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# An analytical model for comparing the profitability of competing online marketing channels: Search engine marketing versus e-commerce marketplace

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**ABSTRACT**
Digital marketing offers entrepreneurs a variety of alternatives to market globally and generate revenues. Recent studies show that there is a strong research interest in developing analytical models to increase the firms' profit, by considering either key variables of specific advertising forms in isolation or cross-channel effects of online and offline channels. This article proposes a new analytical model, which assumes a trade-off between concurrent online marketing channels. Despite their different models, search engines and e-commerce platforms can be seen as competing in the same market when they are targeting the same set of consumers. Accordingly, advertisers need to constantly analyze which of the online activities perform better and why. The proposed model aims at capturing the main parameters a firm should carefully master in order to assess the effectiveness of alternative online channels in a comparative perspective, by suggesting the maximum cost per click that a firm should pay to benefit from search engine marketing, as much as from e-commerce platform.

## Introduction

With the constant expansion of the Internet and e-commerce, online advertisement has become an essential source of both information and revenues (Nakamura & Abe, 2005), with a strong effect on offline sales, as well (Lewis & Reiley, 2014). In today's economy, marketing is mostly carried out digitally by using websites, social media platforms, blogs, and other online channels. Over time, traditional marketing media have become more costly and less effective (Allen & Fjermestad, 2001). Branding efforts via traditional media, such as television, radio, and newspapers, have not disappeared, but they are becoming increasingly obsolete with consumers using social media platforms and the Internet on a daily basis (Bamm et al., 2018), although synergies between traditional and online media should not be undervalued (Olbrich & Schultz, 2014).

Online marketing channels include "any e-marketing campaigns or programs, from search engine optimization (SEO), pay-per-click, affiliate, e-mail, banner, to the latest web-related channels for webinar, blog, RSS, podcast, and Internet TV" (Ramos & Cota, 2009, p. 21). Therefore, companies have a wide array of alternatives to pursue their promotional strategies in a digital context, but their relative effectiveness remains uncertain (De Haan et al., 2016). A fundamental question is what e-commerce channel should be used, since "a firm's channel choice influences the prices of its products and ultimately, its profits" (Neslin & Shankar, 2009, p. 73).

In a broad outline, a firm can choose between pay-per-click (PPC) advertisement and e-commerce marketplace to increase its sales and profit. The implementation of PPC campaigns makes use of the power of search engines, which allow an advertiser to bid for specific keywords for generating both site visits and visitors' purchases, while the advertiser pays for the clicks he receives on the text advertisement. Well-known search engines include Google, Yahoo, and Bing, with Google as the largest player in the world, although its dominance varies by region (Khraim & Alkarablieh, 2015). Instead, e-commerce marketplaces are provided by online intermediaries that, by entering into an affiliation arrangement, agree to place a link to the company on their pages in exchange for a commission that is commonly based on the sales revenues generated by their platforms (Constantinides, 2002). The most known websites for online shopping are Flipkart, Amazon, Paytm, Shopclues, Snapdeal, which are competitors to each other, although a huge number of customers are presently preferring Amazon for making purchases on the web (Verma et al., 2020).

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Despite their different models, search engines and e-commerce marketplaces can be seen as competing in the same market when they are targeting the same set of consumers. Shoppers often use search engines and e-commerce platforms in a very similar way, irrespective of any distinction between channels of communication and channels of distribution (Gillison et al., 2019). The consumers' purpose and the sequence of actions they perform on search engines and on e-commerce platforms are the same, but for potential sellers each online channel features different costs and attributes. Under budget constraints, one of the first problems a company may encounter is to determine the resource allocation to different online channels. Assuming a trade-off between concurrent online marketing channels, the present study compares the two models, suggesting the maximum cost per click that a firm should pay to benefit from search engine marketing as much as from e-commerce marketplace.

Such question, which has never been faced before in computational terms, is likely to become more and more topical in today's world, where an increasing number of firms, including small size enterprises, are forced to use online advertising to survive and be competitive. Compared to larger companies, small- and medium-sized enterprises (SMEs) have, in general, a more limited budget and fewer resources to invest competitively in digital content and media in order to promote their offer (Bamm et al., 2018). Faced with such financial constraints, marketing practitioners and managers need guidance in order to make their investment choices. Therefore, the aim of the model developed here is to explore how firms could increase the performance of their online advertising, by comparing the profitability of different online marketing tools.

To simplify the discussion, the present research looks to Google AdWords and Amazon as reference points for paid search advertising and marketplace options, respectively. This choice is justified by their international and global relevance. Indeed, Google is "one of the most used search engines worldwide" (Bamm et al., 2018, p. 172), while "Amazon is the biggest and most advanced online shopping mall" (Liu & Hong, 2016, p. 111).

The remainder of the article is organized as follows. The literature is reviewed to first explain the main features of paid search advertising and e-commerce marketplace, and then to provide the rationale for the present study, which stems from an examination of studies on profit models for online marketing channels. Subsequently, the conceptual framework adopted in this article is presented and a new theoretical model is proposed to drive the advertisers' decisions under the assumption of a trade-off between alternative and concurrent channels. The methodology and results are presented, by reporting the cases of two companies selling sport shoes and smartphones. Both theoretical and practical implications are then discussed to highlight the relevance of the analytical model within the online marketing strategy of vendors. Finally, research limitations and future research avenues are identified.

## Literature review

### *Search engine marketing and e-commerce marketplace*

Search engine marketing (SEM) is a form of Internet marketing aimed at promoting the firm's website by improving its visibility (Moran & Hunt, 2009). The two main levers of SEM are search engine optimization (SEO) and paid search engine advertising (paid search) (Shih et al., 2013). "The goal of SEO is to optimize a firm's position in the so-called organic listings provided by search engines, that is, the search results based on the algorithms search engines use. On the other hand, paid search allows firms to buy a placement in the so-called sponsored or paid listings of the search engine results page (SERP)" (Rutz & Bucklin, 2013, p. 229). As other search engines do, Google offers organic and paid search results.

