From keyword to keywords: the role of keyword portfolio variety and disparity in product sales

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Received 23 February 2021
Revised 11 July 2021
29 August 2021
8 September 2021
Accepted 8 September 2021

Abstract

Purpose – This study investigates the effect of keyword portfolio characteristics on sales in paid search advertising. The authors propose two keyword portfolio characteristics (variety and disparity) and examine the effects of portfolio variety and portfolio disparity on direct and indirect sales in both PC and mobile environment.

Design/methodology/approach – By conducting a field study at a large e-commerce platform, the authors use a negative binomial model to develop empirical findings that provide insights into paid search advertising strategies.

Findings – For main effect, (1) portfolio variety has a negative effect on direct sales. However, (2) portfolio disparity has positive effects on both direct and indirect sales. Advertising channels influence the contribution of keyword portfolio to sales. (3) On mobile devices, portfolio variety positively affects both direct and indirect sales. However, portfolio disparity negatively affects both direct and indirect sales. (4) On PCs, portfolio variety negatively affects both direct and indirect sales. However, portfolio disparity positively affects both direct and indirect sales on PC.

Practical implications – The findings provide advertisers with insights into how to manage keyword portfolio between mobile devices and PCs.

Originality/value – The current study shifts the attention from keyword to keywords (keyword portfolio), which extends the paid search literature. Moreover, it also contributes to the literature by comparing the relative effectiveness of mobile and PC search advertising.

Keywords Keyword portfolio, Mobile, PC, Search advertising

Paper type Research paper

Introduction

Paid search advertising is the most prominent form of digital advertising and is expected to reach $211.4 billion in 2025 (Statista, 2020). The selection of keywords is crucial to the effectiveness of paid search advertising (Du *et al.*, 2017). A keyword is the search term that consumers use when they search for products on a search engine, consisting of one or multiple words (Klapdor *et al.*, 2014). Many researchers have investigated selecting keywords based on their characteristics (brand-specific, popularity and general) to improve click, conversion rate and product sale (Table 1). Although the literature on the effectiveness of paid search advertising is extensive, most studies focus on single keyword characteristics rather than keyword portfolio characteristics.

The authors acknowledge the financial support from Natural Science Foundation Grant of China (71573079, 72072052, 71772058), the Social Science Foundation of China (18ZDA063), Natural Science Foundation of Hunan Province (2020JJ3018), and the Hunan Provincial Innovation Foundation for Postgraduate (CX20190262).

Asia Pacific Journal of Marketing and Logistics

1355-5855
DOI 10.1108/APJML-02-2021-0145

Reference	Level of analysis	Domain	Attribute	Performance	Findings
Lu and Zhao (2014)	Product-day level	Keyword portfolio	Specific/general	Direct sales, indirect sales	Specific keywords increase the direct sale of target products. General keywords improve indirect sales
Du *et al.* (2017)	Product-day level	Keyword portfolio	Keyword category, keyword match type	Click volume, sales and profit	The exact match is related to the higher sales for generic and focal-brand keywords
Rutz and Bucklin (2011)	Aggregate keyword level	Keyword	Generic/branded	Branded search activity: Impressions, clicks	Generic keywords positively affect sales. Branded keywords increase clicks
Klapdor *et al.* (2014)	Advertiser level	Keyword	Frequency, ambiguity, query variation, location	Click-through rates, conversion rates	Keyword frequency and lexical ambiguity negatively affect a keyword's click-through rate
Jerath *et al.* (2014)	Individual-level	Keyword	Keyword popularity	Clicks per search, share of sponsored clicks	Keyword popularity negatively affects clicks per search
Rutz *et al.* (2011)	Keyword level	Keyword	Branded/ narrow/broader	Number of direct type-in visitors	Branded keywords positively affect direct visitation. Broader searches increase return visits
Yang *et al.* (2014)	Keyword level	Keyword	General/specific/ branded, promotional keywords	Click volume, cost per click	Promotional keywords decrease click volume, and fewer specific keywords increase mean value-per-click
Yang *et al.* (2020)	Individual keyword ad level	Keyword	Hedonic/ utilitarian keyword	Product sales	Hedonic keywords yield more product sales for hedonic products, while utilitarian keywords yield more sales for utilitarian products
This study	*Product-day level*	*Keyword portfolio*	*Portfolio variety, portfolio disparity*	*Direct sales, indirect sales*	*On mobile platforms, portfolio variety increases both direct and indirect sales. On the PC platform, portfolio disparity increases both direct and indirect sales*

Table 1.
Literature review on search engine advertising

In practice, marketers usually select a list of multiple keywords to create a keyword portfolio for an advertised product in paid search advertising (Liu and Toubia, 2018). Multi-keyword selection is different from single keyword selection because the effects of different keywords on keyword performance depend on each other (Du *et al.*, 2017). Keyword portfolio provides information about that budget allocation on keywords because marketers who design the keyword portfolio need to allocate budgets between different keywords (Lu and Zhao, 2014). Marketers cannot bid on all of the relevant keywords of the advertised product due to budget limitations. For example, in deciding a keyword portfolio with nine keywords, marketers need to not only select different keywords (e.g. brand keywords like "*Nike shoes,*" specific keywords like "*Nike Air Max Viva,*" general keywords like "*Men Shoes*"), but also decide the distribution of budgets on those keywords (three brand keywords, three specific keywords, three general keywords vs. one brand keyword, seven specific keywords, one general keyword). Therefore, selecting multi-keywords forming an effective keyword portfolio to increase product sales is vital for sellers in search advertising. This study aimed to fill the gap in the literature by investigating the effect of keyword portfolio characteristics on product sales in paid search advertising.

