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Consumption of pop culture and tourism demand: Through the lens of herding behaviour

Sungkyu Lim [a], Neelu Seetaram [b,*], Sameer Hosany [a], Matthew Li [a]

[a] School of Business and Management, Royal Holloway, University of London, United Kingdom of Great Britain and Northern Ireland
[b] School of Events, Tourism and Hospitality Management Leeds Beckett University, Headingley Campus, Leeds LS6 3QN, United Kingdom of Great Britain and Northern Ireland

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A B S T R A C T

Herding is a social phenomenon where individuals act collectively as part of a group and make decisions based on the behaviour and choices of others. In this study, we conceptualise herding behaviour on social media via a two-step flow communication model and measured through Google and YouTube search volume. The estimated herding behaviour is used to develop a novel index to measure the online consumption of Korean cultural products. Monthly data between 2013 and 2019 were used to analyse tourist arrivals from 10 countries. Findings confirm that Korean wave, captured by the index, is statistically significant in predicting tourist arrivals. The study provides a generalised proxy of cultural consumption, applicable to other destinations.

Introduction

Various forms of popular culture such as movies, TV shows, and pop music, are used to promote a tourist destination. Beeton (2006) discusses the growth in popularity of New Zealand among travellers after the phenomenal commercial success of the movie 'Lord of the Rings'. The late 1990's marked the start in the export of Korean TV dramas to neighbouring countries. Over the years, the infatuation with Korean popular culture has been extended to include movies, animation, and K-pop music (Hanaki et al., 2007) and this phenomenon is known as the "Korean wave". People who consume South Korean (hereafter Korean) popular culture are more likely to have a positive image of Korea (Huang, 2011; Kim et al., 2008; Lee et al., 2015; Lee & Bai, 2016) and are more likely to visit Korea (Kim et al., 2007). Moreover, the consumption of Korean popular culture reduces cultural distances, increases familiarity and generate positive word of mouth recommendations (Choi et al., 2020). Lee et al. (2018) further show that consumption of Korean popular culture is associated with positive fans' attitudes, emotions, desires, and behaviours resulting in visits to Korea.

In recent years, social media has been instrumental to the remarkable success behind the global consumption of Korean cultural products. South Korean boy's band BTS broke their own record for the fastest viral music video, generating 108.2 million views in the first 24 h of release on YouTube. In addition, eight of the top ten most viewed music videos within 24 h of release on YouTube, are Korean popular songs (Statista, 2021). While the linkages between cultural consumption via traditional media and tourism arrivals are well documented, little is known about the effect of cultural consumption via social media on tourism demand. The widespread use of social media and other digital platforms has provided an enormous opportunity for the consump-

* Corresponding author.
E-mail addresses: sung.lim@rhul.ac.uk (S. Lim), N.Seetaram@LeedsBeckett.ac.uk (N. Seetaram), sameer.hosany@rhul.ac.uk (S. Hosany), matthew.li@rhul.ac.uk (M. Li).

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tion of cultural products online while interacting with other consumers implicitly or explicitly. Online platforms provide an infrastructure for social interaction and enhances connectivity (Bennett & Segerberg, 2012; Bimber et al., 2012) among users. Social media facilitates interconnected engagements and situational formation of non-organized collective behaviour (Dolata & Schrape, 2016) which can be studied through the lens of Herding Theory.

The traditional method of evaluating the effect of consumption of culture among tourists on their choice of destinations use export of cultural product between the home and destination countries as a proxy for cultural proximity/distance (see for example, Petit & Seetaram, 2019). The existing approach, however, fails to take into consideration online consumption of pop culture that does not feature in annual national accounts. The aim of this paper is to examine whether consumption of pop culture from a destination has a bearing on tourist arrivals, taking into consideration both traditional media and online platforms. In this study, we provide a novel method to measure tourists' preferences for the pop culture of a destination.

Our research offers a two-fold contribution to the literature. First, this study assesses whether herding behaviour occurs among Google and YouTube users by estimating the size of herding among them. The estimated size of herding behaviour and export of pop culture is used to develop a novel index to measure consumption of Korean pop culture. The index is then employed to assess the link between consumption of Korean pop culture and travel to Korea. Although developed using data from Korea, the method is replicable for other destinations. The next section provides an overview of the relevant literature. Section 3 explains the methodology related to herding behaviour and underlying calculations. Model development and estimation techniques are covered in Section 4. In the last section, we present the empirical findings and discuss the implications.

Literature review

Herding and tourism

Herding has its origins from psychology and zoology literatures and refers to imitation behaviour (Gibson & Höglund, 1992; Giraldeau, 1997). Imitation is the reproduction of actions, preferences, and reflections observed from earlier movers (Khanna & Mathews, 2011). When imitation results in a collective behaviour of adopting the actions of others, it is characterised as herding (Banerjee, 1992). The theory of herding has been applied in the fields of economics (Bikhchandani et al., 1992) and finance (Lakonishok et al., 1992; Shiller, 2002). Herding is not a short-lived phenomenon and slowly disappears over time (Messis & Zapranis, 2014). The core tenets of herding are that it changes over time and grows in size within the population (Langley et al., 2014). Individuals seek information from others (Park & Lessig, 1977), especially in the decision-making process and often make the same choice as that of a group (Banerjee, 1992).

Recently, herding has appeared in tourism studies to explain family travel decision making (Bae & Yeu, 2022) and choice of restaurent (Ha et al., 2016). Bae and Yeu (2022) note the positive consequences of herding behaviour in travel decision making such as enhanced confidence level, relief and satisfaction. Other studies examine herding behaviour in tourism crowdfunding ventures (Kim & Petrick, 2021) and online reviews of hospitality experiences (Xue et al., 2020). A major limitation of these studies is that herding is conceptualised and measured at the simplistic level in terms of tourists copying the review and opinions of others. For instance, Xue et al. (2020) estimate herding in hotel reviews but their definition of herding is problematic. It is not clear whether hotel reviews reflect collective behaviour or whether the reviews are in fact showing comparable experiences and therefore, while similar, are unrelated. In terms of calculations, Xue et al. (2020) estimate herding by the absolute difference between the posted rating of a consumer and the previous average rating of a hotel. Such approach is relevant for one point in time measurement and therefore, misses out on the two important characteristics of herding, namely time-varying property and growth of the herd in a population.

Benítez-Aurioles (2022) purports to explain demand for peer-to-peer accommodation using herding behaviour in relation to online reviews. Although online reviews are useful in stimulating demand, the effect of additional reviews falls and therefore, the herding effect diminishes. The method applied reveals a dramatic non-linear increase or decrease in the effect of online reviews. Again, while Benítez-Aurioles (2022) demonstrates the relevance of online review in decision making process of the consumer, it does not necessarily show the existence of herding behaviour. Kim and Petrick (2021) investigate herding behaviours among crowd funders in visitor economy sector. Herding was measured using three statements: “I participate in visitor economy crowdfunding because many other funders want to engage in it”, “I follow others in deciding whether or not to contribute to visitor economy crowdfunding”, and “I would invest in visitor economy crowdfunding because many other funders have already contributed to it”. These statements measure the willingness to copy other peoples' behaviour. Actual herding behaviour in crowdfunding is not adequately captured. While this approach subjectively identifies attitudes and behaviours related to herding at one point, it fails to account for changes in such behaviour over time.

Although, the theoretical conceptualisation of herding is potentially useful, to date, applications to study tourist behaviours are problematic because the fundamental properties of herding are largely overlooked. In general, prior studies use herding as a simple behavioural construct of copying others. However, herding behaviour in its most fundamental sense should be associated with growing size of the herd in population, often resulting in mass behaviour. The theorisation of herding in the tourism literature presented above fail to differentiate between attitudes based on other peoples' opinions/recommendations and herding in its purest sense, that is, imitation leading to collective behaviour. The methods applied do not capture intertemporal changes in herding occurring in the population and none of previous studies accurately consider herding that occurs on social media.

Herding and social media

The role and influence of social media on consumer behaviour is well documented in the literature (Erkan & Evans, 2016) and the fundamental driving factor of herding is information seeking. Social media platforms, especially YouTube, allow user engagement through actions such as like, dislike, commenting, sharing, and uploading videos that leads to value co-creation (Brodie et al., 2013). Individuals have their own channels, allowing them to create contents through live streaming and sharing of videos. Susarla et al. (2012) investigate information diffusion between content creator on YouTube and subscribers' network. During the initial stage, newly released video is diffused from content creators (youtuber) to subscribers (first cluster). Information diffusion continues through the first clusters' network to their own subscribers (second cluster) and subsequently, to the third cluster (second clusters' network). This information diffusion process on YouTube is in line with Lazarsfeld et al.'s (1948) two-step flow of communication model.

According to this model, members of society frequently ask opinions of influential people. Initial information is further diffused by opinion leaders who interpret the message, through their personal networks to the public (Katz, 1957). In the context of YouTube, a content creator distributes his/her opinions to the followers, in turn express their reactions through like/dislike, sharing and comments. Moreover, the followers' opinions can stimulate other followers to react. For instance, when influential YouTubers upload their reactions of watching K-pop music videos, this generates a large volume of sharing and cross-comments that provoke collective reactions from followers and other individuals in general (Xu et al., 2016). This communication pattern creates information diffusion of the contents (Xie et al., 2011).

Consumption of popular cultural products by active information seeking individuals and the information diffusion process on social media can be studied using Lazarsfeld et al.'s (1948) model. The model is useful to capture the development of collective behaviour. Feick et al. (1986, p. 302) define opinion seekers as “individuals who sought information or opinions from interpersonal sources in order to find about and evaluate products, services, current affairs, or other areas of interest.” This opinion seeking behaviour is the driving force in the creation of herding. When people interact with the reactions of K-pop videos, they may have their own opinions about the music videos and at the same time can potentially seek more information about K-pop. Seeking information can expand dramatically within the population through the information diffusion potential of YouTube. This represents the process of herding behaviour quite accurately whereby, a herd can develop in size over a very short period (Langley et al., 2014).