Organic search results, also called natural search results, are the primary product of a search engine, and they are not influenced by financial payment. The improvement of the relative placement of firms' websites on organic search results pages is achieved by implementing effective SEO techniques, which involve the creation of an efficient website structure, the selection of appropriate web content, and the management of inbound and outbound links to other sites (Xiang & Pan, 2011). A seller engaged in SEO can adjust the title tag, meta-tags, heading tags, links, and other parts of the page to ensure that the search engine's algorithm gives the page a higher score in comparison to other pages displayed in the SERP (Sen, 2005). A better organic search ranking should be pursued by companies wishing to obtain a long-term sustainable branding impact (Dou et al., 2010). Moreover, "unlike pay-per-click advertising, SEO has no cost other than the time required to implement it" (Buxton & Walton, 2014, p. 90). However, many companies do not necessarily have the skills and training to implement SEO on their own. Accordingly, website owners seldom invest in SEO as part of an SEM campaign, while they are more likely to invest in paid listings that, despite being more costly than SEO, "can ensure a website being listed immediately and, furthermore, can ensure high rankings, assuming a high bid price and quality score" (Kritzinger & Weideman, 2013, p. 274).

Unlike the organic results, the sponsored search results are sorted according to the AdWords market, which works as a large auction, where advertisers select certain search words or phrases, and bid what they are available to pay for an impression or a click-through on their link. The main form of paid search is the pay-per-click (PPC) or cost-per-click (CPC) advertising. In this case, companies do not pay for impressions displayed, but for the actual clicks on their paid search ads. This means that a company is not charged if its ad is seen but not clicked, while it only pays once someone clicks on its ad. In most cases, the probability that a click will convert to a sale for the advertiser depends on the ad position, also known as slot, on the SERP (Agarwal et al., 2011).

Being listed in a SERP is clearly not sufficient because engine users do not look beyond the first page of results, so only websites that rank higher will be more likely to be clicked (Quinton & Khan, 2009). The first position should be assigned to the ad that, according to past performances including consumer clicking behaviors, is expected to generate the highest revenues for the search engine (Rutz & Bucklin, 2013), because a search engine company earns revenue from advertised businesses when users click on the ads displayed in response to a relevant search query (Mangold, 2018). In particular, for each click on an advertising link, the search engine charges the advertiser a variable amount, according to the mechanism of the generalized second price auction (Edelman et al., 2007), which is supplemented by the quality score. Based on the enhanced auction, "text advertisements are placed in position rank order as a function of click-through rates, landing page quality scores, and bid amounts. This means that competitive bidding is not the sole determinant" (Rutz & Bucklin, 2011, p. 93).

Since the position of an ad is the result of an auction, higher positions, which cost more, should be justified only if they generate higher returns for the advertisers (Narayanan & Kalyanam, 2015). The advertisers can have basic information on their ad campaign (Haans et al., 2013), including the click-through rate, the conversion rate, and the cost per click. The click-through rate is the ratio between the number of clicks, i.e. the number of times the displayed text ad has been clicked by users, and the number of impressions, i.e. the number of times the text ad has been displayed by the search engine in response to a keyword search. The conversion rate is the ratio between the number of sales and the number of clicks, while the cost per click is the ratio between the total cost charged by the search engine for the ad campaign and the number of clicks over a given period.

The average conversion rates in paid search can be extremely low or even equal to zero if most keywords simply did not generate any sales over a certain period of time. Since the market of search advertising is highly concentrated, advertisers must face stronger competition (X. Cao & Ke, 2018). Pay-per-click "could become costly as advertisers are locked in an ongoing competition for popular keywords" (Kritzinger & Weideman, 2013, p. 277). If many firms compete on the same keywords, the advertisers' bids increase, meaning that higher costs reduce the return on investment on AdWords (Ryan, 2016). Competition is driving the increase in bid prices and, as SEM becomes more common, maintaining top rankings is difficult for advertisers with limited budgets (Shih et al., 2013). The more the keywords chosen by the advertiser are required by other advertisers, the more expensive the click is. Moreover, the effectiveness of the CPC/PPC scheme can be lowered by click fraud, intended "as the practice of deceptively clicking on search ads with the intention of either increasing third-party website revenues or exhausting an advertiser's budget" (Wilbur & Zhu, 2009, p. 293).

According to Quinton and Khan (2009), the CPC/PPC scheme can become an unviable option for SMEs, because top positions for keywords generating higher website traffic are held by large businesses, having a higher bid capacity. Under AdWords campaigns, advertisers are forced to either drop keywords that do not generate sales, or compete on keywords more likely to generate sales. However, if there is an increase in the demand for keywords associated with more traffic and sales, the price (*melius*, the bid) for those keywords increases, as well, and as a result the advertiser's profit decreases. The risk is that naive advertisers with scarce expertise may be incorrectly willing to make a higher bid for some popular keywords, spending more than necessary. Essentially, the AdWords system could be highly profitable for businesses but, in the absence of due vigilance and knowledge, advertising on Google can be an expensive and unproductive investment with a continued net drain of money out of the advertising budget (Miller, 2016). In response to these concerns, the article proposes a mathematical model that should allow an advertiser to compute the maximum value of bids to profit from the CPC/PPC scheme.

Because of the above-mentioned uncertainties underlying paid search advertisements, companies may prefer to pay on the basis of the performance of their advertisements, believing that, in general, impressions and click-through rates overstate advertising effectiveness (Manchanda et al., 2006; Moral et al., 2014). In particular, an advertiser may opt for participating in affiliate marketing programs where a marketing partner, called "affiliate," bears the total risk associated with the cost of marketing the advertiser's products, by earning a commission when the advertiser's product is sold. Essentially, affiliates drive incremental traffic and sales in exchange for commission (Dennis, 2005). Affiliate marketing attracts substantial investment from most online retailers, because of its low risk for merchants who must pay out only upon successful completion of sales (Chachra et al., 2015).

The present research focuses on Amazon's platform, because it has become a dominant e-commerce enabler (Berg & Knights, 2019), but it is also threatening Google in search, because most people looking for a product navigate directly to Amazon to make their purchases (Galloway, 2017). Amazon plays a dual role, acting as a merchant and as the host of the marketplace for third parties (Berg & Knights, 2019). Concerning the latter role, Amazon allows third-party sellers to use its marketplace with the great advantage that, besides a possible fixed fee, no payment is due until the product has been purchased according to a scheme that is sometimes referred to as "zero-risk advertising" (Chaffey et al., 2006). The pay-per-sale advertising differs from the pay-per-click model, where the retailer is asked to pay for the visitors irrespective of whether they purchase anything. Under Amazon's model, merchants are charged each time a consumer buys a product but, in general, they have to pay a monthly subscription fee too, depending on the number of sales per month.

