Differential Effects of Keyword Selection in Search Engine Advertising on Direct and Indirect Sales

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Abstract

Product sales via sponsored keyword advertising on search engines rely on an effective selection of keywords that describe the offerings. In this study, we consider both the direct sales of the advertised products and indirect sales (i.e., cross-selling) of other products, and examine how specific keywords and general keywords influence these two types of sales differently. We also examine how the cross-selling effects may vary across different types of products (main products and accessories). Our results suggest that the use of specific keywords leans towards improving the direct sales of advertised products, while the use of general keywords leans towards improving the indirect sales of other products. The contribution of keywords to indirect sales is influenced by product type. For main products, the use of specific keywords generates a higher marginal contribution to indirect sales than that of general keywords. For accessory products, the use of general keywords generates a higher marginal contribution to indirect sales than that of specific keywords. The key implication of this study is that sellers focusing on different types of sales (direct or indirect sales) or products (main or accessory products) should consider using different types of keywords in search engine advertising to drive sales.

Keywords: Search Engine; Advertising; Cross Selling; Keywords Selection

Introduction

In the current competitive e-commerce environment, search engine advertising (SEA) has been widely adopted by companies to target and acquire consumers online [2, 42, 43]. SEA is often considered as intent related targeted advertising [19, 25]. That is, when consumers search for products, the search terms (or, keywords) they use often reflect their purchase desires or intents. Marketers can use such reflected purchase intents as the basis of keywords targeting advertising. In SEA, marketers or advertisers can bid for the targeted keywords used in sponsored lists of search providers or online platforms (such as Google, Yahoo, eBay etc), hoping that consumers visit their sites through advertisement links and eventually purchase products. According to a recent survey by eMarket, companies nowadays spend more than 45% of their internet marketing budget on SEA[1].

Despite the notable investments in SEA, in practice, the management of SEA lacks key guidance and principles [12, 24]. For advertisers, the match between the keywords that they bid for and the term that consumers use in their queries is critical to SEA performance. If they do not select the appropriate keywords, they may target wrong groups of consumers and eventually exhaust their advertising budget with poor returns [25]. Moreover, advertisers often need to consider bidding for a number of different keywords and the portfolios of keywords need to be adjusted dynamically [51]. However, most advertisers simply use their subjective understanding of the query terms to include relevant keywords that they feel may be used by potential consumers [49]. These keywords may not lead to desired click-through

[1] Source: http://searchengineland.com/emarketer-among-online-ads-search-to-gain-most-new-dollars-in-2011-80707

and conversion rates [24]. Therefore, the spending on the whole keyword portfolio is often suboptimal and the SEA performance in improving the overall sales is not satisfactory [25].

In deciding keyword portfolios, advertisers may include multiples keywords that are relevant to the advertised products to various degrees. Some keywords may be more general in meaning and can be applied to a variety of different brands or even different products. Some keywords may be more specific in meaning and are applied to certain brands/products. Advertisers use both general keywords and specific keywords since they all influence consumer search [1, 17]. Specific keywords tend to induce purchasing from consumers who conduct purposeful search. In this case, consumers often use more narrow terms, such as "Cannon 50D SLR Camera", that reflect unambiguous purchasing goals [12]. On the other hand, when consumers do not have clear purchasing targets (e.g., at initial stages of product search), they may use general and inclusive keywords, such as "digital camera" or "Cannon", to acquire broad product information. General keywords may not necessarily result in the direct selling of the advertised product associated with these keywords. However, these keywords are usually more popular and have higher search liquidity than specific keywords [12], and may attract more consumers to the seller's site for further search and potentially result in the indirect selling of other products (besides the advertised ones) of the seller[43].

In deciding keyword portfolios, advertisers tend to only care more about the direct sales of advertised products [4, 14]. However, in addition to direct sales, keywords used in SEA may also benefit online sellers (i.e., advertisers) [2] in indirect ways, such as through cross-selling. If a single click on a given sponsored ad leads to cross selling of multiple

[2] In practice, advertisers may mean various types of entities, such as ad intermediaries and online sellers themselves. In this study, we mainly use the term *advertisers* to refer to online sellers or retailers.

different products, the online seller essentially reaps higher return from their advertising spending. For example, the study of Ghose and Yang [17] shows that 12.78% of keyword clicks eventually lead to cross-category purchases. Some prior studies (e.g., [48]) suggest that certain types of keywords (e.g., seller-specific keywords) may incur less direct purchases of the advertised products but more indirect purchases of other products by consumers. The study of Rutz et al. [43] also verifies that different types of keywords are heterogeneous in terms of their capabilities of generating return visits to foster indirect sales. Given that most online sellers are multiproduct sellers and cross-selling is a very important source of revenue, sellers may also need to use more general keywords which are less relevant to specific products but help attract traffic and generate indirect sales of other products.

Therefore, in SEA, advertisers (i.e., online sellers) usually face an optimization problem of allocating advertising budgets between different types of keywords to maximize the total revenue. In this study, we explicitly examine how different types of keywords (general versus specific keywords) influence the direct, indirect, and total sales revenue of online sellers. The study should help online sellers better understand the differential marginal benefits of these keywords in improving different types of sales. Such understanding should in turn help them optimize budget allocation between different keywords.

In investigating the sales impacts of keywords, we also consider product type as a moderating factor[6] and examine how it influences the performance of different types of keywords. We distinguish between main products and accessory products. Main products mainly refer to the products whose core functionalities can be used (or consumed) alone. Accessory products mainly refer to the products whose core functionalities are to be used as a complement to their corresponding main products. As recognized by prior literature on cross-selling, e.g., [31, 47], the complementarities between different types of products (such as that between main products and accessory products) often influence consumer's cross-category purchasing decisions. In this regard, examining how keyword type interacts with product type in influencing sales revenue allows us to better understand how SEA impacts online sales and how advertisers may better design their keyword portfolios based on the products they sell. Therefore, the research questions addressed in this study can be summarized as follows:

1. *How do general keywords and specific keywords influence online sales differently, in the presence of cross-selling effect?*
2. *How is the performance impact of keywords on online sales (direct sales as well as indirect sales) influenced by product type?*

We conducted an empirical study using a unique dataset of SEA from the biggest e-commerce platform in China, Taobao.com. The dataset captures information on keyword portfolios and product sales of online sellers that use Taobao.com's SEA service. We chose digital cameras and related accessories as the product categories to study. Digital cameras are suitable for this study for two main reasons. First, as noticed in the e-commerce literature [20, 35], digital cameras are *high-involvement* products that require a significant amount of search by consumers before they make purchase decisions. In this regard, the study of digital cameras helps address the research questions on consumer search. Second, it is relatively easy to identify and distinguish between main products and accessory products in this category. Main products, such as DC, SLR, and camcorders, often need more complementary products than accessory products, such as tripods. In addition, digital camera is also the focus in many other existing e-commerce studies (e.g.,[15]).