Many researchers have adopted the concept of diversity to consider the interdependencies among different elements in a portfolio (Jiang *et al.*, 2010; Cui, 2013; Caner *et al.*, 2018). Drawing upon the work of Harrison and Klein (2007), this study introduces two types of keyword portfolio diversity: *portfolio variety* and *portfolio disparity*. Portfolio variety is a composition of differences in semantic topics (e.g. brand, product type, usage season, usage scenario, user, function, appearance and material) in a keyword portfolio. Portfolio disparity is a composition of differences in subcategory levels in a keyword portfolio. To sum up, portfolio variety and portfolio disparity depict the distribution of semantic topics and subcategory levels within a keyword portfolio.

Marketers use keyword portfolios with multiple keywords containing multiple semantic topics and subcategory levels to improve the effectiveness of search advertising in practice (Lu and Zhao, 2014). However, marketers usually face the distribution problem of allocating advertising budgets among different keywords to maximize search advertising performance. Direct and indirect sales are essential for sellers when evaluating search advertising performance (Lu and Zhao, 2014). This study explicitly examines how different distribution of semantic topics and subcategory levels within a keyword portfolio (portfolio variety and portfolio disparity) influence direct and indirect sales. Thus, the authors proposed the first research question: *How do the two types of keyword portfolio diversity – variety and disparity – influence direct and indirect sales?*

One of the most significant changes in search advertising over the past few years is that most search activities have shifted from PC to mobile devices, with 90% of mobile owners conducting mobile searches (eMarketer, 2020). Advertisers, in practice, can select different keyword portfolios to target consumers on devices (PC vs. mobile). But little is known about whether and how to choose keyword portfolios on devices. Therefore, the authors in this study further proposed the following research question: *How do the effects of keyword portfolio diversity on sales differ by devices (mobile vs. PC)?*

This paper makes several contributions. First, we investigate keyword portfolios in search advertising and shift the attention from "single keyword" to "keyword portfolio." Second, this study refines the keyword portfolio's performance implications (both direct and indirect sales). Third, the relative effectiveness of mobile and online search advertising offers insight to manage multi-channel advertising spending.

In the following sections, we first present the theoretical background and develop our hypotheses. We then report the field study testing our hypotheses. Finally, we discuss the theoretical and managerial implications, followed by the limitations of this study and suggestions for future research.

Theoretical background

Keyword portfolio variety and portfolio disparity

A keyword is the search term that consumers use when they search for products on a search engine, consisting of one or multiple words (Klapdor *et al.*, 2014). A keyword portfolio combines all keywords that a seller bid for one focal product at a certain point in time (Lu and Zhao, 2014). Numerous studies have analyzed keywords in the context of paid search advertising on a single keyword level. Prior results show that different types of keywords generate distinct effects on sales (See Table 1).

Although the literature on the keyword in paid search advertising is extensive, the keyword portfolio has received much less attention. Only two studies have examined search advertising from a keyword portfolio perspective to the best of the authors' knowledge. One study examined the impact of buying different types of keywords (generic, focal brand and competing brand) and choosing keyword match types (exact, phrase and broad) on the performance of advertising campaigns (Du *et al.*, 2017). A more relevant prior work to the current paper is a study that categorized keywords in a portfolio into specific keywords and general keywords and investigated how different types of keywords influence direct and indirect sales differently (Lu and Zhao, 2014). Direct sales mean consumers directly purchased target products advertised by the seller. Indirect sales indicate sales generated not by the advertised product but by other products of the same seller. Lu and Zhao (2014) show that advertisers focusing more on the direct (indirect) sales of their products should use more specific (general) keywords in their portfolios.

In summary, numerous studies have analyzed keywords in the context of paid search advertising on a single keyword level, and two relevant studies took a portfolio perspective and suggested that it is essential to study keyword characteristics in a unified framework. However, they both investigate the effect of keyword portfolios by categorizing portfolios by the proportion of different types of keywords. In other words, these two relevant studies still take a keyword portfolio as a specific type of keyword. They ignore the interdependencies among different keywords and fail to capture the distribution of different types of keywords within a portfolio.

In this study, we investigate the performance of keyword portfolios from a portfolio diversity perspective. Marketers have adopted a diversity perspective to consider the interdependencies among different members in a portfolio based on alliances, new products, stocks (Jiang *et al.*, 2010; Cui, 2013; Caner *et al.*, 2018). According to Harrison and Klein (2007), diversity describes the distribution of differences among members in a portfolio concerning a common attribute, X, such as gender, resources or status. On the one hand, diversity is a compositional construct that describes the portfolio as a whole, not a focal member's differences from other members. On the other hand, it is also attribute-specific, which means that it is diverse concerning one or more specific attributes.

Drawing upon the construct of diversity proposed by Harrison and Klein (2007), we depict keyword portfolio diversity from horizontal and vertical differences within a keyword portfolio. We theorize that there are two types of keyword portfolio diversity concerning attribute "semantic topic" and attribute "subcategory level," namely portfolio variety and portfolio disparity. Portfolio variety is a composition of differences in semantic topics (e.g. brand, product type, usage season, usage scenario, user, function, appearance and material) in a keyword portfolio. A greater portfolio variety indicates a more significant difference in semantic topics, which means a broader distribution of semantic topics. In other words, portfolio variety captures the composition of differences in semantic topics within a keyword portfolio, which depicts the distribution of these topics. The semantic topic has no high or low. Thus, the difference among semantic topics reflects the horizontal differences within a keyword portfolio. In this regard, the portfolio variety indicates the broad distribution of semantic topics.

