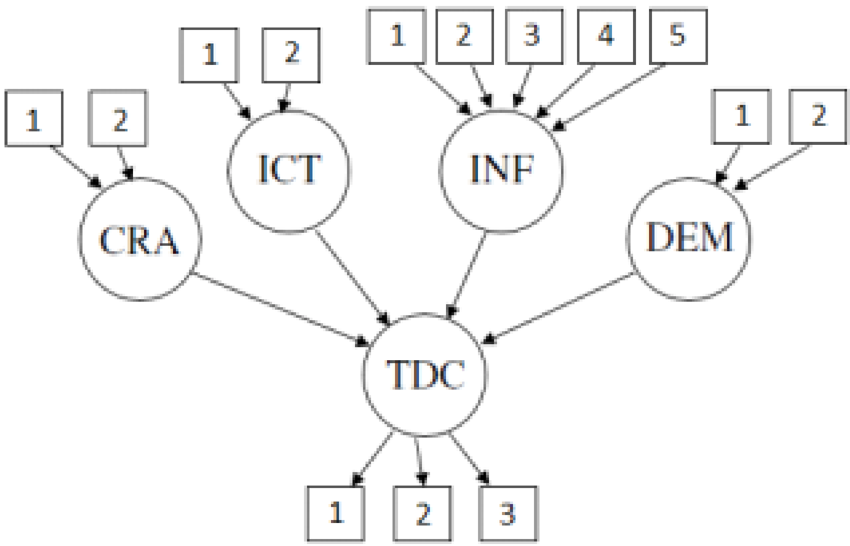

Fig. 1: The path diagram of each PLS-PM.

4. RESULTS AND DISCUSSION

Model estimation was performed using the R package plspm (Sanchez et al., 2017). In the next subsections, results of model estimation, diagnostic indices and ranking of the destinations are reported and discussed.

4.1 MODEL ESTIMATION

Results of estimation for the models including all the considered indicators are reported in Table 3. The correlation between an indicator, for example $X_{\text{CRA},1}$ and the respective construct, for example CRA, is denoted by $X_{\text{CRA},1}$ —CRA, while the path coefficient connecting two constructs, for example CRA and TDC, is denoted by CRA $\rightarrow$ TDC. In the remainder, statistical significancy is understood at 5% level (*p*-value lower than 0.05).

We see that the correlation between the number of hotel rooms to population ($X_{\text{INF},3}$) and the infrastructures (INF) construct is not statistically significant for all the considered time points. This may indicate that the quality of infrastructures for the considered countries does not decisively depend on hotel capability, presumably because it has reached a standard level of acceptability for the most of the considered tourism destinations. Also, the path coefficient relating the demand conditions (DEM) construct to TDC is not statistically significant for all the considered time points. This may indicate that the tourism demand in the considered countries is not sensitive to factors typically influencing the general demand, like price level and inflation.

In order to obtain valid models, we excluded the number of hotel rooms to population ($X_{\text{INF},3}$) and the demand conditions (DEM) construct. The new results are reported in Table 4.

For what concerns the formative part, the correlation between each construct and each of its indicators is statistically significant in all the biannual models, with exception of core resources and attractiveness (CRA) at time point 2006. This suggests that the formative part has a constant composition throughout the considered period.

For what concerns the reflective part, we see that international tourism receipts ($X_{\text{TDC},2}$) is the indicator having the greatest correlation with the TDC construct across all the considered time points, followed by international arrivals ($X_{\text{TDC},1}$) and international tourism expenditure ($X_{\text{TDC},3}$). Also, cultural resources ($X_{\text{CRA},2}$) have higher correlation than natural ones ($X_{\text{CRA},1}$) with the core resources and attractiveness (CRA) construct for all the time points under analysis, indicating that the major attractions of the considered destinations rely more on the cultural heritage than on the natural environment.

Tab. 3: Estimated parameters for the initial models (including all the indicators). Bootstrap *p*-values are shown within brackets.

