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Assessing the Association of Popular Attractions with Taiwan's Inbound Tourist Numbers: The Case of Night-Market Keywords

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Abstract

This study examines the relationship between Taiwan's most popular attractions and inbound tourist arrivals, using night-market–related keywords as a case in point. Leveraging high-frequency Google Trends data, we use search intensity for night-market keywords to forecast lower-frequency inbound arrivals, with the aim of improving prediction accuracy by exploiting timely information. We construct a composite night-market search index via principal component analysis (PCA) and assess its interrelationship with inbound arrivals to identify which keywords are most closely associated with tourism demand. The contributions are threefold: (1) the empirical results robustly show that inbound tourist arrivals are significantly affected by night-market keyword searches; (2) the statistically significant keyword "Shilin Night Market" aligns with actual search behavior, confirming its prominence among international visitors; and (3) to our knowledge, this is the first study to directly analyze the effect of night-market－related online search activity on inbound tourism to Taiwan, thereby filling a gap in the literature. Our findings also reflect the policy context in which night-market branding has been promoted by local governments and private initiatives over the past two decades, suggesting that place-based tourism marketing has effectively stimulated inbound demand and, in turn, intensified related search activity.

JEL classification numbers: C32, M31, R11.
Keywords: Google trends, Inbound tourist arrivals, Night-market keywords, Principal component analysis, Vector autoregression.

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1. Introduction

As an island economy with abundant coastal and geomorphological resources and distinctive cultural assets, Taiwan attracts substantial numbers of international visitors. According to the 2021 survey conducted by Taiwan's Tourism Administration, the most frequently visited sites were night markets (42 visits per 100 respondents), followed by Taipei 101 (14), Ximending (11), Tamsui (11), Yangmingshan (8), and Beitou (7). Notably, both the 2019 and 2021 surveys list night markets, Taipei 101, and Ximending as the top three attractions. Long-run statistics indicate that over 70% of inbound visitors include night markets in their itineraries, with Shilin Night Market the most visited (8 per 100), followed by Raohe Street Night Market (7 per 100). Night markets combine local street-food culture with leisure and shopping, and several (e.g., Shilin in Taipei and Ruifeng in Kaohsiung) have become internationally recognized destinations drawing diverse age groups.

Night-market promotion has been actively pursued through public and private marketing. Internationally, local governments have showcased night-market culture in destination campaigns, enhancing awareness among potential visitors. Domestically, initiatives have included city-level branding and, during the COVID-19 period, consumption-voucher programs to revitalize night-market economies; Hualien's Dongdamen Night Market has also received recognition for service quality, with media exposure (e.g., Korean variety programs and visits by international celebrities) further elevating its profile. Motivated by these observations and by the increasing use of big-data indicators in tourism research, this study investigates whether real-time online search activity for night-market keywords—an observable proxy for visitor interest—helps explain and forecast inbound arrivals to Taiwan.

Relative to prior Google Trends–based tourism studies, this paper focuses on a specific class of culturally salient attractions—night markets—and directly evaluates how their online search intensity relates to inbound tourism at the destination level. Our contributions are threefold: (1) we address a gap by analyzing the impact of night-market keyword searches on inbound arrivals; (2) we document a robust, bidirectional association between night-market search activity and inbound demand, and pinpoint which keywords most effectively signal increases in arrivals; and (3) we show that "Shilin Night Market" emerges as a statistically significant and practically relevant predictor, consistent with its prominence in actual search behavior. These results underscore the value of incorporating timely, attraction-specific online search data into tourism-demand analytics for Taiwan.

2. Literature Review

The rise of big data has spurred extensive research leveraging online search and social-buzz indicators. A common finding is that high-frequency, web-based measures contain richer and timelier information than conventional low-frequency official statistics, thereby improving the prediction of economic outcomes. Building on this literature, we examine how night-market–related keywords derived from Google Trends relate to inbound tourist arrivals to Taiwan, with the aim of capturing turning points in visitor flows more precisely. Two strands of prior work are especially relevant.

