GOOGLE SEARCH EFFECT ON EXPERIENCE PRODUCT SALES AND USERS' MOTIVATION TO SEARCH: EMPIRICAL EVIDENCE FROM THE HOTEL INDUSTRY

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ABSTRACT

As individuals increasingly rely on the Internet to access product information, search engines have become an important navigation tool to enhance information collection efficiency. Although there are plenty of user-generated reviews to help consumers evaluate product quality, individuals often seek further information using search engines such as Google before making a purchase, especially for experience products. With the accelerated pace of economic activities and the development of the internet and mobile technologies, consumers' shopping dynamics have been intensified. Therefore, it is of both theoretical and practical significance to track the shifts in customer interest with minimum time delay. Unlike previous studies that have used monthly or weekly data, we focus on the near-term relationship between Google search and product sales. The search requests recorded by Google Trends provide us an ideal database to learn the collective attention of potential customers in a timely fashion. Combined with the hotel data collected from Expedia.com, this study first investigates the relationship between Google search volumes and the related product sales with 48-hour time-lag intervals. The results confirm a two-way positive effect between these two factors. We further explore the influence of price discounts on consumer search behaviors and the moderate effect of retailers' online reputations. The results suggest that offering a price discount has a positive impact on the Google search volume of the promoted product, however the retailer's online reputation negatively moderates this influence. The findings not only have significant practical implications for the hotel industry but also benefit the experience products industry in general. Moreover, the findings contribute to the literature on consumer behavior in the online market as well as on online WOM.

Keywords: Information search; Experience products; Google trend; Online WOM; Price discount;

1. Introduction

Recent years have witnessed the dramatic growth of the global e-commerce market. Nowadays, online shopping has become a popular daily activity of people all over the world. In 2017, the worldwide Internet retail sales totaled 2.3 trillion US dollars [Statista 2017]. Online transactions of experience goods (e.g., hotels, restaurants and spas), which were traditionally purchased in the offline face-to-face market, has shown an upward trend. In 2016, 55% of global web users purchased travel-related products and services through the Internet, which ranked second among all online shopping categories after fashion-related products (e.g., clothing and shoes) [Statista 2016]. Featured with unobservable characteristics before consumption, the qualities of experience goods are difficult to infer only through the information provided by sellers [Nelson 1970; Klein 1998]. As a result, compared with traditional face-to-face buying, purchasing experience products online involves a higher degree of uncertainty and perceived risk [Liebermann & Stashevsky 2002]. Consumers generally search for additional information to help them make purchase decisions [Shim et al. 2001; Haubl & Trifts 2000]. Zillow.com, an online real estate company conducted a survey to study American consumers' online search behavior before purchase and found that the average amount of time they spend on searching for a new home is 40 hours, 10 hours for a major home improvement, 10 hours for a car, 5 hours for a vacation or a mortgage, and 2 hours for a television set [Zillow.com 2010]. This practice reflects, to a certain extent, how consumers in today's world favor online shopping and information searching before making purchase decisions.

As Eric Schmidt, the former CEO of Google, said the volume of total information generated from the beginning of human civilization to year 2003 is the same as the volume of information generated in two days in 2010. On one hand, the huge amount of information available on the Internet provides people with a rich database from which they can obtain the information they need. On the other hand, the sheer amount of data available often times makes individuals feel overwhelmed. As a result, people rely on search engines, such as Google, to find relevant information pertinent to their decision-making process. In recent years, the search engine penetration rate has maintained its high-speed growth all over the world. By the end of 2017, the number of search engine users in China reached 640 million. Among Chinese web surfers, 82.8% use search engines to collect information [China Internet Network Information Center 2018]. Search engines can be used not only by individual users to obtain product information, but also be used in advanced commercial applications, such as help improving the accuracy of economic forecasting models [Dergiades et al. 2018].

Google is the world's most famous and widely utilized search engine. Google records every search request of all Internet users around the world in its database. It has built the free analytic tool Google Trends on the basis of the search volume of each keyword used by web surfers. Users can visit Google Trends website and download the aggregate search frequency of a particular keyword of a certain time period. Google Trends provide up-to-date search dynamics that accurately reflect public's current interest, so search query data can be used to predict web users' subsequent economic activities. This important implication brings great potential for possible real-world applications. Using the search volume data of 45 flu-related keywords on Google, Ginsberg et al. [2009] built a forecasting model to predict influenza outbreaks. Their model had correctly detected flu outbreaks one to two weeks before the Centers for Disease Control and Prevention released its official reports. As a result, managers from different industries have been giving more attention to Google Trends, trying to utilize the data obtained in order to benefit marketing operations and support business decision making. For example, in the tourism and hospitality industry, predicting travelers' arrivals or hotel room bookings is important for hotel owners and other relevant businesses to allocate their resources. The search volume of related keywords can be used to understand travelers' visiting intentions and further establish predictive models to forecast tourist destination arrivals or hotel occupancy rates. Pan et al. [2012] verified that hotel search data on Google can be used as an indicator of room reservation intention and can increase the accuracy of forecasting potential tourists' demand.