More specifically, Amazon's e-commerce platform enables both individuals and businesses to sell their products or inventory. By the so-called "Fulfillment by Amazon" (FBA), third-party sellers can store their merchandise at Amazon's fulfillment centers where inventory items are boxed and shipped, when orders are placed. Instead, for those willing to sell products without additional services (such as storage, packaging, shipping, and customer services), Amazon offers two selling plans requiring the payment of "Selling on Amazon" fees for orders placed. The "professional selling plan" is available for a monthly subscription fee of € 39 plus per-item selling fees, which vary by product category and range mainly from 6 to 25 percent. Instead, the "individual selling plan" is conceived for those who sell fewer than 40 items a month. In this case, no monthly fee is charged and the cost for the seller is € 0.99 per item plus per-item selling fees, which always vary by product category.

Since many products on Amazon are sold by multiple sellers, Amazon employs a proprietary algorithm to determine which seller's offer is displayed to the customers. Its algorithm is different from that of Google, which focuses mainly on delivering the best and most valuable information to people typically interested in finding information. While Google focuses on matching search intent, Amazon focuses on customer purchase intent. More specifically, Amazon's ranking algorithm puts at the top of the search results the products that, because of their relevance and good reviews, will get people to convert, by performing the purchase. Firms are interested in being ranked on the first page of results because 70 percent of Amazon consumers never scroll beyond the first page (WebFX, 2019).

The different charging system (pay-per-click vs pay-per-sale) by Google vs Amazon may be mainly explained by their different business models. "AdWords is Google's keyword-triggered advertising program" (Lim, 2007, p. 266). Google sells targeted advertisements to companies that want to be associated with certain search terms, by displaying commercial results, i.e. sponsored links (Argenton & Prüfer, 2012). Therefore, it is consistent with its function that Google is rewarded by the advertisers when the targeted advertising is displayed to the users (i.e., according to the pay-per-impression scheme) or when the targeted advertising is clicked by the users (i.e., according to the pay-per-click scheme). Instead, the pay-per-sale scheme is the more natural way to reflect the evolution of Amazon's business model, which rests heavily upon the firm's competitive strategies that involve sharing platforms, resources, capabilities, risks, costs but also benefits, and profits (Ritala et al., 2014).

## *Studies on profit models for online marketing channels*

The use of web analytics is essential to design profitable and effective campaigns. Many scientific studies have suggested specific web metrics, e-commerce indicators, and advertising indices to implement effective online marketing activities (e.g., Bucklin & Hoban, 2017; Bucklin et al., 2017; Chaffey & Ellis-Chadwick, 2019; Kozielski, 2017; Kwan et al., 2005; Moral et al., 2014; Plaza, 2011; Ramos & Cota, 2009; Ryan, 2016; Tonkin et al., 2011; Wiesel et al., 2011). More importantly, the academia has shown a growing interest in analytical models able to better understand how certain variables can impact sellers' profits.

An extensive stream of literature proposed profit models to cope with the intense competition between online and traditional channels, which may cause price war leading to decreased profitability for both channels. For instance, Yan et al. (2010) used a game theoretical model to show that both the online and the traditional channels can improve their individual profits, if channel integration is strategically implemented with profit sharing. Similarly, Yan (2011) used mathematical models to highlight the benefits of cooperation mechanisms between traditional retailers and manufacturers, who are increasingly using online channels to sell directly to customers. The author proved that both manufacturers and retailers can achieve the full channel coordination and improve their individual profits, if they implement brand differentiation and profit-sharing strategies. To investigate the optimal cooperative advertising strategies from the manufacturer's perspective, X. Cao and Ke (2018) built a game-theoretic model to demonstrate that, in deciding whether to participate in search advertising directly or indirectly via retailers, the manufacturer should compare his profit per click with the retailers' channel profit per click.

Other studies implemented profit models to emphasize the importance of cross-channel effects. For instance, Wiesel et al. (2011) considered a variety of marketing activities, including catalogs, faxes, flyers, Google AdWords, e-mails, and discounts. By estimating vector-autoregressive models to measure the direct and indirect effects of the marketing communication on offline and online purchase funnel metrics, the study found evidence of many cross-channel effects and showed that online customer-initiated contacts have a higher profit impact than offline firm-initiated contacts. Moreover, more recently, Mark et al. (2019) highlighted the important role of traditional media despite the increasing prominence of digital marketing. They developed a dynamic segmentation model to study the effect of catalogs and e-mail marketing communications on consumers, by performing profitability analysis based on different segments. Their findings suggested that marketing managers should not undervalue the positive cross-channel effects of catalogs on sales and profits. To shed light on the synergistic effects of multichannel strategies, Lawrence et al. (2019) analyzed the profitability of business-to-business customers in a digital context where sellers are increasingly motivated to reduce costly sales forces and to build their own online channels enabling automation and self-service. The authors showed that sellers should continue to invest in salesperson channels, because salesperson channels and customer-specific discounts complement online channels, thus enhancing the seller's sales and profit. Instead, Chan et al. (2011) developed an integrated model to measure the value of customers acquired from Google search advertising by accounting for both the lifetime value of acquired customers and the spillover effect of search advertising on customer acquisition and sales in offline channels. They found that, on average, the customers acquired through Google search advertising have higher transaction rates and generate higher gross margins than those obtained from offline channels.

Another literature stream studied profit models from the advertiser standpoint by focusing on a single online channel, mostly the option of search engine advertising, to provide important theoretical foundations to modeling advertisers' bidding. For example, Ghose and Yang (2009) used a hierarchical Bayesian modeling framework to examine the relationship between different sponsored search metrics (such as click-through rates, conversion rates, CPC) and ad position using keyword-specific data from one retailer. They found that keywords that have higher positions on the SERP and, hence, experience higher click-through rates and conversion rates, are not inevitably the most profitable ones. Similarly, Agarwal et al. (2011) used a hierarchical Bayesian model to analyze the impact of ad position on both click-through and conversion rates. They found that while the click-through rate decreases with the ad position, the conversion rate increases with the ad position, suggesting that, contrary to conventional wisdom, the revenue or profit-maximizing position for keywords is not necessarily linked to the topmost position, because the net effect on profits is not easily predictable. Additionally, Skiera and Abou Nabout (2013) developed a bidding decision model to help advertisers to maximize the profits per keyword in Search Engine Advertising (SEA) campaigns, based on the rank, time, and quality score. Their study used the data set of a small company to demonstrate how a bidding decision support system can significantly increase profits, primarily because of reduced bids and, consequently, lower costs per click. Instead, Moon and Kwon (2011) analyzed the profit effects of the two most popular ways of pricing online advertisements, namely the method based on cost-per-impression (CPM) and the method based on cost-per-click (CPC), to then suggest a hybrid pricing scheme, where advertisers may avoid future high costs by purchasing an option from publishers to pay the lowest CPM and CPC fees.

