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Tracking Destination Image through Time: The Case of Aruba

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TRACKING DESTINATION IMAGE THROUGH TIME: THE CASE OF ARUBA

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ABSTRACT

This study proposes a methodology to track changes in destination images through time. Dynamic Destination Image Index (DDII) monthly time series are obtained applying content analysis to media materials about a particular destination and reflect news volume, topics raised, and favorability of media coverage. The methodology is demonstrated using articles about Aruba published in U.S. newspapers in May 2004-April 2006, a period that encompasses disappearance of American teenager Natalee Holloway in Aruba. The DDII index was validated by using it in a model of tourism arrivals to Aruba. The DDII concept is proposed to be of interest to the destinations' DMOs.

Key Words: Content analysis, Dynamic Destination Image Index (DDII), Destination image, Media messages, Time series, Tourism demand

DYNAMIC DESTINATION IMAGE INDEX (DDII)

Destination image construct is lacking an objective integral numerical measure which would reflect the dynamics in destination image perception among potential travelers through time. The concept of destination image expressed as a numerical time series has a number of potential benefits: such numerical series could be used (1) in models of tourism demand to account for a destination image factor in consumer decision-making and/or (2) by destinations' marketing organizations (DMOs) in assessing the effectiveness of promotional campaigns, since numerical changes in image would be clearly visible. Destination image indices that have been proposed to date (Mallou et al., 2006) are primarily based on consumer surveys and, therefore, static, i.e., reflect the current state of image perception. Obtaining such indices on a regular basis is simply not feasible for DMOs, since the survey process involving human subjects is costly and time consuming. At the same time, media materials, such as newspaper archives, travel journals, and/or travelers' postings in virtual communities, through which destination image is manifested, are virtually at our fingertips – they are readily available for analysis through electronic databases.

The media heavily influences public awareness, perceptions, and behavior, including buying decisions (Macnamara, 2006). There is an age-old and still ongoing debate over whether mass media creates public opinion, attitudes, and perceptions or simply reflects existing attitudes, perceptions, and culture; most media researchers agree that, with some limitations, mass media does both (Hall, 1980). Representations of destination images in media and their influence on destination choice have been an area of inquiry since the 1970s (Bandyopadhyay & Morais, 2005; Crompton, 1979; Gartner, 1993; Mayo, 1973; Mercille, 2005, among others). Urry (1990:3) argued that the tourist impression "is constructed and sustained through a variety of non-tourist practices, such as film, TV, literature, magazines, records, and videos." In the marketing literature, researchers maintain that media representations shape image, having described this process through several typologies (Butler, 1990; Gartner, 1993;

Phelps, 1986). Mercille (2005) used a theoretical model provided by Hall (1980) and compared media productions consulted by tourists to Tibet with tourists' perceptions of the region. Medium to strong congruence was found between representations and destination images. Studies of media communication content reveal that data derived from media messages correlate with other indicators obtained independently, and as such validate media content analysis results (Krippendorf, 2004).

This study proposes to look at media materials published about a destination as a record of destination image changes through time and, using a methodology of content analysis, quantify media messages as weekly, monthly, quarterly, or annual time series. It is proposed that such series, or Dynamic Destination Image Index (DDII), should reflect the volume of the materials published about the destination in the source market, the topics raised, and favorability of media coverage. The study demonstrates the proposed methodological procedure using a Caribbean island of Aruba. On May 30, 2005 an Alabama teen, Natalee Holloway, disappeared in Aruba, a mature "sea, sand, and sun" destination. The incident was widely covered in the U.S. general press, with the attempts to organize a boycott of travel to Aruba in the media (for an example, see "States, landmarks facing tourism boycotts" in *USA Today*, March 10, 2006). Aruba was selected to find out whether a proposed DDII is sensitive enough to capture increased negativity in media coverage. The time period for which the DDII-Aruba was constructed is May 2004-April 2006, a year before and a year after Natalee Holloway's disappearance. To see whether the index correlated with other data obtained independently, a validation of the DDII-Aruba was conducted using the DDII-Aruba as an independent variable in a regression model of tourism demand for Aruba.