2.1 Nowcasting with Online Search Indicators

The first strand employs high-frequency online search data to nowcast lower-frequency target variables such as GDP, consumption, unemployment, and stock market activity. Early work (e.g., Klein and Park, 1993, 1995) showed that incorporating higher-frequency statistics can alleviate the difficulty of forecasting low-frequency aggregates, proposing a Current Quarter Model for the United States. Askitas and Zimmermann (2009) documented strong correlations between monthly German search intensities and unemployment, demonstrating the predictive content of web activity under complex, evolving conditions. D'Amuri and Marcucci (2010) used Google search intensity for "Jobs," frequency-converted from weekly to monthly and then to quarterly indicators, as a leading signal for U.S. unemployment; their Google Trends -based models outperformed professional benchmarks. Focusing on financial markets, Takeda and Wakao (2014) linked Google Trends queries for Nikkei-related terms to Japanese equity trading, finding search volumes more closely associated with turnover than with prices, suggesting that heightened attention translates into activity rather than directional price changes.

2.2 Tourism Demand, Online Buzz, and Machine Learning

A second strand—closer to our study—integrates online buzz into tourism forecasting, increasingly with machine-learning methods. Matsumoto et al. (2013) analyzed how travel-related searches around the Great East Japan Earthquake affected private consumption. Choi and Varian (2012) showed that Google Trends keywords enhance explanatory power in tourism applications relative to traditional models. Höpken et al. (2020) compared ARIMA with artificial neural networks (ANN), finding that (i) Google Trends captures travelers' online search behavior and significantly improves arrivals forecasts beyond autoregressive baselines, and (ii) ANN outperforms ARIMA. Cebrián and Domenech (2022) assessed Google Trends data quality dimensions and illustrated variability by repeating the same queries across six dates. De Luca and Rosciano (2024) proposed a transfer-function forecasting approach using Google Trends to predict U.S. travel to Italy, offering decision-ready insights for industry stakeholders. Bi et al. (2020) combined multivariate time series—historical visits, search-engine data, and weather—within an LSTM framework to forecast daily attraction visits, showing that adding search and weather improves accuracy. Hu et al. (2022) forecasted Hong Kong inbound visitors from seven English-speaking markets, demonstrating that augmenting traditional time-series models with high-frequency online reviews via a MIDAS specification outperforms competing models. Kulshrestha et al. (2020) introduced a Bayesian BiLSTM for Singapore tourism demand that outperformed LSTM, SVR, RBFNN, and ADLM benchmarks. Law et al. (2019) developed a deep-learning framework for monthly visitor arrivals to Macao, showing substantial gains over SVR and ANN when numerous search-intensity indices are used as demand proxies.

2.3 Construction of Night-Market Keyword Taxonomy

Guided by Taiwan's Tourism Administration and prior studies, we categorize night-market–related keywords by municipality into 17 major groups, further disaggregated into 34 markets (Table 1):

1) *Taipei*: Shilin Night Market; Ningxia Night Market; Raohe Street Night Market.
2) *New Taipei*: Lehua Night Market; Nanya Night Market.
3) *Keelung*: Miaokou Night Market.
4) *Taoyuan*: Zhongyuan Night Market.
5) *Hsinchu*: Cheng Huang Temple Night Market; Zhubei Night Market; Shulintou Night Market.
6) *Miaoli*: Yingcai Night Market.
7) *Taichung*: Feng Chia Night Market; Yizhong Street Night Market.
8) *Changhua*: Jingcheng Night Market; Hemei Night Market; Beidou Night Market.
9) *Nantou*: Strawberry Night Market.
10) *Yunlin*: Douliu Night Market; Huwei Night Market; Xiluo Night Market; Tounan Night Market.
11) *Chiayi*: Wenhua Road Night Market; Dalin Night Market; Chia-Le-Fu Night Market.
12) *Tainan*: Tainan Flowers Night Market; Dadong Night Market; Wusheng Night Market; Xiao Bei Night Market.
13) *Kaohsiung*: Liuhe Tourist Night Market; Ruifeng Night Market.
14) *Pingtung*: Kenting Street.
15) *Taitung*: Taitung Tourism Night Market.
16) *Hualien*: Hualien Dongdamen Night Market.
17) *Yilan*: Yilan East Gate Night Market.