Basically, the review of the previous research on profit models for online channels reveals two interesting categories of analysis. The first category embraces the articles which studied profit impact by considering both online and offline channels, while the second category includes the articles that strictly focused on a single online channel, mostly the option of search engine advertising. In contrast, relatively little research can be classified as being of the third form, concerned with using a comparative approach to analytically investigate how firms may improve the profits by reallocating their budgets between concurrent online channels. Essentially, researchers have investigated the use of an e-commerce channel in isolation or in conjunction with traditional channels, but less research has been dedicated to choosing which online channels should be used under limited resource constraints. The present article tries to fill this gap in the literature by examining how to make the choice among different and alternative online channels.

## Research question and propositions

The conceptual framework adopted in this study is based on relevant propositions derived from previous theories and research on digital advertising. As noticed, pervasive digital media enable consumers to access information any time and any place, with significant effects on their purchase decisions. Digital marketing has changed customers' buying behaviors and it has brought various advantages to users. Specifically, digital media allow the consumers to be continuously updated about companies' products or services, to have a greater engagement with companies' activities, to get clearer information about the products or services, to increase their shopping convenience by comparing quality and cost among products or services proposed by different suppliers, to share the content of the products or services to others, to shop without time restrictions, to save time and to purchase the products or services instantly (L. Cao & Li, 2015; Yasmin et al., 2015). Thanks to the advances in technology and the Internet, consumers' online shopping has boomed around the world (Schultz & Block, 2015). Hence, the following research proposition may be formulated:

*P1: Consumers use increasingly online platforms to purchase products and services.*

In order to meet the evolving needs of consumers, online channels are increasingly recognized as an important vehicle by which firms can influence consumers' purchases (Guo, 2012). Global online advertising spending has become a substantial portion of all advertising spending (Liu-Thompkins, 2019). Online advertising is a relevant source of revenue for a wide range of businesses because of its numerous advantages. When compared with traditional advertising, online advertising is less expensive and it allows firms to cover wider geographical areas, to have a 24/7 year-round exposure, to reach the targeted audience better and faster, to plan campaigns over a shorter period of time, to track, and analyze the performance more easily, to get more feedback from consumers and, thereby, to improve the quality of ads (Deshwal, 2016). The previous considerations are summarized in the following proposition.

*P2: Firms make increasingly use of online channels to attract consumers and increase sales.*

Firms have a wide array of alternatives to pursue their promotional strategies in a digital context (Ramos & Cota, 2009). Engaging in multiple online channels is highly recommended (Duffy, 2004) to target a broader group of consumers (Duch-Brown, 2017). Advertisers engage in multi-homing to access larger potential markets, to offer their items to the same customers across different platforms, and to reduce the dependency on a single market (Hyrynsalmi et al., 2016). In the absence of substantial barriers and financial constraints, any advertiser would gain from spreading an ad campaign over multiple platforms to maximize the return on investment from each online platform (Etro, 2013). These considerations lead to the following proposition:

*P3: Investing in multiple online channels is a highly recommended strategy.*

New additional digital channels create new opportunities but also various complexities for advertisers, who must leverage their multiple channels appropriately to avoid cannibalization and produce synergies, by implementing channel integration to achieve consumer trust, satisfaction, loyalty, and retention (L. Cao & Li, 2015; Neslin & Shankar, 2009; Verhoeff et al., 2015; Zhang et al., 2018). Moreover, investing in multiple online channels may be a costly and time-consuming activity. Indeed, "multi-homing also generates costs associated with converting a product to different platforms, additional marketing efforts, and also maintaining the product for several platforms" (Hyrynsalmi et al., 2016, p. 121). The problem is that many firms have prespecified budgets that they can use for advertising expenditures, so that they cannot place as many commercials at each channel as they wish. Budget-limited advertisers must rather decide whether to allocate their online advertising budget to one platform or split it across platforms. Recently, this interesting question has been faced by Zia and Rao (2019), who investigated advertisers' budgeting and bidding strategies across multiple search platforms. They found that firms can potentially benefit from allocating their budget across multiple search engines, but the benefit from differentiation for advertisers decreases if search engines strategically increase their reserve prices to maximize their revenues. Therefore, the following proposition can be posited.

*P4: Budget constraints impose major challenges on multi-platform design and lead to an allocation problem for advertisers.*

It is worth pointing out that Zia and Rao (2019) studied the problem by considering the presence of two search engines that compete for search advertising. However, in a multiplatform environment, the advertising competition may exist not only between two search engines, but also between a search engine and an e-commerce platform. Indeed, as observed by Visnjic and Cennamo (2013), the "big four," namely Apple, Facebook, Google, and Amazon, and the incumbent Microsoft are platforms that, despite their diverse business models, are increasingly competing in a single and encompassing competitive arena, by blurring the market boundaries. Broos and Ramos (2017) explained that intermediaries with different business models, such as Google and Amazon, can compete within the same market when they are targeting the same set of consumers, because the "service that they offer and are paid for is the intermediation that they provide between consumers and manufacturers" (p. 395). Actually, consumers searching for a particular item may visit Amazon or Google to obtain an ordered list of items that link to retailers' websites. Moreover, although Google dominates both user search and search advertising, as the range of products that Amazon "sells expands, users are now going straight to it to search for them, bypassing Google and enabling it to sell search advertising" (Barwise & Watkins, 2018, p. 40). Therefore, Amazon or Google are used by potential consumers as substitutes. The same is true for advertisers, who may see the two intermediaries as substitutes and answers to the same need of facilitating the sale of their products. "For online retailers, it does not make a difference whether the consumer comes through advertising put on Google or a link on Amazon, as long a sale occurs. The only distinction in use is the payment system" (Broos & Ramos, 2017, p. 397). From an advertiser's standpoint, Google AdWords and Amazon are regarded as alternative solutions to the extent an individual customer willing to buy an item online makes a purchase only once at each opportunity. The previous considerations lead to the following proposition:

*P5: Google and Amazon can be regarded as interchangeable or substitutable by consumers and retailers.*

In terms of new theoretical modeling, this study focuses on a particular business choice, i.e. how advertisers should allocate their limited budgets across heterogeneous platforms, while prior researches focused on a single-platform environment or on a multiplatform environment with homogenous platforms (Zia & Rao, 2019). More plainly, the research question addressed by this article is how advertisers should allocate their budget between different online channels using different charging systems. To address this issue, a comparative approach is introduced. More specifically, according to different charging systems used by Google (i.e., the pay-per-click model) and by Amazon (i.e., the pay-per-sale approach), the study intends to determine what is the maximum cost per click advertisers should pay for to profit from Google AdWords, as well as from Amazon affiliate programs. Therefore, the proposed model does not recommend to make a definite choice between Google or Amazon, but rather intends to suggest, for a certain ad, how to allocate a given budget, being very careful not to exceed a specific cost per click in Google AdWords. This maximum cost per click is affected not only by Google's parameters but also by Amazon's parameters.