	2006	2008	2010
$X_{\mathrm{CRA},1}$ — CRA	0.147 (0.155)	0.544 (0.028)	0.517 (0.009)
$X_{\mathrm{CRA},2}$ — CRA	0.988 (0.147)	1.000 (0.014)	1.000 (0.000)
$X_{\mathrm{ICT},1}$ — ICT	0.848 (0.000)	0.784 (0.000)	0.672 (0.000)
$X_{\mathrm{ICT},2}$ — ICT	0.946 (0.000)	0.963 (0.000)	0.963 (0.000)
$X_{\mathrm{INF},1}$ — INF	0.885 (0.000)	0.889 (0.000)	0.875 (0.000)
$X_{\mathrm{INF},2}$ — INF	0.634 (0.000)	0.509 (0.000)	0.536 (0.000)
$X_{\mathrm{INF},3}$ — INF	0.024 (0.601)	0.020 (0.648)	0.011 (0.730)
$X_{\mathrm{INF},4}$ — INF	0.668 (0.000)	0.655 (0.000)	0.616 (0.000)
$X_{\mathrm{INF},5}$ — INF	0.684 (0.000)	0.679 (0.000)	0.692 (0.000)
$X_{\mathrm{DEM},1}$ — DEM	0.584 (0.000)	0.524 (0.000)	0.482 (0.000)
$X_{\mathrm{DEM},2}$ — DEM	0.880 (0.000)	0.956 (0.000)	0.943 (0.000)
$X_{\mathrm{TDC},1}$ — TDC	0.900 (0.000)	0.906 (0.000)	0.882 (0.000)
$X_{\mathrm{TDC},2}$ — TDC	0.960 (0.000)	0.957 (0.000)	0.964 (0.000)
$X_{\mathrm{TDC},3}$ — TDC	0.827 (0.000)	0.824 (0.000)	0.791 (0.000)
CRA $\longrightarrow$ TDC	0.312 (0.255)	0.310 (0.014)	0.226 (0.003)
ICT $\longrightarrow$ TDC	0.180 (0.050)	0.174 (0.066)	0.208 (0.095)
INF $\longrightarrow$ TDC	0.540 (0.000)	0.555 (0.000)	0.506 (0.000)
DEM $\longrightarrow$ TDC	−0.018 (0.624)	−0.005 (0.800)	−0.056 (0.438)

	2012	2014	2016
$X_{\mathrm{CRA},1}$ — CRA	0.583 (0.009)	0.631 (0.013)	0.762 (0.019)
$X_{\mathrm{CRA},2}$ — CRA	0.998 (0.000)	0.991 (0.000)	0.946 (0.000)
$X_{\mathrm{ICT},1}$ — ICT	0.609 (0.000)	0.506 (0.000)	0.519 (0.000)
$X_{\mathrm{ICT},2}$ — INF	0.969 (0.000)	0.965 (0.000)	0.965 (0.000)
$X_{\mathrm{INF},1}$ — INF	0.868 (0.000)	0.892 (0.000)	0.906 (0.000)
$X_{\mathrm{INF},2}$ — INF	0.587 (0.000)	0.555 (0.002)	0.664 (0.004)
$X_{\mathrm{INF},3}$ — INF	−0.022 (0.813)	−0.017 (0.896)	−0.035 (0.608)
$X_{\mathrm{INF},4}$ — INF	0.564 (0.000)	0.475 (0.000)	0.333 (0.002)
$X_{\mathrm{INF},5}$ — INF	0.667 (0.000)	0.646 (0.000)	0.604 (0.000)
$X_{\mathrm{DEM},1}$ — DEM	0.490 (0.000)	0.556 (0.000)	0.545 (0.000)
$X_{\mathrm{DEM},2}$ — DEM	0.986 (0.000)	0.900 (0.000)	0.851 (0.000)
$X_{\mathrm{TDC},1}$ — TDC	0.860 (0.000)	0.869 (0.000)	0.875 (0.000)
$X_{\mathrm{TDC},2}$ — TDC	0.968 (0.000)	0.970 (0.000)	0.971 (0.000)
$X_{\mathrm{TDC},3}$ — TDC	0.792 (0.000)	0.803 (0.000)	0.823 (0.000)
CRA $\longrightarrow$ TDC	0.244 (0.005)	0.278 (0.000)	0.301 (0.000)
ICT $\longrightarrow$ TDC	0.197 (0.090)	0.205 (0.061)	0.130 (0.118)
INF $\longrightarrow$ TDC	0.504 (0.000)	0.493 (0.000)	0.536 (0.000)
DEM $\longrightarrow$ TDC	−0.030 (0.535)	−0.021 (0.313)	−0.078 (0.342)