Our empirical findings indicate that among the observations on SEA advertisements that convert to sales, about 40% eventually result in the indirect sales of other products. In this regard, the indirect sales revenue, or cross-selling, should be a key consideration in developing SEA strategies. Moreover, our results suggest that the return-of-investment (ROI) of SEA can be as high as 783% when indirect sales revenue is taken into account. Regarding the impact of keywords on online sales, our empirical analysis shows that the use of specific keywords in SEA leads to higher direct sales revenue, compared to the use of general keywords. The use of general keywords, however, performs better in generating indirect sales revenue, compared to that of specific keywords. We also differentiate between the main products (e.g., digital cameras and camcorders) and accessory products (e.g., tripods and lens caps). The results illustrate how the performance of keywords varies across different types of products. For main products, the contribution of specific keywords to the indirect sales is higher than that of general keywords. For accessory products, however, the contribution of general keywords to the indirect sales is higher than that of specific keywords.

Theory and Hypothesis Development

Theoretical Background

The theoretical foundation of our research is the shopping goals theory [30], which combines the lenses of Trope and Liberman’s construal-level theory [46] and Gollwitzer’s mind-set theory [18] in consumer research to characterize the increasing concreteness of shopping goals in consumers’ shopping processes. According to the shopping goals theory, the initial stage of shopping is a stage where consumers are generally uncertain about what to buy or how much to spend. In this stage, the main objective of consumers is to develop their shopping goals. Therefore, they have open consideration sets and are susceptible to contextual and external influences. Once consumers have constructed concrete shopping goals, they move to a second stage. In this stage, the main objective of consumers is to attain the shopping goals they have set. As a result, consumers largely adhere to their goals and are thus less susceptible to contextual and external influences such as promotions.

The theoretical lens of shopping goals theory can be used to explain the use of different types of keywords in consumer search. The existing marketing literature has identified that consumers conduct multiple types of information search in different stages of their shopping (Moe [34]; Jansen et al. [23]). The key idea is that in their early stages of shopping, consumers use search primarily to collect information and build knowledge for subsequent shopping decisions [8, 45]. The reason is that they do not have concrete shopping goals in these stages [7]. In their late stages of shopping, consumers use search primarily to find the specific products that they decide to buy [12, 43]. This is because they already have concrete shopping goals in these stages. In this regard, we can expect that general keywords are used more by consumers without shopping goals and in their early shopping stages to collect information. Specific keywords, on the other hand, are used more by consumers with concrete shopping goals and in their late shopping stages to locate the products they want.

The shopping goals theory, in conjecture with the lens of consumer search, also helps explain the direct sales and indirect sales that are generated in search engine marketing. For example, in early stages of shopping when consumers do not have concrete shopping goals, their main purpose of search is to collect information. Therefore, they are less likely to directly buy the products they locate in search. Rather, they are likely to browse other options, which may result in indirect sales [42, 43]. On the other hand, in late stages of shopping when consumers have concrete shopping goals, their main purpose of search is to locate their planned shopping targets. In this case, they search is more likely to result in direct sales of the advertised products [17].

Direct Sales and Indirect Sales

When evaluating the performance of SEA, the existing literature has primarily focused on the *direct sales*, which refers to the case where consumers are attracted to the seller's page by a specific advertisement link and directly buy the advertised product shown on the landing page. The performance measure of *conversion rate* (the ratio between transaction volume and click volume generated by the advertisement link) is mainly used to capture direct sales. In general, the existing research suggests that the conversion rates of SEA links are not very high (about 1%~3%) ([16], [50]), but they are much higher than those of general Web links [26]. There is also a stream of SEA research considering how conversion rates of SEA links are influenced by various factors, such as the ranking of SEA links [1], the features of search keywords [42], the use of consumer targeting techniques [41], the bidding strategies of advertisers [16], and the interrelationship between SEA links and organic search links [17].

It is worth noting that SEA may not only benefit online sellers in improving the direct sales of the advertised products. It may also lead to the indirect sales of other products. *Indirect sales* refer to the case where consumers are attracted to the seller's site by the advertisement of a certain product, but eventually end up with buying not the advertised product on the landing page but other related products from the same seller [36]. In the existing literature, however, there has been scant research attention paid to the contribution of SEA to indirect sales. The extant marketing literature on cross-selling and multi-category purchases has focused largely on offline shopping (e.g., [10, 31, 33, 37, 40, 47]). Recent research on online advertising (e.g., [49]) has clearly pointed out that bidding keywords to maximize the sales across multiple product categories is a very challenging and important problem for online advertisers. Among the few recent studies that have considered the impact of SEA on cross-category indirect sales, Ghose and Yang [17] found a considerable spillover effect when consumers proceed from initial search to final purchases. In particular, they found that retailer–specific keywords are likely to induce cross-category purchases, while brand-specific keywords are not likely to induce cross-category purchases. Chan et al. [9] proposed a new metric in measuring the ROI of search advertising by incorporating the long-term lifetime value of acquired customers and the spillover of search advertising to offline sales. Their study showed that the traditional method that only considers the direct online sales significantly underestimates the impact of SEA. Rutz et al. [43] considered how paid search ads may potentially induce future visits so as to generate indirect sales. Our study contributes to this stream of research, as well as the general SEA literature, by simultaneously considering the contribution of SEA to both the direct sales of the advertised products and the indirect sales of other products (different from the advertised products) from the same seller.

Direct sales often occur when consumers have specific shopping targets and the advertisements in SEA help them find their favored targets. Indirect sales, however, may arise for various reasons. Here we mainly consider two key effects that generate indirect sales: the *substitution effect* and *complementary effect* [33, 40]. Substitution effect refers to the case where consumers clicking the sponsored ad do not eventually buy the advertised products on the landing page. However, they are attracted by some other competing or related products offered from the same seller and eventually buy these products. In this case, consumers do not generate direct sales of the advertised products but generate indirect sales of other products. Such shopping behaviors also correspond to the cross-item or cross-brand purchasing recognized in the cross-selling literature (e.g, [21]).

Complementary effect refers to the case where consumers buying the advertised products also buy other products from the same sellers due to the complementarities between these products. (e.g., consumers deciding to buy digital cameras are also interested in complementary items such as SD cards or filters). According to the literature on cross-selling (e.g, [33]), complementary effect is a key antecedent driving the consumers' cross-category purchasing. Due to this effect, the promotion or sales of products in one category significantly influences the sales of related products in other categories [31, 33, 40, 47]. In online retailing, sellers often use various approaches to utilize product complementarities to achieve more cross-selling. For example, sellers can recommend SD cards to those consumers who buy digital cameras. Sellers can also offer bundling discounts to encourage consumers to buy other products related to the advertised products. The literature has noticed the more dominant role of complementary effect in cross-selling [31, 33, 40, 47], we therefore also expect a positive relationship between direct sales and indirect sales, i.e., the direct sales of the advertised products are higher, the indirect sales of other products from the same seller also tend to be higher. The consideration of the cross selling effect helps us better understand the underlying mechanisms through which keyword advertising influences the overall sales. Therefore, before we consider the impact of keywords, we formally develop the following hypothesis on cross selling:

H1: There is a positive association between the direct sales of advertised products (advertised in SEA) and the indirect sales of other products for the seller.

Moreover, we expect that the influence of direct sales on indirect sales varies across different types of products. The main reason is that the existing research on multicategory shopping [33] suggests that the cross-selling effects are often asymmetric across different product categories. Some product categories are strong drivers of the sales of other categories, while some product categories can only weakly drive the sales of other categories. For example, in the context of digital camera, we can distinguish between main products and accessory products. Main products are products that have clear core competencies and stand-alone functional value, such as digital SLR cameras and camcorders. Main products may need accessory products to better realize their core functional value. However, even without accessories, the consumption value of main products is still clear and significant. Accessory products are peripheral items that help realize the functional competencies of main products, add certain additional functionalities to main products, and keep consistent style connection with the corresponding main products [22]. For example, a special power cord is a typical accessory product that is needed for charging the digital camera. Without the corresponding main products, the value of accessory products is fairly limited.