Existing measures of Korean wave

Previous studies investigate and measure the impact of Korean wave using either survey methods (e.g. Lee et al., 2015), or by the size of Korean cultural product exports (Chang & Lee, 2017; Lim & Giouvris, 2020). The latter is a more direct measurement of Korean wave. Chang and Lee (2017) capture Korean wave by TV program exports. Physical exports of Korean cultural products have an impact on trade and Foreign direct investment (Chang & Lee, 2017). Lim and Giouvris (2020) also assess the impact of Korean wave using physical cultural exports (TV programs, movies, and music). Lim and Giouvris (2020) developed a proxy of cultural consumption per visitor (CCV). The proxy successfully predicts international tourist arrivals in Korea. Other studies (e.g. Kim et al., 2008; Lee & Bai, 2016) further provide evidence that foreign consumers, frequently watching Korean dramas, movies, and music videos, develop positive images about Korea and have a positive influence on purchasing decisions, including tourism. Existing methods, however, ignore the popularity of social media in propagating culture across the world.

Google trend is a public service providing time series of search activity on Google search engine and YouTube. This metadata can detect real-time public interest of Google and YouTube users across regions. In other words, the overall volume of information seeking activity for a specific interest is captured by Google trend. Several studies adopt Google trend for forecasting tourist arrivals (see for e.g. Bangwayo-Skeete & Skeete, 2015; Sun et al., 2019) and hotel registrations (Rivera, 2016). Park (2015) investigates the impact of Korean wave using Google trend and show that high search volume of Korean drama and music has a statistically significant positive impact on cosmetic exports. However, existing studies associated with the Korean wave omit the collective herding behaviour as an escalating force of the phenomenon. Drawing on Lim and Giouvris (2020) and Park (2015), this paper develops an alternative proxy to capture Korean wave effect combining both consumption of cultural products via traditional and on social media platforms. The new proxy is then used to estimate the effect of the wave on tourism demand in Korea.

Methodology

Sources of data

In this study, we use data on tourist arrivals from Statistics Korea. The sample includes tourist arrivals from 10 countries: Japan, Malaysia, Hong Kong, Singapore, Taiwan, Thailand, Canada, the US, Germany and the UK. These countries are key markets for Korea for which google trend data are available. The selected countries constitute 51 % of total arrivals in Korea. Consumer Confidence Index, Consumer Price Index, financial indices and exchange Rates were retrieved from Datastream. The search volume for Google and YouTube are downloaded from Google trends, and data on exports of cultural products were obtained from Korea Creative Content Agency (KCCA). Data availability from KCCA was the key factor in the selection of countries.

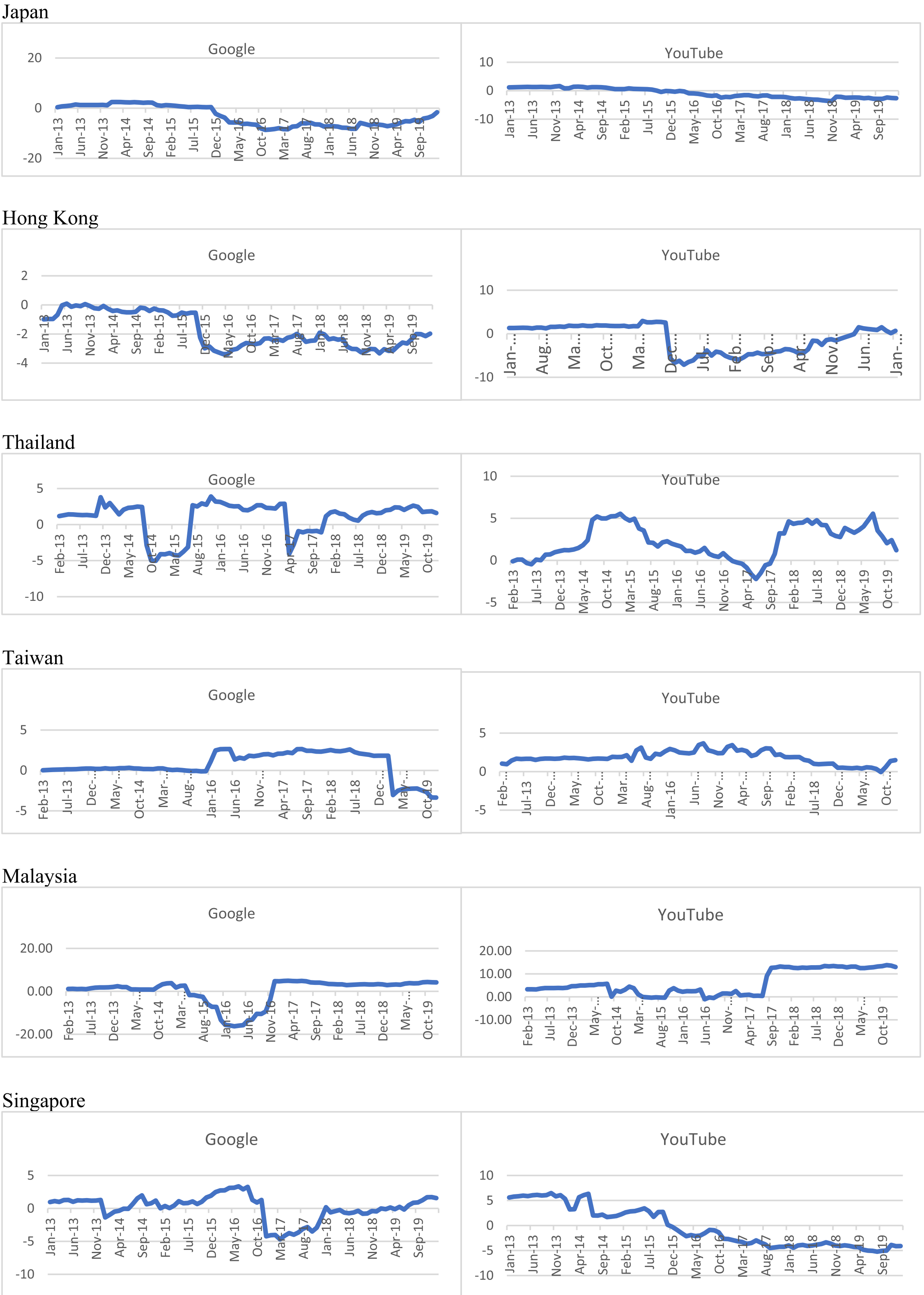


Fig. 1. The Herding coefficient: 60 months rolling window estimation
Note: The herding is estimated using Google search volume and YouTube search volume. A 60 months rolling window method is used for each country. The first window uses the sub-sample between Feb 2008 and Jan 2013 to estimate the herding in Feb 2013. The process is repeated until the last 60 months window (from Dec 2014 to Nov 2019) is covered with a final herding index for Dec 2019. The negative value represents herding behaviour in Korean wave.

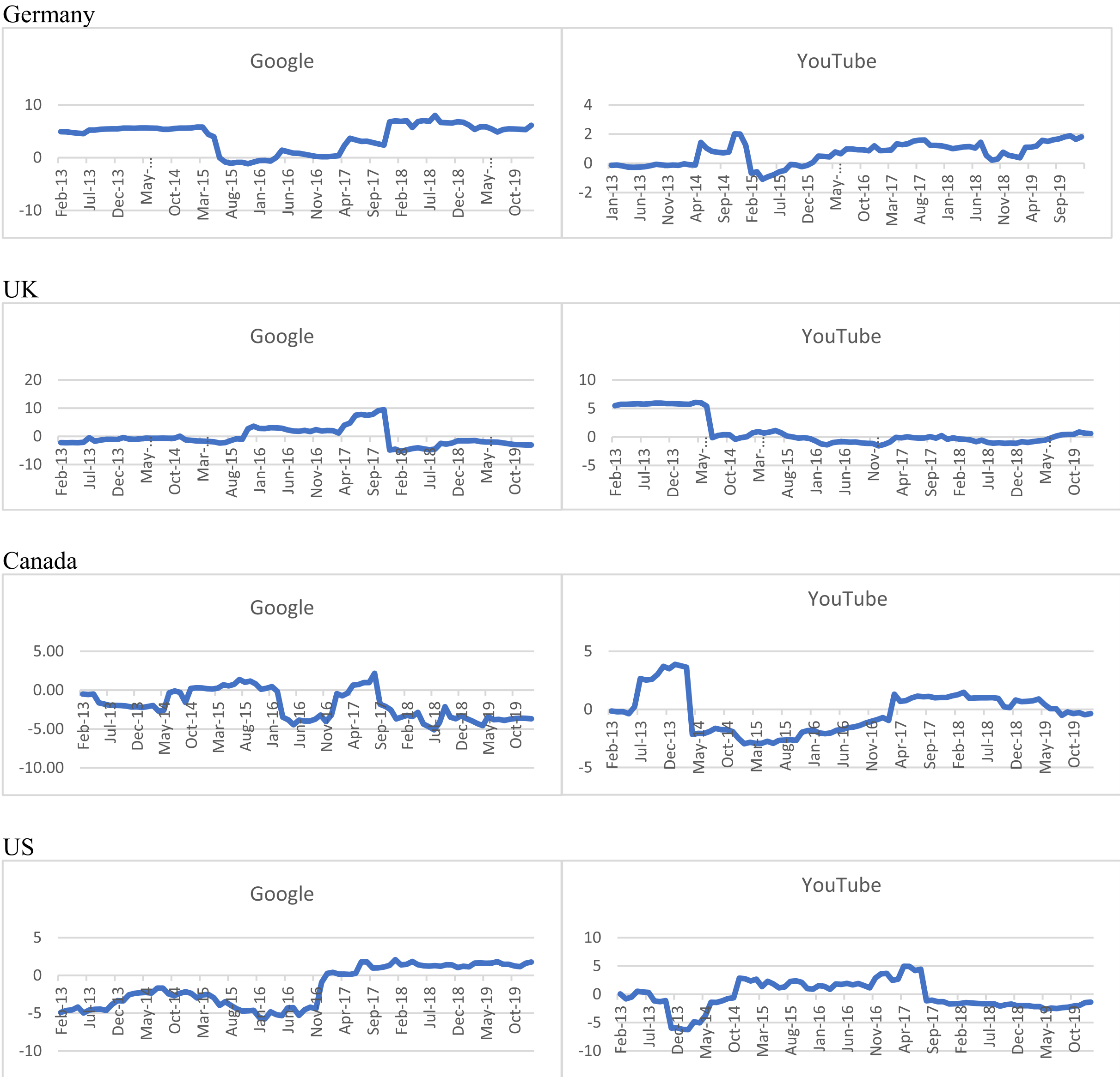


Fig. 1 (*continued*).