Portfolio disparity is a composition of differences in subcategory levels in a keyword portfolio. The subcategory level means the extent relevant to the target product, similar to keyword specificity in prior studies (Wang *et al.*, 2019). The lower subcategory level applies to a specific product (e.g. Nike women's shoe A09820). The higher subcategory level applies to even a whole category (e.g. women's shoes). A greater portfolio disparity indicates a more significant difference in subcategory levels. For example, a portfolio with an uneven distribution of subcategory levels has more significant disparity than one with even distribution. In other words, portfolio disparity captures the composition of differences in subcategory levels within a keyword portfolio, which depicts the distribution of subcategory levels. Subcategory level has a high or low level. Thus, the difference among subcategory levels reflects the vertical differences within a keyword portfolio. In this regard, the portfolio disparity indicates the uneven distribution of subcategory levels.

The advertising on different devices

Advertisers launching paid search ads can select keyword portfolios to target consumers on different devices (PC vs. mobile). Prior studies suggested that device usage can affect various aspects of consumer behavior (Wang and Genç, 2019). On the one hand, some studies showed that mobile use positively impacts consumer behavior. For example, mobile users who search broadly also search deeply, and their advertising response positively relates to the breadth of their search (Goh *et al.*, 2015). Another research suggested that mobile users (compared to PC users) are more likely to click the top paid search ad and more sensitive to ad position change (Lu and Du, 2020). More relevant work shows that mobile keywords increase direct sales (Wang *et al.*, 2019). On the other hand, some studies showed that mobile usage has some negative impacts. For instance, Wang *et al.* (2019) show that mobile keywords decrease indirect sales.

In summary, those studies do not suggest consistent advertising effectiveness on different devices (PC vs. mobile). Mobile devices have become the dominant channel for reaching consumers (Jain *et al.*, 2021; Ghazali *et al.*, 2018; Le and Wang, 2020). It is vital to investigate the relative effectiveness of mobile channels so that sellers may take advantage of such knowledge when deciding on multi-channel advertising spending (Ghose *et al.*, 2013). We thus extend the literature by empirically investigating the differential effects of keyword portfolio variety and disparity on online and mobile advertising.

This study will investigate the effects of portfolio variety and portfolio disparity on direct and indirect sales in both PC and mobile environments, as shown in Figure 1.

Hypothesis development

Main effect of keyword portfolio diversity

From the perspective of consumer heterogeneity, different keyword portfolios attract different types of consumers, resulting in direct sales of the advertised product and then leading to indirect sales of other products (Lu and Zhao, 2014). According to the shopping goal theory (Lee and Ariely, 2006), consumers are generally uncertain about buying in their early shopping stage. In their later stage, they are likely to have a transactional goal (Humphreys *et al.*, 2020). To generate direct sales, advertisers need to attract consumers with clear preferences at their later stage of shopping (Lu and Zhao, 2014). Consumers with clear preferences have already collected information about the target product (Humphreys *et al.*, 2020), so they may focus on just one product's attributes rather than on all of them. Thus, when a seller uses a keyword portfolio with concentrated topics (low variety), the portfolio will attract consumers with clear shopping goals, generating more direct sales. As for indirect

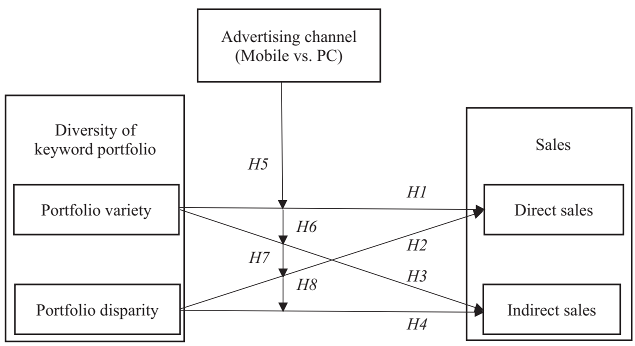

Figure 1.
Research framework

sales, prior studies suggested that both the substitution effect and the complementary effect contribute to indirect sales (Russel and Peterson, 2000). The substitution effect occurs when consumers who click on search advertising do not buy the advertised product but purchase other products from the same seller. This effect is more likely to contribute to indirect sales of competing products of the same sellers (Lu and Zhao, 2014). The complementary effect occurs when consumers buy both the advertised and related products from the same seller. These products are complementary, a crucial driver of cross-selling (Manchanda *et al.*, 1999). According to the extant literature, the complementary effect will dominate the generation of indirect sales (cross-selling) (Russell and Petersen, 2000). From this perspective, more direct sales result in more indirect sales. We hypothesize the following:

H1. Portfolio variety negatively affects direct sales.

H2. Portfolio variety negatively affects indirect sales.

Consumers will use more concrete keywords with a clear preference (Humphreys *et al.*, 2020). When consumers with clear goals search for their target product, they are more likely to use product-specific keywords (e.g. Nike shoe A09820) and purchase the product directly (Lu and Zhao, 2014). Thus, when sellers bid for a keyword portfolio whose relative concentration of subcategories is that most of its keywords belong to the product level (high disparity), the portfolio is more likely to attract consumers with clear goals, generating more direct sales. More direct sales will lead to more indirect sales (Russell and Petersen, 2000). In this regard, keyword portfolios with concentrated subcategories (high disparity) leading to more direct, also result in more indirect sales. We hypothesize the following:

H3. Portfolio disparity positively affects direct sales.