Tab. 4: Estimated parameters for the final models (without the indicator $X_{INF,3}$ and the DEM construct). Bootstrap *p*-values are shown within brackets

	2006	2008	2010
$X_{CRA,1}$ — CRA	0.146 (0.156)	0.545 (0.028)	0.517 (0.009)
$X_{CRA,2}$ — CRA	0.988 (0.147)	1.000 (0.000)	1.000 (0.000)
$X_{ICT,1}$ — ICT	0.848 (0.000)	0.784 (0.000)	0.672 (0.000)
$X_{ICT,2}$ — ICT	0.947 (0.000)	0.963 (0.000)	0.963 (0.000)
$X_{INF,1}$ — INF	0.904 (0.000)	0.910 (0.000)	0.890 (0.000)
$X_{INF,2}$ — INF	0.648 (0.000)	0.521 (0.000)	0.546 (0.000)
$X_{INF,4}$ — INF	0.681 (0.000)	0.670 (0.000)	0.628 (0.000)
$X_{INF,5}$ — INF	0.698 (0.000)	0.695 (0.000)	0.705 (0.000)
$X_{TDC,1}$ — TDC	0.899 (0.000)	0.905 (0.000)	0.884 (0.000)
$X_{TDC,2}$ — TDC	0.960 (0.000)	0.956 (0.000)	0.965 (0.000)
$X_{TDC,3}$ — TDC	0.829 (0.000)	0.826 (0.000)	0.788 (0.000)
CRA $\longrightarrow$ TDC	0.326 (0.242)	0.331 (0.011)	0.245 (0.001)
ICT $\longrightarrow$ TDC	0.197 (0.031)	0.179 (0.063)	0.223 (0.082)
INF $\longrightarrow$ TDC	0.517 (0.000)	0.536 (0.000)	0.497 (0.000)
	2012	**2014**	**2016**
$X_{CRA,1}$ — CRA	0.583 (0.009)	0.631 (0.013)	0.762 (0.019)
$X_{CRA,2}$ — CRA	0.998 (0.000)	0.991 (0.002)	0.946 (0.000)
$X_{ICT,1}$ — ICT	0.610 (0.000)	0.506 (0.000)	0.519 (0.000)
$X_{ICT,2}$ — ICT	0.969 (0.000)	0.965 (0.000)	0.965 (0.000)
$X_{INF,1}$ — INF	0.881 (0.000)	0.901 (0.000)	0.912 (0.000)
$X_{INF,2}$ — INF	0.597 (0.000)	0.559 (0.002)	0.668 (0.004)
$X_{INF,4}$ — INF	0.573 (0.000)	0.478 (0.000)	0.335 (0.002)
$X_{INF,5}$ — INF	0.677 (0.000)	0.651 (0.000)	0.607 (0.000)
$X_{TDC,1}$ — TDC	0.861 (0.000)	0.867 (0.000)	0.874 (0.000)
$X_{TDC,2}$ — TDC	0.968 (0.000)	0.970 (0.000)	0.971 (0.000)
$X_{TDC,3}$ — TDC	0.790 (0.000)	0.806 (0.000)	0.825 (0.000)
CRA $\longrightarrow$ TDC	0.262 (0.003)	0.288 (0.000)	0.297 (0.000)
ICT $\longrightarrow$ TDC	0.206 (0.094)	0.208 (0.059)	0.157 (0.085)
INF $\longrightarrow$ TDC	0.491 (0.000)	0.488 (0.000)	0.541 (0.000)