METHOD

Textual Population and Sample Selection

Sample selection for media content analysis consists of three steps: selection of media publications, selection of the documents, and sampling of the relevant content within the documents (Holsti, 1969). Textual data were taken from the LexisNexis Academic database, one of the world's largest general news databases, widely used in media research. Lasswell et al. (1952) as well as Riffe and his colleagues (Riffe, 1998, among others) make a strong case for newspapers as suitable sources for content analysis research: newspapers appear regularly and frequently, have uniform formats, and many of their parameters, such as circulation, geographical area of distribution, social and political orientation, as well as ownership are known. Newspapers are conveniently accessible from electronic databases, and archives date well back into the past.

For this study, top ten U.S. newspapers were selected as data sources for the reasons of their strong influence on public opinion, high circulation and, therefore, high accessibility to the general public, as well as geographical dispersion. A list of 100 U.S. newspapers with the largest circulation was consulted (www.infoplease.com/ipea/a0004420.html; Audit Bureau of Circulation). Ten publications from the top of the list were regarded as a representative sample of the U.S. influential newspapers. The final string *aruba and (tour! or travel) and date aft 1 may 2004 and date bef 30 april 2006* instructed Lexis-Nexis to return all articles which had the word "aruba" and at the same time the word "travel" or words starting with "tour," for a period May 1, 2004 – April 30, 2006. The words "travel" and "tour!" were included to ensure that the articles were indeed travel-related. It was noted that choosing articles with only the word "aruba" in the body expanded the sample significantly by including a great many business and financial texts. At the same time, choosing only the articles with the words "aruba" or "aruban" in the headlines significantly decreased the sample. The total number of articles collected was 229: The Washington Post (42); The New York Times (39); The Houston Chronicle (38); USA Today (35); The Boston Globe (29); Daily News (New York) (25); The Philadelphia Inquirer (17); The Denver Post (2); and Star Tribune (Minneapolis MN). The sample was examined for suitability for the study, and 54 articles were excluded. Examples of non-relevant materials would be TV programs, lists of Caribbean websites and travel agencies, or publications like "Wife, Police Seek Answers in Md. Teacher's Slaying" *(The Washington Post,* June, 26, 2005) and

"U.S. Against the World: It Seems to Be a Fair Fight" (*The New York Times*, January 22, 2006). The final sample included 175 articles, with the largest number of articles (25) published in June 2005.

Categories and Units of Content

The set of standardized categories for Aruba was developed using a combined approach: about 40% of the selected articles were first read in order to surmise the main topics about destination Aruba (Glaser & Strauss, 1969; Neuendorf, 2002), while the seminal studies by Echtner's and Ritchie's (1993) and Crompton (1979) provided the theoretical groundings for category formalization with respect to destination image. As a result, the following twelve categories were identified for Aruba: (1) **Disasters (DIS)** – high impact, low frequency events: e.g., hurricanes, political unrests, or ecological catastrophes; (2) **Major Events (EV)** – events at the destination that are not regular and can influence people to come: e.g., golf tournaments, music festivals, or poker world tours; (3) **Safety and Crime (S&C)** – issues related to tourists' safety: e.g., crime rates, street pick-pocketing, or publicized criminal cases; (4) **Infrastructure and Service (INF)** – references to, for example, hotels, restaurants, or facilities for beach activities and sports; (5) **Accessibility (ACC)** – news about how to reach the destination: e.g., new flights, cruise routes, or visa regulations; (6) **Things to Do (TTD)** – news about museums, excursions, shopping, nightlife, local festivals, etc.; (7) **Money (MON)** – information about special deals, offers, VAT return, etc.; (8) **Tourism Issues (TOUR)** – news about tourism initiatives like sustainable development efforts or plans by the DMO to attract new categories of tourists, for example, seniors or honeymooners; (9) **Socio-Economic Development (ECON)** – includes references to overall development of the destination, cleanness and hygiene, crowdedness of cities and/or beaches, food availability, etc.; (10) **Gossip (GOSS)** – refers to what happens at the destination with respect to famous people; (11) **Nature and Scenery (N&S)** – references to country's landscape; climate; beauty; wildlife, natural and man-made landmarks, etc.; and (12) **Cultural Heritage (CH)** – includes traditions and culture; cuisine, arts and literature, local people, etc.

In the coding procedure, recording unit was a theme, or reference, to Aruba, which was classified to one of the 12 pre-established categories. A context unit consisted of the sentence with the reference, the preceding one, and the following one. A single sentence could have contained themes from several different categories but no more than one reference to any particular category. All data were aggregated and reported in monthly units (Krippendorf, 2004).