Interest in the extensive usage of search engines has also increased among academic researchers. Following Ginsberg's experiment, scholars have conducted a number of studies on the public data provided by Google Trends. Similar results have been obtained in other fields, such as stock markets, healthcare, biology, and car markets [Preis et al. 2013; Ruohonen & Hyrynsalmi 2017; Seifter et al. 2010]. Relevant to this study, some studies explored the predictive power of Google search data on product sales in online and offline marketplaces. Fantazzini and Toktamysova [2015] proposed a new multivariate model to forecast monthly car sales using economic variables and Google online search data. Their model significantly outperformed competing models for most of the car brands and forecast horizons. Ruohonen and Hyrynsalmi [2017] used Google search volume data to predict weekly video game sales, however they found that only a few games (44 out of 96) exhibit instantaneous causality relations. Constrained by the data availability, however, previous studies have used either monthly or weekly data to explore the impacts of search volume on forecasting related product sales. With the continuous development of Internet technology and the expansion of electronic transaction channels, people can search for product information and make purchases at any time and any place through their mobile phones or other internet connected electronic devices. As a result, consumers' intra-week shopping dynamics have been intensified [Jöckel et al. 2008]. For retailers of experience goods (e.g., hotels and airlines), being able to track the changes in consumer interest with minimum time delay and implementing a dynamic pricing strategy accordingly have become crucial for business to remain competitive. However, it seems that academic research has not kept pace with this practice; short-run trend (e.g., hourly or daily instead of weekly or monthly) analysis is an important extension to better understand consumers' information searching behaviors on Google and their purchase decisions. In recognition of this research lacuna, the current study selects hotel room as the representative of experience products and collects related data, such as hotel sales, room price, hotel ratings from the online travel website Expedia.com, and the matched Google search data from Google Trends. The panel vector autoregressive (VAR) model is adopted to explore the relation between hotel search volume data and related hotel sales with 48-hour time-lag frequency. The results provide important empirical support for practitioners to track the dynamics of consumers' shopping behavior and develop reasonable marketing strategies timely and accordingly.

Although considerable studies have been conducted on the application of keyword search volume in all aspects of life, most of previous studies treat searching behavior as users' endogenous intention. To the best of our knowledge, however, only a few studies have considered information seeking as an exogenous variable and explored the factors that motivate users' information searching behavior. Because actively seeking for product information is a critical step in the purchasing process [Becerra & Korgaonkar 2009], the factors that influence consumers' purchase decisions may also have an impact on their searching behaviors. Finding from the American car market, Du et al. [2014] suggested that the impact of advertisement can be decomposed into two underlying components: (1) generating consumer's interest in product information search and (2) converting this interest into sales. Branco et al. [2012] modeled consumers' prepurchase information search as a gradual learning process in which individuals update their expected utility of the product with considerable search costs. The authors further proposed that both sellers' pricing strategy (e.g., offering a discount) and social learning (e.g., observing previous consumers' choices) can influence the intensity of users' information searching. Different from Branco's modeling research, the current study focuses on the search requests on Google and empirically investigates the impact of price discounts on the Google search volume related to the product. In addition, the moderate effect of retailers' online reputation on this impact is also discussed. Thus, the results further our understanding of the customer information search and decision-making process for experience products.

The remainder of this paper is organized as follows. Section 2 presents the literature review and the hypotheses of this study. Section 3 describes the data and the model variables. We perform two empirical studies, the results and the robustness test are presented in Section 4. It is followed by the conclusions, implications, and current research limitations discussed in Section 5 of the paper.

2. Literature review and hypotheses development

2.1. Google search and purchase decision

In the Internet era, the overabundance of online information has provided opportunity for studying the impacts and implications of information searching behaviors. Information searching behavior on Google can be regarded as the direct measurement of the public attention and likely to correlate with their subsequent outcomes. Da et al. [2011] proposed that aggregate search frequency for stock code on Google reflects investors' specific attention concerning the stock market. By examining the relationship between stock search index and asset prices, they found that an increase in search volume for Russell 3000 stocks predicts higher stock prices in the next two weeks or better first-day return performance for a sample of IPO stocks. Using the online media coverage collected from Baidu Index, Liu and Ye [2016] divided the stock search volume into two categories: news-driven and self-initiated; they found that self-initiated and news-driven search volume is more likely to generate buy and sell pressure, respectively, and media coverage can negatively moderate the impact of search volume on stock prices. In forecasting the unemployment rates, Askitas and Zimmermann [2009] demonstrated strong correlations between keyword searches and unemployment rates in the German labor market. Tefft [2011] found that the depression search index is positive in relation to the unemployment rate, while it is negative in relation to the initial unemployment insurance claims. Choi and Varian [2009] built a model by adding the Google search frequency to forecast initial unemployment claims; using their model, the mean absolute error of the weekly prediction was reduced by 15.74%. Aside from economic activities, the related keywords search queries also generate notable value for medical applications [Chan et al. 2011; Pelat et al. 2009; Seifter et al. 2010]. For example, Althouse et al. [2011] used search engine queries to predict the incidence of dengue fever in Singapore and Thailand, confirming the model performed better than other predictive models. Ginsberg [2009] proposed that flu-related searching trends have a strong capability of predicting flu outbreaks in certain areas.