H4. Portfolio disparity positively affects indirect sales.

Moderating role of mobile platforms

Mobile usage has become a way of life for consumers since smartphones became widely used (Lamberton and Stephen, 2016). According to Goh *et al.* (2015), mobile users who search broadly also search deeply. Compared to online searching using a PC, consumers can search for product information anywhere and anytime using mobile devices (Bart *et al.*, 2014; Ghose, 2017). Thus, mobile users may search broadly and deeply before making a purchase decision. Mobile devices are now essential in daily life, but the relative effect of mobile (vs. PC) search advertising on sales remains unknown. Therefore, we explore the moderating role of mobile devices and shed light on whether and when mobile search advertising outperforms PC search advertising in terms of sales.

High portfolio variety suggests a diversity of topics. As we hypotheses before, portfolio variety harms direct sales and indirect sales. Consumers may search broadly and deeply on mobile devices and compare product attributes before purchasing (Goh *et al.*, 2015). In this case, consumers will use keywords with diverse topics even in their later stages of shopping. Thus, a seller using a keyword portfolio with diverse topics for mobile advertising attracts more consumers to the advertised product. Thus, high portfolio variety on mobile advertising generates more direct sales. In other words, the negative association between portfolio variety and direct sales is weaker for mobile devices than for PCs. Mobile devices weaken the negative effect of portfolio variety on indirect sales. A seller using a keyword portfolio with diverse topics for mobile advertising attracts more consumers to the landing page (Lu and Zhao, 2014). Therefore, regardless of whether these consumers are satisfied with the advertised product, they can still browse the seller's other related sites and products (Moe, 2003). Thus, for mobile devices, a keyword portfolio with great variety creates opportunities for sellers to cross-sell other products indirectly. In other words, the negative association between the diversity of portfolio variety and indirect sales is weaker for mobile devices than for PCs.

H5. The negative association between portfolio variety and direct sales is weaker for mobile devices than PCs.

H6. The negative association between portfolio variety and indirect sales is weaker for mobile devices than PCs.

High portfolio disparity reflects a relative concentration of subcategories that most of its keywords belong to the product level. When sellers bid for a keyword portfolio with high disparity, it is more likely to attract consumers with clear goals, generating more direct sales. However, consumers may search broadly and deeply on mobile devices and compare product attributes before purchasing (Goh *et al.*, 2015). In this case, consumers will use keywords with more diverse subcategories to search broadly and deeply even in their later stages of shopping on mobile devices. Thus, a keyword portfolio with a relative concentration of subcategories for mobile advertising is less likely to attract more consumers at their later shopping stage than a portfolio with dispersive subcategories. Those consumers in the later stage of shopping, on the one hand, likely increase motivation to process information during mobile searching and leads to more direct sales (Wang *et al.*, 2019); on the other hand, they are likely to have transactional goals and generate more direct sales on mobile devices (Humphreys *et al.*, 2020). Therefore, a keyword portfolio with concentrated subcategories generates less direct sales than a portfolio with dispersive subcategories on mobile devices. In other words, the positive association between portfolio disparity and direct sales is weaker for mobile devices than for PCs. Mobile devices weaken the positive effect of portfolio disparity on indirect sales because more direct sales will lead to more indirect sales (Russell and Petersen, 2000). Thus, the positive association between portfolio disparity and direct and indirect sales is weaker for mobile devices than PCs. We hypothesize the following:

H7. The positive association between portfolio disparity and direct sales is weaker for mobile devices than PCs.

H8. The positive association between portfolio disparity and indirect sales is weaker for mobile devices than PCs.

Method

Research context

We conducted a randomized field study to test the effects of keyword portfolios on the largest e-commerce platform. Mobile devices have intensified marketing activity, with active monthly users reaching 699 million in December 2018 (Alibaba, 2019). The platform provides a keyword auction service whereby sellers bid on the display of their products based on keywords. For a consumer search query with a keyword (e.g. "men's shoes black winter") on a PC or mobile device, sellers bid on this keyword to display their products. The higher the bid price is, the higher the display position. A seller pays for this auction when a consumer clicks on its displayed product. Consumers are guided to the landing page to browse and purchase the advertised focal product by clicking on the displayed product, generating direct sales. Once on the landing page, consumers may click on other links on the seller's sites, visit the seller's other product and buy those items, generating indirect sales.

Research design

A men's shoe seller participated in the field study from 1 February 2016 to 30 April 2016, during which time the seller ceased all other promotions. Footwear is one of the most popular online shopping categories. This medium-sized seller had annual sales of approximately 4 million units on the platform, serving to control for the popular effect of the firm. Men are less likely to make a repeat purchase of shoes during three months, helping to eliminate the impact of repeated purchases.

The seller used 182 keywords to display its products. There are 40 products involved in this study. Each day, sellers randomly chose several keywords to bid using Excel's random number generator. The average daily number of keywords was 31 (maximum: 49; minimum: 3). Daily, the sellers bid for keywords on both PC and mobile platforms to avoid the channel's self-selection bias. We also identified keyword features and observed how they generated product sales daily.