Category and Favorability Coding

The task of classifying the content of the articles into pre-specified categories "by hand," without any content analysis software, was judged as manageable. All articles were read in full, sentence by sentence, and the references to Aruba and its features were assigned into 12 respective categories. In the articles about the Caribbean region, only references to Aruba were classified. In addition, only textual references from the article body were coded, thus, excluding graphics and titles to pictures. A single article could have had zero, one, or multiple references in each category. The article length ranged from 32 to 5,466 words, with the average length of 704 words. To account for this factor and to ensure that impacts of a single reference from two articles of different length differ, the number of references, which the article scored in a single category, was divided by the article's length (Namenwirth, 1973; Neuendorf, 2002; Weber, 1990).

Simultaneously, each reference to Aruba was evaluated with regard to its "favorability" on a three-point scale: favorable (+1), unfavorable (-1), or neutral (0) (Krippendorff, 2004). To assess favorability, a desirability of an event for the destination was considered. For example, references to the collapse of the island's most visited wonder, coral bridge ("100-foot-long coral bridge collapses into Aruban cove." *USA Today*, Sept 9, 2005) were evaluated as unfavorable in the Nature and Scenery category. Similarly, all references to disappearance of Natalee Holloway, which were classified into Safety and Crime category, were evaluated as unfavorable on the grounds that crimes against tourists are damaging to the destination's reputation. At the same time, when an article pointed out

that crime rates in Aruba were much lower than in the U.S. and Netherlands, such references were classified as positive. When a paper mentioned friendliness of local people or great beach facilities in Aruba, or pleasantness of its climate, such references were coded as a favorable in respective categories. It was also considered whether newspapers reported something new with regard to Aruba; thus, references to opening new air routes to Aruba were coded as favorable in the Accessibility category, while information about passports and visas was coded as neutral. On the whole, references to Aruba's infrastructure, accessibility of the destination for various groups of tourists, and activities available on the island were evaluated favorably or neutrally. Information about costs and deals was classified mostly as neutral, unless the author described the offer in elevated terms or emphasized savings. References from Nature & Scenery, Cultural Heritage, and Socio-Economic Development categories were classified as favorable or neutral in most cases. References in the category Tourism Issues were classified as favorable if they described DMO's initiatives, e.g., of making the island more receptive to needs of senior tourists. References to boycott of travel to Aruba, initiated in some U.S. states, were classified as negative in the Tourism Issues category.

Each reference to Aruba divided by the article length was multiplied by "1" if the reference was judged favorable, by "-1" if the reference was considered unfavorable, and by "0" if it was classified as neutral. (Multiplication by zero, in fact, removed a reference from "active participation" in constructing the DDII.) Resulting values in each category were added up to form a category score C(t) (C(t), t=1, 2, …, 24) for each one of 24 months. Category scores over the two-year period are shown in Table 1.

Table 1
Category scores

Per	DIS	EV	S&C	INF	ACC	TTD	MON	TOUR	GOSS	N&S	CH	ECON
1	0	0	0	0	0.0060	0.0204	0	0.0177	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0.0084	0	0
3	0	0.0013	0	0	0	0	0	0	0	0	0	0
4	0	0.0128	0	0.0012	0	0	0.0012	0.0169	0	0.0017	0.0008	0
5	-0.0013	0	0	0.0007	0.0019	0	-0.0008	0	0	-0.0020	0	0
6	-0.0036	0	0	0.0030	0.0010	0.0019	0.0034	0	0	0.0008	0.0010	0
7	0	0.0024	0	0.0014	0	0.0062	0	0.0007	0	0.0027	0.0014	0
8	0	0.0012	-0.0040	0	0	0.0006	0	0	0	0.0006	0	0
9	0	0.0315	-0.0009	0	0.0032	0	0	0	0	0.0021	0.0009	0
10	0	0	0	0.0007	0	0	0.0150	0	0	0.0007	0.0007	0
11	0	0.0012	0	0	0.0010	0	0.0018	0	0	0	0	0
12	0	0	0	0	0	0	0	0.0023	0	0	0	0
13	0	0	0	0.0156	0	0.0173	0	0	0	0.0023	0.0036	0.0023
14	0	0	-0.2653	0.0014	0	0.0035	0	0	0	0.0063	0.0021	0.0014
15	0	0	-0.0522	0.0032	0.0123	0	0.0073	0.0032	0	0	0	0
16	-0.0010	0	-0.0214	0	0	0.0049	0	0	0	0.0048	0	0
17	-0.0024	0	-0.0450	-0.0016	0.0078	0.0035	-0.0006	0	0	-0.0046	0.0012	0
18	-0.0066	0	-0.0198	0.0051	0.0024	0	0.0016	-0.0078	0.0055	0.0039	0.0041	0
19	0	0	-0.0172	0.0022	0	0	0.0000	-0.0239	0	0.0013	0	0
20	0	0	-0.0365	0	0	0.0038	0.0011	-0.0152	0	0	0	0
21	0	0	-0.0009	0.0014	0.0040	0	0	0.0014	0	0.0076	0	0
22	0	0	-0.0094	0.0626	0	0	0	0.0174	0	0.0000	0	0.0087
23	-0.0017	0	-0.0051	0.0068	0	0	-0.0017	0.0051	0	0.0017	0.0034	0.0068
24	0	0	-0.0235	0	0	0	0	0	0	0	0	0