When consumers buy main products, they usually need accessory items and thus often purchase them together with main products. Therefore, the direct sales of main products are likely to lead to indirect sales of accessory products. The direct sales of accessory products, however, are less likely to lead to indirect sales of main products. Such asymmetric cross-selling externalities have been evidenced in the literature [33], where main product categories can be considered as “primary” categories and accessory product categories as “secondary” categories. Consumers usually buy accessories from “secondary” categories to fit with their already-owned or just-brought main products, rather than buying main products from “primary” categories to match with accessories. Therefore, we expect:

H2: Compared to the direct sales of accessory products, the direct sales of main products are more strongly associated with the indirect sales of other products.

Keyword Type and SEA performance

According to the shopping goals theory [30], in different stages of shopping, consumers have different levels of shopping goal concreteness. Therefore, they are likely to use different types of search keywords in different stages of shopping. In their early stages of shopping, consumers may not necessarily have well-defined shopping goals when they start searching for products [7]. They often seek to discover their preferences and build knowledge using more general searches [8, 45]. Therefore, consumers usually start with general keywords (e.g., “digital camera”) to acquire broad information which facilitates subsequent steps of product selection and purchasing decision [14] . The use general keywords may not lead to actual sales in a very direct manner. The conversion rates of keywords at these stages are relatively low. However, general keywords generate a “spillover” effect and induce consumers to conduct more subsequent searches than specific keywords [42, 43]. For example, Enquiro [14] investigates the shopping search behaviors of potential consumers and finds that 70% of search processes start with general search terms and are narrowed down to more specific terms after a few rounds of interaction between consumers and the search engine.

In their late stages of shopping, when consumers have clear preference and targets, they would turn to conduct more deliberated searches using specific keywords (e.g. "Cannon 50D SLR Camera"). The use of specific keywords enables consumers to locate the exact products they want to buy [12, 43]. As a result, specific keywords may lead to actual sales in a more direct manner. The keywords used by consumers in different types of search often reflect their distinct goals and shopping intents. In this regard, the different keywords used by an online seller in SEA may attract different consumers in terms of their shopping stages, and thus generate differential impacts on the likelihood of actual purchase.

When an online seller uses more specific keywords to advertise its products, it is rational to expect that it can improve the direct sales of the advertised products. This is mainly because the use of more specific keywords in SEA allows the seller to attract more consumers at their late stages of shopping. These consumers are more likely to have specific shopping preferences and targets in mind, and these shopping targets are likely to match with the advertised products in the sponsored ads. Therefore, they are more likely to directly buy the advertised products. In this regard, the use of more specific keywords in SEA is likely to result in more direct sales of products. We develop the following hypothesis:

H3: The use of more specific keywords in SEA is positively associated with the direct sales of the advertised products for the seller.

The use of more specific keywords, however, may negatively impact the indirect sales through SEA. Consumers who search using specific keywords are usually planned buyers with specific shopping targets [41]. Therefore, the use of more specific keywords, rather than other types (i.e., general keywords and irrelevant keywords), allows a seller to draw more planned buyers and less undecided buyers. Planned buyers, however, are less engaged in indirect sales compared to undecided buyers. Planned buyers tend to use specific keywords to directly find their desired products. They are less likely to browse and switch to other brands or products of the same sellers. In other words, the indirect sales caused by the substitution effect will diminish. In this regard, the use of more specific keywords should have a negative impact on the indirect sales. It is worth noticing that as the use of more specific keywords is expected to increase direct sales (as captured in Hypothesis 3), it may also indirectly contribute to indirect sales through the complementarity between direct sales and indirect sales. Such complementary effect is considered in the above Hypothesis 1. Therefore, we expect that controlling for the direct sales of advertised products, the use of more specific keywords in SEA negatively affects indirect sales:

H4: With the direct sales (of advertised products) controlled, the use of more specific keywords in SEA is negatively associated with the indirect sales of other products.

When a seller uses more general keywords to advertise its products, it is likely to attract more undecided consumers who are at their early stages of shopping and without clearly defined preference [7]. These consumers usually follow the advertisement links to visit the seller's site in search for more product information to know available product options and attributes, as well as build their preferences [29]. However, they may not buy the advertised products immediately since these advertised products may not necessarily fit their needs. For example, consumers searching using a general keyword "digital camera" may find that those top ranked brands are not what they eventually favor. Therefore, the use of more general keywords is not likely to directly improve the sales of the advertised products.

The use of general keywords, however, is likely to improve the indirect sales of other products for the seller. First, most online sellers carry multiple brands for each type of products. Consumers who are referred to the seller's site by a general keyword advertisement may not necessarily be satisfied with the specific advertised product on the landing page. However, they can still navigate the seller's site to search for more information [34], browse other brands and may find more favorable ones [13]. In this regard, the use of general keywords in SEA may not directly lead to the sales of the advertised products, but it creates opportunities for the seller to expose its various choices to consumers and sell other brands and products indirectly. In other words, the seller can leverage the substitution effect of product categories to generate more indirect sales.

Second, a multi-product seller may carry other products that are related to the advertised products. The use of general keywords in search may reflect consumers' general interests in related product categories at their early stages of shopping [43]. They may not have a specific idea about what to buy exactly but would like to browse around to further build knowledge and discover their favorite items [14]. In this case, no matter whether these consumers are satisfied with the advertised products or not, they are likely to also browse other related products offered by the same seller. The seller can take these opportunities to cross-sell other related products in many ways (e.g., recommendation, bundling discounts, etc) [11, 38]. If consumers buy other products together with advertised products, this improvement on indirect sales is already captured by the complementary effect considered in Hypothesis 1.

However, even if consumers do not buy advertised products, there is still a possibility that consumers with broad shopping interests may shop in other related categories. Considering the potential contribution of general keywords to indirect sales, given the spillover effect of direct sales, we develop the following hypothesis:

H5: With the direct sales (of advertised products) controlled, the use of more general keywords in SEA is positively associated with the indirect sales of other products.

Keyword Type and Product Type on Indirect Sales

The impact of keyword specificity on indirect sales may also be influenced by the type of products advertised in SEA, especially considering that the spillover from direct sales to indirect sales may vary between different types of products. Such relationship, however, has been underexplored in the literature. We therefore also examine how product type and keyword specificity interact with respect to their impacts on indirect sales.

The use of specific keywords helps attract more consumers with specific interests. For main products, consumers are often more deliberate in pre-purchase research and decision making as these products are usually more expensive. For example, Gu et al. [20] consider digital cameras as high-involvement products which require extensive decision making in purchase due to the relatively high prices and more choices. Consumers shopping for main products usually need to conduct comprehensive comparison between different features of competing brands before actual purchases. Even if they start their store visits with a specific brand, the complex research and decision-making processes may eventually divert them and lead to the purchases of other competing brands. In this regard, specific keywords of main products are still likely to result in certain indirect sales. On the other hand, accessories are often purchased to match with specific main products and the purchases decisions are much less complex. In addition, the relatively low prices of accessories may reduce consumers' incentives to extensively browse and consider other alternatives. When specific keywords allow consumers to quickly find the matched accessory items they look for, they are more likely to directly buy these items rather than turning to other alternatives. In this sense, specific keywords of accessory products are less likely to lead to indirect sales, compared to specific keywords of main products. As we have hypothesized in H4 a negative association between specific keywords and indirect sales, with direct sales controlled, here we expect that this negative association is weaker for main products than for accessory products.