The choice of focusing only on Google vs Amazon is motivated by their leading role in the respective market segments, where other search engines operate with different algorithms (Verma et al., 2020) and other affiliates compete with different schemes and commission percentages (Ariely et al., 2005; Chachra et al., 2015; Krishnamurthy, 2004). Indeed, the differences in the online environment should not be underestimated. On the one hand, "unlike other cost-per-click models that place advertisements based on the amount paid for the advertisement, Google determines advertisement placement based on a number of factors in addition to the amount bid by the advertiser for the space" (Lim, 2007, p. 268). On the other hand, some affiliates could apply a referral fee arrangement different from the pay-per-conversion or pay-per-sale methods, by preferring to use the pay-per-lead method, "whereby affiliates are paid for referrals regardless of whether their referrals are converted into buyers" (Libai et al., 2003, p. 303).

That said, the basic assumption is that the advertisers' ultimate goal is to increase and maximize their profit. One of the initial steps in this maximization process is to identify the benefits and costs associated with different strategies for increasing web traffic and sales (Baye et al., 2016). The profitability for a given online marketing channel could be captured by the gross profit margin, "i.e., total revenue net of supply cost, without accounting for handling and other costs" (Chan et al., 2011, p. 840). In particular, a firm investing in an ad campaign on Google expects to earn a gross profit margin ($\pi_G$), determined as follows:

$$\pi_G = TR_G - TC_G \quad (1)$$

where the subscript $G$ denotes the values related to Google, while $TR_G$ and $TC_G$ are the "total revenue" and "total cost per click," respectively, associated with the Google-sponsored search advertising over a certain period. On the one hand, the "total revenue" earned by Google ads ($TR_G$) can be expressed as the product of the "order number" ($ON_G$) and the average "revenue per order" ($RPO_G$), so that the following expression can be written (2):

$$TR_G = ON_G \times RPO_G \quad (2)$$

Moreover, the number of sales from Google ads, i.e. the "order number" ($ON_G$), is the product of the "click number" ($CN_G$) and the "conversion rate" ($CONV_G$). Therefore, the $ON_G$ can be quantified as follows (3):

$$ON_G = CN_G \times CONV_G \quad (3)$$

Ultimately, the term $TR_G$ (2) can be reformulated as (4):

$$TR_G = CN_G \times CONV_G \times RPO_G \quad (4)$$

On the other hand, the "total cost per click" ($TC_G$) can be expressed as the product of the "click number" ($CN_G$) and the "cost per click" ($CPC_G$), as specified below (5):

$$TC_G = CN_G \times CPC_G \quad (5)$$

Therefore, the formula (1) can be analytically rewritten in the following form (6):

$$\pi_G = CN_G \times CONV_G \times RPO_G - CN_G \times CPC_G \quad (6)$$

However, to assess the profitability of online marketing investments under budget constraints, a company should compare not only the costs and revenues of PPC advertisements, but also the costs and revenues related to e-commerce platforms. Indeed, in order to decide whether and where to spend for marketing activities, one needs to understand the profitability of each channel.

Unlike Google, Amazon charges sellers a fixed fee and a commission per item sold (Hagiu, 2007). The charging scheme of Amazon ($A$) is commission-based, because the seller pays a commission percentage ($CP$) plus a periodic fixed fee ($FF$). The benefit of using Amazon's platform can be again measured by the gross profit margin, determined by subtracting the commission percentage and the fixed fee from the total revenue that are Amazon-related in a given period. Therefore, if a company sells on Amazon over a certain period, the expected gross profit margin ($\pi_A$) can be written in mathematical terms as follows (7):

$$\pi_A = TR_A \times (1 - CP_A) - FF_A \times M \quad (7)$$

where the subscript $A$ denotes the values related to Amazon, $TR_A$ is the total revenue earned by Amazon, $CP_A$ is the commission percentage (value between 0 and 1) paid to Amazon per single sale performed through its platform, $FF_A$ is the monthly fixed fee and $M$ is the number of months included in the data-collection period, because the net price received by the seller is computed by simply multiplying the total revenue by the factor (1 – $CP_A$) and by subtracting the monthly fixed fee (currently equal to € 39) per each month.

According to the previous propositions, it is now possible to determine if and how much the commissions due to Amazon can compensate for the PPC cost, by generating the same gross profit. This question can be answered by comparing, over a certain time period, the performances of the different marketing channels, based on a set of Google and Amazon variables, which are denoted by the subscripts $G$ and $A$, respectively. Assuming that the Google ad campaign generates no additional order beyond the orders subtracted to Amazon ($TR_G$ = $TR_A$), the competition between the two models of gross profit margin ($\pi_G$ = $\pi_A$) can be expressed in mathematical terms by the Equation (8):

$$TR_G - TC_G = TR_G \times (1 - CP_A) - FF_A \times M \quad (8)$$

Note that the present research does not propose that Google and Amazon are *always* competitors but only that, if a consumer buys a merchandise promoted by both channels, they are, because the consumer purchases only once. By performing the multiplication, the Equation (8) can be rewritten also as (9):

$$TR_G - TC_G = TR_G - TR_G \times CP_A - FF_A \times M \quad (9)$$

By removing the common term ($TR_G$) from the two sides of the Equation (9) and by moving the variables so to have parameters with positive signs, the Equation (10) can be obtained:

$$TC_G = TR_G \times CP_A + FF_A \times M \quad (10)$$

By replacing $TR_G$ in (10) with the formula (4), the Equation (10) can be rewritten as (11):

$$TC_G = CN_G \times CONV_G \times RPO_G \times CP_A + FF_A \times M \quad (11)$$

By replacing $TC_G$ in (11) with the formula (5), the Equation (11) can be rewritten as (12):

$$CN_G \times CPC_G = CN_G \times CONV_G \times RPO_G \times CP_A + FF_A \times M \quad (12)$$

By dividing both sides of the Equation (12) by $CN_G$, the following expression is obtained (13):

$$CPC_G = CONV_G \times RPO_G \times CP_A + \frac{FF_A \times M}{CN_G} \quad (13)$$

The formula (13) states that the maximum cost per click ($CPC_G$) to be incurred by the advertiser to gain from Google AdWords the same gross profit attainable via Amazon is equal to the conversion rate ($CONV_G$) multiplied by the average revenue per order ($RPO_G$) and the commission percentage ($CP_A$) applied by Amazon, plus the ratio between the fixed fee per period ($FF_A$ x $M$) required by Amazon and the number of clicks on Google ($CN_G$). In this way, the model incorporates and captures the variables which should drive the marketers' and managers' decisions to address the question of a trade-off between Google and Amazon. Interestingly, although the model deals with the case in which Google and Amazon are confronted, the modeling results can be extended to other search engines and e-commerce platforms that use conditions and charging schemes similar to those adopted by the two big players.