Research data and coding

Our original data contained 10,966 records of keyword bidding for focal products on a single keyword level. Based on the semantic features of the keyword (Yang *et al.*, 2020), two research assistants from the field of Chinese linguistics code the semantic topics and subcategories that each keyword containing. For the semantic topics coding, the two assistants classify eight semantic topics common for shoes: brand, product type, usage season, usage scenario, user, function, appearance and material. For example, the keywords "men's winter leather shoes" contain three topics: user, usage season and material. Then these three topics are coded to 1, and the other five topics are coded to 0. One keyword can contain multiple topics. We classify six subcategory levels based on whether a keyword is general or specific for the subcategories coding. The highest level is the shoe category (e.g. keyword "shoes"), and the lowest is in a particular product or brand (e.g. "3,515 strong army boots"). Thus, a keyword can belong to a spectrum of subcategories ranging from 1 to 6. In this regard, one keyword can only belong to a specific subcategory. At the beginning of the coding process, the two research assistants code each keyword separately. If the coding results are inconsistent, the two research assistants discuss the item until they reach a consistent decision.

The average size of a keyword portfolio consists of 6 keywords. In this case, we combine the dataset from a single keyword level into a keyword portfolio level. After deleting the missing observation, we ended up with a total of 794 valid samples on the product portfolio level.

Measurement

Product sales: The platform tracks all browsing behavior on the seller's sites, from the consumer's first click on search advertising to the consumer reaching the landing page making any purchases. The platform can be used to track the direct and indirect sales generated by keyword advertising daily. For product i on day t, its $Direct\ Sales_{i,t}$ are measured as the sales volume of the focal product generated by the keywords in the keyword portfolio. The $Indirect\ Sales_{i,t}$ are measured as the sales volume of the other products generated by the keywords in the keyword portfolio.

Diversity of keyword portfolio: For keyword portfolio i, we assume there to be n_i keywords. $Portfolio\ variety_i$ is used to evaluate the distribution of the semantic topics within portfolio i. Each keyword may be in one or multiple $k = 1, \ldots 8$ possible semantic topics (brand, product type, usage season, usage scenario, user, function, appearance and material). Portfolio variety captures the spread of keywords across different semantic topics. Here, variety does not reflect continuous distance but a rather qualitative distinction. The Blau Index is the most common measurement of diversity-as-variety, measuring qualitative differences (Blau, 1977). Thus, we use the Blau Index to measure the distribution of keywords across the eight topics within a portfolio. Its computational formula is following:

$$\text{Portfolio variety}_i = 1 - \sum P_k^2$$

Notes: p_k is the percentage of keywords in the kth semantic topic (brand, product type, usage season, usage scenario, user, function, appearance and material). The value of this index ranges from 0 to $(k-1)/k$. For example, if a portfolio with eight keywords spreading equally across $k = 8$ semantic topics, the value of portfolio variety is 0.875.

Portfolio Disparity$_i$ is used to evaluate the relative dispersion of subcategory levels of the keywords. Each keyword in this portfolio belongs to a specific subcategory level D (D range from 1 to 6). The disparity reflects the distances among keywords and the dispersion of subcategories. The Gini index is the most commonly used measurement of dispersion ratio (Gastwirth, 1972). In this regard, we use the Gini index to measure the inequality and dispersion of p_i keywords on the six levels. Its computational formula is following:

$$\text{Portfolio disparity}_i = \left(\sum D_i - D_j\right) \Big/ \left(2 * n^2 * D_{\text{mean}}\right)$$

Notes: D is the subcategory level of each keyword within a portfolio. N is the keyword number within a portfolio. D ranges from 1 to 6. And the value of this index ranges from 0 to $1-(1/n)$.

Mobile: Our moderator *Mobile$_{i,t}$* equals 1 if a keyword portfolio is bid for on the mobile channel and 0 if on the PC channel on day t.

Control variables: We control the mean of pi keyword relevance for each keyword portfolio because a keyword related to a particular advertised product significantly influences the conversion rate (Du *et al.*, 2017). As keyword specificity may affect direct and indirect sales (Lu and Zhao, 2014), we control the percentage of specific keywords in a keyword portfolio. To control the size effect, we add the number of keywords in the portfolio as a control variable, *Portfolio Size$_i$*. We also include the mean of p_i keywords' number of topics, the mean of p_i keywords' category levels and the average display ranking of the focal product on the landing page on day t (*Rank Average$_{i,t}$*). We control for product price because it may influence sales. Moreover, to control for the time effect, we use six dummies to capture the seven days of each week.

Analysis and results

The two dependent variables are the volume of direct and indirect sales. They are count variables. Traditional regression using ordinary least squares is biased when the dependent variable is a count variable. Poisson models are often used instead. However, our data also show that over-dispersion, the variance of the dependent variable, is substantially larger than its mean. When the data are over-dispersed, the Poisson model is biased, and therefore, a negative binomial model is preferred. Thus, we use negative binomial regressions. Based on the theoretical framework in Figure 1, we specify a model with two simultaneous equations:

$$\begin{aligned}\text{Direct Sales}_{i,t} = {} & \alpha_{1,0} + \beta_{1,1}\,\text{Mobile}_{i,t} + \beta_{1,2}\,\text{Portfolio variety}_{i,t} \\ & + \beta_{1,3}\,\text{Portfolio disparity}_{i,t} + \beta_{1,4}\,\text{Mobile}_{i,t} \times \text{Portfolio variety}_{i,t} \\ & + \beta_{1,5}\,\text{Mobile}_{i,t} \times \text{Portfolio disparity}_{i,t} + \beta_{1,6}\,\text{keywords relevance}_{i,t} \\ & + \beta_{1,7}\,\text{Mean of topic}_{i,t} + \beta_{1,8}\,\text{Mean of category}_{i,t} \\ & + \beta_{1,9}\,\text{Percentage of specificity}_{i,t} + \beta_{1,10}\,\text{Portfolio size}_{i,t} \\ & + \beta_{1,11}\,\text{Average display rank}_{i,t} + \beta_{1,12}\,\text{Product price}_{i,t} + \varepsilon_{1,i,t}\end{aligned} \quad (1)$$