By the same token, we expect that the positive association between general keywords and indirect sales is stronger for main products than for accessory products. General keywords attract more undecided buyers with board interests. Regarding main products, the more complex pre-purchase research and decision making processes are more likely to divert undecided buyers to other choices. Accessory products, due to their lower prices and more specific needs (to match with corresponding main products), often require relatively simpler decisions and are thus less likely to divert consumers to other choices. Therefore, given that Hypothesis 5 has considered a positive association between general keywords and indirect sales, with the direct sales controlled, here we also expect that this positive association is stronger for main products than for accessory products. We thus hypothesize:

H6a: With direct sales controlled, the negative association between specific keywords and indirect sales is weaker for main products than for accessory products;

H6b: With direct sales controlled, the positive association between general keywords and *indirect sales is stronger for main products than for accessory products.*

The theoretical framework of this study is illustrated in Figure 1.

[INSERT FIGURE 1 ABOUT HERE]

Research Methodology

Research Context and Data

We obtain data from the advertising department of Taobao.com, the largest e-commerce marketplace in China that allows sellers of a variety of consumer products (including electronics, cloths, books) to sell to individual consumers. Using Web services, Taobao.com allows online sellers to present their product information on its site, provides the search function to consumers to look for products and sellers, and helps sellers to fulfill transactions. Taobao.com also provides a sponsored search advertising service, i.e., P4P (pay for performance), to online sellers. It is similar to Google's search engine advertising service. When individual consumers search for products using keywords, Taobao.com returns both paid search advertisements and organic search results. The advertisements are listed in the descending order of biding CPCs (cost-per-click) for search keywords.[3] Online sellers can bid on multiple keywords for a single product to increase the impression of the advertisement. Sellers independently decide their keyword portfolios based on their own needs.

When consumers click a specific sponsored ad, they are redirected to the landing page of the advertised product. Taobao.com keeps track of consumers' browsing behaviors. If a consumer eventually buys this product in the same session, Taobao.com records it as a transaction of direct sales. In this way, Taobao.com keeps track of the direct sales of all the

[3] Over the time period of our sample, Taobao.com used only CPC in ranking search results and did not use any quality weight of advertisers or landing pages in its ranking algorithm. In this regard, in our study, CPC is sufficient to control for the effect of rank position.

advertised products. Consumer may also click other links on the landing page, and browse and buy other products from the same seller. Since online sellers use Taobao.com's Web service, Taobao.com also traces more of consumer browsing behaviors in the sellers' sites. If a consumer leaves the landing page to other pages of the same seller and buys other products, Taobao.com records these transactions as indirect sales transactions, regardless whether a direct sales transaction occurred before or not. In this way, Taobao.com also keeps track of all indirect sales that generated from sponsored ads.[4] Figure 2 shows the relationships between clicks, direct sales transactions, and indirect sales transactions.

[INSERT FIGURE 2 ABOUT HERE]

Taobao.com keeps track of the daily biding information of each keyword and the direct sales of each advertised product. It also keeps track of the indirect sales of other products generated by consumers drawn to the seller's site by each advertisement. In this research, we obtained search and sales data of the product category of digital camera (DC hereafter) over a 60-day period (from June 1 to July 30, 2010).

Variables

Table 1 lists the definitions and notations of all variables used in this study.

[INSERT TABLE 1 ABOUT HERE]

Dependent Variables. Our analysis is conducted at the product-day level. There are two dependent variables (DVs) in our main empirical model. The first DV is the daily direct sales of a specific advertised product in SEA. The second DV is the daily indirect sales (of all other products from the same seller) generated within the same sessions of the ad clicks of this

[4] A consumer redirected to the retailer's site by a certain sponsor ad may buy another product that is in another sponsor ad of the same retailer. Such transaction is also considered as indirect sales since it is initiated by a different advertisement.

advertised product. Both of these measures are obtained directly from Taobao.com. As aforementioned, Taobao.com keeps track of click-through and sales data using its Web services. In measuring sales, Taobao.com uses both sales volume and sales revenue. We focus on sales revenue to be consistent with prior studies on cross purchase (e.g., [31]).[5]

Explanatory Variables. Two key explanatory variables in our empirical model are the general keywords (measured as a percentage of all keywords) and the specific keywords (measured as a percentage of all keywords) used for a specific advertised product in SEA. Sellers often use a portfolio of different keywords in SEA. In the dataset provided by Taobao.com, we were able to observe all keywords used by each seller for each advertised product. We then coded these keywords into three categories: general keywords, specific keywords, and other irrelevant keywords. General keywords are defined as the terms referring to a product category or brand name without any product specification, such as "DC", "Camcorder", "Len", "Cannon", or "Sony". We also consider the combinations of category and brand name such as "Cannon DC" as general keywords, because searches using such keywords usually return a long list of different products. In contrast, specific keywords are defined as the terms referring to a specific product without ambiguity, such as "Cannon 50D Digital Cameras". Searches using such keywords usually return specific products.

In addition to general and specific keywords, sellers often choose other types of keywords. For example, some sellers use highly irrelevant keywords, such as "shoes" for digital camera products, to lower the bidding cost (and still generate a small portion of sales). Some other sellers use extremely ambiguous keywords, such as "50" (possibly for "Canon 50D"), which

[5] It is worth noticing that product-level sales data does not reflect the specific sales generated by each keyword. Keyword-level sales data may be better to reflect specific contribution of each keyword to the sales of the product. Unfortunately, such data is not available in our sample. However, using the product-level sales data and sellers' keyword portfolios still allows us to make inferences about how different types of keywords (used in advertising the product) contribute to the sales of the product.

may lead to totally irrelevant results such as “Vitamin for 50 plus”. We consider these irrelevant or extremely ambiguous keywords as other keywords. Due to the existence of other irrelevant keywords, we are able to use the percentages of general and specific keywords number over all keywords as two independent variables in the regression analysis without causing the collinearity issue. A VIF test of these two explanatory variables also indicates that their VIFs are well below 9, the suggested level for multicollinearity [28]. Apart from the keywords number, we also measure the quality of keywords by the percentage of clicks generated by general keywords and specific keywords. In the analysis hereafter, we will use the number and quality measures alternately to measure the effects of general and specific keywords on SEA performance.

We also include product type as another key explanatory variable. As we focus on the product category of digital camera in this study, we distinguish between main products and accessory products in this category. Main products are defined as products that have clear core competencies of their own and may need accessory items to better realize their own core functional value. For example, digital SLR camera and camcorder are considered as main products. On the other hand, accessory products are defined as items that are mainly used to better realize the core value of other products. When used alone, accessory products are generally of very limited value. For example, lens caps, UV film, and tripod are all accessory products since they are used to better realize the core value of lens.