## Methodology

The model of this study aims at providing answers to basic questions, such as which web marketing channels a firm should choose to increase its profitability, and which parameters should be carefully mastered to assess their effectiveness in a comparative perspective. More specifically, the method introduced by this article could enable companies to fine-tune their online advertising campaigns, suggesting how much they can invest in major search engines to have the same profit as the one obtained from e-commerce marketplaces. Such analysis is crucial in supporting advertisers' decisions, especially under budget constraints.

In agreement with Danaher and van Heerde (2018), the present study maintains that the profit-maximizing allocation for a fixed budget should be a function of the advertising effectiveness, but not a function of past exposure levels. Specifically, the proposed model ignores the number of impressions, which is a measure of advertising exposure, while it takes into account the conversion rate that is based on the number of products actually sold, and therefore is a measure of advertising effectiveness.

To illustrate the formula, data on return for different marketing investments have been used. To collect marketing data related to a period of six months, a structured and self-reported questionnaire, including the items reported in Tables 1 and 2, was sent by e-mail to almost 50 small and medium firms, which were selected from public database. On asking for the participation of companies in the study, data anonymity was guaranteed. However, most of the companies replied that all the required data were not available, while other SMEs declined to participate in the study for reasons of data protection. Notwithstanding these difficulties, four firms answered the questionnaire completely. However, for the sake of clarity and brevity, this study presented the marketing metrics related to only two companies, selling different products, namely sport shoes and smartphones, because these firms showed opposite results. Both companies can be classified as SMEs, and in particular small entities, as defined by Directive 2013/34/EU, because they did not exceed the limits of at least two of the three established criteria (balance sheet total of € 4,000,000; net turnover of € 8,000,000; and average number of employees of 50). Neither company name is reported, in compliance with the data-sharing agreement between the researchers and the firms.

The collected data and metrics refer to the period from May to October 2018 with regard to the seller of sport shoes and from July to December 2018 with regard to the seller of smartphones. Key descriptive statistics for each data set are reported in Table 1 for Google data and in Table 2 for Amazon data. Both companies adhere to Amazon's "professional selling plan." It should be noticed that the commission percentage paid to Amazon is 15 percent for the seller of sport shoes, while it is 7 percent for the seller of smartphones, because the sold items belong to different product categories. Regardless of this difference,

**Table 1.** Descriptive statistics for Google data.

| *Parameters* | Seller of sport shoes | Seller of smartphones |
|---|---|---|
| Number of impressions | 9,230,769 | 3,629,032 |
| Number of clicks ($CN_G$) | 36,011 | 11,607 |
| Number of sales or order number ($ON_G$) | 1,019 | 430 |
| Total costs ($TC_G$) | € 9,032 | € 7,251 |
| Total revenues ($TR_G$) | € 88,653 | € 63,210 |
| Revenue per order ($RPO_G$) | € 87 | € 147 |
| Average website's position | 4° in the 1st page | 4° in the 1st page |
| Click-through rate ($CTR_G$) | 0.3901 percent | 0.3198 percent |
| Conversion rate ($CONV_G$) | 2.8297 percent | 3.7047 percent |
| Cost per click ($CPC_G$) | € 0.2508 | € 0.6247 |
| Cost per sale | € 8.8636 | € 16.8628 |

**Table 2.** Descriptive statistics for Amazon data.

| *Parameters* | Seller of sport shoes | Seller of smartphones |
|---|---|---|
| Commission percentage ($CP_A$) | 15 percent | 7 percent |
| Fixed fees per period ($FF_A$ x $M$) | € 234 | € 234 |

the previous formula allows to examine the efficacy of marketing investments and the return for each company.

It should be noticed that among the data collected from questionnaires, there are some figures which do not appear in the formula. Following the literature of position auctions (X. Cao & Ke, 2018; Edelman et al., 2007), the consumers' searching and clicking behaviors are not explicitly modeled, and click-through rates for each position are assumed as exogenous variables. Therefore, the relative position of the firm's website in the SERP is not explicitly reported in the formula, because it is indirectly accounted by the conversion rate.

## Results

The underlying principle of the present research is that the analysis of the effectiveness of a site's traffic source lies necessarily in the use of time series analysis. More plainly, this study assumes that a firm must decide whether to invest in Google ads or in Amazon programs, by also taking into account the numbers of products that in the past have been sold through the two online channels. Consequently, a firm should allocate a certain budget across different advertising channels, by selecting the best solution in terms of profitability in the light of past performances.

Applying the formula (13) to data collected for the seller of sport shoes, the maximum cost per click ($CPC_G$) is equal to € 0.3758, obtained as the sum of 0.3693, which is the product of $CONV_G$ (2.8297 percent) and $RPO_G$ (€ 87) and $CP_A$ (15 percent), and 0.0065, which is the ratio between the product of $FF_A$ x $M$ (234) and $CN_G$ (36,011). It can be inferred that, for the vendor of sport shoes, the Google ad campaign can be deemed competitive with the Amazon channel because the advertiser is able to curb his cost for click, keeping it below the maximum $CPC_G$ resulting from the formula (13). Indeed, the seller of sport shoes has an actual $CPC_G$ of € 0.2508, i.e. a cost below the maximum $CPC_G$ of € 0.3758.

Instead, applying the formula (13) to data collected for the seller of smartphones, the maximum cost per click ($CPC_G$) is equal to € 0.4014, obtained as the sum of 0.3812, which is the product of $CONV_G$ (3.7047 percent) and $RPO_G$ (€ 147) and $CP_A$ (7 percent), and 0.0202, i.e. the ratio between the product of $FF_A$ x $M$ (234) and $CN_G$ (11,607). In this case, an opposite conclusion could be drawn. For the seller of smartphones, the Google ad campaign proves less profitable than the Amazon channel, because the vendor is not able to keep the actual cost for click, equal to € 0.6247, below the maximum $CPC_G$ resulting from the formula (13), i.e. € 0.4014. Therefore, the seller of smartphones should carefully evaluate whether the Google channel should be kept or replaced with the Amazon channel.