Herding behaviour is measured using YouTube and Google search volume between 2008 and 2019. Korean wave has three components - music, drama, and movie. We use the broader search word "K-pop" in English language to adequately capture each dimension. Moreover, Korean major cultural products providers such as SM, YG, JYP Entertainment and Big Hit release their contents using related key words in English on their YouTube channels. Digital communication is an important part of interactions with others. The dominant language in written communication is English as a lingua franca (Androutsopoulos, 2006) and global K-pop fans use English as a form of online interaction (Lee, 2018). Key search words on YouTube and Google were extracted for each country using: "Kpop" + "Korean music" + "Kpop music video" for popular music; "Kdrama" + "K-drama" + "Korean drama" for drama; "Kmovie" + "Korean movie" + "Korean film" for movie. We use double quotation marks to keep words together in our search. The search volume of Korean across the three components of music, drama, and movie, is used to calculate an average of percentage. According to Bokelmann and Lessmann (2019), Google trend data, consisting of search activity on Google and YouTube, is generated as follows:

$$G_{i,r,t} = c_i * \frac{q_{i,r,t}}{Q_{r,t}} \tag{1}$$

where $q_{i,\ r,\ t}$ is a query i, r is a geographical region, t is a time period. $Q_{r,\ t}$ is the total number of searches in the region r at time t. The Google time series is multiplied by a constant c_i to maximise the series at 100.

The study of herding behaviour is well established in economics and finance literatures and commonly draws on Christie and Huang's (1995) 'CH model'. The model requires arbitrary 1 % or 5 % cut off point to define herding behaviour. Chang et al. (2000) propose an alternative model that eliminates the subjective cut off points and incorporate the non-linear nature of herding. The model estimates a cross-sectional absolute deviation as a herd indicator rather than creating direct utilisation of deviation levels that could be potentially ambiguous to interpretate. Accordingly, we draw on Chang et al. (2000) and develop a non-linear regression model for herding behaviour as follows:

$$CSAD_{i,t} = \frac{1}{N}\sum_{i=1}^{N} |V_{i,t} - V_{m,t}| \tag{2}$$

$$CSAD_{i,t} = a_1 + a_2|V_{m,t}| + a_3(V_{m,t})^2 + e_t \tag{3}$$

where $CSAD_{i,\,t}$ is defined as the cross-sectional absolute deviation of the i-th dimension, $V_{i,\,t}$ is the search volume of the i-th dimension of Korean wave at time t, and $V_{m,\,t}$ is the average of the $V_{i,t}{}'$s. If herding is present, a_3 will be negative implying that the level of interest in Korean wave is closely correlated with the opinion of others. When there is no herding behaviour, the dispersion in cross-sectional search volume will increase, indicating individual interests do not result in collective behaviour. Herding from Google search (hereafter GHD) and YouTube search (hereafter YHD) are considered. We adopt Stavroyiannis and Babalos (2019) rolling window regression technique to capture the time varying properties of herding behaviour. The rolling window regression is a recursive method that use subsamples by shifting the start and end points.

In our study, the subsample size of the window is determined by the time varying nature of herding behaviour. Herding is not a short-lived phenomenon but appears abruptly and disappears slowly (Hwang & Salmon, 2009). Kumar (2021) suggests that for high frequency daily data, a short window is desirable, while for lower frequency data, a longer rolling window is needed. Therefore, consistent with Messis and Zapranis (2014), our study adopts a 60-months rolling window with the first subsample between Feb 2008 and Jan 2013 to calculate the herding index for Feb 2013. The process is repeated until the last 60 months window (from Dec 2014 to Nov 2019) is covered with a final herding index for Dec 2019. The sample period for the herding index (between 2013 and 2019) was the basis for the selection period for all the other variables in this study.

Fig. 1 presents coefficients of $(V_{m,\,t})^2$ in Eq. (3) and a negative value indicates herding behaviour. Most of the Asian countries exhibit herding behaviour on both platforms while we observe herding on Google only from Malaysia and Taiwan. For the western countries, herding is present on both YouTube and Google. Fig. 1 confirms the time varying properties of herding, and the patterns are different in each country.

The strength of herding behaviour on YouTube is stronger and persistent compared to Google in Singapore and Canada. Hong Kong shows similar strength of herding across Google and YouTube. However, Google herding in Japan, Thailand, Malaysia, the UK, and the US is substantially stronger. Next, we examine the causal relationship between Google and YouTube herding. Table 1 shows the results from granger causality tests and one period lagged causal impact between Google and YouTube, denoted as GHD1 and YHD1. Noticeably, Japan shows a unidirectional causality from YHD to GHD and bidirectional causal relationship between one period lagged and current herding. It implies that the main consumers of Korean popular cultural products in Japan are actively searching on both Google and YouTube. More importantly, previous and current herding behaviour on YouTube can increase consumption and create herding on Google. There is also a causal impact of YouTube herding on Google herding in Thailand, and Germany. People are potentially influenced by contents creators on YouTube as opinion leaders and engage in further information search on Google. Finally, Hong Kong and the US receive a unidirectional causal impact from YouTube to Google. Overall, the popularity of Korean pop culture has been on the rise around the world and people are influenced by frequent media

Table 1
Granger causality test between herding of Google and YouTube.

	YHD↛GHD	GHD↛YHD	YHD t-1↛GHD	GHD t-1↛YHD
Japan	**2.53 (0.08)**	2.05 (0.14)	**2.49 (0.08)**	**2.47 (0.09)**
Hong Kong	**5.28 (0.02)**	**35.0 (0.00)**	0.45 (0.51)	0.06 (0.80)
Singapore	0.01 (0.99)	0.88 (0.42)	0.25 (0.78)	0.83 (0.44)
Taiwan	0.09 (0.91)	0.48 (0.62)	2.05 (0.14)	0.12 (0.89)
Thailand	**0.87 (0.06)**	0.47 (0.62)	2.36 (0.10)	0.001 (0.99)
Malaysia	0.24 (0.79)	0.27 (0.76)	0.32 (0.83)	0.15 (0.88)
UK	0.19 (0.82)	0.12 (0.88)	0.09 (0.91)	0.03 (0.97)
US	**1.85 (0.08)**	**4.87 (0.00)**	0.36 (0.95)	**4.78 (0.00)**
Canada	1.05 (0.39)	0.18 (0.95)	**2.11 (0.08)**	0.09 (0.98)
Germany	**2.69 (0.04)**	0.24 (0.91)	**2.38 (0.06)**	0.25 (0.90)

Notes: the table shows results off the Granger causality test. YHD is herding from YouTube search volume, GHD is herding from Google search volume. GHD t-1 and YHD t-1 indicate one month lag of Google and YouTube herding respectively.
Statistically significant coefficients are highlighted in bold.

exposure through YouTube. Thus, media exposure increases public interests and results in herding behaviour on YouTube and then expands to Google search.

Other countries such as Singapore, Taiwan, Malaysia, and the UK do not display any causal relationship between Google and YouTube herding. People in these countries are using Google and YouTube as separate search tools. After estimating the online herding behaviour, we develop an alternative proxy to capture the Korean Wave Effect (hereafter KWE). To date, total export of Korean cultural products remains the most common proxy. This proxy is stable and increase over time. However, public interests in cultural products are time varying and can be long-term, mid-term or short-term. To accurately estimate the impact of Korean wave, total export of Korean cultural products should consider the herding phenomenon. Therefore, we multiply the KWE variable by the estimated herding coefficient. The adjustment made to capture herding is defined as Korean Wave Effect from Google (hereafter KWEG) and Korean Wave Effect from YouTube (hereafter KWEY). The proxies (KWEG and KWEY) are more stable than YHD and GHD index and are hypothesised to have an impact on tourist arrivals.

Other control variables

We included four control variables. Sentiment is captured by consumer confidence index (CCI) and mood by stock market index (MOOD). Sentiment and mood are important determinants of consumption (Ludvigson, 2004). Consumer confidence index and mood are key economic indicators, representing confidence level in current and future financial and economic prospects (Bock et al., 2014). Prior studies identify a positive relationship between CCI, mood and consumer spending (e.g. Croce, 2016; Dragouni et al., 2016; Lim & Giouvris, 2020). Therefore, favourable CCI and mood of tourists have a direct link to tourism demand and holiday spending. CCI is not available for Hong Kong, Malaysia, and Singapore. The mean value of CCI is negative for all countries except Germany (Table 2). When countries have a negative mean value for CCI, the impact on tourist arrivals in Korea from these countries is negative. Since a positive CCI mean value is observed for most countries, overall, the impact on tourist arrivals is positive. For MOOD, a positive mean value is detected for all countries, but the magnitude is small.