In addition to the macroeconomics analysis, other scholars attempted to make contributions from the perspective of microeconomics. These studies illustrated product sales, tourism demand, and marketing strategies as examples of activities that could be forecasted by Google Trends data. For example, search query volume can be a useful tool for predicting the sales of both search goods and experience products such as automobiles, video games, and tourism-related items [Fantazzini & Toktamysova 2015; Geva et al. 2017; Ruohonen & Hyrynsalmi 2017]. Geva et al. [2017] found that adding search trend data to social media data-based predictive models significantly improve the predictive accuracy in the automotive industry. Jun et al. [2017] and Dotson et al. [2017] suggested that keywords search queries help enterprises measure customers' attitudes toward their brand and/or product(s). As most tourism products are perishable, researchers have paid much attention to the use of online data for forecasting travelers' demands and consumption patterns. For example, Choi and Varian [2012] empirically validated that the volume of search queries on Google can be used as an indicator of visiting intentions for tourism destinations. They found the search volume of the keyword “Hong Kong” from a certain country was positively related to the number of visitors from that particular country. Yang et al. [2015] found that, in China, due to its large market share, search data provided by Baidu performed more effectively than Google in predicting visitor numbers for tourist destinations. Pan et al. [2012] found that the hotel search data on Google may be used as an indicator of purchase intentions as well as a means for increasing the accuracy of forecasting potential tourists’ weekly demand for hotel rooms. Specifically, the authors incorporated five travel-related queries into a model to predict hotel room demand in Charleston; result showed that search engine volume data significantly reduce the mean absolute percentage error of the model. Similarly, Li et al. [2017] proposed a composite model which integrated search volume data to forecast tourism demand and outperformed traditional models.

Koulayev [2009] proposed that individuals’ search queries are featured with two important attributes: (1) they are limited and (2) they are directly related to the users’ preferences. Since there are usually many potential sellers and alternatives available, consumers often have to expend considerable search costs in order to gather the information necessary for making a purchase decision. Therefore, before conducting the information search process, rational consumers would first filter the search target based on their preferences. As a result, consumers’ online search behavior is considered as a strong predictor of his/her purchase intention, which can often lead to real purchase behavior [Shim et al. 2001]. Reversely, a product with higher sales may also motivate users’ searching behavior. Previous studies have shown that popular products signal higher quality and create social influence that makes the product more appealing [Hellofs & Jacobson 1999]. Li and Wu [2013] found that for Groupon daily-deals, a 10% increase in past sales will, on average, stimulate 1.4 more vouchers sold in the next hour. Similarly, because of the herding effect, observing a product with higher sales may enhance consumers’ purchase intention, thus motivating information searching on the focal product. Based on the above analysis, we propose the following hypotheses:

$H1_a$: A greater volume of search queries on Google is positively correlated with the greater number of product sales.

$H1_b$: A greater volume of product sales is positively correlated with the greater number of search queries on Google.

2.2. Motivation to search

In the online environment, due to information asymmetry, customers often lack sufficient and accurate information about products before making a purchase, especially for experience products. Therefore, consumers tend to look for other signals that may reflect the quality of the product to help them distinguish low-quality goods from high-quality ones. Signaling theory may explain the relationship between signals and product quality as well as help customers evaluate the credibility of certain products [Connelly et al. 2010]. Extant literature suggests that, before making purchase decision, consumers often engage in a costly search for product information to (1) reduce perceived transaction risk [Forsythe & Shi 2003], (2) update the expected utility concerning how much they might enjoy the product [Branco et al. 2012], or (3) consider alternative choices [Bayer & Ke 2011]. Besides the inner desires that motivate individuals’ information seeking, other factors may also influence users’ searching behavior for products. Du et al. [2014] studied the impact of product advertising in the context of the US automobile market and discovered that advertisements may generate greater consumer interest in a product, thus motivating information search behavior. Branco et al. [2012] conducted a modeling research and proposed that sellers’ pricing strategy may influence online users’ information searching intensity relative to a product. Extend on Branco’s research, this study further explores how price discounts may influence consumers’ information searching behavior using empirical data from Google Trends and Expedia.com. We propose that price promotion motivates consumer’s information seeking behavior from two perspectives; from the motivation perspective, price discount creates a higher perceived transaction value and increases the overall appeal of the product, thus enhancing potential consumers’ purchase intention [Amir & Dawson 2007]. When a product is observed possessing a deep discount, consumers often consider it as a bargain therefore search for related information necessary to guide the purchase decision. From the attribution perspective, a deep discount may trigger the inferior quality concern or force consumers to question the motives of the seller(s) offering such promotions [Ashworth et al. 2005]. In order to eliminate uncertainty and reduce the perceived risk consumers tend to seek additional signals to help them verify the product quality. One popular and effective way is to search for related information online using search engines, such as Google. The increased search tendency is reflected in the higher search volume for the focal product or the retailer.