$$
\begin{aligned}
\text{Indirect Sales}_{i,t} = {} & \alpha_{2,0} + \beta_{2,1}\,\text{Mobile}_{i,t} + \beta_{2,2}\,\text{Portfolio variety}_{i,t} + \beta_{2,3}\,\text{Portfolio disparity}_{i,t} \\
& + \beta_{2,4}\,\text{Mobile}_{i,t} \times \text{Portfolio variety}_{i,t} \\
& + \beta_{2,5}\,\text{Mobile}_{i,t} \times \text{Portfolio disparity}_{i,t} + \beta_{2,6}\,\text{keywords relevance}_{i,t} \\
& + \beta_{2,7}\,\text{Mean of topic}_{i,t} + \beta_{2,8}\,\text{Mean of category}_{i,t} \\
& + \beta_{2,9}\,\text{Percentage of specificity}_{i,t} + \beta_{2,10}\,\text{Portfolio size}_{i,t} \\
& + \beta_{2,11}\,\text{Average display rank}_{i,t} + \beta_{2,12}\,\text{Product price}_{i,t} \\
& + \beta_{2,12}\,\text{Direct Sales}_{i,t} + \varepsilon_{2,i,t}
\end{aligned} \tag{2}
$$

Table 2 presents the statistics and correlations for the above variables. The correlations are below the levels that generate a collinearity problem. The highest variance inflation factor is 4.33, which is below the acceptable level of 5. We standardize the independent variables before creating the interaction terms to facilitate the interpretation and comparison of the results. We consider both the full model and a benchmark model without interaction terms.

For the main effects of a keyword portfolio on direct sales, the estimation results in Table 3 indicate that portfolio variety (portfolios with diverse topics) significantly negatively affects direct sales ($\beta = -0.166, p < 0.01$), supporting H1. Portfolio disparity (portfolio with category dispersion) significantly increases direct sales ($\beta = 0.361, p < 0.01$), supporting H3. Regarding the main effects of keyword portfolio diversity on indirect sales, the estimation results indicate that portfolio variety does not significantly influence indirect sales. Thus, H2 is not supported. However, portfolio disparity significantly increases indirect sales ($\beta = 0.645$, $p < 0.05$), supporting H4.

For the moderating effects of mobile devices on direct sales, the interaction term between mobile and portfolio variety is significantly positive ($\beta = 0.728$, $p < 0.001$), supporting H5. Portfolios with diverse topics increase direct sales on mobile devices (see Figure 2). The interaction term between mobile and portfolio disparity is significantly negative ($\beta = -0.322$, $p < 0.05$), supporting H7. This result indicates that a portfolio with a subcategory concentration decreases direct sales on mobile devices (see Figure 3). Similarly, for the moderating effects of mobile platforms on indirect sales, the interaction term between mobile and portfolio variety is significantly positive ($\beta = 3.076, p < 0.01$), supporting H6. This result suggests that portfolios with diverse topics increase indirect sales on mobile devices (see Figure 4). The interaction term between mobile and portfolio disparity is significantly negative ($\beta = -1.127$, $p < 0.05$), supporting H8. This finding indicates that portfolios with subcategory concentration decrease indirect sales on mobile devices (see Figure 5). In other words, portfolios with diverse subcategories increase indirect sales on mobile devices. The interaction coefficient of indirect sales being higher than direct sales is understandable because a seller's keyword portfolio bid for an advertised product creates opportunities for that same seller to expose 39 other products. Thus, the effect of portfolio diversity on indirect sales is stronger than that on direct sales.

Discussion

This study examines how different keyword portfolios exert distinct effects on sales and provides essential findings concerning the performance of keyword portfolios. Portfolio variety increases direct and indirect sales on mobile devices, while portfolio disparity decreases direct and indirect sales. On PCs, portfolio variety decreases direct and indirect sales while portfolio disparity increases direct and indirect sales.

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. Direct sales	0.75	1.30	1											
2. Indirect sales	0.10	0.51	0.28*	1										
3. Portfolio variety	0.60	0.17	0.26*	0.12*	1									
4. Portfolio disparity	0.12	0.08	0.06	0.02	0.23*	1								
5. Mobile	0.50	0.50	−0.08	−0.17*	0.00	0.00	1							
6. Keyword relevance	0.14	0.04	0.17*	0.13*	0.27*	−0.27*	0.00	1						
7. Mean of topic	3.06	0.56	0.08	0.12*	0.19*	−0.07	0.00	0.67*	1					
8. Mean of category	3.69	0.60	0.11*	0.02	0.03	−0.63*	0.00	0.07	−0.35*	1				
9. Percentage of specificity	0.40	0.26	0.02	0.04	0.18*	−0.40*	0.00	0.55*	0.63*	−0.13*	1			
10. Portfolio size	6.01	5.04	0.48*	0.24*	0.59*	0.18*	0.00	0.34*	0.30*	0.02	0.21*	1		
11. Average display rank	41.74	21.53	0.06	0.13*	0.07	0.02	−0.63*	0.10*	0.14*	−0.11*	0.08	0.15*	1	
12. Product price	255.21	75.84	0.02	0.03	−0.05	0.08	0.00	0.22*	0.03	0.11*	−0.29*	0.04	0.09*	1