DDII-Aruba

Step 1: Monthly scores. To construct monthly DDII-Aruba scores out of category scores, all category scores for each period were summed up and divided by a number of categories, i.e. 12:

$S_t = (\sum_{j=1}^{12} C_t^{\,j})/12$, where $C_t^{\,j}$ - is a news score in category j in month t.

The division by the same number does not affect the comparative dynamics of scores; however, it makes easier to compare results from different DDII construction projects when removal or addition of the categories is required. If, for example, another content analysis project requires a wider category set, the resulting DDII indices will be on the same scale.

Step 2: Applying "memory" feature. In August 2005, the number of articles decreased from 25 to 9; however, the topic remained in the news for almost the whole year after the incident. Since images do not change at once (Gartner, 1993), it was hypothesized that images have "memory," i.e. destination images that news evokes stay in the readers' memory for some time. Thus, it was proposed that DDII for a certain month *t* is a weighted average of the DDII(t) for this month, DDII(t-1) for the previous month with some coefficient k1, which is smaller than 1.0, DDII(t-2) from two months ago with even smaller coefficient k2, and so on. Two DDII graphs with memory feature – the one which goes two months back (k1=0.5 and k2=0.25) and the other which goes four months back (k1=0.8; k2=0.6; k3=0.4; k4=0.2) were constructed. Coefficients were arbitrary chosen.

Step 3: Transforming the DDII to a more convenient numerical range. In the process of constructing the DDII, the following proposition was accepted: the image of a destination which seldom appears in the news cannot be estimated. Therefore, it was proposed that if the combined monthly score S(t) for a particular period is smaller than a certain, arbitrary chosen number, that score does not affect the image. To somehow rationalize that arbitrary number, the following reasoning was applied. Let us suggest that for a whole month there was only one reference to Aruba in the news sample. Its input in the monthly DDII score, on average, would be 1/704=0.00142, since the average article length is 704 words. If we divide this value by 12 (the number of categories for Aruba), we will obtain the value which is approximately 0.0001. Therefore, we can consider this and the smaller values as zeros, claiming that one reference or less does not count. With this in mind, the following transformation was applied to the combined monthly scores:

$DDII_t$=SIGN(S_t)*MAX(1,ABS(S_t)*10000), where S_t is a combined monthly score for period t.

By applying this transformation, the DDII values are brought to a more convenient numerical range: the absolute values of all $DDII_t$ scores became 1.0 or larger. The value $DDII_t = 1$ is obtained when the combined monthly score $S_t = 0.0001$ or smaller.

Step 4: Logarithmic transformation of monthly scores. The logarithmic transformation on the values obtained at Step 3 of the procedure was carried out:

$\log DDII_t$=SIGN($DDII_t$)*LOG(ABS($DDII_t$),10), where $DDII_t$ are monthly DDII scores.