The lower performances achieved by the smartphone vendor in Google AdWords could be explained by several factors such as a low quality of the landing page or a low level of transparency and navigability of the website (Weller & Calcott, 2012). The lack of specialist skills and expertise in Google AdWords could be another possible explanation (Buxton & Walton, 2014). However, the most likely reason could be the relatively lower percentage (7 percent) paid to Amazon, with the consequence that the seller of smartphones should further improve his conversion rate to profit from Google AdWords more than from Amazon.

Moving beyond specific situations and solutions, both results show the paramount importance of conducting comparative analysis between complementary or alternative online channels by using a scientific and effective approach to choose the more profitable option. A further great advantage of the suggested method is also the easy application of the formula, which requires focusing only on few parameters. By thoroughly examining specific historical data and performances, managers and marketers may decide if and how their companies should arrange the advertisement strategy to improve their profits in the future. Similarly, advertisers charging a web marketing agency with the task of promoting their products and services should request the same web marketing agency to report periodically to them at least on the parameters helpful in computing the maximum $CPC_G$, which should be then compared to the actual $CPC_G$. Obviously, such metrics are relevant to web marketing agencies *in primis* to well advise their clients about the best marketing strategy.

## Discussion

As previously explained, most models proposed by the reviewed studies focused on key variables of specific advertising forms, considered in isolation or in conjunction with traditional channels; therefore, they offer little guidance for driving budget allocation decisions between different online channels. Unlike previous studies, the purpose of this research is to support advertisers in their decision-making regarding different online marketing options. In particular, the research contributes to a better understanding of current digital opportunities, by comparing the two most important markets that advertisers can rely on for attracting online shoppers of goods at international level, i.e. Google and Amazon.

The two sellers in our study show evidence that the use of Google AdWords complements the online presence at Amazon marketplace in marketing strategies. However, we found that the two companies profit from two online channels in different ways. In particular, the smartphone vendor seems to have patterns of channel activities inconsistent with our theorized model, which elucidates how sellers can enhance the efficacy of their online activities. Indeed, a company engaged in Google AdWords campaign should strive to have an actual cost for click lower or equal to the maximum $CPC_G$ resulting from the formula (13).

Therefore, as long as the actual $CPC_G$ does not exceed a certain threshold, the Google AdWords campaign always benefits the advertiser. A clear effect of variables on the maximum $CPC_G$ can be studied just by directly observing the parameters of the model, especially those under the firms' control. Some parameters, such as the commission percentage ($CP_A$) and the fixed fee ($FF_A$), are not under the firms' control, being under the decision power of Amazon. The higher the $CP_A$ and $FF_A$, the higher the maximum $CPC_G$. Conversely, an advertiser willing to increase the maximum $CPC_G$ may act on the remaining variables by increasing the conversion rate ($CONV_G$) and the average revenue per order ($RPO_G$) or by decreasing the number of clicks ($CN_G$) on Google.

However, an increase in the average revenue per sale is not easy because of the effect of world competition on the prices of goods. An increase in price is likely to reduce the demand for the product, because of the intensity of price competition. The ease of price comparison brought about by the Internet has made price competition fiercer in the online environment than in traditional stores (Brynjolfsson et al., 2010; Chakrabarti & Scholnick, 2002). Similarly, focusing on reducing the number of clicks can be a risky or counterproductive endeavor, because it may decrease the likelihood of sales. Indeed, consumers could make an online purchase only if they first click on the advertiser's link.

It follows that the best strategy to improve the maximum $CPC_G$ lies with improving the conversion rate ($CONV_G$). The increase in the conversion rate is the ultimate goal for every ad campaign on search engine marketing but, as previously explained, this goal is a challenging task and it could be achieved by improving the quality of the ads, and hence by supporting the costs associated with high-skilled personnel for SEM analytics. However, such costs can lower the profit, if they are not offset by an adequate increase in revenues. Indeed, for complexity reasons, firms, above all small- and medium-sized enterprises, often do not self-manage their paid search advertising, but outsource it to external web marketing agencies, which must be paid for this service. Alternatively, the time-consuming process of paid search advertising can be internally managed by firms themselves by recruiting relevant profiles and by remunerating the specialized workers, while no additional staff cost is in general required when companies are involved with Amazon. Therefore, the compliance with the rule of the maximum cost per click, as formulated above, should be deemed even more stringent, considering that the underlying formula omits the additional cost of expert staff for time spent adjusting Google AdWords campaigns.

Moreover, in the context of paid-search advertising, the effects of competition, measured by the number of ads on the paid-search listings, should be taken into account. Yang et al. (2014) recommended advertisers to adjust their bidding and keyword portfolio strategies with respect to competition, because the number of competing ads has significant impacts on baseline click volume, decay factor, and value per click, which in turn determine the expected click volume, CPC, and revenue of search advertisers from a keyword.

## Theoretical and managerial implications

The model discloses clear managerial implications. For a firm, the Google ad campaign can be regarded as more effective than the Amazon program when the advertiser is able to keep his actual $CPC_G$ under control, by effectively limiting it below the maximum $CPC_G$ resulting from the formula (13). An opposite conclusion could be drawn if the advertiser has an actual $CPC_G$ higher than the maximum $CPC_G$, because this could mean that the Google ad campaign is less profitable than the Amazon channel. In this case, the seller should carefully reassess the choice to continue to advertise on Google and consider whether it is opportune to migrate the resources associated with the specific ad to Amazon. Obviously, the same situation could also be managed by improving the advertisement's quality on Google, but the problem is that "quality improvements lead to higher weighted bids, which decrease prices per click only if the weighted bids do not improve the ad ranking. Otherwise, better ranks likely lead to higher prices per click and higher costs for SEM, with ambiguous consequences for profit" (Abou Nabout & Skiera, 2012, p. 142). In particular, as explained by Abou Nabout and Skiera (2012), the increase in ad quality has direct and indirect price and quantity effects. The sign and magnitude of these effects on profit are different and complex, although advertisers may benefit from improving their advertisement's quality if they lower their bids after improvements to advertising quality. Therefore, for advertisers and especially SME managers, a key challenge is to carefully consider ad quality improvements together with other elements (e.g., prices per click, SEM costs, and ultimately profit after SEM costs) to then compare the outcome of pay-per-click model with the outcome of pay-per-sale advertising.