For what concerns the structural part, the relationship of the core resources and attractiveness (CRA) construct with TDC is not statistically significant at time point 2006, while the relationship of the communication technology (ICT) construct with TDC is statistically significant only at time points 2006 and 2014. The infrastructures (INF) construct has the highest path coefficient, thus it is the most important TDC determinant, followed by core resources and attractiveness (CRA) and by communication technology (ICT). Also, *p*-values from MGA, reported in Table 5, show that all the path coefficients are unchanged across the most pairs of bienniums. On these grounds, the pooled model is useful to perform an overall evaluation of the relationships between TDC and its determinants. Parameter estimation of the pooled model, shown in Table 6, are coherent to those of the biannual models, as they report similar magnitude for the relationships between each construct and its indicators, and between TDC and its determinants.

Tab. 5: *p*-values from MGA using bootstrap *t*-test with Bonferroni adjustment. *p*-values indicating statistical significance at 5% level are bolded.

	CRA — TDC	ICT — TDC	INF — TDC
2006 vs. 2008	0.104	1.000	1.000
2006 vs. 2010	1.000	1.000	1.000
2006 vs. 2012	1.000	1.000	1.000
2006 vs. 2014	0.182	1.000	0.263
2006 vs. 2016	0.112	0.737	1.000
2008 vs. 2010	**0.006**	0.159	1.000
2008 vs. 2012	0.863	0.926	0.247
2008 vs. 2014	1.000	0.164	**0.007**
2008 vs. 2016	1.000	1.000	1.000
2010 vs. 2012	1.000	1.000	1.000
2010 vs. 2014	**0.003**	1.000	1.000
2010 vs. 2016	**0.001**	**0.048**	1.000
2012 vs. 2014	1.000	1.000	1.000
2012 vs. 2016	0.828	0.343	1.000
2014 vs. 2016	1.000	**0.047**	0.142

Tab. 6: Estimated parameters for the pooled model. Bootstrap *p*-values are shown within brackets.

Parameter	Estimate
$X_{\text{CRA},1}$ — CRA	0.583 (0.000)
$X_{\text{CRA},2}$ — CRA	0.994 (0.004)
$X_{\text{ICT},1}$ — ICT	0.644 (0.000)
$X_{\text{ICT},2}$ — ICT	0.977 (0.000)
$X_{\text{INF},1}$ — INF	0.908 (0.000)
$X_{\text{INF},2}$ — INF	0.593 (0.000)
$X_{\text{INF},4}$ — INF	0.539 (0.000)
$X_{\text{INF},5}$ — INF	0.660 (0.000)
$X_{\text{TDC},1}$ — TDC	0.877 (0.000)
$X_{\text{TDC},1}$ — TDC	0.965 (0.000)
$X_{\text{TDC},3}$ — TDC	0.811 (0.000)
CRA $\longrightarrow$ TDC	0.281 (0.004)
ICT $\longrightarrow$ TDC	0.184 (0.020)
INF $\longrightarrow$ TDC	0.523 (0.000)

4.2 DIAGNOSTIC INDICES

We computed several diagnostic indices to assess the validity of the final models (see Hair et al., 2017 for details).

The goodness of fit (GoF) index proposed by Tenenhaus et al. (2005) indicates the proportion of explained variance, and is computed as the geometric mean between the mean R-squared in the structural part and the mean squared correlation in the formative and reflective part. GoF provides a practical solution for the global assessment of the model, although its capability of discriminating among alternative models has been questioned (Henseler and Sarstedt, 2013).

For reflective constructs (TDC in our analysis), the first eigenvalue of the correlation matrix of the indicators indicates adequacy of the reflective specification for values greater than 1, the composite reliability index (CRI) greater than 0.7 indicates good composite reliability, and the average variance extracted (AVE) indicates good convergent validity for values greater than 0.7. Good discriminant validity of a reflective construct is indicated by AVE indices greater than the squared correlations between the scores of the construct and of each of its determinants (Fornell-Larcker's criterion).