Relative Consumer Price Index (RCPI) is used to control for prices. Consistent with Seetaram (2010), relative CPI is calculated as follows:

$$RCPI_{i,t} = \frac{CPI_{k,t}}{CPI_{i,t}} \tag{4}$$

where $RCPI_{i,\ t}$ and $CPI_{i,\ t}$ are the relative CPI for country i at time t and CPI for country i at time t respectively. The i indicates countries in our sample including Japan, Hong Kong, Singapore, Malaysia, Taiwan, the UK, Germany, the US, and Canada. $CPI_{k,\ t}$ represents CPI of Korea at time t. Table 2 summarises the statistics for RCPI across the ten countries. The mean value of the ratios is lower than 1 for all countries implying that price level from the countries in our sample is higher than Korea. It could be an attractive factor to visit Korea. EX is the exchange rate that origin countries' currency converted into Korean won (see Table 2). The prevailing exchange rate is an important tourism demand determinant (Seetaram, 2010). From Table 2, countries show negative mean value of percentage changes in exchange rate, except for Hong Kong, Taiwan, Thailand and the US, implying that the value of Korean won has appreciated during the sample period. Data for all control variables were obtained from Datastream.

Modelling tourist arrivals in Korea

Unit root tests

Before performing regression analysis, it is imperative to test for stationarity. The Augmented Dickey-Fuller test is performed for all variables and reported in Table 3. The variables are all in first difference and statistically significant at the conventional level, providing evidence of stationarity. We further tested for seasonality effects associated with visitor per capita using a trend variable as dummy. Results indicate that the trend variable is statistically not significant for all countries, confirming that the absence of seasonality effect.

VAR model

Vector Autoregressive Regression (hereafter VAR) (Sims, 1980) is an effective and flexible technique to analyse multivariate time series via the use of a single econometric model. The key structure of a VAR model embraces current observations of a variable with its past observations and include other variables as regressors, thus capturing the potential dynamic inter-relationship. The incorporation of latent information allows a more accurate reflection of real-world behaviour. VAR has been successfully applied to model tourism demand (see for e.g. Song & Witt, 2006; Gounopoulos et al., 2012; Gunter & Önder, 2015).

In this paper, to examine the dynamic relationship between tourist arrivals and various determinants, we apply the following VAR(p) model:

$$Y_t = A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + CX_t + u_t \tag{5}$$

Table 2
Descriptive statistics.

	KWEG	GHD	KWEY	YHD	RCPI	CCI	MOOD	EX	VISIT
Japan									
Mean	−0.0001	−0.004	0.0002	−0.004	−0.004	−0.983	−0.0003	−0.0007	−0.0008
S·D	0.079	0.064	0.055	0.029	1.640	2.366	0.064	0.030	0.390
Max	0.283	0.236	0.159	0.153	10.453	6.052	0.186	0.106	1.010
Min	−0.272	−0.265	−0.176	−0.080	−6.518	−9.737	−0.151	−0.066	−1.024
Hong Kong									
Mean	0.0002	−0.001	0.0007	−0.001	0.046		1.232	0.001	−0.003
S·D	0.653	0.028	0.674	0.105	2.076		17.818	0.023	0.694
Max	3.998	0.065	4.049	0.199	11.526		121.39	0.047	3.792
Min	−4.033	−0.170	−4.071	−0.814	−13.234		−56.495	−0.064	−2.796
Malaysia									
Mean	1.01E-05	0.0004	3.1E-05	0.001	0.466		−0.906	−2.38E-03	0.0004
S·D	0.129	0.016	0.126	0.014	2.317		7.174	0.021	0.499
Max	0.665	0.084	0.659	0.086	14.61		47.98	0.058	1.234
Min	−0.668	−0.061	−0.657	−0.056	−2.624		−31.25	−0.070	−1.035
Singapore									
Mean	0.0002	0.007	0.0007	−0.120	0.514		−0.763	−0.0001	0.004
S·D	0.232	0.858	0.311	0.764	2.897		4.404	0.016	0.718
Max	0.907	1.688	1.257	2.376	21.287		32.072	0.045	1.498
Min	−0.903	−5.505	−1.179	−4.331	−8.147		−7.911	−0.031	−1.486
Taiwan									
Mean	4.64E-05	−0.004	−0.0003	0.0007	−0.424	−1.284	0.258	0.0009	−0.0005
S·D	0.139	0.061	0.102	0.039	5.072	3.562	8.261	0.016	0.315
Max	0.596	0.137	0.305	0.135	12.822	5.825	57.984	0.038	1.926
Min	−0.637	−0.487	−0.306	−0.129	−35.695	−15.928	−15.723	−0.041	−0.784
Thailand									
Mean	0.0006	0.0004	0.002	0.001	0.003	−0.0002	−0.0002	0.033	−0.002
S·D	0.245	0.133	0.164	0.068	9.269	0.018	0.049	0.699	0.446
Max	0.981	0.579	0.595	0.244	51.965	0.069	0.159	1.648	1.102
Min	−1.074	−0.696	−0.364	−0.199	−58.231	−0.041	−0.092	−1.844	−1.393
UK									
Mean	−0.0004	−0.009	0.0001	−0.062	0.204	−1.520	−1.605	−0.0004	−0.009
S·D	0.279	1.790	4.024	0.676	1.317	10.269	2.813	0.028	0.381
Max	1.659	3.776	25.533	0.804	10.453	17.768	9.592	0.058	0.988
Min	−1.668	−14.265	−25.224	−5.521	−1.266	−85.292	−11.241	−0.116	−0.889
US									
Mean	0.001	0.007	−0.0003	−0.0008	−0.007	−1.068	1.479	0.001	−0.005
S·D	0.341	0.061	0.315	0.111	1.966	2.355	15.804	0.023	0.209
Max	1.782	0.351	1.742	0.347	10.453	6.819	126.33	0.048	0.539
Min	−1.696	−0.103	−1.696	−0.557	−10.902	−8.939	−17.449	−0.066	−0.450
Canada									
Mean	0.0006	0.386	0.004	0.141	0.925	−0.0005	0.002	−0.003	0.017
S·D	0.116	2.749	0.071	1.447	0.546	0.031	0.023	0.025	0.158
Max	0.412	16.352	0.239	9.867	3.277	0.076	0.049	0.073	0.397
Min	−0.375	−8.621	−0.425	−2.467	0.293	−0.087	−0.065	−0.076	−0.387
Germany									
Mean	−0.002	0.001	0.0004	0.002	0.265	0.213	−0.401	−0.001	−0.002
S·D	0.377	0.083	0.265	0.038	1.884	7.004	11.622	0.023	0.284
Max	1.887	0.441	1.497	0.154	12.362	51.667	77.592	0.045	0.717
Min	−1.701	−0.399	−1.511	−0.191	−4.588	−32.934	−36.93	−0.064	−0.748

Notes: the table shows mean value, standard deviation, minimum value and maximum value for all variables. KWEG and KWEY indicate Korean wave effect adjusted by Google herding and by YouTube herding respectively, GHD and YHD are herding index from Google search volume and YouTube search volume respectively, CCI is for the consumer confidence index, RCPI is relative consumer price index, MOOD is financial indexes, EX is exchange rate, VISIT is the total visitor per capita to Korea.

where Y_t is a vector endogenous variable: tourist arrivals (tourist per capita) in Korea, and X_t is a vector of exogenous variables such as Korean wave effect adjusted by Google herding (KWEG) and by YouTube herding (KWEY), herding index for Google (GHD) and YouTube (YHD), relative consumer price index (RCPI), consumer confidence index (CCI), exchange rate (EX), and stock market index (MOOD); p is the number of lags determined by Akaike information criterion (AIC). The coefficients of the VAR, $(A_1, \ldots, A_p)$ and C, are obtained by regressing tourist arrivals on an intercept and k-lags of KWEG, KWEY, GHD, YHD, RCPI, CCI, EX and MOOD.

Table 3
Stationarity.

Stationarity test after taking the first difference									
Country	VISIT	GHD	YHD	KWEG	KWEY	CCI	RCPI	EX	MOOD
Japan	−5.54	−9.28	−9.28	−10.72	−9.81	−8.15	−9.58	−11.41	−9.22
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Hong Kong	−9.15	−7.06	−8.13	−15.04	−9.15		−8.93	−9.79	−9.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Malaysia	−8.34	−5.96	−8.34	−8.72	−8.59		−9.95	−8.68	−9.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Singapore	−8.45	−8.45	−9.44	−11.08	−8.16		−9.55	−10.13	−9.12
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Taiwan	−10.13	−9.13	−7.08	−10.83	−9.77	−9.15	−8.79	−10.39	−9.29
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Thailand	−11.54	−8.66	−7.17	−10.78	−16.43	−9.65	−11.51	−8.96	−9.66
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UK	−6.39	−9.06	−8.52	−8.73	−8.75	−8.90	−3.58	−8.20	−8.75
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
US	−12.22	−8.42	−8.98	−10.93	−7.88	−9.54	−10.17	−9.90	−9.18
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Canada	−7.28	−9.25	−8.92	−8.54	−9.99	−8.99	−10.58	−7.13	−8.91
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Germany	−7.29	−7.89	−8.57	−9.97	−8.97	−8.93	−10.35	−7.77	−8.84
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: the table shows results from Augmented Dickey-Fuller tests. VISIT is the total visitors per capita from country or origin. KWEG and KWEY indicate Korean wave effect adjusted by Google herding and by YouTube herding respectively, GHD and YHD are herding index from Google search volume and YouTube search volume respectively, CCI is for the consumer confidence index, RCPI is relative consumer price index, MOOD is financial indexes, EX is exchange rate. H_0= unit root presented. We report *t-statistics* and *p-value* is in ().