In the context of the current study, hotel accommodation is one of the crucial determinants of consumers’ overall trip experience. However, due to the enormous number of hotel choices and the amount of information available online, finding the right hotel is always a complex and time-consuming task during vacation planning. To enhance the efficiency of the planning process, travelers commonly resort to search engines for hotel information and make decisions accordingly. If the traveler knows that a hotel is offering a sale, he/she may perceive this as an opportunity to enjoy luxurious facilities and special services at a lower cost. Therefore, the traveler may consider this hotel for selection and seek further information before making a reservation. On the other hand, the price itself may be interpreted as a signal of product quality [Völckner & Hofmann 2007]. Due to the information asymmetry, consumers frequently doubt products with low prices or heavy discounts. If the price cut is too deep, the discount may lead consumer to question the service quality of the hotel. Therefore, travelers often urgently seek alternative reliable information to verify the hotel's quality; as a result, the search intensity on Google is increased. In summary, the above discussions lead to the following hypothesis:

$H2_a$: The price discount offered by the retailer has a positive impact on the user's Google search behavior.

2.3. The moderate effect of online WOM

For experience products, aside from search engines' navigation tools, online review is widely recognized as another crucial and reliable information source for consumers in learning about product quality [Dellarocas et al. 2007; Wang et al. 2015]. Review valence and review volume are two major branches in the research of online review. The valence of Word-of-Mouth (WOM) refers to the average rating across all individuals' overall evaluation relative to the product's performance. Regarded as the signal of product quality, review valence is generally accepted to have a significant impact on consumers' judgments and purchase intentions [Grewal et al., 2003]. For example, Luca [2016] investigated the relationship between online reputation and restaurant revenue and found that online consumer review ratings significantly affected the demand. Chevalier and Mayzlin [2006] proposed that online review valence has a positive impact on book sales, while Ye et al. [2011] suggested that the valence of travelers' reviews has a significant impact on online hotel room sales. The volume of reviews refers to the aggregated amount of consumer reviews specific to the focal products or services, which reflects the momentum of the product. Duan et al. [2008] found the volume of online WOM had a positive impact on movie box office performance. Liu [2006] stated that online review volume may increase consumer awareness and directly impact sales in the movie industry.

Although, online WOM is widely recognized as a reliable information source for acquiring knowledge about a product. Sometimes, online review itself cannot fully and accurately reflect a product's attributes. First, online reviews are usually provided by an anonymous, voluntary, and non-representative sample of product users who have no connection to the reader. Because most attributes are unquantifiable, the satisfaction and quality evaluation of an experience product is largely subjective and determined by personal preferences. Thus, the reviews may suffer from biased representation or self-selection effect [Li & Hitt 2008; Dellarocas & Narayan 2006]. Second, in order to gain profits, some retailers even intentionally manipulate opinions or pay for better reviews [Luca & Zervas 2016; Moe & Schweidel 2012]. These practices may lead the review signal to deviate from product quality. Third, although the number of online reviews for various products and services is growing rapidly, most online WOM merely consists of texts, making it difficult to form concrete, reputable perceptions specific to the focal product. Since the majority of experience goods fall into the category of hedonistic product—the feature of which lies in the fulfillment of happiness, excitement, or fun during the consumption process—it is difficult to convey the feelings and experiences relative to consuming such goods or services only using textual information. As a result, consumers usually resort to multimedia content (e.g., images and videos) through search engines to form a more intuitive impression. Thus, to some extent, online WOM and information search are complementary in reflecting a product's overall characters. In fact, search engine and online reviews have become two crucial tools for Internet users in acquiring information necessary for supporting and/or guiding a decision [Anderson 2014; Moat et al. 2016]. Users tend to combine knowledge obtained from both to make more sensible decisions.

As discussed earlier, a generous price cut may trigger the concern of inferior quality, thus motivating consumers' information searching behavior. If the promotion is offered by a reputable dealer (e.g., retailer with higher rating), consumers may infer the product quality through review signals, which can significantly reduce the quality concern caused by the price discount. To save the time and mental effort perpetrated by the information searching process, some users will make judgments based solely on online WOM, tending to believe that, even if the price is with the price cut, the retailer can still provide high-quality products or services. Thus, information searching requests for the related product are reduced. Based on the above analysis, the following hypothesis is proposed:

$H2_b$: Online product rating plays a negative moderating role in the relationship between price discount and Google search volume.