Variance inflation factors (VIFs) suggest no evidence of collinearity between the indicators of a formative construct for values lower than 2, thus indicating adequacy of the formative specification.

Diagnostic indices for the final models are provided in Table 7. According to the GoF index, the final models explain each from 64% to 70% of total variance. The average variance extracted (AVE) for the TDC construct ranges from 77% to 80%, indicating good convergent validity. The reflective specification for the TDC construct appears adequate since the first eigenvalue of the correlation matrix of its indicators is always greater than 1. Good discriminant validity of the TDC construct is indicated by the AVE indices which are all greater than the squared correlations between the scores of TDC and of each of its determinants. Also, the composite reliability index (CRI) for TDC is quite high (at least 0.9). Variance inflation factors (VIFs) for formative constructs are all lower than 2, showing no evidence of collinearity between the formative indicators.

4.3 RANKING OF THE DESTINATIONS

TDC ranks by biennium, reported in Table 8, show that Iceland is the most competitive destination, followed by Austria, Cyprus and Qatar. Interestingly, only Iceland and Qatar are ranked at least one time in the first position, and no destination besides Iceland, Austria, Cyprus and Qatar is never ranked in the first three positions. Non-European destinations among the top 20 ones include United Arab

Tab. 7: Diagnostic indices for the final models. GoF: goodness of fit index. AVE: average variance extracted. CRI: Convergent reliability index.

Indices for TDC construct	2006	2008	2010	2012	2014	2016	pooled
GoF	0.702	0.703	0.650	0.639	0.644	0.671	0.659
AVE	0.802	0.801	0.778	0.767	0.779	0.810	0.786
CRI	0.924	0.923	0.913	0.908	0.913	0.927	0.936
1st eigenvalue	2.418	2.416	2.333	2.306	2.343	2.388	2.358

Squared correlations with TDC	2006	2008	2010	2012	2014	2016	pooled
CRA	0.404	0.379	0.315	0.348	0.399	0.508	0.350
ICT	0.492	0.508	0.491	0.443	0.429	0.261	0.420
INF	0.653	0.634	0.600	0.587	0.592	0.634	0.605

Variance inflation factors for formative indicators	2006	2008	2010	2012	2014	2016	pooled
$X_{\mathrm{CRA},1}$	1.099	1.416	1.372	1.379	1.368	1.355	1.322
$X_{\mathrm{CRA},2}$	1.099	1.416	1.372	1.379	1.368	1.355	1.322
$X_{\mathrm{ICT},1}$	1.665	1.531	1.252	1.185	1.073	1.084	1.277
$X_{\mathrm{ICT},2}$	1.665	1.531	1.252	1.185	1.073	1.084	1.277
$X_{\mathrm{INF},1}$	1.780	1.526	1.585	1.546	1.528	1.528	1.512
$X_{\mathrm{INF},2}$	1.421	1.239	1.381	1.367	1.378	1.378	1.315
$X_{\mathrm{INF},4}$	1.577	1.606	1.417	1.316	1.207	1.207	1.367
$X_{\mathrm{INF},5}$	1.501	1.526	1.403	1.354	1.268	1.268	1.375

Emirates, New Zealand and Australia.

Our results partially agree with the ones of Mazanec and Ring (2011) obtained from 2008 and 2009 WEF data. In particular, we found remarkable differences between the results of the (unweighted) method used by WEF to compute the TTCI, too. Austria is the only top rated country by WEF maintaining a high position in our results (3rd). Switzerland, heading the 2008 and 2009 WEF chart, ranks 7 according to our results. Generally, large economies (Germany, France, Spain, Canada, Australia, United Kingdom, USA) seem to benefit from the WEF method, while smaller destinations scoring in the first 10 positions in our results (Iceland, Cyprus, Ireland, Denmark, Greece) are excessively penalized.

Tab. 8: TDC ranks by biennium computed from TDC scores of biannual models.