Impulse response function

VAR estimation also provides impulse functions (IRFs) graphs and show the impact of each exogeneous variable on the endogenous variable. If the VAR(p) model is stable with orthogonalized innovation, we can derive its infinite moving average representation by the lag operators. Since the VAR(p) can be simplified as the VAR (1), Eq. (5) is written as:

$$Y_t = \mu + A_1 Y_{t-1} + u_t \tag{6}$$

Using recursive substitution of the lagged variables into Eq. (6), Y_t represents the moving average of current and past values of u_t. We thereby obtain following equation:

$$Y_t = \varphi + \sum_{j=0}^{\infty} A_1^j u_{t-j} \tag{7}$$

Eq. (7) shows the moving average representation of the VAR. However, the equation does not capture the impact of individual shock because the error terms are correlated and cannot be separated. To overcome the problem of combined shocks, the correlated error terms need to be orthogonalized by Choleski decompositions. After the decomposition process, Eq. (7) is written in terms of the moving average coefficients as:

$$Y_t = \varphi + \sum_{j=0}^{\infty} B_j u_{t-j} \tag{8}$$

where the B_j represents the impulse response function (IRF). The model measures time varying pattern of tourist arrivals in Korea in response to the one standard deviation shock in KWEG, KWEY, GHD, YHD, RCPI, CCI, EX, and MOOD.

Empirical results

Effect of KWE, herding and control variables on tourist arrivals

Results of the panel VAR model is presented in Table 4. The countries in our sample are categorised into two groups, Asian and Western, due to complexity in performing country level analysis. The Asian group includes Japan, Hong Kong, Malaysia, Singapore, Taiwan, and Thailand. Western countries are Canada, the US, Germany and the UK. Optimal number of lags is determined by Akaike information criterion. Outputs of the VAR model are too large and only significant coefficients at 10 % are presented. Table 4 indicates how sensitive the change in tourist arrivals (ΔVISIT) is to changes in the exogenous variables.

Table 4
Panel VAR estimation.

Asian countries: (10 lags)

$$\begin{aligned}\Delta \mathrm{VISIT}_t = & -\underset{(0.05)}{0.257}\,\Delta KWEG_{t-8} + \underset{(0.06)}{0.171}\Delta KWEG_{t-10} - \underset{(0.07)}{0.331}\,\Delta KWEY_{t-1} \\ & -\underset{(0.01)}{0.157}\,\Delta YHD_{t-1} + \underset{(0.07)}{0.112}\,\Delta YHD_{t-2} + \underset{(0.00)}{0.177}\,\Delta YHD_{t-6} \\ & -\underset{(0.01)}{0.018}\,\Delta CCI_{t-3} + \underset{(0.05)}{0.017}\,\Delta CCI_{t-8} - \underset{(0.09)}{0.004}\,\Delta MOOd_{t-3} \\ & +\underset{(0.03)}{0.004}\,\Delta MOOD_{t-9}\end{aligned}$$

Western Countries: (9 lags)

$$\begin{aligned}\Delta \mathrm{VISIT}_t = & +\underset{(0.06)}{0.004}\,\Delta KWEG_{t-2} + \underset{(0.04)}{0.005}\,\Delta KWEG_{t-3} + \underset{(0.09)}{0.012}\,\Delta KWEG_{t-6} \\ & +\underset{(0.01)}{0.007}\,\Delta KWEG_{t-7} - \underset{(0.02)}{0.016}\,\Delta KWEG_{t-9} + \underset{(0.09)}{0.002}\,\Delta KWEY_{t-1} \\ & +\underset{(0.04)}{0.003}\,\Delta KWEY_{t-2} - \underset{(0.00)}{0.005}\,\Delta KWEY_{t-3} - \underset{(0.02)}{0.004}\,\Delta KWEY_{t-4} \\ & -\underset{(0.06)}{0.002}\,\Delta KWEY_{t-8} + \underset{(0.06)}{0.007}\,\Delta GHD_{t-1} - \underset{(0.00)}{0.012}\,\Delta GHD_{t-2} \\ & -\underset{(0.00)}{0.024}\,\Delta GHD_{t-3} + \underset{(0.07)}{0.016}\,\Delta GHD_{t-6} + \underset{(0.02)}{0.018}\,\Delta YHD_{t-2} \\ & -\underset{(0.01)}{0.021}\Delta YHD_{t-3} + \underset{(0.01)}{0.026}\Delta YHD_{t-7} - \underset{(0.00)}{0.003}\,\Delta CCI_{t-1} \\ & -\underset{(0.04)}{0.015}\,\Delta RCPI_{t-2} - \underset{(0.02)}{0.009}\,\Delta RCPI_{t-3} + \underset{(0.03)}{0.010}\,\Delta RCPI_{t-4} \\ & -\underset{(0.06)}{0.017}\,\Delta RCPI_{t-9} + \underset{(0.06)}{0.378}\,\Delta EX_{t-5} + \underset{(0.05)}{0.812}\,\Delta EX_{t-9} \\ & +\underset{(0.02)}{0.001}\,\Delta MOOD_{t-2} - \underset{(0.01)}{0.002}\,\Delta MOOD_{t-5}\end{aligned}$$

Notes: This table presents a panel VAR estimation. Asian countries include Japan, Hong Kong, Taiwan, Thailand, Malaysia, and Singapore. Western countries include Canada, the US, Germany, and the UK. ΔVISIT is the change in total visitors per capita to Korea, ΔKWEG is the change in Korean wave effect adjusted by Google herding, ΔKWEY is Korean wave effect adjusted by YouTube herding, ΔGHD is the change in Google herding index, ΔYHD is the change in YouTube herding index, ΔCCI is the change in consumer confidence index, ΔRCPI is the change in relative consumer price index, ΔEX is the change in exchange rate, and ΔMOOD is the change in financial indexes. The optimal number of lags is selected based on the Akaike information criterion. P-value is in ( ). Only significant coefficients at 10 % level are reported.

We observe that Korean wave effect associated with Google herding (ΔKWEG) and YouTube herding (ΔKWEY) are important variables for both the Asian and Western groups. Asian group shows statistically significant impact of ΔKWEG at t-8 and t-10, the coefficients are 0.257 and 0.171 respectively. The coefficient of ΔKWEY is −0.331 and it is statistically significant at 10 %. In the Western group, we observe more pertinent results. The ΔKWEG coefficient is statistically significant at time t-2 (0.004), t-3 (0.005), t-6 (0.012), t-7 (0.007) and t-9 (−0.016). The coefficient of ΔKWEY, 0.002 at t-1, 0.003 at t-2, −0.005 at t-3, −0.004 at t-4 and −0.002 at t-8, are statistically significant. The magnitude of Korean wave effect is much greater in the Asian group. Finally, tourist arrivals are sensitive to changes in KWEG for the Asian group, but the Western group is sensitive to both changes in KWEG and KWEY.

Herding index is also an important factor and shows consistent impact on visitation in both groups. For the Asian group, ΔYHD coefficient is statistically significant at t-1 (−0.157), t-2 (0.112) and t-6 (0.177). No statistically significant impact of Google herding on tourist arrivals is observed. For the Western group, ΔGHD and ΔYHD show statistically significant impact on tourist arrivals. The coefficient of ΔGHD at time t-1 is 0.007, significant at 10 % level, −0.012 at t-2 (1 % level), −0.024 at t-3 (1 % level), and 0.016 at t-6 (10 % level). The coefficient of ΔYHD at t-2 is 0.018, −0.021 at t-3, 0.026 at t-7, and statistically significant at 5 % level.

Regarding the control variables, the most significant factor in the Asian group is the consumer confidence index. ΔCCI is statistically significant at t-3 and t-8. ΔMOOD is also important for Asian tourists while ΔEX and ΔRCPI are not the main determinants in visiting Korea. For the Western group, ΔRCPI is the most persistent predictability of arrivals to Korea with statistically significant coefficients across four months. The next key determinant is ΔEX. Consistent with the Asian group, ΔMOOD and ΔCCI are the least important variables for tourists visiting Korea.

It is important to interpret statistically significant impact of herding index on tourist arrivals with the causality test. High information seeking individuals are likely to search for a wide range of Korean cultural products such as background music, fashion, books and foods (Kim et al., 2007). Furthermore, interest has escalated into fandom on social media (Kang et al., 2021). Further search can be explained by the causal impact from YouTube herding to Google herding for Japan, Hong Kong, Thailand, the US, Canada, and Germany. Noticeably, Western group shows more consistent impact of GHD on tourist arrivals in Korea. Additionally, Google and YouTube herding effect is incorporated in our alternative proxy of Korean wave. In other words, Korean wave estimated by combining exports in trade and online consumption herding behaviour, successfully explain tourist arrivals in Korea for both the Asian and Western groups.

Overall, tourists who consume Korean pop cultural products on YouTube, especially from Japan, Hong Kong, Thailand, the US, Canada, and Germany, use Google to seek further information. Tourists from other countries tend to use YouTube and Google independently when searching for information about Korean pop-cultural products. Our results confirm the importance of Korean wave effect in predicting tourist arrivals. The findings show that even if the impact of KWE is specific to the destination, the KWE derived from the social media herding behaviour has an impact on tourist arrivals. To further understand the potential behavioural patterns of Asian and Western tourists, impulse functions are analysed for the period 2013 to 2019.

Finally, we check the model predictive capacity. Each forecast model is re-estimated using the sub-sample 2013 M04-2018 M12 for 12 months and sub-sample 2013 M04-2017 M12 for 24 months. We employ root mean squared error (RMSE) and mean absolute error (MAE) for measures of model predictability (see Table 5). For the Asian countries, RMSE for 12 months shows that M2a outperforms all other models but is marginally better while M1 is the best model according to MAE. For the 24 months sub-sample, M2b is the best model based on both RMSE and MAE. Overall, herding variables and KWE variables are important predictors in the Asian countries. However, for the Western countries, we observe a weaker predictability of herding and KWE variables over the control variables.