Together, these studies motivate our use of high-frequency online search indicators to construct timely, information-rich predictors of tourism demand, while the curated keyword taxonomy anchors the measurement of night-market–specific interest pertinent to inbound travel to Taiwan.

Table 1: List of night markets by city/county

City/County	Night Market Name	City/County	Night Market Name
Taipei	Shilin Night Market	Yunlin	Douliu Night Market
	Ningxia Night Market		Huwei Night Market
	Raohe Street Night Market		Xiluo Night Market
New Taipei	Lehua Night Market		Tounan Night Market
	Nanya Night Market	Chiayi	Wenhua Road Night Market
Keelung	MiaoKou Night Marke		Dalin Night Market
Taoyuan	Zhongyuan Night Market		Chia-Le-Fu Night Market
Hsinchu	Cheng Huang Temple Night Market	Tainan	Tainan Flowers Night Market
	Zhubei Night Market		Dadong Night Market
	Shulintou Night Market		Wusheng Night Market
Miaoli	Yingcai Night Market		Xiao Bei Night Market
Taichung	Feng Chia Night Market	Kaohsiung	Liuhe Tourist Night Market
	Yizhong Street Night Market		Ruifeng Night Market
Changhua	Jingcheng Night Market	Pingtung	Kenting Street
	Hemei Night Market	Taitung	Taitung Tourism Night Market
	Beidou Night Market	Hualien	Hualien Tungtamen Night Market
Nantou	Strawberry Night Market	Yilan	Yilan East Gate Night Market

3. Empirical Model

This study employs high-frequency keyword data related to Taiwanese night markets to forecast low-frequency annual data on inbound tourism. The keyword data are sourced from Google Trends, starting in January 2008. The empirical analysis focuses on the 2008–2022 period and follows a two-step approach: (1) constructing diffusion indices using principal component analysis (PCA) and (2) applying a vector autoregression (VAR) model to explore dynamic relationships between the diffusion indices and inbound tourist arrivals.

3.1 Step 1: Constructing Diffusion Indices via Principal Component Analysis

To reduce dimensionality and extract common factors from multiple keyword time series, we apply PCA to generate diffusion indices. Let X denote a T×N matrix of N keyword time series over T time periods. We assume a linear relationship:

$$X = F\beta + \varepsilon \tag{1}$$

where F is a $T \times k$ matrix of unobserved common factors (diffusion indices), β is the $k \times N$ factor loading matrix, and ε represents the error term assumed to be white noise. The model assumes that the time series are stationary, and all variables in X are tested for unit roots using the Augmented Dickey-Fuller (ADF) test. Non-stationary series are log-differenced to achieve stationarity.

Estimation follows a two-step procedure. In the first step, F is estimated by extracting the top k eigenvectors of the covariance matrix XX', corresponding to the largest eigenvalues. These eigenvectors represent the diffusion indices that capture the strongest co-movement across the night market keywords. In the second step, we use ordinary least squares (OLS) to estimate the factor loadings:

$$\hat{\beta}_{OLS} = (F'F)^{-1}F'X \tag{2}$$

These diffusion indices are interpreted as composite indicators of night market search intensity, which we refer to as the "Night Market Search Index." Following Stock and Watson (1998, 1999), we denote the estimated components as DF1 to DFn. These indices serve as latent common factors potentially influencing inbound tourism flows.

3.2 Step 2: Vector Autoregression (VAR) Model

The estimated diffusion indices are then incorporated into a vector autoregression (VAR) model to examine their dynamic interaction with inbound tourist arrivals. Although diffusion indices are purely statistical constructs with no explicit causal structure, their temporal patterns can provide insights into the driving forces behind tourism fluctuations.

The VAR model captures the joint dynamics of the form:

$$Z_t = AZ_{t-1} + \varepsilon_t \tag{3}$$

where Z_t includes both the diffusion indices and the inbound tourism variable. This system allows us to assess lead-lag and feedback relationships. Forecasting performance and impulse response functions are used to interpret how shocks to night market keyword indices affect future tourism demand.