Top 20 destinations	2006	2008	2010	2012	2014	2016
Iceland	1	1	5	2	2	1
Austria	3	3	2	3	3	3
Cyprus	2	2	3	4	4	4
Qatar	9	5	1	1	1	2
Ireland	4	4	4	7	6	6
Croatia	6	6	7	6	5	5
Switzerland	5	7	6	5	7	7
Norway	7	8	8	8	8	8
Denmark	8	9	9	9	10	11
Belgium and Luxembourg	10	10	10	10	11	10
Estonia	15	11	12	12	9	9
Greece	12	12	13	13	12	13
Montenegro	18	14	11	11	13	12
United Arab Emirates	11	13	14	14	14	14
Spain	14	16	17	17	15	16
Slovenia	19	15	15	15	16	17
Sweden	13	17	16	20	20	18
New Zealand	17	19	19	18	17	15
France	16	18	18	16	18	23
Australia	23	22	20	19	22	24

Worst 20 destinations	2006	2008	2010	2012	2014	2016
Indonesia	107	104	105	105	103	101
Yemen	106	102	100	108	107	105
Algeria	105	106	108	106	108	107
Mozambique	112	107	104	104	109	110
Kenya	102	109	107	107	111	113
Cameroon	109	112	114	109	105	109
Tanzania	110	111	111	111	110	108
Malawi	108	110	110	113	114	114
Uganda	116	114	109	110	113	111
Angola	118	117	112	112	104	115
Nepal	114	115	113	114	112	112
Benin	111	113	115	115	115	116
Ivory Coast	115	118	117	116	116	104
Nigeria	113	108	116	117	117	118
Mali	117	116	118	120	119	119
India	121	121	120	119	118	117
Burkina Faso	120	120	119	118	121	120
Burundi	119	119	121	121	120	121
Sierra Leone	122	122	122	122	122	122
Bangladesh	123	123	123	123	123	123

5. CONCLUDING REMARKS

The present research addresses the analysis of tourism destination competitiveness (TDC) at national level in the period 2006–2016, and collocates within the recent literature (Alves and Nogueira, 2015; Assaker et al., 2014; Estevao et al., 2015; Mazanec and Ring, 2011; Mazanec et al., 2007; Weldearegay, 2017) using structural equation models (SEMs) to overcome the great limitation of constant weights underlying the Tourism and Travel Competitiveness Index (World Economic Forum, 2007). In fact, SEMs allow to estimate the weights of each indicator and each determinant of competitiveness from data.

Our application relies on the use of partial least square path models (PLS-PMs), which, according to several authors, have introduced a substantial improvement in the methodology for tourism research compared to covariance-based (CB) SEMs (see the review in do Valle and Assaker, 2016). Our research is innovative because a long period (11 years) is considered, changes over time are assessed, and an overall evaluation is performed. Indicators, data sources and model specification are coherent with the ones in current applied researches on the topic, thus comparison with other recent empirical findings is possible.

Our results show that competitiveness does not significantly depend on demand conditions; the formative constructs have a constant composition throughout the considered period; the most important competitiveness determinants are infrastructures, followed by core resources and attractiveness and by communication technologies; the effect of competitiveness determinants is stable throughout the considered period.

Our ranking, in partial agreement with the one of Mazanec and Ring (2011), indicates that Iceland, Austria, Cyprus and Qatar are the most competitive destinations, and suggests that empirically estimating the weights helps to consistently assess competitiveness for small economies, compared to assume them as constant like in the case of the Touring and Travel Competitiveness Index.

The selection of the indicators is a critical step of our research. In the present contribution, we focused on a limited set of TDC determinants. Future work could consider a broader set of TDC determinants, like public expenditure for the tourism sector, regulation and social aspects.

Our research provides important implications for policy makers on how to strengthen TDC in the last decade, and, more important, poses the basis for an empirical approach supporting longitudinal benchmark analysis for tourism destinations at national level. We hope that future applications follows our recommendations and focus on as long as possible time periods, thus producing long-term conclusions on the relationships between TDC and its determinants, which might hopefully stimulate a wider discussion on the topic.

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