Impulse response function (IRF)

The IFR graphs in Fig. 2 provide a clear picture for the impact of ΔKWEG, ΔKWEY, ΔGHD, ΔYHD, ΔCCI, ΔRCPI, ΔEX, and ΔMOOD on tourist arrivals in Korea. Impulse responses for the Asian group show that shocks in the explanatory variables impact future tourist arrivals to Korea. KWEG has an immediate negative impact in the first month and then bounce back to positive in month 2. The impact is smoothing out in the second half of the year. A one standard deviation of KWEY has immediate positive impact on tourist arrivals but the wave effect associated with herding has greater impact in month 8. For the herding variables, both of GHD and YHD are not responsive until the second month and then increase in month 3. There is a decreasing trend from both variables and then a bounce back in month 5. YHD reveals similar level of fluctuation in response while GHD shows a big increase from month 5 and 7. Overall, our analysis shows that Korean wave effect and online consumption herding behaviour have an immediate impact but stronger and persistent effect on tourist arrivals has 6 to 7 months lag time for Asian tourists to visit Korea.

For the control variables, tourist arrivals from the Asian group are largely affected by the consumer confidence index (CCI) of origin countries. For instance, tourists' confidence level has a big positive impact in month 5 and starts to decline and stabilises around zero (except for Month 10). The finding implies that tourists' confidence level has a short-term impact on the decision on whether to travel. RCPI shows visible impact on tourist arrivals in Korea. Our results show an immediate negative impact and followed by a positive impact in month 3, gradually stabilizing with big fluctuation in month 8. EX and MOOD display an immediate positive impact and remain sluggish until month 7 with fluctuation in the second half of the year.

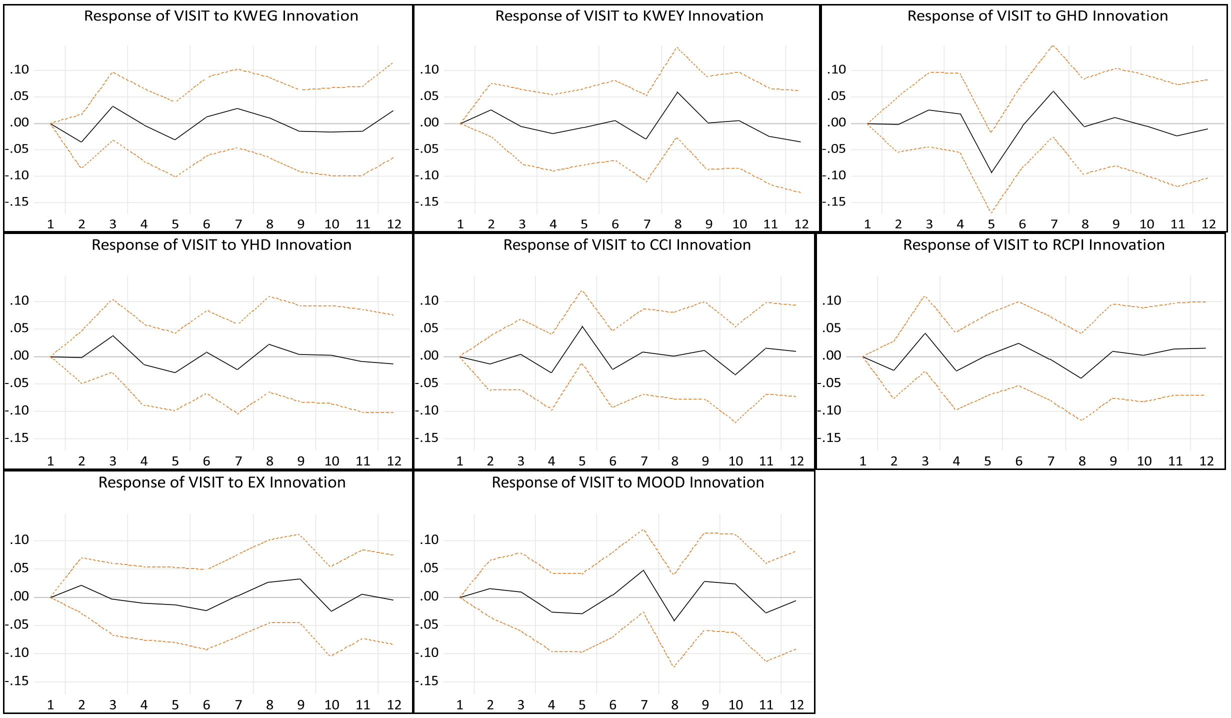
The Western group has a weak immediate positive impact from KWEY in the first two months. The response decreases gradually month 2 until month 4, followed by a rise in the fifth month and decreases gradually until month 8. The biggest rise is

Table 5
Model evaluation of predictive capacity.

Groups	Models				12 months		24 months	
					RMSE	MAE	RMSE	MAE
Asian Countries	M1	CCI, RCPI, MOOD, EX			0.2999	0.2207	0.3172	0.2355
	M2a	CCI, RCPI, MOOD, EX	GHD YHD		0.2985	0.2231	0.3481	0.2481
	M2b	CCI, RCPI, MOOD, EX	KWEY KWEG		0.2992	0.2243	0.3027	0.2300
	M3	CCI, RCPI, MOOD, EX	GHD YHD	KWEY KWEG	0.3331	0.2516	0.3631	0.2663
Western Countries	M1	CCI, RCPI, MOOD, EX			0.2157	0.1606	0.1936	0.1508
	M2a	CCI, RCPI, MOOD, EX	GHD YHD		0.2216	0.1659	0.2134	0.1625
	M2b	CCI, RCPI, MOOD, EX	KWEY KWEG		0.2193	0.1615	0.7137	0.3543
	M3	CCI, RCPI, MOOD, EX	GHD YHD	KWEY KWEG	0.2187	0.1620	0.5881	0.2155

Note: M1 indicates model 1 and includes control variables such as Relative consumer price index (RCPI), Consumer confidence index (CCI), Exchange rate (EX) and Mood (MOOD). M2a includes control variables and YouTube herding (YHD) and Google herding (GHD). M2b includes control variables and Korean wave effect of YouTube (KWEY) and Google (KWEG). M3 is the full model and include all variables. Each forecast model is re-estimated on a monthly data of sub-sample 2013 M04 –2018 M12 for the forecasting period of 2019 M01-2019 M12 (12 months) and sub-sample 2013 M04 -2017 M12 for the forecasting period of 2018 M01-2019 M12 (24 months). RMSE is root mean square error and MAE is mean absolute error.

Asian group (Japan, Hong Kong, Taiwan, Thailand, Malaysia, and Singapore)



Western group (Canada, the US, Germany, and the UK)

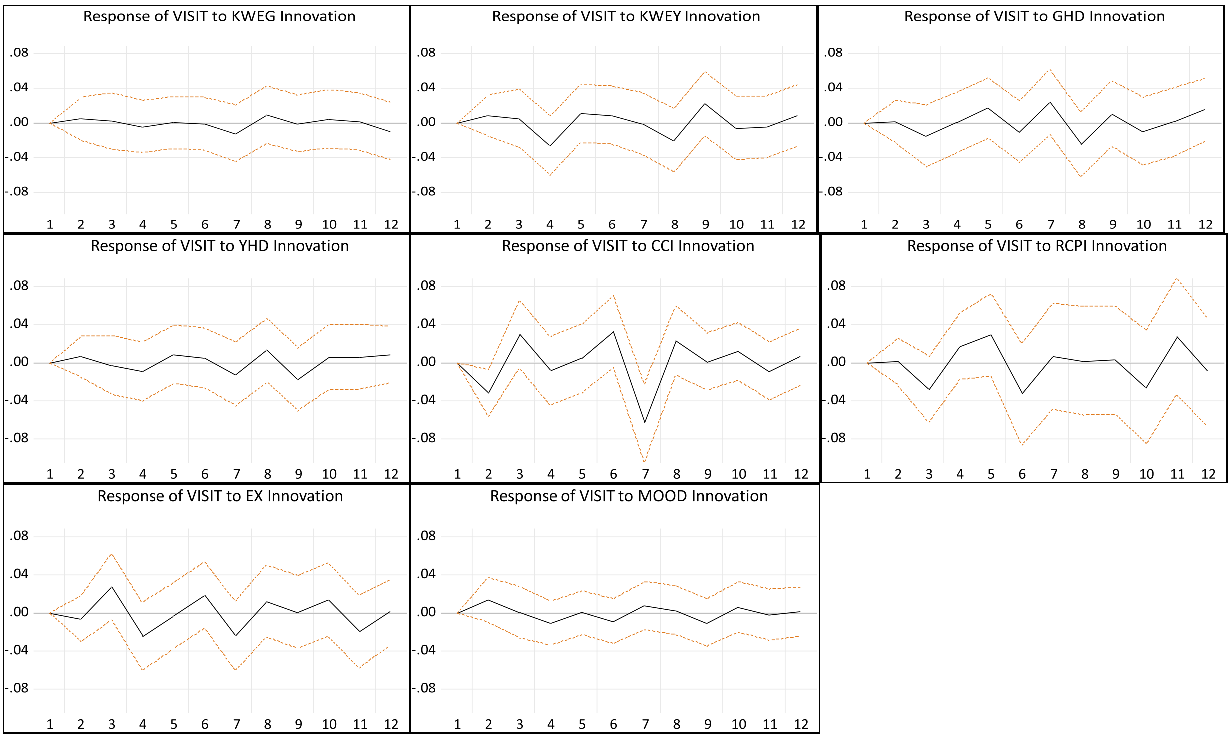


Fig. 2. Impulse response analysis.

observed in month 9, after stabilizing around zero. However, there are sluggish responses from KWEG on VISIT. Responses associated with herding variables tend to be initially weak and becoming stronger in the second half of the 12 months. GHD has stronger impact in comparison with responses from YHD. In other words, although not substantial, YHD provides some degree of predictability for tourist arrivals. Overall, the Korean wave effect and online consumption herding behaviour routinely and positively influence tourist arrivals until month 10.