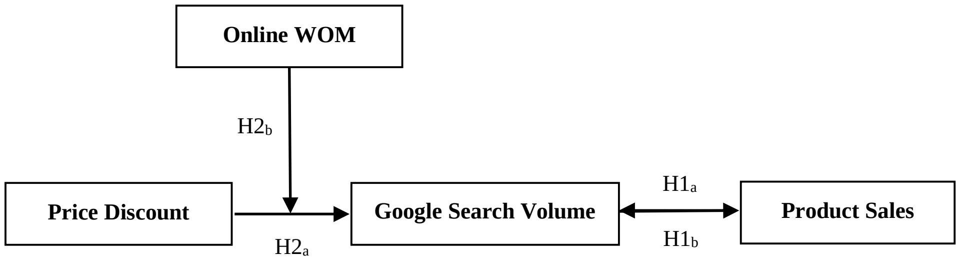

Figure 1: Research Model

3. Data and variables

3.1. Data

The dataset consists of 29 3-5-star themed hotels with more than 500 rooms located on the city center of Las Vegas in the US. The hotels were selected based on two criterions: data availability in Google Trends and the hotel location. First, Google only exhibits the history of search queries for keywords that exceed a specific amount. As one of the major travel destinations in the US, Las Vegas attracts tourists from all over the world. The hotels on the center of the city are well-known among travelers, which makes the cumulative search queries for these hotels sufficient enough to be recorded by Google Trends. Second, location is an important determinant in influencing a traveler's choice when selecting a hotel during trip planning. The hotels in this study are located next to each other alongside the Vegas strip, which may reduce the potential bias influenced by different hotel locations.

Hotel data such as hotel price, sales, and review rating were manually retrieved from one of America's largest online travel agent, Expedia.com. Expedia.com is ranked the world's top online travel community, providing travel-related products and services (e.g., hotels, airline tickets, car rental, etc.) to more than 20 countries and regions around the world. As Expedia.com shows the number of rooms booked within the past 48 hours for each hotel, we are able to obtain the real two-day hotel sales data. The data collection was conducted every other day from June 20, 2015 to August 18, 2015. The hotel page displays the number of users who are currently browsing this page; this information was also collected. Aside from the sales and number of page visitors, there are other related data captured, including the available price of the standard room, the original price of the standard room, the available price of the elite suite, the original price of the elite suite, and the average rating of consumers' reviews for each hotel.

The search quires for each hotel were collected from Googletrends.com. Google Trends provides a free search-based tool presenting the aggregate search frequency of a particular keyword entered into Google.com across various regions and languages worldwide. Using certain algorithms, Google normalizes the actual number of searches for a keyword against the number of all search requests received by the engine at about the same time. An integer between 0 and 100 is calculated and displayed in a graph format; the horizontal axis represents time and the vertical axis plots the keyword's relative percent frequency. Registered users may convert the graph into a digital document and download it for further analysis. Google Trends also allows users to compare the volume of searches between two to five terms and refine the resulting graph by specific region and time period. To avoid the potential bias caused by the mismatch of search quires, we set the keyword for hotel search with "hotel name + Vegas" and transferred the vertical figure into the relative number for each hotel. Finally, we combined the hotel data from Expedia.com with search data from Google Trends to form our dataset with a panel structure consisting of 29 hotels over 30 time periods.

3.2. Variables

As information searching plays an intermediate role in the purchase process, two studies are designed to investigate the research content. The first study focuses on the relationship between Google search requests and the related product sales, while the second study explores the influence of price discounts on consumers' information-searching behavior and the moderate effect of retailers' online ratings.

In the first study, the dependent variable is the hotel room sales on Expedia.com. The independent variable is the search volume of the matched hotel on Google. Modern life is fast-paced, and users' shopping dynamics have intensified as a result. The monthly or weekly forecast models developed by previous studies can no longer meet business requirements for supporting effective operating strategies in the current market environment. There is an urgent need for short-run trend analysis with minimum time delay. As Expedia.com can provide hotel room sale data going back 48 hours and Google Trends can provide daily search volume data for related hotels, this study combines these two data sources and explores the impact of information search on hotel room sales within the future 48-hour period. Thus, the dependent variable, *Sales*, captures the picture of hotel room sales on Expedia.com within a 48-

hours-window, and the independent variable, *Google search volume*, measures the search volume of matched hotels on Google Trends within the same period of time.

In the second study, the dependent variable is the same Google search volume, which has the same meaning as in Model 1. The independent variables include the price discounts offered by the hotels (*Discount*) and the valence of the online reputations of the hotels (*Rating*). A control variable, *Watching*, is also included in the model to measure the number of users browsing a hotel's page during the time the data were collected. The dataset consists of all the 3-5-star hotels on Las Vegas strip. Due to the significant price discrepancies observed among these hotels: the price range is between $84 to $573. Thus, for the variable *Discount*, using absolute terms could not accurately reflect the degree of reduction across different hotels. We adopted the relative terms, a technique widely applied in both marketing practice and research [e.g., Chen et al. 1998; Krishna et al. 2002; Hu et al. 2006], to calculate the price discount as the ratio of the lowest available price for a standard room to its original price. To obtain the lowest available prices, we randomly selected September 5, 2015, as the check-in date and September 7, 2015, as the check-out date.