Note(s): '*' is significant at the 0.05 level
$N = 794$

Table 2.
Descriptive statistics and correlations

Table 3. Estimation results

		DV = direct sales					DV = indirect sales			
		Model 1		Model 2			Model 3		Model 4	
		Coefficient	SE	Coefficient	SE		Coefficient	SE	Coefficient	SE
Main effects										
Mobile		−0.851	0.138***	−0.862	0.151***		−3.510	0.529***	−6.138	1.254***
Portfolio variety	H1	−0.009	0.076	−0.166	0.072**	H2	−0.100	0.178	−0.112	0.179
Portfolio disparity	H3	0.248	0.140	0.362	0.133**	H4	−0.599	0.365	0.645	0.365*
Moderating effects										
Portfolio variety × mobile	H5			0.728	0.124***	H6			3.076	1.210**
Portfolio disparity × mobile	H7			−0.322	0.160*	H8			−1.127	0.655*
Control variables										
Keyword relevance		9.955	2.991***	10.127	3.079***		0.870	6.073	1.440	6.201
Mean of topic		−0.253	0.210	−0.289	0.212		2.332	0.445***	2.297	0.460***
Mean of category		0.455	0.204*	0.501	0.204**		2.132	0.731**	2.155	0.733**
Percentage of specificity		−0.875	0.378*	−0.823	0.371*		−0.328	0.813	−0.304	0.818
Portfolio size		0.129	0.014***	0.114	0.013***		0.094	0.041*	0.082	0.041*
Average display rank		−0.012	0.003***	−0.009	0.003**		−0.018	0.010	−0.017	0.010
Product price		−0.003	0.001*	−0.003	0.001*		0.001	0.005	0.001	0.005
Direct sales							0.356	0.079***	0.347	0.081***
Six-day dummies		*Yes*	*Yes*	*Yes*	*Yes*		*Yes*	*Yes*	*Yes*	*Yes*
Intercept		−1.784	1.177	−1.952	1.171		−17.802	3.881***	−17.826	3.932***
N		794		794			794		794	
Log likelihood		−751.502		−728.604			−162.3784		−161.074	

Note(s): *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

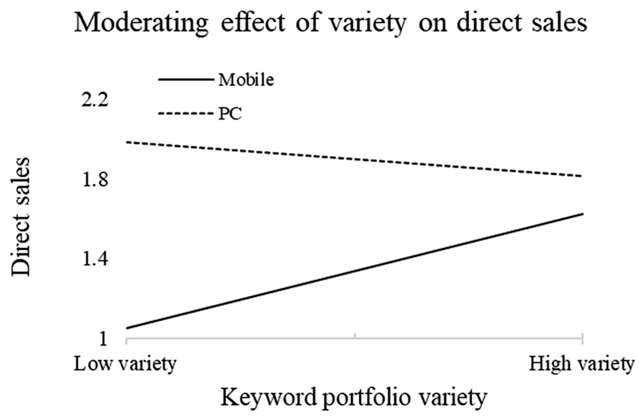

Figure 2.
Moderating effect of variety on direct sales

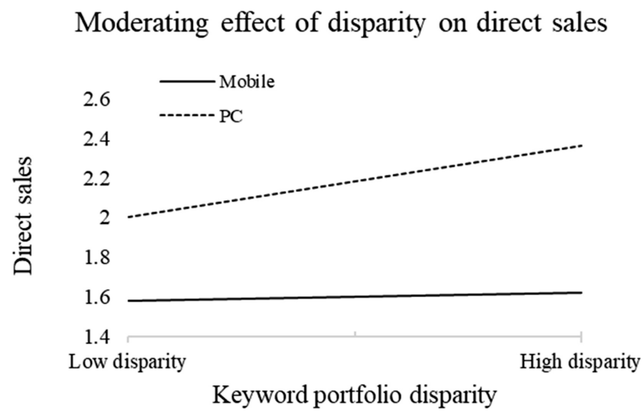

Figure 3.
Moderating effect of disparity on direct sales

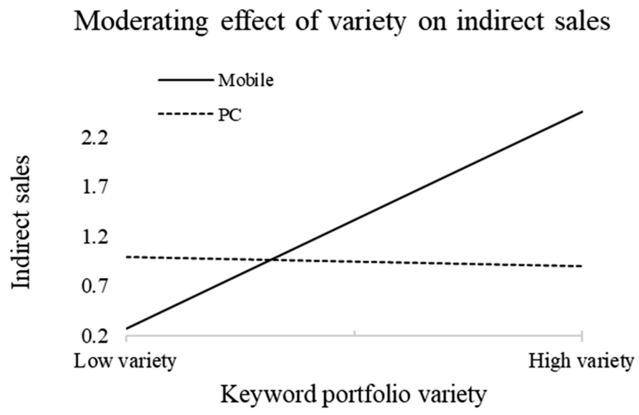

Figure 4.
Moderating effect of variety on indirect sales

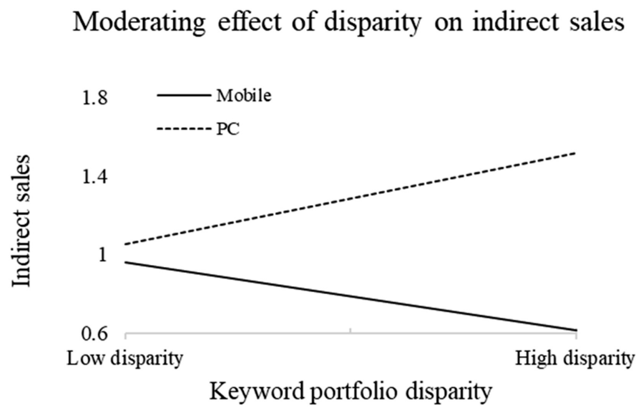

Figure 5.
Moderating effect of disparity on indirect sales

Theoretical implications

Search advertising has received much attention in digital marketing research. Still, little is known about designing a keyword portfolio that increases product sales on different channels, which should entail more than size effects on product sales. We investigate the above question and make three contributions to the literature.