This research has also theoretical implications for competitive strategy. Advertisers have to face strong competition because the current market structure of search advertising and e-commerce platforms is highly concentrated. The dominance of well-known Internet firms is a result of competitive forces. Successful Internet-based companies, such as Google and Amazon, are almost monopolists, because large platform sizes and high concentration are quite indispensable to achieve the economies of scale and indirect network effects, which occur when "users on one side of the market indirectly benefit from an increase in the number of users on their market side, as this increase attracts more potential transaction partners on the other market side" (Haucap & Heimeshoff, 2014, p. 51). As explained by Argenton and Prüfer (2012), a competitive oligopoly is rooted in the high-quality levels triggered by intense competition, so that Google's dominance is also a result of the superior quality of its search algorithm. In order to sustain its market share and profits, the same Google cannot rest on its high-quality level, but it has strong incentives to innovate constantly so to improve its algorithms and increase its collections of data. Similarly, the dominance of some online trading platforms is not detrimental to sellers because the likelihood to sell their goods is higher in e-commerce platforms attracting a large number of potential buyers (Haucap & Heimeshoff, 2014).

Therefore, the concentration in the online distribution industry is not an issue, because it is not inherently bad. If the concentration is the result of a fair competition on algorithm quality, narrow control, either by government or by corporations, is not required. What is rather needed is a deeper understanding on profitability of different digital platforms to enable sellers and buyers to make their well-informed decision. The present contribution should be regarded as an effort in this direction, being aimed at enabling firms to fine-tune their online marketing strategy, again by acknowledging and leveraging the competitive nature of alternative digital solutions.

Consequently, the computation method suggested for advertisers could have implications for intermediaries too. The traffic leading to the demand for goods and services is deeply dominated by powerful online media. The dynamics of online market can push up the costs of acquiring and retaining demand, hindering a firm's ability to achieve acceptable profit levels. However, the competition between intermediaries can be leveraged to the firm's advantage by proactively managing channel costs and by choosing the best option. By making more optimal decisions, advertisers could induce different intermediaries to change the price clauses for their marketing services.

## Limitations and future research

This study has several limitations, each of which suggesting avenues for future research. First, it focuses exclusively on identifying which online channel is economically the most advantageous, by setting Google AdWords against Amazon marketplace, therefore ignoring the positive effect, over time, of a variety of tools based on multiple online channels. Essentially, the analysis supposes a trade-off between Google campaigns and Amazon programs, and it proposes a model that is based on some specific parameters to increase profits in the short term. However, customer trust, satisfaction, retention, and loyalty are further crucial factors that, in addition to short-term improvements in financial performance, should be considered for driving budget allocation decisions between different online channels (Zhang et al., 2018). Accordingly, future models should include additional variables to help advertisers design their multiple online channel strategy in the long term.

Second, this study assumes that a firm should assess the investment in Google AdWords versus Amazon, which use different charging systems (pay-per-click vs pay-per-sale, respectively). However, it is possible that a firm may use simultaneously multiple search engines (e.g., Google and other domestic engines) or multiple e-marketplaces (e.g., Amazon and local e-marketplaces). Therefore, further studies should analyze in-depth how firms may be confronted with a choice among different channels with the same charging system, as recently done by Zia and Rao (2019).

Third, the computation model suggested here is applicable when the advertiser is a retailer selling products. When the advertiser sells services, the computation model should be slightly adjusted, according to the specific charging scheme of other players. For instance, if the advertiser is a tourism organization, the models of Google and Booking.com could be compared. In this case, the formula should be arranged to consider that, unlike Amazon, Booking.com charges firms only a percentage on the prices of services sold, without a fixed fee.

Moreover, data collection and analysis for this study are limited to two companies operating in different market segments, where Amazon applies different commission percentages, namely 15 percent for sport shoes and 7 percent for smartphones. Having assessed only one firm for each market segment, any generalization is not possible. Research based on a representative sample of firms in the two industries is necessary to derive general conclusions. Further research should build on our model by analyzing historical data sets from firms belonging to the same industry or selling the same product category to detect the effectiveness of their web marketing strategies as a whole, because search campaigns tend to be very different across industries and product categories in terms of their impact on customers' purchases and firms' profits (Li et al., 2016). This analysis could reveal that, from the advertisers' perspective, Google AdWords may suit better some products, whereas Amazon performs better with other products, depending on the item category and underlying high (or low) percentage of the Amazon-related commission fee. Such findings could induce Amazon to reduce its commission percentages for product categories for which the Google AdWords platform is more attractive to sellers.

## Conclusions

The web provides organizations with numerous chances to increase their monetary utility and consumer loyalty (Niavand & Mahesh, 2018). Multi-channel marketing is increasingly becoming an essential strategy for successful companies (Duffy, 2004). Despite the usefulness and growth of search advertising, there is still little understanding of how advertisers can profit from alternative advertisement options. Several academic studies offer interesting firm-level insights, but they fail to mention how the seller should choose between different types of online channels under budget constraints.

Unlike previous studies, the issue at the heart of the present study is how firms with limited budgets should select different online channels, such as Google AdWords vs Amazon. Information on the return from paid search ads, such as Google AdWords, is insufficient for marketing decisions, which should be made after taking into consideration the sales that could be generated by other channels, among which the most important is Amazon as regards the market of products. Both Google and Amazon "answer the same intrinsic need of consumers: the search for a website selling a particular good" (Broos & Ramos, 2017, p. 396). Therefore, from the consumers' perspectives, it seems difficult to see Google and Amazon as belonging to different markets. Despite their different business models, Google and Amazon operate in the same relevant market, so a formula is introduced and recommended to understand which solution performs better for the sellers.

By developing a model that helps managers evaluate different performances, the study suggests the maximum cost per click that every firm should calculate and consider in order to make decisions about future resource allocation to online marketing channels. Basically, the research implements a computation model helpful in making decisions under limited resource constraints, by investigating the mathematical relationship between different metrics, namely the cost per click, the conversion rate, the revenue per order and the number of clicks on Google, and the commission percentage and the fixed fee on Amazon. By comparing and selecting the best combination of parameters, each firm is empowered to assess and improve its marketing strategy. In this way, this article models a parsimonious approach to support advertisers' decisions in the realm of online marketing, by shedding light on the complex advertising landscape. The computational requirement of the method developed here is small enough to make its use very practical and helpful.

The computational model should help advertisers to see different online channels as competitive in order to keep their costs under control. Moreover, the sellers' awareness of competitive channels in online marketing and distribution should urge online intermediaries (Google and Amazon) to reduce their price conditions (cost-per-click and fees). Indeed, a careful selection of marketing strategies used by firms may lead to a cost reduction in the prices of online mediation. Such potential benefits provide additional incentives to further explore the challenging questions of online marketing strategy from the advertiser's perspective.

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