Control Variables. We include several control variables in the model. First, we use two variables to control for the cost issue in SEA: the average CPC of all keywords for an advertised product and the total number of keywords used for this product. The average CPC reflects the overall ranking position of the advertised product across keywords, and the total number of keywords reflects the general exposure of the product. Both of these are key factors that influence the CTRs of sponsored ads, and eventually the sales revenue of the product [16, 50]. Second, we control for the product price. Product price is usually displayed in the advertisement, and therefore, may generate a critical impact on the clicking behaviors of consumers and the final sales.

Finally, we also control some attributes of sellers, e.g. reputation, the number of total products offered, the average price of all products. E-commerce literature (e.g., [5]) suggests that these attributes of online sellers influence consumers' purchasing decisions. Reputation is measured by the number of positive ratings that a seller gets from customers minus the number of negative ratings. Taobao.com classifies the sellers into different level from 0 to 20 according to reputation numbers. Usually, consumers will pick sellers with high value of reputation. Li et al. [32] suggest that sellers may employ the marketing strategy that attracts consumers by under-priced advertised product to increase the cross selling of other products. Therefore, products number and the average price of all products may have some impacts on sellers' direct and indirect sales.

We have also control the time fixed-effect and product sub-category[6] fixed-effect using dummies. Although a better approach is to control for the product fixed-effect, our data does not allow us to identify that. Taobao.com prevents direct comparison between different sellers on the same product by using different identifiers for the same product offered by different sellers. Therefore, despite the limitation, controlling the fixed-effect at the product

[6] Taobao.com divides digital camera category into 44 sub-categories, such as camcorder, lens, tripods, film, et al.

sub-category level is the best we can do.

Model Specification

Based on the theoretical framework in Figure 1, we specify an econometric model with two simultaneous equations: one for direct sales (as shown in Eq. (1)) and one for indirect sales (as shown in Eq. (2)). The subscript *i* is used to denote product and *j* is used to denote advertiser (i.e., seller). The subscript *t* denotes the index of day.

$$\begin{aligned} \mathrm{TdAmt_{it}} = {} & \beta_1 GenKW_{it} + \beta_2 SpeKW_{it} + \beta_3 Type_{it} + \beta_4 AvgCPC_{it} + \beta_5 Bidwords_{it} \\ & + \beta_6 Price_{it} + \beta_7 Repu_{jt} + \beta_8 TNProd_{jt} + \beta_9 Avgprice_{jt} + \gamma_{s(i)} + \delta_t + \mu_{ijt} \end{aligned} \tag{1}$$

$$\begin{aligned} \mathrm{TIndAmt_{it}} = {} & \gamma_0 + \gamma_1 GenKW_{it} + \gamma_2 SpeKW_{it} + \gamma_3 Type_{it} + \gamma_4 TdAmt_{it} + \gamma_5 GenKW_{it} \\ & \times Type_{it} + \gamma_6 SpeKW_{ij} \times Type_{it} + \gamma_7 TdAmt_{it} \times Type_{it} + \gamma_8 AvgCPC_{it} \\ & + \gamma_9 Bidwords_{it} + \gamma_{10} Price_{it} + \gamma_{11} Repu_{jt} + \gamma_{12} TNProd_{jt} + \gamma_{12} Avgprice_{jt} \\ & + \gamma_{s(i)} + \delta_t + \varphi_{ijt} \end{aligned} \tag{2}$$

Equations (1) and (2) capture how direct sales and indirect sales, respectively, are influenced by the use of different types of keywords and other control variables. $\gamma_{s(i)}$ and δ_t represent product sub-category fixed-effect and time fixed-effect, respectively, where s(i) is a function that maps product *i* to its sub-category. We use log values of all dependent and independent variables in the estimation, except for the categorical variable *Type* and dummies.

We also take into consideration the potential endogeneity of AvgCPC [16]. Specifically, the general performance of keywords may influence the advertisers' willingness to bid and eventually the CPC. A Hausman test also confirms the existence of endogeneity bias for AvgCPC. Therefore, we use the number of keyword competitors as an instrumental variable for AvgCPC to address the endogeneity issue. The number of keyword competitors is closely related to the biding prices of keywords, i.e., CPC. However, it should have no direct impact on the error term of direct sales since this value is not exposed to consumers. The whole system of two simultaneous equations is estimated using 2-stage least square (2SLS).

Empirical Results

Descriptive Statistics

The sample used in this study includes 4,903 advertised products with total 134,953 observations. Table 1 indicates that in the category of digital camera, sellers use on average 3 keywords for each advertised product and the average CPC for these keywords is $0.03. About half of keywords used for each product are specific keywords. This is reasonable since it is relatively easy to identify the specific attributes (e.g., the models) of digital cameras and specify them in keywords. The clicks generated by general keywords and specific keywords are consistent with the numbers of these two types of keywords. Moreover, about 61% of advertised products in our dataset are main products, and the average product price is $221.

Regarding the SEA performance, Table 1 indicates that if we only consider direct sales, the conversion rate is about 1.27% (i.e., 0.11/8.63). If indirect sales is also considered, the conversion rate is about 3.01%. Furthermore, if we assume that the profit ratio for these products is 10%,[7] the overall ROI (return on investment) of SEA in our case is [(direct sales + indirect sales) × (profit ratio)]/[(average clicks) × (average CPC)] = (14.86 + 5.41) × 0.1/(8.63 × 0.03) = 783%, which is very attractive to sellers.

However, Figure 3 shows that the direct and indirect sales are not balanced in our dataset. About 90.5% of the observations did not have any sales. For the remaining observations, about 40% of them led to indirect sales. This result indicates that indirect sales are important

[7] We use an estimated value provided by Taobao.com

in creating revenue for sellers (i.e., the advertisers).

[INSERT FIGURE 3 ABOUT HERE]

Simultaneous Equations Model

Table 2 reports the estimation results of the equation for direct sales and the equation for indirect sales. We consider both the full model and a basic model with only control variables and a benchmark model without interaction terms. As shown in Table 2 column 3, in the equation for indirect sales, the coefficient of direct sales is positive and significant (p<0.01), suggesting that the direct sales of the advertised products generate a positive impact on the indirect sales of other products. This is consistent with H1. In addition, in the equation for indirect sales in the full model, the coefficient of the interaction between direct sales and product type is positive and significant (p<0.01). This suggests that compared to the direct sales of accessory products, the direct sales of main products generate a stronger contribution to the indirect sales of other products. Therefore, H2 is supported.

[INSERT TABLE 2 ABOUT HERE]

The benchmark model in Table 2 shows that in the equation for direct sales, the coefficient of general keywords is insignificant, while that of specific keywords is positive and significant (p<0.01). These results suggest that the use of more general keywords in SEA has no significant impact on the direct sales of the advertised products for the seller. However, the use of more specific keywords helps improve the direct sales of the advertised products. H3 is therefore supported.

In the equation for indirect sales, the coefficient of specific keywords is negative and significant (p<0.05). It means that the use of more specific keywords reduces the indirect sales of other products for the seller, supporting H4. This result makes sense since specific keywords usually draw consumers with planned shopping targets. These consumers are thus less likely to just browse the advertised products and turn to alternative brands or products. Moreover, the extant literature suggests that consumers with planned targets are less likely to conduct "impulse purchase" [39, 44]. Therefore, their visits to sellers through search ads should trigger less indirect sales of other related products. In addition, the coefficient of general keywords is positive and significant ($p<0.05$). This suggests that the use of more general keywords in SEA helps improve the indirect sales of other products (other than the advertised ones) for the seller. This provides support to H5.