The valence of online WOM is regarded as the signal of product quality, which has a significant impact on consumers' judgments and purchase intentions. To make information more visible, most platforms calculate overall rating scores by averaging across all individual ratings and display the result using a 0-to-5-star scoring system. This rating system has also been widely adopted by scholars to study the impact of online reputations on product sales [e.g., Chevalier & Mayzlin 2006; Ye et al. 2009; Wang et al. 2014]. Thus, for the variable *Rating*, this study adopts the hotel average rating on Expedia.com as a proxy for hotel reputation. When assessing the control variable *Watching*, it is assumed that every hotel has a similar distribution of attention (page view) across different hours in a day, and the hotel data is collected at a fixed time every other day. Thus, this variable serves as a proxy for travelers' attention to the hotel. Table 1 lists the variables used in this paper, along with their descriptions, and Table 2 provides variables' descriptive statistics. Table 3 reports the correlations between these variables (some of the variables were transformed to logarithms).

Table 1: Description of variables in this study

Variable	**Description**
$Sales_{i,t}$	Number of rooms sold for hotel *i* at period *t*
$Google_{i,t}$	Google search volume for hotel *i* at period *t*
$Discount_{i,t}$	Discount (currently available price / original price) of a standard room for hotel *i* at period *t*
$Rating_{i,t}$	Average cumulative rating for hotel *i* at period *t*
$Watching_{i,t}$	Number of users who are currently viewing hotel *i* at period *t*

Table 2: Descriptive statistics of variables

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Sales	870	153.576	153.5346	2	988
Google	870	32.997	18.2862	0	91
Discount	870	0.902	0.1322	0.5	1
Rating	870	4.127	0.3956	3.4	4.8
Watching	870	67.294	39.5035	5	232

Table 3: Correlations among variables

		1	2	3	4	5
1	*Ln(Google)*	1.000				
2	*Ln(Sales)*	0.422	1.000			
3	*Discount*	-0.193	-0.361	1.000		
4	*Rating*	-0.222	-0.516	0.3818	1.000	
5	*Ln(Watching)*	0.383	0.616	-0.255	-0.194	1.000

4. Empirical analysis

4.1. Study 1: the effect of Google search on hotel sales

The relationship between hotel sales and Google search volume is studied first. As discussed earlier, one critical issue is that hotel sales and Google search volume might influence each other. To address this issue, we have implemented the vector autoregressive model (VAR). According to a survey by Zillow.com [2010], online users spend 5 hours on average on information collection for vacation planning. Thus, only one period lag term is included in the VAR model since an individual is less likely to book a hotel after a search performed four days (two periods) prior. Model 1 is depicted in the following equation, where $\varepsilon_{i,t}$ and $\eta_{i,t}$ are random errors:

$$\begin{bmatrix} 1 & \gamma_1 \\ \gamma_2 & 1 \end{bmatrix} \begin{bmatrix} ln(Google_{i,t}) \\ ln(Sales_{i,t}) \end{bmatrix} = \begin{bmatrix} \beta_{0,1} \\ \beta_{0,2} \end{bmatrix} + \begin{bmatrix} \beta_{1,1} & \beta_{1,2} \\ \beta_{2,1} & \beta_{2,2} \end{bmatrix} \begin{bmatrix} ln(Google_{i,t-1}) \\ ln(Sales_{i,t-1}) \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t} \\ \eta_{i,t} \end{bmatrix}$$

$$(\varepsilon_{i,t}, \eta_{i,t}) \sim MVN\left(\mathbf{0}, \begin{pmatrix} \delta^2 & 0 \\ 0 & \theta^2 \end{pmatrix}\right) \qquad \text{Model (1)}$$

Model 1 results are presented in Table 4. As the primary focus is on the effect of Google search volume on hotel sales, the most important part of the table is the coefficient of the lagged Google search volume in the first column. The coefficient is significantly positive, which indicates a positive effect of Google search on hotel sales. A 1% search increase on Google can lead to a 0.824% increase in hotel sales. On the other hand, the positive significance of the lagged sales in the second column suggests that hotel sales also have a positive effect on Google search volume. A Granger Causality Wald test is performed to formally examine the causality relationship between hotel sales and Google search volume. The results show that hotel sales and Google search volume can influence each other. The effect of Google search on hotel sales is $\chi 2 = 5.114$ (p-value = 0.024); the effect of hotel sales on Google search is $\chi 2 = 5.630$ (p-value = 0.018). Thus, our $H1_a$ and $H1_b$ are both supported.

Table 4: The Vector Auto-regression Model (VAR) results (48-hour period)

	Ln(Sales)	*Ln(Google)*
Lag.ln(Google)	0.824 (0.347) **	0.637 (0.155) ***
Lag.ln(Sales)	0.777 (0.075) ***	0.062 (0.027) **
N	812	

* p < 0.1, ** p < 0.05, *** p < 0.01, Standard errors are reported in parentheses

As most of the prior studies adopted the weekly Google search data to predict individuals' related activities for the next period, we also conduct the VAR analysis for Model 1 using the six-day period lag term for reference. The results presented in Table 5 suggest that the number of room sales in the past six days may be used to predict the future hotel booking for the next period. However, the coefficient between lagged Google search volume and room sales is not significant, which means the Google search volume can no longer serve as a useful indicator to forecast the room sales for the following week. Overall, the results reported from Table 4 and Table 5 suggest that, within the hotel industry today—compared with long-term forecasting (i.e., weekly frequency)—the Google search volume is more effective in forecasting near-term demand (i.e., for the next two days).