Moreover, we decompose the factor loadings to identify which specific keywords have the greatest influence on inbound tourist flows. This step enables a more granular understanding of how online interest in different night markets translates into actual visitor behavior.

Finally, we conduct Wald tests on the VAR coefficients to evaluate model specification and validate dynamic linkages. If the null hypothesis of parameter restrictions is rejected, the model is shown to capture meaningful interactions.

$$\begin{bmatrix} y_t \\ DF1_t \\ DF2_t \\ DF3_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix} + \begin{bmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \beta_6 & \beta_7 & \beta_8 & \beta_9 & \beta_{10} & \beta_{11} & \beta_{12} \\ \beta_{13} & \beta_{14} & \beta_{15} & \beta_{16} & \beta_{17} & \beta_{18} & \beta_{19} & \beta_{20} & \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{25} & \beta_{26} & \beta_{27} & \beta_{28} & \beta_{29} & \beta_{30} & \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} & \beta_{35} & \beta_{36} \\ \beta_{37} & \beta_{38} & \beta_{39} & \beta_{40} & \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} & \beta_{45} & \beta_{46} & \beta_{47} & \beta_{48} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ DF1_{t-1} \\ DF1_{t-2} \\ DF1_{t-3} \\ DF2_{t-1} \\ DF2_{t-2} \\ DF2_{t-3} \\ DF3_{t-1} \\ DF3_{t-2} \\ DF3_{t-3} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{DF1t} \\ \varepsilon_{DF2t} \\ \varepsilon_{DF3t} \end{bmatrix} \quad (4)$$

"The variable y_t denotes the annual number of inbound tourists to Taiwan. The variables $DF1_t$ $DF2_t$ $DF3_t$ are the first three principal diffusion indices derived from annual keyword search data via principal component analysis (PCA), capturing the underlying trends in public interest toward night markets."

4. Data and Empirical Results

4.1 Data and descriptive patterns

We assemble an annual dataset for 2008-2022, the period over which Google Trends is consistently available, linking night-market–related online search activity to Taiwan's inbound tourist arrivals. Chinese-language keywords are sourced from Google Trends; annual arrivals are taken from Taiwan's National Statistics. To align frequencies, keyword indices are aggregated to the calendar year (Table 2 details definitions and sources). Although realized at the annual level for estimation, the Google Trends series originate from higher-frequency, timely web activity, thereby preserving much of the informational advantage emphasized in the literature.

Descriptively, *Feng Chia Night Market* (Taichung) registers the highest search intensity in the sample, followed by *Lehua* (New Taipei), *Shilin* and *Ningxia* plus *Raohe Street* (Taipei), and *Dadong* (Tainan). By municipal grouping, leading searches concentrate in Taichung (Feng Chia), New Taipei (Lehua), Taipei (Shilin/Ningxia/Raohe Street), and Tainan (Dadong), indicating both geographic breadth and persistent prominence of these destinations in online attention (Table 3).

Table 2: Data description

	Variable		**Source**	**Period**	**Frequency**
	Inbound Tourist Arrivals to Taiwan		**National Statistics, Taiwan**	**2008-2022**	**Annual**
Night Market–Related Keywords	Taipei	Shilin Night Market	Google Trends	2008-2022	Annual
		Ningxia Night Market			
		Raohe Street Night Market.			
	New Taipei	Lehua Night Market			
		Nanya Night Market			
	Keelung	MiaoKou Night Market			
	Taoyuan	Zhongyuan Night Market			
	Hsinchu City	Cheng Huang Temple Night Market			
		Zhubei Night Market			
		Shulintou Night Market			
	Miaoli	Yingcai Night Market			
	Taichung	Feng Chia Night Market			
		Yizhong Night Market			
	Changhua	Jingcheng Night Market			
		Hemei Night Market			
		Beidou Night Market			
	Nantou	Strawberry Night Market			
	Yunlin	Douliu Night Market			
		Huwei Night Market			
		Xiluo Night Market			
		Tounan Night Market			
	Chiayi	Wenhua Road Night Market			
		Dalin Night Market			
		Chia-Le-Fu Night Market			
	Tainan	Tainan Flowers Night Market			
		Dadong Night Market			
		Wusheng Night Market			
		Xiao Bei Night Market			
	Kaohsiung	Liuhe Tourist Night Market			
		Ruifeng Night Market			
	Pingtung	Kenting Street			
	Taitung	Taitung Tourism Night Market			
	Hualien	Tungtamen Night Market			
	Yilan	Yilan East Gate Night Market			