The results of the full model in Table 2 indicate that the coefficient of the interaction between product type and specific keywords is positive and significant ($p<0.05$), suggesting that the negative impact of specific keywords on indirect sales is weaker for main products than for accessory products. Therefore, H6a is supported. Considering this interaction effect, we can also see that for main products, the overall impact of specific keywords on indirect sales is positive, i.e., (1.182-0.608) = 0.454 ($p<0.01$). This suggests that using more specific keywords to advertise main products in SEA may actually improve indirect sales. A potential explanation is that the decision making processes for main products are complex and are thus likely to introduce uncertainty on consumers' final decisions. Even if buyers using specific keywords to first locate products/brands they may prefer initially, they are still likely to change their mind eventually and switch to other choices. In contrast, the decisions for accessories are relatively simpler as accessories are often purchased to match with their corresponding main products and they are also relatively less expensive. The decision making processes for accessory products are thus less likely to introduce uncertainty. When planned buyers with initial preferences use specific keywords to locate their favorite accessories, they are less likely to switch to other choices. That is why the overall impact of specific keywords on indirect sales is negative for accessory products.

The results of the full model show that the coefficient of the interaction between product type and general keywords is not significant. Therefore, H6b is not supported. This suggests that the positive impact of general keywords on indirect sales does not vary by product type. In other words, for those consumers who have broad interests and use general keywords in search, no matter whether they search for main products or accessory products, they are equally likely to switch from the advertised products to other competing brands/products and incur cross-purchases.

Robustness Analysis

Keywords Quality

In above analysis, we considered the percentages of general and specific keywords used in the keyword portfolio. While these measures may reflect sellers' choices in SEA, they do not capture the differential quality of different types of keywords in attracting click-throughs. Considering that the ability to attract click-thoughs may also affect the subsequent conversion, we conduct a robustness analysis using the click rates of general keywords and specific keywords as the independent variables (for general keywords and specific keywords, respectively). We redo the simultaneous equations model estimation and the results are qualitatively very consistent with those in Table 2, i.e., the clicks attracted by specific keywords mainly contribute to direct sales while the clicks attracted by general keywords mainly contribute to indirect sales.[8]

The Impact of Direct Sales on Indirect Sales

In the above testing of the impact of direct sales on indirect sales in H1 and H2, we used the entire sample of direct sales and indirect sales. It is worth noticing that in reality, some direct sales may not necessarily lead to indirect sales, and some indirect sales may not necessarily be generated with prior direct sales. Therefore, we conduct another robustness analysis using a subsample with only those observations with positive direct sales and indirect sales (in total 4184 observations). We re-run the simultaneous equations model estimation with this subsample and the results are consistent with the main analysis. The coefficient of direct sales in the indirect sales equation of the benchmark model (without interaction) is 0.991 ($p<0.01$), and the coefficient of the interaction between direct sales and product type in full model is 0.189 ($p<0.01$). These findings further support H1 and H2.

The Effects of Keywords on Total Sales

As a robustness check to verify the key findings, we also report the estimate results of an additional model using total sales as the dependent variable. The independent variables include all those independent variables in the simultaneous equations model, except the direct sales. We run the additional analysis using all observations. Both the benchmark model (without interactions) and the full model indicate that the use of more specific keywords generates a significant positive impact on the total sales revenue. Moreover, the interaction term between specific keywords and product type in the full model is significant, which suggests that the impact of specific keywords on total sales is bigger for main product. While

[8] Due to page limit, the detailed results of all robustness analysis in Section 4 are not included in the paper. They are available from the authors upon request.

for the general keywords, the main effect is significant but the magnitude is smaller than specific keywords. The interaction with product type is not significant.

The additional analysis may suggest that the marginal impact of specific keywords on total sales is higher than that of general keywords. This result is consistent with the findings in the simultaneous equations model. Table 2 suggests that specific keywords outperform general keywords in improving direct sales, and general keywords outperform specific keywords only in improving the indirect sales of accessory products. For main products, general keywords and specific keywords are comparable in their contribution to indirect sales. These results help explain why specific keywords may perform better in improving the total sales. However, it is also worth noticing that in our sample, indirect sales only account for 25% of the total sales, and less than 40% of products are accessory products. In this case, the advantage of specific keywords over general keywords may be exaggerated to certain extent.

Search Spillover of General Keywords

The extant literature has also noticed the potential search spillover of general keywords (e.g., [42]). The key idea is that consumers searching with general keywords in the initial stages may also come back and search again using specific keywords. In this regard, general keywords may influence the impact of specific keywords.[9] Rutz and Bucklin [42] examined consumer searches in initial stages and in subsequent stages, and found a significant spillover effect from general keywords to branded keywords. We have also conducted an additional analysis on total sales to consider such potential spillover effect of general keywords. Specifically, we incorporated an interaction term between general keywords and specific

[9] We would like to thank an anonymous referee for suggesting this consideration.

keywords to explore whether general keywords may enhance the sales impact of specific keywords. If consumes use general keywords for initial scanning before they conduct more targeted search using specific keywords, we may observe a positive moderating effect of general keywords on specific keywords. The results of this analysis indicate that the coefficient of the interaction between general keywords and specific keywords is positive and significant, suggesting that general keywords enhance the sales contribution of specific keywords.

Discussion

Theoretical Implications

Our analysis generates several important theoretical implications that contribute to the existing theories and literature. First, the main findings of this study are in congruence with the theoretical lens of the shopping goals theory [30]. The contribution of specific keywords to direct sales suggests that users of specific keywords often have concrete shopping goals and therefore are not easy to be attracted away by other products of the same sellers. In contrast, the contribution of general keywords to indirect sales suggests that users of general keywords may not have concrete shopping goals and therefore are easy to switch to other products. Our results also suggest SEA can be used to target different types of consumers with respect to their shopping goal concreteness. While the use of specific keywords allows sellers to profit from consumers with concrete shopping goals by generating direct sales from them, the use of general keywords enables sellers to also profit from consumers without concrete shopping goals by generating indirect sales from them.

Second, our findings provide an integrated view on SEA performance that contributes to the existing literature. Prior studies on SEA have focused separately on either the direct performance (e.g., click-through, direct sales) [16, 17, 26, 50] or the indirect performance (e.g., cross-selling) [9, 17, 43] of SEA. Using a unique dataset, we examine the direct sales of the advertised products and the indirect sales of other products in the same study. Our analysis illustrates that SEA contributes to both direct sales and indirect sales. More importantly, SEA influences direct sales and indirect sales differently through different types of keywords. Our findings suggest that the use of more specific keywords in SEA, while improving the direct sales of the advertised products, may negatively influence the indirect sales (or cross-selling) of other accessory products. On the other hand, the use of more general keywords improves the indirect sales of other products, although it may not directly drive the sales of the advertised products.