Table 5: The Vector Auto-regression Model (VAR) results (six-day period)

	Ln(Sales)	*Ln(Google)*
Lag.ln(Google)	1.147 (1.112)	0.088 (0.516)
Lag.ln(Sales)	0.572 (0.115) ***	0.066 (0.062)
N	232	

* p < 0.1, ** p < 0.05, *** p < 0.01, Standard errors are reported in parentheses

4.2. Study 2: The motivation to perform Google search

The factor that influences consumers' pre-purchase information-seeking behavior on Google is also studied. As proposed in $H2_a$ and $H2_b$, the price discount offered by retailers motivates consumers to search for product information on Google, and the retailers' online ratings moderate this relationship. The following econometrics model is proposed to examine the effects of price discounts and hotel ratings. There might be some unobservable, hotel-specific heterogeneity that could influence search volume on Google, such as hotel awareness or brand reputation. Hence, we introduce μ_i to capture the fixed effect on hotel level:

$$ln(Google_{i,t}) = \beta_0 + \beta_1 Discount_{i,t} + \beta_2 Discount_{i,t} * Rating_{i,t-1} + \beta_3 Rating_{i,t-1} + \beta_4\, ln(Watching_{i,t}) + \mu_i + \varepsilon_{i,t} \qquad \text{Model (2)}$$

The Ordinary Least Squares (OLS) regression is applied to estimate the fixed effect model, and the results are reported in the first column of Table 6. As the number of watching users might not fully represent the popularity of a hotel, we have also included the one-period lag term of hotel sales and Google search volume to Model 2 and the results are reported in the second and third columns of Table 6.

Table 6: Model 2: Results of the effect of price discount

Ln(Google)	(1)	(2)	(3)
Discount	-7.025*	-6.989**	-7.090**
	(3.7640)	(3.2712)	(3.2739)
*Discount*Lag.Rating*	1.896*	1.866**	1.897**
	(0.9876)	(0.8580)	(0.8589)
Lag.Rating	-2.127	-1.863	-1.839
	(1.6451)	(1.4331)	(1.4336)
Ln(Watching)	0.039		0.020
	(0.0259)		(0.0231)
Lag.ln(Google)		0.512***	0.511***
		(0.0318)	(0.0318)
Lag.ln(Sales)		0.031*	0.028*
		(0.0158)	(0.0162)
Constant	11.002*	8.395	8.208
	(6.6212)	(5.7702)	(5.7753)
N	841	841	841
R^2	0.007	0.250	0.251
F	1.525	53.932	45.050

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, Standard errors are reported in parentheses

In the model, Discount represents the ratio of the currently available price to the original price. A smaller Discount means a hotel is offering a higher magnitude of discount. The coefficient of Discount is negative and significant, which supports $H2_a$. This result suggests that each 10% decrement in price leads to roughly 0.7% higher Google search volume. $H2_b$ proposes that a hotel's online reputation moderates the influence of price discount on product information search. The coefficient of the interaction term Discount*Lag.Rating is significantly positive while the coefficient of Discount is significantly negative, thus, $H2_b$ is also supported. The result indicates that good hotel rating diminishes the effect of price discount on Google search volume. More specifically, a one-star-higher hotel rating weakens the effect of price discount on Google search by 1.896%. In order to test the robustness of the proposed model, the price discount of a standard room is further replaced with the price discount of an elite suite to perform a robustness check. The results provided in Table 7 are consistent with the results shown in Table 6.

Table 7: Robustness check for the effect of price discount

Ln(Google)	(4)	(5)	(6)
Discount	-8.563**	-7.904**	-8.094**
	(4.1555)	(3.6081)	(3.6148)
*Discount*Lag.Rating*	2.294**	2.113**	2.166**
	(1.0880)	(0.9445)	(0.9465)
Lag.Rating	-2.451	-1.994	-1.997
	(1.6371)	(1.4290)	(1.4292)
Ln(Watching)	0.039		0.021
	(0.0258)		(0.0231)
Lag.ln(Google)		0.511***	0.511***
		(0.0318)	(0.0318)
Lag.ln(Sales)		0.030*	0.027*
		(0.0158)	(0.0162)
Constant	12.189*	8.801	8.717
	(6.5378)	(5.7130)	(5.7145)
N	841	841	841
R^2	0.008	0.251	0.252
F	1.671	54.025	45.143

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, Standard errors are reported in parentheses

5. Conclusion and discussion

5.1. Contributions

In recent years, online transactions of experience goods have become an essential part of the e-market and have shown great potential. Because of the inherent characteristics of experience products (unmeasurable quality before consumption), consumers generally search for additional information to reduce perceived risk and uncertainty before purchase. Search engines have become an important navigation tool to enhance information search efficiency. This study empirically explores the relationship between Google search queries and related product sales, as well as factors that might influence users' information-searching behavior. There are three main findings. First, the volume of keyword search queries on Google is positively correlated with related product sales in the future 48-hour-period. This result suggests that consumers' shopping dynamics are intensified by the fast pace of modern life. Second, the price discount offered by retailers has a positive impact on the Google search volume for the promoted products. Third, the influence of price discounts on Google search requests is negatively moderated by retailers' online reputations. As online WOM can also provide signals of product quality, for retailers with good reputations, the impact of price discounts on information searching behavior is thus diminished. These findings have significant theoretical and practical implications.