For the control variables, the responses of tourist arrivals associated with CCI are different from the Asian group. CCI shows an initial negative impact on tourist arrivals within the first 2 months and then fluctuates with a huge drop in month 7. The response bounces back to positive in month 8, to eventually maintain an impact around zero. RCPI and EX show persistent responses across 12 months implying the shocks in these variables cause movements in tourist arrivals. The response associated with MOOD shows an immediate positive impact but remains sluggish across the 12 months. Overall, these IRFs suggest that the impact on tourist arrivals is more prominent in the Western group.

In general, results highlight tourists are motivated to visit Korea through the consumption of cultural products but decision making occurs within the second 6 months. Control variables are important in explaining travel to Korea. When Asian tourists are contemplating a visit, the visitation is influenced by CCI and RCPI in the first 6 months while EX and MOOD tend to have an impact in the second 6 months. For Western tourists, CCI, RCPI and EX are the most important determinants.

Discussions and conclusion

In this study, we conceptualise herding behaviour in the context of online consumption of Korean popular cultural products and assess the impact on tourism demand. The theoretical explanation of online herding behaviour tends predominantly draws on word of mouth (WOM). WOM is an influential factor in consumer behaviour (Bickart & Schindler, 2001; Canhoto & Clark, 2013). In purchasing goods and services, attitudes of consumers are formed by the information achieved from electronic word of mouth (eWOM) conversations on social media (Erkan & Evans, 2016). Attitudes, in turn, can influence consumption but it does not lead to herding behaviour. Moreover, herding behaviour in tourism is often confounded with WOM on social media, leading to incorrect applications and interpretations. In this paper, we propose an alternative framework to provide a better understanding of how herding develops on social media platforms.

The study makes important contributions to the literature and provides an in-depth analysis of herding behaviour related to the consumption of cultural products. The developmental process of herding is conceptualised via a two-step flow communication model (Lazarsfeld et al., 1948). The most important aspect in the development of herding, omitted in studies of tourist behaviour, is the consideration of active information seeking individuals who engage in online activities such as like, dislike, commenting, and sharing content. This engagement often develops high volume of relevant information searches and overtime it grows within the population to represent herding behaviour. The first findings of this study show that the current propagation of Korean wave is mainly driven by herding behaviour.

The other important aspect, again largely ignored in prior tourism studies, is time varying nature of herding. Time varying implies that herding appears and disappears across time. In other words, herding represents the degree of public interests and can have a mid- to long-term effect as well as a very short-term one. However, the tourism literature tends to misinterpret herding as a long term or permanent effect. In this study, we provide a novel approach to estimate herding. The results confirm the time varying nature of herding behaviour and the patterns are different across the countries in our sample. One useful implication of the herding index is that the time varying trend in public interest can be identified more accurately. Thus, our standardised index is capable to support benchmarking and allows for comparisons across various tourism services, products, and popularity of tourism destinations.

In addition, we developed an alternative proxy: KWE. Previous studies (e.g. Chang & Lee, 2017; Lim & Giouvris, 2020) use the total export of cultural products as a proxy for the Korean wave. Exports of Korean cultural products are mainly provided to the public through conventional media platforms such as TV, radio, and newspapers. The main consumers of conventional media platforms are more likely to consist of middle aged and elderly people (Jin, 2018) and passive information receiver (Groshek & Koc-Michalska, 2017). As the Korean wave has become a global phenomenon, social media users, mainly young and middle-aged (Jin, 2018) and active information seeking individuals (Lee & Ma, 2012), should be considered. The proxy in this study includes cultural consumption from both traditional sources and social media, reflecting broader public interests of Korean cultural products.

Empirical findings confirm that KWE through online platforms has a consistent impact on inbound tourists to Korea. Hosany et al. (2020) emphasise that tourists can develop an emotional bonding toward unvisited via prior exposure to famous TV series and films. The pre-consumed cultural products offer familiarity and create cultural preferences and influence the selection of travel destination (Petit & Seetaram, 2019). In other words, the pre-visit emotional connection and cultural preferences are reflected in tourists' expectations. If the expectation has been developed through the consumption of cultural products, tourists might seek other related experiences. When tourists' experiences at the destination are complementarily interacted with their expectations, it creates a greater sense of place attachment with higher levels of satisfaction (Hosany et al., 2017).

The study provides interesting perspectives into the behaviour of travellers and offer a novel approach to monitor and forecast demand for tourism. It provides insights into different markets, explain their individualities which can be an important tool for decision-makers. The data used here pertains to South Korean culture, but the existence of online herding behaviour can be determined for other phenomenon and destinations. Further applications can help to determine which products and/or destinations may become trendy or lose their appeal and therefore, have implications for resource allocation. The technique used in this paper can be applied to gain insights into the popularity of shows such as Game of Thrones and House of the Dragon and model the effect they have on Irish tourism products. Analysing potential herding behaviour can provide useful information on future tourist arrivals to locations related to these shows. Herding behaviour however, is not limited to cultural phenomena. For example, it can be linked to sports, politics, and history which can also create interest in a destination. Our study shows that monitoring search engines and social media data are valid investments for tourism professionals.

The study has some limitations, offering opportunities for future research. First, we could not specifically identify the causal effects between Google and YouTube herding. This is a critical aspect and to rectify the model, future research should specify how YouTubers can create spillover effects and influence public opinions at the micro level. Future research can also collect data from different search engines such as the popular Chinese Weibo platform. In addition, the study can be expanded geographically to include Latin American and Middle East countries, as Korean popular culture is growing in these regions. Beyond the confirmation of Korean wave effect and identification of different behavioural patterns in destination choices, future research should consider the role of cultural assimilation. Psychological distance toward different cultural destination is an important antecedent of heritage tourism (Massara & Severino, 2013). Pre-consumed cultural products such as films, pop-music and drama enhance cultural familiarity and preferences (Petit & Seetaram, 2019), thus reducing psychological distance. Korean wave could have positive impact on psychological distance in the process of cultural assimilation. Finally, Korean cultural products consist of various derivational elements in addition to the consumption of film, music and drama. For instance, consumers are also interested in fashion items, books, food tasting, background music (Kim et al., 2007), TV drama & film production town (Kim et al., 2017) and fan club/membership related activities (Lee et al., 2019). Therefore, future research should broaden the scope of the proxy to include other elements of cultural consumption.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Androutsopoulos, J. (2006). Introduction: Sociolinguistics and computer-mediated communication. *Journal of SocioLinguistics*, *10*(4), 419–438.

Bae, S. Y., & Yeu, M. (2022). Herding behaviors in family travel decision-making in mothers' online communities: A netnographic approach. *Journal of Tourism and Cultural Change*, *20*(6), 756–773.

Banerjee, A. (1992). A simple model of herd behavior. *Quarterly Journal of Economics*, *107*(3), 797–817.

Bangwayo-Skeete, P., & Skeete, R. W. (2015). Can Google data improve the forecasting performance o tourist arrivals? Mixed-data sampling approach. *Tourism Management*, *46(Feb*, 454–464.

Beeton, S. (2006). Understanding film-induced tourism. *Tourism Analysis*, *11*(3), 181–188.

Benítez-Aurioles, B. (2022). The exhaustion of the herding effect in peer-to-peer accommodation. *Tourism Economics*, *28*(1), 27–43.

Bennett, W. L., & Segerberg, A. (2012). The logic of connective action. *Information, Communication & Society*, *15*(5), 739–768.

Bickart, B., & Schindler, R. M. (2001). Internet forums as influential sources of consumer information. *Journal of Interactive Marketing*, *15*(3), 31–40.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom and cultural change as informational cascades. *Journal of Political Economy*, *100*(5), 992–1026.

Bimber, B., Flanagin, A., & Stohl, C. (2012). *Collective action in organizations: Interaction and engagement in an era of technological change.* New York, NY: Cambridge University Press.

Bock, D. E., Eastman, J. K., & McKay, B. (2014). The impact of economic perceptions on status consumption: An exploratory study of the moderating role of education. *Journal of Consumer Marketing*, *31*(2), 111–117.

Bokelmann, B., & Lessmann, S. (2019). Spurious patterns in Google trends data – An analysis of the effects on tourism demand forecasting in Germany. *Tourism Management*, *75(Dec*, 1–12.

Brodie, R. J., Ilic, A., Juric, B., & Hollebeek, L. (2013). Consumer engagement in a virtual brand community: An exploratory analysis. *Journal of Business Research*, *66*(1), 105–114.

Canhoto, A. I., & Clark, M. (2013). Customer service 140 characters at a time: The users' perspective. *Journal of Marketing Management*, *29*(5–6), 522–544.

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behaviour in equity markets: An international perspective. *Journal of Banking & Finance*, *24*(10), 1651–1679.

Chang, P., & Lee, H. J. (2017). The Korean wave: Determinants and its impacts on trade and FDI. Retrieved July 13, 2021, from Singapore Management University https://economics.smu.edu.sg/sites/economics.smu.edu.sg/files/economics/Events/SNJTW2017/Hyojung%20Lee.pdf.

Choi, K., Meng, B., & Kim, S. B. (2020). The influence of cultural familiarity on Tanzanian millennials' perceptions of Korea: The mediating roles of involvement. *Asia Pacific Journal of Tourism Research*, *25*(1), 64–75.

Christie, W. G., & Huang, R. D. (1995). Following the pied piper: Do individual returns herd around the market? *Financial Analysts Journal*, *51*(4), 31–37.

Croce, V. (2016). Can tourism confidence index improve tourism demand forecasts? *Journal of Tourism Futures*, *2*(1), 6–21.

Dolata, U., & Schrape, J. F. (2016). Masses, crowds, communities, movements: Collective action in the internet age. *Social Movement Studies*, *15*(1), 1–18.

Dragouni, M., Filis, G., Gavriilidis, K., & Santamaria, D. (2016). Sentiment, mood and outbound tourism demand. *Annals of Tourism Research*, *60(Sep*, 80–96.