Third, our findings also contribute to the research on cross-selling. Past literature primarily focuses on how product complementarity can be utilized in various ways to achieve cross-selling, such as bundling ([36]) and personalized recommendation ([3]). Our finding of the positive impact of direct sales on indirect sales is consistent with this view of product complementarity. Our analysis further illustrates how cross-selling can be influenced jointly by the features of keywords used in SEA and the nature of products advertised in SEA. The key theoretical implication is that the keyword portfolios used by advertisers in SEA may serve as a way to differentiate between different consumers regarding their cross-purchase likelihood. Consumers using general keywords in search are likely to have broad purchasing interests, and sellers should have more chances to cross sell to them. On the other hand, consumers using specific keywords in search are likely to have specific interests, and sellers may find it difficult to cross sell to them. Therefore, using different types of keywords influences the performance of cross-selling through attracting different groups of consumers.

Practical Implications

This research also generates important practical implications for advertisers using SEA. First, our study shows, alongside with previous research on SEA [2, 16, 41, 50], that SEA does contribute significantly to online selling. The return of SEA in our study is as high as 783%, well justifying the advertising expenditure.

Second, the key insights from this study, as summarized in Table 3, provide practical implications for advertisers to better design their keyword portfolios based on their business focuses. In general, advertisers focusing more on the direct (indirect) sales of their products may lean towards using more specific (general) keywords in their keyword portfolios. Sellers of main products, however, can use more general keywords as well as specific keywords (against irrelevant keywords) to improve indirect sales. These insights may also help search engines to better understand consumers' potential interests related to search terms, so as to improve the search design [27].

[INSERT TABLE 3 ABOUT HERE]

The third practical implication is that sellers of different types of products may focus their SEA budgets on different types of keywords. For sellers focusing on selling main (accessory) products, when they consider adjusting their keyword portfolios, they may gearing their SEA budgets towards more specific (general) keywords and replace irrelevant keywords with more specific (general) keywords. Such strategy enable them to better increase total sales through direct sales (indirect sales).

Conclusion

The objective of this study is to examine how the use of different types of keywords in SEA influences online selling in the presence of cross-purchase by consumers. The selection of keywords is critical to the SEA performance because different types of search keywords are often used by consumers with different purchase intents [23, 25]. This study distinguishes between general keywords and specific keywords and explicitly examines how they influence the direct sales and indirect sales (cross-selling) of sellers. Moreover, we consider how the influences of general keywords and specific keywords are moderated by product type. The findings of this research generate important theoretical contributions to multiple streams of literature and practical implications for advertisers to optimize their keywords selection in SEA and eventually improve the ROI of SEA. This study has also some limitations which deserve future research extensions. First, we only consider the difference between general keywords and specific keywords. Many other attributes can be considered in distinguishing between keywords, e.g., keyword length, brand-specific information and seller-specific information. We focus on general and specific keywords mainly because they are better indicators of the concreteness of consumers' shopping goals (i.e., general keywords reflect the less concrete shopping goals and specific keywords reflect the more concrete shopping goals of consumers) and therefore help better anchor our research on the theory of shopping goals. Future studies may examine how other keyword attributes may influence the direct sales and indirect sales of products. Second, our study focuses on the sales generation at the product level. Data limitation prevented us from examining more detailed sales generation at the keyword level. Future research may consider using keyword-level sales data to study the exact sales generated by different types of keywords and verify the insights of this study.

Third, in this study, we choose the category of "Digital Camera" as the research context. The key advantage of examining this product category is the relatively easy distinguishing between main products and accessories. Future studies may explore whether the insights of this study can be generalized into other high-involvement product categories. Considering the potential large price difference between main products and accessory products in digital cameras, future research may also consider extending the similar research to some low-involvement product categories and see whether product type still influences keyword performance. In addition, when distinguishing between main products and accessory products, we mainly consider the complementary relationships between products. Prior literature on cross-selling also identifies more relationships between products, e.g., substitution and independence [33, 40]. In future studies, researchers may consider how different types of product relationships influence the impact of SEA on the direct sales and indirect sales of products. Such studies should generate richer insights on the performance of SEA.

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Table 1. Variable Definition and Descriptive Statistics						
Variables	**Notation**	**Definition**	**Mean**	**Std.**	**Min**	**Max**
General Keywords Number	GenKW (%)	The percentage of general keywords number among all bided keywords for product *i*	0.37	0.42	0	1
Specific Keywords Number	SpeKW (%)	The percentage of specific keywords number among all bided keywords for product *i*	0.49	0.45	0	1
General Keywords Click	GenClick (%)	The percentage of general keywords clicks among all bided keywords clicks for product *i*	0.38	0.43	0	1
Specific Keywords Click	SpeClick (%)	The percentage of specific keywords clicks among all bided keywords clicks for product *i*	0.47	0.45	0	1
Total Clicks	TClick	Total click number of sponsored search advertisement	8.63	18.66	0	532
Direct Sales Volume	Dcnt	Direct sales volume of advertised product *i* lead by sponsored search advertisement	0.11	0.50	0	30
Indirect Sales Volume	Indcnt	Indirect sales volume of other products of advertiser *j*	0.15	0.95	0	63
Direct Sales	TdAmt	Direct sales revenue of advertised product *i* lead by sponsored search advertisement ($)	14.86	108.72	0.00	10050.71
Indirect Sales	TIndAmt	Indirect sales revenue of other products of advertiser *j* ($)	5.41	186.24	0.00	34758.87
Total Sales	TAmt	Total sales revenue generated by sponsored search advertisement ($)	20.27	231.81	0.00	39533.91
Bidword Num	Bidwords	Number of bided keywords for product *i*	3.00	3.69	1.00	68.00
Average CPC	AvgCPC	Averaged CPC of bided keywords for product *i* ($)	0.03	0.05	0.00	2.16
Product Price	Price	Price of product *i* ($)	218.91	884.44	1.00	34065.93
Product Type	Type	Product type, 1=main products, 0=accessory products	0.61	0.49	0.00	1.00
Reputation	Repu	Advertiser *j*'s reputation	8.96	2.15	0.00	14.00
Total Products	TNProd	The total number of products sold by advertiser *j*	605.06	747.64	0.00	7351.00
Average Price	Avgprice	The average price of advertiser *j*'s products($)	539.45	4637.15	0.26	66375.98

Note: N=134953

Table 2: Regression Result

	Basic Model		Benchmark Model		Full Model	
	Direct Sales	**Indirect Sales**	**Direct Sales**	**Indirect Sales**	**Direct Sales**	**Indirect Sales**
Variable	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**
General Keyword			-0.128 (0.091)	0.078*** (0.036)	-0.056 (0.061)	0.445** (0.169)
Specific Keyword			0.170*** (0.050)	-0.071**(0.036)	0.125**(0.063)	-0.608** (0.230)
Direct Sales (DS)		0.303*** (0.002)		0.289*** (0.005)		2.363*** (0.171)
Main Product (Type)	0.682(0.753)	0.402(0.538)	1.641 (1.737)	0.011(0.04)	-0.375 (0.048)	-0.565 (0.465)
Type × General KW						-0.224 (0.406)
Type × Specific KW						1.182*** (0.319)
Type × DS						0.625*** (0.183)
Bidwords	0.720(0.010)***	0.199*** (0.008)	0.675** (0.058)	0.290*** (0.024)	0.124*** (0.014)	0.130*** (0.032)
AvgCPC	0.559(0.011)***	0.225*** (0.008)	1.222*** (0.038)	0.386*** (0.028)	0.201*** (0.019)	0.626*** (0.155)
Product Price	-0.111(0.10)***	0.015** (0.007)	-0.111*** (0.028)	0.113*** (0.020)	-0.778*** (0.016)	1.054 *** (0.189)
Reputation	0.605(0.028)***	0.173*** (0.020)	0.771*** (0.071)	0.092**(0.042)	0.232*** (0.048)	0. 303 (0.376)
Tot Number of Products	-0.132(0.07)***	0.047*** (0.005)	-0.241***(0.018)	0.032***(0.013)	-0.023** (0.009)	0.057 (0.074)
Avgprice of all Products	-0.055(0.009)***	-0.107***(0.007)	-0.118***(0.023)	-0.226***(0.016)	0.032** (0.014)	-0.867*** (0.112)
R square	0.089	0.220	0.120	0.222	0.128	0.223
F value	247.32***	689.11***	82.66***	173.20***	433.45***	137. 35***