First, we research keyword portfolios in the domain of search advertising. We describe the horizontal and vertical differences between keywords in a keyword portfolio and develop keyword portfolio diversity, influenced by Harrison and Klein (2007). Keyword portfolio diversity for the keywords in a portfolio is defined by portfolio variety, which reflects horizontal differences, and portfolio disparity, which reflects vertical differences. Therefore, we shift the attention from a single keyword to multiple keywords (to a keyword portfolio), which extends the keyword literature (Lu and Zhao, 2014) and deepens our understanding of the role of keywords.

Second, we develop the research on search advertising by relating keyword portfolio performance to both direct and indirect sales. The literature has examined the direct and indirect effects of keywords (Lu and Zhao, 2014). However, we investigate the performance of the keyword portfolio from a portfolio diversity perspective. Our results show that keyword portfolio diversity contributes to both direct and indirect sales. Different types of keyword portfolio diversity influence sales differently since portfolios attract different types of consumers, which results in distinct effects on product sales. Notably, our findings illustrate that low portfolio variety (portfolios with concentrated topics) and high portfolio disparity (portfolios with concentrated subcategories) will get higher direct and indirect sales since such a portfolio will attract consumers with clear shopping goals.

Third, we offer insight into mobile search advertising and compare the relative effectiveness of mobile and online search advertising. Prior studies do not suggest consistent results concerning the effectiveness of advertising on mobile (Wang and Genç, 2019; Madan and Yadav, 2018). We find that the efficacy of search advertising on mobile is different from that on PC. Specifically, PC devices can intensify the negative effects of portfolio variety on product sales and increase the effectiveness of portfolio disparity on product sales. Conversely, mobile devices can increase the effectiveness of portfolio variety and weaken the positive effects of portfolio disparity on product sales. These results enrich understanding of the dual role of mobile on product sales.

Managerial implications

We generate several managerial implications for advertisers using search advertising. First, we provide advertisers with critical insight into how the diversity of keyword portfolios contributes to online sales. Our findings imply that advertisers should attach importance to search advertising, which remains an effective advertising tool.

Second, our results give advertisers practical instructions regarding selecting multiple keywords to form daily keyword portfolios based on their business goals (to increase direct and indirect sales). According to our study, sellers may assess the performance of a keyword portfolio by considering the direct sales that portfolios generate and the indirect sales to which they contribute. Thus, advertisers must account for the overall effects of portfolios instead of just direct sales when evaluating keyword portfolio performance. Based on such evaluations, sellers can adjust their keyword portfolio strategies according to their business goals. For example, sellers can choose a keyword portfolio with concentrated topics and subcategories when sellers focus on direct sales. In contrast, when sellers emphasize indirect sales, it is helpful for them to select a keyword portfolio with concentrated subcategories. We propose that sellers consider the importance of keyword portfolio diversity when deciding on their daily keyword portfolios.

Third, our results provide advertisers with insight into managing keyword portfolios between mobile devices and PCs. Portfolio variety has a more positive effect on direct and indirect sales in a mobile setting than PC. Therefore, advertisers should consider the effective performance of uniform distributions of semantic topics among keywords when they bid on keywords for mobile channels. In other words, sellers should design a portfolio with various semantic topics for mobile channels and develop a portfolio with concentrated semantic topics for PCs. However, portfolio disparity exerts more negative effects on direct and indirect sales in a mobile setting than PC. This finding has practical implications for sellers choosing keyword portfolios with category concentrations for PC, aiming to increase direct and indirect sales while choosing keyword portfolios with diverse topics for mobile devices. We strongly suggest that advertisers take advertising channels into account in keyword portfolio management.

Limitations and future research directions

This study's limitations mainly concern its restricted data. First, we examine the effects of keyword portfolios on sales at the product level. We do not have detailed information on each keyword level. Second, we only use the sales generated by keywords as dependent variables and do not have the bidding costs of keywords. Thus, the exact returns of different keyword portfolios cannot be determined. Third, we do not differentiate between mobile devices. Whether the device is a mobile phone or tablet is unknown in our data set. Although Xu *et al.* (2016) show that the tablet channel complements the smartphone channel, separating mobile devices into tablets and smartphones is more desirable because these are different channels. Moreover, we only consider one meaning of a keyword when coding its and semantic features even though our data set includes some polysemous words.

Future research may follow several directions. First, future studies may distinguish between the effects of keyword portfolios on tablets versus smartphones and explore whether there is a complementary channel effect between tablets and smartphones. Different device systems may also be considered, such as iOS and Android. Second, future studies may investigate how other semantic attributes of a keyword portfolio influence sales. Third, it is worthwhile to investigate the exact returns of different keyword portfolios by examining the bidding costs of keywords. This way may provide advertisers with more precise guidelines on optimizing their keyword portfolio strategies.

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