Table 3: Search frequency statistics

Night Market–Related Keywords	Mean	Median	Max	Min
Shilin Night Market	524.3	476	957	201
Ningxia Night Market	501	540	824	208
Raohe Street Night Market.	492.2	460	817	130
Lehua Night Market	547.3	565	896	175
Nanya Night Market	362	385	539	115
MiaoKou Night Market	448.1	305	890	126
Zhongyuan Night Market	339.2	339	550	64
Cheng Huang Temple Night Market	42.7	42	95	7
Zhubei Night Market	84.2	95	132	9
Shulintou Night Market	78.5	73	153	14
Yingcai Night Market	38.3	42	78	9
Feng Chia Night Market	668.3	665	995	339
Yizhong Night Market	82.8	86	136	29
Jingcheng Night Market	116.9	131	224	11
Hemei Night Market	50.9	46	133	0
Beidou Night Market	61.6	55	162	20
Strawberry Night Market	48	47	119	21
Douliu Night Market	395.1	474	634	30
Huwei Night Market	68.2	72	128	18
Xiluo Night Market	67.1	76	93	33
Tounan Night Market	22.7	22	53	8
Wenhua Road Night Market	144.1	114	279	45
Dalin Night Market	48.9	46	91	13
Chia-Le-Fu Night Market	53.3	52	73	27
Tainan Flowers Night Market	264.1	238	566	103
Dadong Night Market	494.3	521	788	91
Wusheng Night Market	303.7	334	479	46
Xiao Bei Night Market	100.2	107	147	25
Liuhe Tourist Night Market	265.1	270	442	121
Ruifeng Night Market	475.9	484	740	189
Kenting Street	416.7	415	725	111
Taitung Tourism Night Market	40	39	82	9
Tungtamen Night Market	491.4	437	866	76
Yilan East Gate Night Market	320.6	329	590	25

4.2 Construction of diffusion indices

Table 4 summarizes the principal-component construction of the diffusion indices. Based on the Kaiser (eigenvalue-greater-than-one) criterion, DF3 is the most salient component. The six keywords with the largest absolute factor loadings on DF3 are, in order: Chia-Le-Fu Night Market (Chiayi), Hemei Night Market (Changhua), Xiluo Night Market (Yunlin), Shilin Night Market (Taipei), Douliu Night Market (Yunlin), and Liuhe Tourist Night Market (Kaohsiung). These keywords anchor the DF3 signal and are the principal drivers of its predictive strength for arrivals. Notably, Shilin is both highly loaded in the factor structure and among the most frequently searched markets in the descriptive statistics, aligning the econometric results with observed search behavior.

Table 4: The factor loadings of diffusion indices

	Inbound Tourist Arrivals to Taiwan		
	$DF1$	$DF2$	$DF3$
Components of Diffusion index (keywords)	**Ranking of components (by weight)**		
Shilin Night Market	---	---	*4*
Ningxia Night Market	---	---	
Raohe Street Night Market.	---	---	
Lehua Night Market	---	---	
Nanya Night Market	---	---	
MiaoKou Night Market	---	---	
Zhongyuan Night Market	---	---	
Cheng Huang Temple Night Market	---	---	
Zhubei Night Market	---	---	
Shulintou Night Market	---	---	
Yingcai Night Market	---	---	
Feng Chia Night Market	---	---	
Yizhong Night Market	---	---	
Jingcheng Night Market	---	---	
Hemei Night Market	---	---	*2*
Beidou Night Market	---	---	
Strawberry Night Market	---	---	
Douliu Night Market	---	---	*5*
Huwei Night Market	---	---	
Xiluo Night Market	---	---	*3*
Tounan Night Market	---	---	
Wenhua Road Night Market	---	---	
Dalin Night Market	---	---	
Chia-Le-Fu Night Market	---	---	*1*
Tainan Flowers Night Market	---	---	
Dadong Night Market	---	---	
Wusheng Night Market	---	---	
Xiao Bei Night Market	---	---	