This research can contribute to the literature on information searching and online WOM from the following perspectives. First, due to the constraints of data availability, previous studies have used either monthly or weekly Google search data to forecast product sales or other economic activities. As the results provided by Zillow's survey depict, in recent years consumers' shopping dynamics have intensified [Park et al. 2018]. In theory, there is an urgent need for short-run trend analysis regarding the influence of information seeking on purchase decisions with minimum time delay. By combining the data collected from Expedia.com and Google Trends, this research explored this impact in a timelier fashion (within 48-hour-delay). Second, this study is one of the first attempts to empirically investigate the influence of experience product sales on Google search volume, with previous literature mostly focusing on the opposite relationship (i.e., the predictive power of Google Trends data on product sales). The results suggest that, due to social influence and herding effect, products with higher sales may enhance consumers' purchase intentions and thus motivate information-searching behavior on that product. Third, different from most previous studies, which have treated users' information-searching behavior as an endogenous factor, this study is among the first to empirically explore the factors that influence consumers' information-searching behavior. The results suggest that the price discounts offered by retailers motivate consumers to search for product information on Google either result in enhanced purchase intentions or triggering concerns about product quality. Fourth, this study has contributed to the literature on online WOM. The results indicate that both search engines and online reviews are important information resources to allow users to obtain knowledge about experience products and make purchase decisions accordingly. To some extent, the above two resources are complementary in reflecting a product's quality. Retailers' online reputations moderate the influence of price discounts on product information searches.

5.2. Practical Implications

This study also yields several direct managerial implications. First, the results highlight the dynamics of consumers' economic activities in the online market and demonstrate that a product's search volume can be viewed as a reflection of the purchase intention and is correlated with the product's sales in the future 48 hours. Practitioners of experience products should keep pace with both the changes in consumer shopping behavior and the development of Internet technology. As most experience products are also perishable, it is important for the retailers to promptly track the shifts in their customers' attention to create effective marketing strategies. Google Trends is a free, effective, and valuable tool that provides real-time and high-frequency data to the public. Thus, it has provided a new way to trace small changes in trends in a timely fashion. In terms of business operations, practitioners should take advantage of the search data on Google Trends to predict demand changes and respond accordingly (e.g., by defining proper and dynamic pricing strategies).

Second, businesses must try their best to improve the quality of their products or services. The results of this study clearly show that people increasingly rely on search engines to collect product information before making purchase decisions. With the online market becoming more mature, various tools are being developed to solve the information asymmetry problem. The growth in multi-channel information content, such as online WOM, has made product information more transparent. Consumers are also getting more sophisticated in utilizing different tools (e.g., search engines) to verify product quality. The retailers who provide inferior-quality products will gradually be eliminated from the online market.

Third, retailers should be more cautious when conducting price promotions. In most cases, the aim of offering a price discount is to boost sales. However, the results of this study suggest that the price reduction will motivate consumers' information searching behavior, which will ultimately disclose the product's true quality. Since consumers are becoming more sophisticated in terms of their ability to cope with various marketing strategies, low-price strategies no longer guarantee higher sales. What really drives sales is not the price discount, but the product's quality. As price also serves as a signal of product quality, exorbitant discounts may arouse suspicions that the lower prices reflect lower product quality [Ashworth et al. 2005]. Thus, retailers, especially high-end businesses, should be more cautious when conducting promotional campaigns.

Last, but not least, practitioners may adopt keyword advertising or search engine optimization (SEO) tools as a marketing media. As search engines become increasingly intelligent, a growing number of people are using them as a navigation tool to collect pre-purchase information. The keyword advertising or SEO can help companies increase online exposure and enhance brand awareness. In addition, when consumers search for a specific retailer or product using search engines, after searching for and verifying the related information they are sometimes transferred to another retailer that provides a similar product for purchase. This phenomenon is called "free riding" [Huang et al. 2009]. The search engine-based services above can effectively enhance the company's display rate in a prominent position on the results page, thus increasing its sales of high-quality products.

5.3. Limitations and Future Research

This study bears several limitations. First, we only collected information from 29 hotels in Las Vegas. This sample size cannot adequately represent the entire hotel industry, especially cannot reflect all lower-end hotels. To make the conclusions more convincing, data from more hotels located in various cities will be collected in the future. Second, only two months of data were collected, which is a short period of time in which to observe changes in online WOM. The ratings of most hotels do not change much over two months. Data reflecting a longer period will be collected to further investigate the role of retailer's reputation. Third, although we introduced the hotel-specific fixed-effect model to control for the time-invariant effect, there is still some unobservable heterogeneity across hotels that might influence their sales, such as brand reputation. Further studies will retrieve more data to address this issue.

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