Erkan, I., & Evans, C. (2016). The influence of eWOM in social media on consumers' purchase intentions: An extended approach to information adoption. *Computers in Human Behaviour*, *61(Aug*, 47–55.

Feick, L. F., Price, L. L., & Higie, R. A. (1986). People who use people: The other side of opinion leadership. In J. Richard, & P. Lutz (Eds.), *NA - Advances in Consumer Research. Vol. 13*. (pp. 301–305). UT: Association for Consumer Research.

Gibson, R. M., & Höglund, J. (1992). Copying and sexual selection. *Trends in Ecology & Evolution*, *7*(7), 229–232.

Giraldeau, L. A. (1997). The ecology of information use. In J. Krebs, & N. B. Davies (Eds.), *Behavioral ecology, an evolutionary approach* (4th ed.). Oxford: Blackwell.

Gounopoulos, D., Petmezas, D., & Santamaria, D. (2012). Forecasting tourist arrivals in Greece and the impact of macroeconomic shocks from the countries of tourist' origin. *Annals of Tourism Research*, *39*(2), 641–666.

Groshek, J., & Koc-Michalska, K. (2017). Helping populism win? Social media use, filter bubbles, and support for populist presidential candidates in the 2016 US election campaign. *Information, Communication & Society*, *20*(9), 1389–1407.

Gunter, U., & Önder, I. (2015). Forecasting international city tourism demand for Paris: Accuracy of uni- and multivariate models employing monthly data. *Tourism Management*, *46(Feb*, 123–135.

Ha, J., Park, K., & Park, J. (2016). Which restaurant should I choose? Herd behaviour in the restaurant industry. *Journal of Foodservice Business Research*, *19*(4), 396–412.

Hanaki, T., Singhal, A., Han, M. W., Kim, D. K., & Chitnis, K. (2007). Hanryu sweeps East Asia: How winter sonata is gripping Japan. *International Communication Gazette*, *69*(3), 281–294.
Hosany, S., Buzova, D., & Sanz-Blas, S. (2020). The influence of place attachment, ad-evoked positive affect, and motivation on intention to visit: Imagination proclivity as a moderator. *Journal of Travel Research*, *59*(3), 477–495.
Hosany, S., Prayag, G., Van Der Veen, R., Huang, S., & Deesilatham, S. (2017). Mediating effects of place attachment and satisfaction on the relationship between tourists' emotions and intention to recommend. *Journal of Travel Research*, *56*(8), 1079–1093.
Huang, S. (2011). Nation-branding and transnational consumption: Japan-mania and the Korean wave in Taiwan. *Media, Culture & Society.*, *33*(1), 3–18.
Hwang, S., & Salmon, M. (2009). *Sentiment and Beta HerdingWorking Paper: Available at SSRNhttp://ssrn.com/abstract=299919. . https://doi.org/10.2139/ssrn.299919.*
Jin, D. Y. (2018). An analysis of the Korean wave as transnational popular culture: North American youth engage through social media as TV becomes obsolete. *International Journal of Communication*, *12*, 404–422.
Kang, J., Kim, J., Tang, M., Park, E., Ko, M., Lee, M., & Han, J. (2021). Behind the scenes of K-pop fandom: Unveiling K-pop fandom collaboration network. *Quality and Quantity*. https://doi.org/10.1007/s11135-021-01189-5.
Katz, E. (1957). The two-step flow of communication: An up-to-date report on an hypothesis. *Public Opinion Quarterly*, *21*(1), 61–78.
Khanna, N., & Mathews, R. D. (2011). Can herding improve investment decisions? *The Rand Journal of Economics*, *42*(1), 150–174.
Kim, M. J., & Petrick, J. M. (2021). The effect of herding behaviours on dual-route processing of communications aimed at tourism crowdfunding ventures. *Journal of Travel Research*, *60*(5), 947–964.
Kim, S., Kim, S., & Oh, M. (2017). Film, tourism town and its local community. *International Journal of Hospitality & Tourism Administration*, *18*(3), 334–360.
Kim, S. S., Agrusa, J., Chon, K., & Cho, Y. (2008). The effects of Korean pop culture on Hong Kong residents' perceptions of Korea as a potential tourist destination. *Journal of Travel & Tourism Marketing*, *24*(2–3), 163–183.
Kim, S. S., Agrusa, J., Lee, H., & Chon, K. (2007). Effects of Korean television dramas on the flow of Japanese tourists. *Tourism Management*, *28*(5), 1340–1353.
Kumar, A. (2021). Empirical investigation of herding in cryptocurrency market under different market regimes. *Review of Behavioral Finance*, *13*(3), 297–308.
Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, *32*(1), 23–43.
Langley, D. J., Hoeve, M. C., Ortt, J. R., Pals, N., & van der Vecht, B. (2014). Pattern of herding and their occurrence in an online setting. *Journal of Interactive Marketing*, *28*(1), 16–25.
Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1948). *The people's choice: How the voter makes up his mind in a presidential campaign*. New York: Columbia University Press.
Lee, B., Ham, S., & Kim, D. (2015). The effect of likability of Korean celebrities, dramas, and music on preferences for Korean restaurants: A mediating effect of a country image of Korea. *International Journal of Hospitality Management*, *46(Apr*, 200–212.
Lee, C. S., & Ma, L. (2012). News sharing in social media: The effect of gratifications and prior experience. *Computers in Human Behaviour*, *28*(2), 331–339.
Lee, J. (2018). The Korean wave, k-pop fandom and multilingual microblogging. In C. Cutler, & U. Røyneland (Eds.), *Multilingual youth practices in computer mediated communication* (pp. 205–223). Cambridge: Cambridge university Press. https://doi.org/10.1017/97813161135570.012.
Lee, S., Song, H., Lee, C., & Petrick, J. F. (2018). An integrated model of pop culture fans' travel decision-making processes. *Journal of Travel Research*, *57*(5), 687–701.
Lee, S. J., & Bai, B. (2016). Influence of popular culture on special interest tourist' destination image. *Tourism Management*, *52(Feb*, 161–169.
Lee, S. J., Bai, B., & Busser, J. A. (2019). Pop star fan tourists: An application of self-expansion theory. *Tourism Management*, *72(Jun*, 270–280.
Lim, S. K., & Giouvris, E. (2020). Tourist arrivals in Korea: Hallyu as a pull factor. *Current Issues in Tourism*, *23*(1), 99–130.
Ludvigson, S. C. (2004). Consumer confidence and consumer spending. *Journal of Economic Perspectives*, *18*(2), 29–50.
Massara, F., & Severino, F. (2013). Psychological distance in the heritage experience. *Annals of Tourism Research*, *42(Jul*, 108–129.
Messis, P., & Zapranis, A. (2014). Herding behaviour and volatility in the Athens stock exchange. *The Journal of Risk Finance*, *15*(5), 572–590.
Park, M., & Lessig, V. (1977). Students and housewives: Differences in susceptibility to reference group influence. *Journal of Consumer Research*, *4*(2), 102–110.
Park, Y. S. (2015). Does the rise of the Korean wave lead to cosmetics export? *The Journal of Asian Finance, Economics and Business*, *2*(4), 13–20.
Petit, S., & Seetaram, N. (2019). Measuring the effect of revealed cultural preferences on tourism exports. *Journal of Travel Research*, *58*(8), 1262–1273.
Rivera, R. (2016). A dynamic linear model to forecast hotel registrations in Puerto Rico using Google trends data. *Tourism Management*, *57(Dec*, 12–20.
Seetaram, N. (2010). Use of dynamic panel cointegration approach to model international arrivals to Australia. *Journal of Travel Research*, *49*(4), 414–422.
Shiller, R. C. (2002). Bubbles, human judgment, and expert opinion. *Financial Analysis Journal*, *58*(3), 18–26.
Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, *48*(1), 1–48.
Song, H., & Witt, S. F. (2006). Forecasting international tourist flows to Macau. *Tourism Management*, *27*(2), 214–224.
Statista (2021). Fastest viral videos as of august 2021, based on number of views in 24 h after upload. Retrieved 03 October 2021, fromhttps://www.statista.com/statistics/478082/fastest-viral-videos-views-in-24-hours/.
Stavroyiannis, S., & Babalos, V. (2019). Herding behaviour in cryptocurrencies revisited: Novel evidence from a TVP model. *Journal of Behavioral and Experimental Finance*, *22(Jun*, 57–63.
Sun, S., Wei, Y., Tsui, K. L., & Wang, S. (2019). Forecasting tourist arrivals with machine learning and internet search index. *Tourism Management*, *70*(Feb), 1–10.
Susarla, A., Oh, J. H., & Tan, Y. (2012). Social networks and diffusion of user-generated content: Evidence from YouTube. *Information Systems Research*, *23*(1), 23–41.
Xie, L., Natsev, A., Kender, J. R., Hill, M., & Smith, J. R. (2011). Tracking visual memes in rich-media social communities. *Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media* Retrieved from: Visual-memes-in-social-media-tracking-real-world-news-in-YouTube-videos.pdf (researchgate.net).
Xu, W. W., Park, J. Y., Kim, J. Y., & Park, H. W. (2016). Networked cultural diffusion and creation on YouTube: An analysis of YouTube memes. *Journal of Broadcasting & Electronic Media*, *60*(1), 104–122.
Xue, F., Dong, L., Gao, B., Yu, Z., & Taras, V. (2020). Understanding the relationships between distances and herd behaviour in online reviews: The moderating effects of hospitality experience. *International Journal of Contemporary Hospitality Management*, *32*(10), 3295–3314.

Sungkyu Lim's research focuses on financial management, corporate finance and tourism economics.
Neelu Seetaram is an expert in Tourism Economics with a focus on tourism demand, taxation, development and impact.
Sameer Hosany's research interests lie at the intersection of psychology, marketing and tourism, focussing on consumer (tourist) behaviour and emotional experiences.
Matthew Li's interests are behavioural economics and finance, and energy markets.