Liuhe Tourist Night Market	---	---	*6*
Ruifeng Night Market	---	---	
Kenting Street	---	---	
Taitung Tourism Night Market	---	---	
Tungtamen Night Market	---	---	
Yilan East Gate Night Market	---	---	
First r eigenvalues of the correlation matrix	7.51	2.38	16.99
Variability explained	0.79		

Note: 1. In Table 4, we choose those diffusion indices having significant effects on dependent variables in VAR tests in Table 5, that's $DF3$. 2. Based on the ranking of components, we conclude the higher-weight variables in bold italics, which are "Chia-Le-Fu, Hemei, Xiluo, Shilin, Douliu, and Liuhe."

4.3 VAR results

Table 5 reports vector autoregression (VAR) estimates. In model 1, the third diffusion index ($DF3$)—constructed from the keyword set via principal components—exhibits statistically significant predictive content for current arrivals Y_t. In Model 2, $DF3_{t-2}$ and $DF3_{t-3}$ are significant predictors of Y_t, indicating that surges in the $DF3$ composite precede increases in inbound arrivals by two to three years. By contrast, we do not find evidence that Y_t helps predict $DF3$, suggesting asymmetric predictability from search intensity to arrivals rather than the reverse.

Table 5 reports the VAR estimates. Across both specifications, DF3 has statistically significant predictive power for current arrivals:

- In Model 2, $DF3_{t-2}$ and $DF3_{t-3}$ are positive and significant, implying that a surge in the $DF3$ attention factor precedes higher inbound arrivals by two to three years.

- We do not find evidence that arrivals Granger-cause $DF3$: lagged Y_t does not significantly predict the $DF3$ index. The direction of predictability therefore runs from online attention to subsequent visitation, not the reverse.

Taken together, these findings indicate that sustained, multi-market shifts in night-market search intensity—summarized by $DF3$—serve as reliable early signals of future inbound tourist flows to Taiwan.

Table 5: VAR results

Model 1		Model 2		Model 3		Model 4	
Coefficient estimates							
$\hat{\alpha}_1$	*2.53*(1.49)*	$\hat{\alpha}_2$	-0.02(0.14)	$\hat{\alpha}_3$	0.04(0.15)	$\hat{\alpha}_4$	0.12(0.18)
$\hat{\beta}_1$	*1.38***(0.27)*	$\hat{\beta}_{13}$	0.0002(0.02)	$\hat{\beta}_{25}$	-0.001(0.03)	$\hat{\beta}_{37}$	-0.05(0.03)
$\hat{\beta}_2$	*-0.84**(0.43)*	$\hat{\beta}_{14}$	-0.03(0.04)	$\hat{\beta}_{26}$	-0.03(0.04)	$\hat{\beta}_{38}$	0.07(0.05)
$\hat{\beta}_3$	0.10(0.28)	$\hat{\beta}_{15}$	0.03(0.03)	$\hat{\beta}_{27}$	0.02(0.03)	$\hat{\beta}_{39}$	-0.03(0.03)
$\hat{\beta}_4$	-1.66(2.40)	$\hat{\beta}_{16}$	0.34(0.22)	$\hat{\beta}_{28}$	0.15(0.23)	$\hat{\beta}_{40}$	-0.12(0.28)
$\hat{\beta}_5$	2.30(2.26)	$\hat{\beta}_{17}$	*0.40*(0.21)*	$\hat{\beta}_{29}$	0.04(0.22)	$\hat{\beta}_{41}$	-0.30(0.27)
$\hat{\beta}_6$	1.19(2.86)	$\hat{\beta}_{18}$	0.20(0.26)	$\hat{\beta}_{30}$	0.34(0.28)	$\hat{\beta}_{42}$	0.02(0.34)
$\hat{\beta}_7$	-4.45(2.97)	$\hat{\beta}_{19}$	-0.19(0.27)	$\hat{\beta}_{31}$	0.22(0.29)	$\hat{\beta}_{43}$	0.19(0.35)
$\hat{\beta}_8$	0.82(2.94)	$\hat{\beta}_{20}$	0.37(0.27)	$\hat{\beta}_{32}$	-0.26(0.29)	$\hat{\beta}_{44}$	-0.001(0.35)
$\hat{\beta}_9$	-0.63(2.71)	$\hat{\beta}_{21}$	-0.44(0.25)	$\hat{\beta}_{33}$	0.06(0.26)	$\hat{\beta}_{45}$	0.02(0.32)
$\hat{\beta}_{10}$	1.01(2.13)	$\hat{\beta}_{22}$	*-0.10*(0.19)*	$\hat{\beta}_{34}$	0.03(0.21)	$\hat{\beta}_{46}$	0.05(0.25)
$\hat{\beta}_{11}$	*-3.92*(2.09)*	$\hat{\beta}_{23}$	0.28(0.19)	$\hat{\beta}_{35}$	0.08(0.20)	$\hat{\beta}_{47}$	0.01(0.25)
$\hat{\beta}_{12}$	*5.30**(2.32)*	$\hat{\beta}_{24}$	-0.26(0.21)	$\hat{\beta}_{36}$	0.36(0.23)	$\hat{\beta}_{48}$	-0.40(0.27)
det (SSE)	0.00005						
AIC	-7.11						
BIC	-4.95						
HQ	-6.37						