The logarithmic transformation has the following interpretation:

- The transformation returns positive values for positive $DDII_t$ (prevalence of positive news about the destination for a given period t) and negative values for negative $DDII_t$ (prevalence of unfavorable news). It should be noted that the log function is applied to absolute values of $DDII_t$ which are equal or greater than 1, see Step 3 of the procedure. The SIGN transformation is applied to account for favorability of the news.
- The transformation returns zero values when $DDII_t = 1$, i.e. when the combined monthly score S is 0.0001 or smaller (very few mentions about the destination during the period and/or few articles during the period.
- The base of 10 for the log transformation was chosen for easier interpretation and comparisons of different DDII values. Based on the properties of the logarithmic function, DDII value with $\log DDII = 2$, is 10 times greater than when $\log DDII = 1$, and 100 times greater when $\log DDII = 0$.

- According to our estimates, low-interest topics will have $\log DDII$ between -1 and 1, moderately popular topics will have $\log DDII$ around -2 or 2, and extremely popular topics will have $\log DDII$ ~3 or higher in absolute values. Thus, negative press about the disappearance of Natalee Holloway should be classified as a topic of moderate coverage. However, considering that before the incident DDII-Aruba was low, the surge in visibility is significant.

Figure 1 illustrates the log-transformed DDII with and without "memory" feature. Series with "no memory feature, two- and four months back memory feature are called ddii, ddii2, and ddii4, respectively. The obtained DDII clearly reflects the surge in negative media coverage of Aruba in connection with the disappearance of Natalee Holloway on May 30, 2005. The curve with the longer memory feature is smoother.

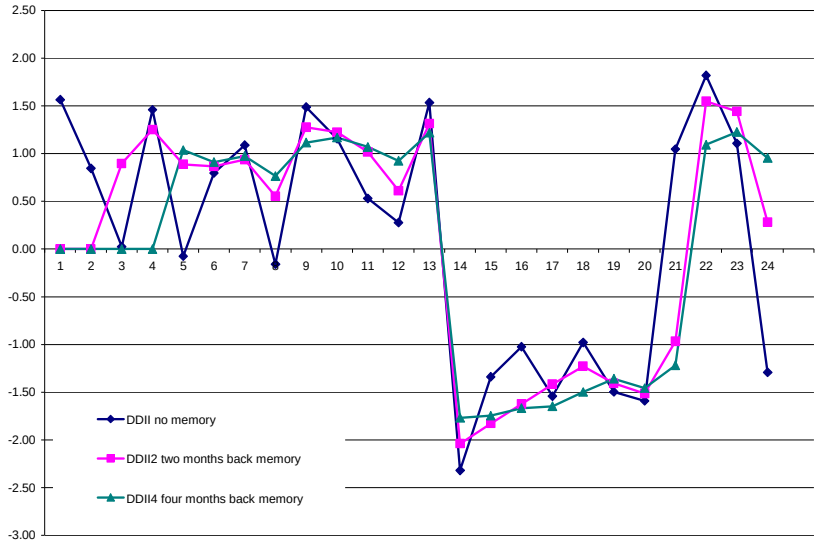

Figure 1. Log-transformed DDII with and without "memory" feature

VALIDATION

In constructing the DDII-Aruba, several arbitrary decisions were applied to the frequency data obtained in the coding process. Therefore, it was decided to validate the index using a simple regression model in order to see whether the DDII is a significant factor in explaining total arrivals to Aruba. Arrivals to Aruba were used as the dependent variable, and total arrivals to Bonaire and Curacao combined as the independent variable. Aruba, Bonaire, and Curacao are the three Caribbean islands which are known as the ABC islands. The islands are very similar in geographical location, as well as historical, political, and cultural heritage. They are situated very favorably, far from the hurricane belt in the Southern Caribbean and experience pleasant weather year-round. Aruba, Bonaire, and Curacao belong to the Netherlands, and the level of economic development of the islands is also similar. The main markets for the ABC islands are the U.S., The Netherlands, and Venezuela. In 2007, American tourists accounted for 67 %, 43%, and 15% of total arrivals to Aruba, Bonaire and Curacao respectively (as calculated from the data found at www.onecarribean.org). It was reasoned that the combined arrivals to Bonaire and Curacao would serve as an approximation of all economic and other factors which would normally be used in a traditional econometric

model to explain arrivals to Aruba. Thus, if the DDII would come as a significant factor in explaining the total variance in the regression model for arrivals to Aruba, it would be an indication that the index reflects the perceptions of potential visitors about the Aruba destination.