Note: (1) N=134953; (2) Unstandardized coefficients are reported; (3) $^{***}p$<0.01; $^{**}p$<0.05; $^{*}p$<0.1;

(4) In parenthesis are values of standard errors (SE); (5) product sub-category fixed effects and time fixed effects are also controlled; (6) log-log specification is used in estimation.

Table 3. Main Insights on the Contribution of Keywords to Sales		
	Direct sales	**Indirect Sales**
Main product	Specific keywords	General and specific keywords
Accessory product	Specific Keywords	General keywords

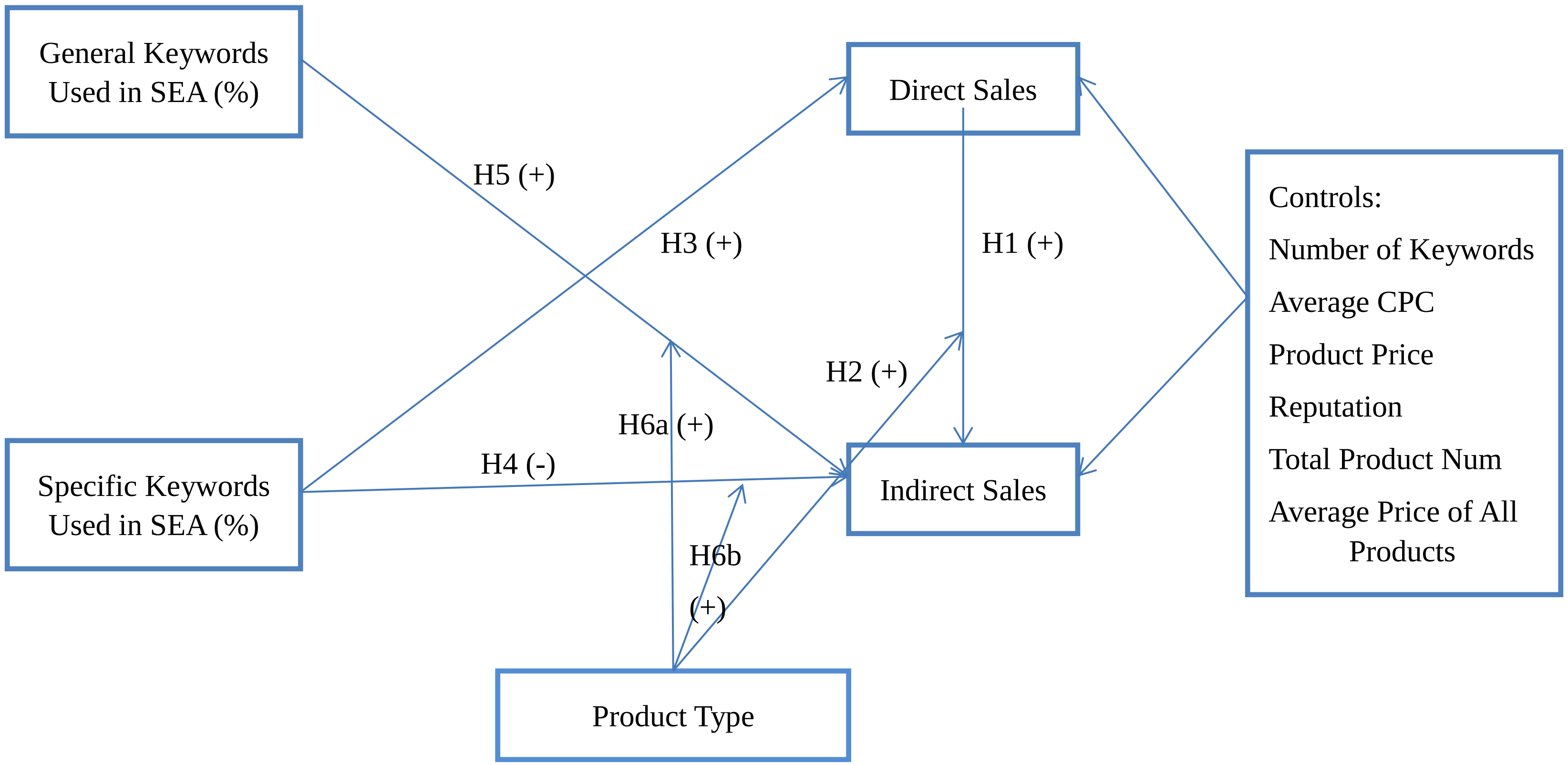

Figure 1: Theoretical Framework

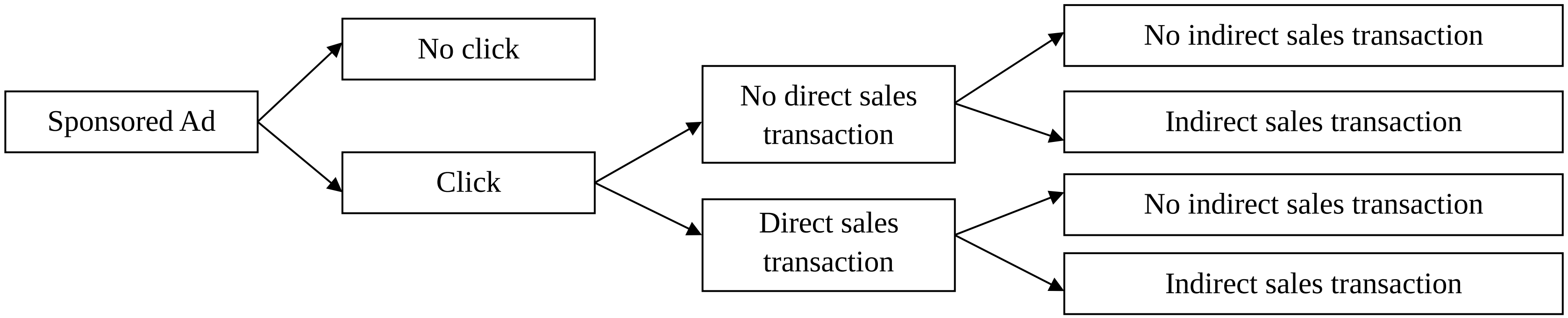

Figure 2: The Relationships between Clicks, Direct Sales Transactions, and Indirect Sales Transactions

Indirect sales Volume	Direct Sales Volume: NO	Direct Sales Volume: Yes
No	122098 (90.47%)	5788 (4.29%)
Yes	2883 (2.14%)	4184 (3.10%)

Figure 3: Cross Purchase Distribution Graph of All Observations