Note: 1.Here, the results of the VAR model are presented with its four equations labeled sequentially as Model 1, Model 2, Model 3, and Model 4. The following are the specifications for Models 1 through 4:

Model 1: $Y_t = \hat{\alpha}_1 + \hat{\beta}_1 Y_{t-1} + \hat{\beta}_2 Y_{t-2} + \hat{\beta}_3 Y_{t-3} + \hat{\beta}_4 DF1_{t-1} + \hat{\beta}_5 DF1_{t-2} + \hat{\beta}_6 DF1_{t-3} + \hat{\beta}_7 DF2_{t-1} + \hat{\beta}_8 DF2_{t-2} + \hat{\beta}_9 DF2_{t-3} + \hat{\beta}_{10} DF3_{t-1} + \hat{\beta}_{11} DF3_{t-2} + \hat{\beta}_{12} DF3_{t-3}$

Model 2: $DF1_t = \hat{\alpha}_2 + \hat{\beta}_{13} Y_{t-1} + \hat{\beta}_{14} Y_{t-2} + \hat{\beta}_{15} Y_{t-3} + \hat{\beta}_{16} DF1_{t-1} + \hat{\beta}_{17} DF1_{t-2} + \hat{\beta}_{18} DF1_{t-3} + \hat{\beta}_{19} DF2_{t-1} + \hat{\beta}_{20} DF2_{t-2} + \hat{\beta}_{21} DF2_{t-3} + \hat{\beta}_{22} DF3_{t-1} + \hat{\beta}_{23} DF3_{t-2} + \hat{\beta}_{24} DF3_{t-3}$

Model 3: $DF2_t = \hat{\alpha}_3 + \hat{\beta}_{25} Y_{t-1} + \hat{\beta}_{26} Y_{t-2} + \hat{\beta}_{27} Y_{t-3} + \hat{\beta}_{28} DF1_{t-1} + \hat{\beta}_{29} DF1_{t-2} + \hat{\beta}_{30} DF1_{t-3} + \hat{\beta}_{31} DF2_{t-1} + \hat{\beta}_{32} DF2_{t-2} + \hat{\beta}_{33} DF2_{t-3} + \hat{\beta}_{34} DF3_{t-1} + \hat{\beta}_{35} DF3_{t-2} + \hat{\beta}_{36} DF3_{t-3}$