Table 2
Modeling arrivals to Aruba: Model comparisons

Base Model: laruba=lboncur	DF	SS	MS	F	p-value	R^2/Adj R^2
Model	1	0.107	0.107	15.75	0.0007	0.42/ 0.39
Error	22	0.149	0.007			
Corrected Total	23	0.256	0.256			
	PE	SE	t-value	p-value	VIF	Durbin-Watson
intercept	5.18	1.47	3.53	0.0019	0	0.972
lboncur	0.58	0.15	3.97	0.0007	1.00	
DDII No Memory Model	DF	SS	MS	F	p-value	R^2/Adj R^2
Model	3	0.153	0.051	24.77	<0.0001	0.83/0.80
Error	15	0.031	0.002			
Corrected Total	18	0.185				
	PE	SE	t-value	p-value	VIF	Durbin-Watson
intercept	4.27	1.08	3.93	0.0013	0	1.664
lboncur	0.67	0.11	6.22	<0.0001	1.24	
ddii (lagged 3 periods)	0.03	0.01	3.03	0.0084	1.26	
ddii (lagged 5 periods)	0.04	0.01	4.06	0.0010	1.46	
DDII 2-Month Memory Model	DF	SS	MS	F	p-value	R^2/Adj R^2
Model	3	0.147	0.049	18	<0.0001	0.81/0.76
Error	13	0.035	0.003			
Corrected Total	16	0.183				
	PE	SE	t-value	p-value	VIF	Durbin-Watson
intercept	4.21	1.29	3.26	0.0062	0	1.826
lboncur	0.67	0.13	5.27	0.0002	1.33	
ddii2 (lagged 3 periods)	0.03	0.01	2.17	0.0492	2.04	
ddii2 (lagged 5 periods)	0.03	0.02	2.16	0.0503	2.42	
DDII 4-Month Memory Model	DF	SS	MS	F	p-value	R^2/Adj R^2
Model	3	0.138	0.046	14.14	0.0004	0.79/0.74
Error	11	0.036	0.003			
Corrected Total	14	0.174				
	PE	SE	t-value	p-value	VIF	Durbin-Watson
intercept	4.19	1.49	2.81	0.0170	0	1.735
lboncur	0.68	0.15	4.59	0.0008	1.48	
ddii4 (lagged 3 periods)	0.04	0.02	2.05	0.0645	2.30	
ddii4 (lagged 3 periods)	0.03	0.02	1.50	0.1612	2.90	

The data on arrivals to Aruba, Bonaire, and Curacao (in thousands of visitors) were collected from the official website of the Caribbean Tourism Organization (www.onecaribbean.org). The arrival figures to Bonaire and Curacao were added up. The logarithmic transformation was applied to the Aruba arrivals (variable laruba) and combined arrivals to Bonaire and Curacao (variable lboncur) on the grounds that (1) DDII-Aruba is a logarithmic

transformation of the frequency data and (2) log-log models perform better than models in a non-log-transformed form for the Aruba data (Croes & Vanegas, 2004). Each of the three unrestricted models was separately tested with the non-lagged and lagged DDII series. The DDII variables lagged two, three, and five periods came significant in each of the three models. It was noted that models which simultaneously included two DDII variables were also an improvement of the base model. Table 2 provides comparisons between the base model and three unrestricted models using the DDII, DDII2, and DDII4 series as independent variables.

DISCUSSION

Quantification of media messages is a central part of constructing the DDII series. In constructing the DDII-Aruba, several content analysis techniques have been considered and/or applied. The length of the article was used to decide on the "weight" of each reference in DDII. To account for changes in amount of media coverage in certain months, a "visibility score" has been defined as the number of articles per month divided by the average number of articles per month. However, since all articles in the sample were coded and every single reference counted, DDII index automatically reflected the amount of media coverage for each particular month; therefore, the visibility score was not applied to the data. In larger content analysis projects, a visibility score can be applied when only a certain number of articles per period are coded. A coefficient to account for whether the words "Aruba" or "Aruban" were used in headlines was also considered, but the idea was rejected. It was rationalized that while the articles with the words "Aruba" or "Aruban" in headlines were definitely more influential, their influence was automatically incorporated into the index, since such articles generally had more references to the Aruba destination, and, thus, their total contribution in the DDII was "heavier." "Memory" feature was defined and incorporated into the DDII as well on the grounds that it takes time for images to change. Finally, several transformations were applied to the DDII monthly scores in order to bring the index to a more interpretable and comparable scale.