Model 4: $DF3_t = \hat{\alpha}_4 + \hat{\beta}_{37} Y_{t-1} + \hat{\beta}_{38} Y_{t-2} + \hat{\beta}_{39} Y_{t-3} + \hat{\beta}_{40} DF1_{t-1} + \hat{\beta}_{41} DF1_{t-2} + \hat{\beta}_{42} DF1_{t-3} + \hat{\beta}_{43} DF2_{t-1} + \hat{\beta}_{44} DF2_{t-2} + \hat{\beta}_{45} DF2_{t-3} + \hat{\beta}_{46} DF3_{t-1} + \hat{\beta}_{47} DF3_{t-2} + \hat{\beta}_{48} DF3_{t-3}$

2.The values in parentheses represent standard deviations. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

The $DF3$ drivers—*Chia-Le-Fu*, *Hemei*, *Xiluo*, *Shilin*, *Douliu*, and *Liuhe*—span central and southern Taiwan as well as Taipei, suggesting that predictive attention is not confined to a single metropolitan area. Notably, *Shilin* is both heavily loaded in the factor structure and one of the most searched markets in the search frequency statistics, aligning the econometric signal with observed search behavior and enhancing external validity.

Contextual developments during the sample window plausibly reinforce these patterns (illustrative rather than causal):

- *Shilin* benefited from elevated culinary visibility in international guides and spillovers from nearby cultural infrastructure, raising its global profile.
- *Hemei* lies near Lukang Old Street, where bilingual-service initiatives and heritage branding broadened reach to foreign visitors.
- *Douliu* and *Xiluo* are embedded in a regional tourism bundle (theme-park access, specialty coffee, agro-food heritage), with digital payment adoption and market modernization initiatives improving visitor experience.
- *Chia-Le-Fu* advanced "low-plastic" environmental upgrades consistent with destination quality cues.
- *Liuhe* retained its status as Kaohsiung's flagship night market and a focal point for first-time international visitors.

These place-based narratives are consistent with $DF3$ capturing coordinated attention toward markets that are either systematically promoted, embedded in richer cultural circuits, or continuously amplified by digital media.

4.4 Alignment and non-alignment with raw search leaders

While *Feng Chia* and *Lehua* rank among the top raw searches, their influence does not dominate DF3 once we account for common components across the keyword set. Conversely, markets like Shilin simultaneously appear as raw search leaders and as high-impact DF3 drivers. Such non-one-to-one mapping underscores the value of diffusion indices: they recover shared variation that forecasts arrivals beyond any single headline market.

5. Conclusion

Using annual data for 2008–2022, this study shows that night-market online search intensity—summarized by a diffusion index ($DF3$)—is a statistically significant leading indicator of Taiwan's inbound tourist arrivals, with effects materializing over two to three years. We find no reverse predictability from arrivals to the search-based index, pointing to asymmetric information flow from digital attention to realized visitation. The six $DF3$-defining markets—*Chia-Le-Fu*, *Hemei*, *Xiluo*, *Shilin*, *Douliu*, and *Liuhe*—constitute the core attention cluster that systematically foreshadows inbound flows.

Two broad implications follow. First, monitoring search-based diffusion indices provides destination managers with timely, low-cost signals to anticipate demand and allocate resources (e.g., transport capacity, crowd management, staffing) before peaks materialize. Second, place-based marketing and service readiness matter: markets that invest in heritage storytelling, environmental upgrades, language accessibility, and digital payments are more likely to occupy the high-impact attention cluster that leads arrivals.

At the same time, several legacy commercial districts—despite historical prominence—do not exhibit significant predictive effects in our models. Pandemic-era business exits, rising rents, and comparatively weaker destination marketing likely reduced online buzz and, in turn, dampened subsequent visitation. This heterogeneity highlights concrete policy levers: targeted revitalization of legacy markets, continuous digital promotion (including influencer partnerships and video-first content), and event programming that refreshes destination narratives.

Overall, the results validate online-attention diffusion as a practical, information-rich proxy for tourism demand and provide a scalable template for destination analytics centered on culturally salient marketplaces.

Future research can extend this work by (i) enriching the information set with social-media text and sentiment, video metadata (e.g., YouTube), and mobility traces; and (ii) designing identification strategies to separate marketing interventions from confounders, thereby sharpening causal interpretation.

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