The feasibility of the obtained DDII was tested using regression analysis of the total arrivals to Aruba. Three models including the DDII-Aruba (no memory, 2-months back memory, and 4-months back memory) were compared to the base model which used combined arrivals to Bonaire and Curacao as a single predictor. Since the ABC islands share many geographical and socio-economic characteristics, it was reasoned that arrivals to the other two islands indirectly incorporate traditional econometric variables such as price, exchange rate, transportation costs, and income, which would help explain arrivals to Aruba. The results confirmed feasibility of the DDII: all three models with the DDII were significantly better than the base model, which reduces the probability that the validation result is due to chance. The fact that the DDII with different lag structure improve the model strengthens the argument that the DDII is not only a feasible measure of how a destination is covered in general media in terms of the amount of material and its favorability but also that DDII affects decision-making behavior of potential tourists. However, more research is needed to investigate the optimal lag structure for demand models involving DDII indices.

Twelve standardized news categories were identified for Aruba. There is a question with respect to these categories: Are news that belong to different categories equally important for the image? This question has very much in common with the question about importance of destination attributes. While there have been a number of studies about importance of destination attributes (e.g., O'Leary & Deegan, 2005; Zhang & Chow, 2004), a universal answer has not been obtained. Such studies are often destination specific and, therefore, rank attributes in importance with regard to a particular destination. In the absence of clear methodological indications about importance of destination attributes, the constructed DDII does not differentiate between the categories in terms of "importance" of their individual input. Exploration whether categories comprising the DDII should be weighted based on their importance for the potential travelers is one of the directions of future research.

One of the research limitations was using only one researcher for coding the media materials. Thus, reliability of category coding, as well as favorability assessment, was not estimated. Since the main objective of the

Aruba study was to demonstrate the method itself rather than to obtain a reliable DDII-Aruba, such a "short-cut" in the investigation was accepted. Nevertheless, the reliability issue in constructing the DDII is a very important one. There are serious theoretical considerations, in general, regarding favorability assessment in content analysis studies. Reliability, or inter-coder agreement, for "directional" content analysis (favorable-unfavorable distinction is considered "directional") is generally lower than for "standard" content analysis, e.g., when issues are classified into pre-specified categories (Lasswell et al., 1965). With this point in mind, two-point favorability scale (favorable-unfavorable) and three-point standard scale (favorable-neutral-unfavorable) need to be comparatively evaluated for the studies which involve construction of the DDII. Since neutral references do not add to the index, should categories with most neural references be excluded from the coding process altogether? Or, can all neutral references be considered as favorable and added to a total category score? It can be argued that every reference to a destination, unless it is negative, reminds about that destination and, from this angle, is favorable. This question needs more investigation.

For constructing DDII-Aruba, this study used newspaper materials. As Gartner (1993) argues, more credible agents are those that do not have a vested interest in promoting a destination, i.e., general newspapers, mass-media broadcast news, television programs, documentaries, travel guides, books, as well as word of mouth, which are collectively referred to as organic information sources. More research is needed to understand what media sources better reflect destination images and, therefore, more appropriate for constructing DDII indices. Destination marketing organizations (DMOs) may be interested in the DDII instrument, since summarizing materials from Internet travel forums and blogs in a form of DDII series can help them monitor how visitors describe the destination, whether frequency and favorability of mention increase or decrease and whether images that the DMO wants to transmit are "catching up." However, practical relevance of the DDII for destinations' DMOs can be jeopardized by a time-consuming process of constructing the DDII series. Among the factors that can slow down the adoption of the approach is absence of readily available standardized categories for coding that would be suitable for each and every destination-market pair of countries. The fact that the coding process is done "by hand" is another factor that can prevent adoption of the DDII concept. Therefore, feasibility of computer-assisted methodology for constructing DDII series is an important issue to investigate.

To summarize, the study proposes a methodology to quantify media messages in a form of time series, or DDII indices. The DDII indices are constructed using content analysis of qualitative data and reflect volumes and topics of news published about the destination in a particular country and favorability of coverage. The DDII index can be obtained for any origin/destination pair of countries in the form of weekly, monthly, quarterly, or annual time series. The proposed DDII has a potential to represent a qualitative factor of destination image in modeling and forecasting tourism demand as well as monitoring the image in different target markets and assessing the effectiveness of the promotional campaigns.

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