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ACHIEVING MORE BY PAYING LESS? HOW RETAILERS CAN BENEFIT BY BIDDING LESS AGGRESSIVELY IN PAID SEARCH AUCTIONS

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Research in Progress

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Abstract

Current research on paid search highlights its ability to enhance online as well as offline conversions. Yet, research investigating the impact of placing paid search ads on less prominent positions on subsequent consumer behavior is limited to the online environment. This paper presents a controlled field experiment which investigates whether the targeting of a less prominent ad position can be beneficial for bricks-and-mortar retailers who sell their products via local stores. Preliminary Results indicate that paid search advertising budgets could be allocated more efficiently by targeting less prominent ad positions, thus allowing a bricks-and-mortar retailer with a limited marketing budget to increase the reach of their marketing campaign, attract more consumers to its website and achieve an overall increase in conversions. These findings illustrate that search theory continues to apply in the realm of paid search and that different consumer types are likely to click on differently positioned ads. Advertisers could leverage this behavior to reach preferred types of customers by targeting specific ad positions. Bricks-and-mortar retailers could consider targeting less prominent ad positions when seeking to reduce advertising costs while simultaneously extending their reach to customers and achieve an increase in conversions.

Keywords: paid search, ad positioning effects, field experiment, bricks-and-mortar

1 Introduction

In this paper we analyze the effectiveness of paid search marketing campaigns for bricks-and-mortar retailers by comparing a more expensive ad position to a less expensive one. Paid search – the mechanism of placing online ads in response to consumer search queries on search engine result pages (SERP) – currently represents the main source of Internet advertising revenue and is expected to grow by a further 10% annually over the next four years (eMarketer, 2015). All major search engines sell their ads via an auction mechanism in which advertisers interested in a particular search keyword place bids based on their maximum willingness to pay for each consumer click.

While there is consensus among researchers that advertising costs drop significantly for less prominent positions (Ghose and Yang, 2009; Agarwal *et al.*, 2011) there is an ongoing discussion about whether advertisers can benefit by targeting less prominent ad positions. Ghose and Yang (2009) argue that advertisers should target top positioned slots because consumers perceive those to be more qualitative and trustworthy. They empirically show that consumers acquired via top positioned ads are more likely to perform a desired action (conversion) such as buying a product. These findings are supported by Rutz et al. (2012) and Jansen et al. (2013) who also report a negative relationship between less prominent ad positions and conversions. Yet, these results conflict with findings from other research studies which conclude that targeting less prominent ad positions could be favorable as conversions for less prominent positioned ads might be unaffected (Narayanan and Kalyanam, 2015) or even increase (Agarwal *et al.*, 2011). Agarwal et al. (2011) argue that especially non-serious buyers who are less interested in the firms' offerings tend to click on top positioned ads. More serious buyers can be acquired by targeting lower positioned ads. Those conflicting results pose a problem for advertisers as they need to approximate ad positions impact on costs as well as operational benefits (i.e. conversions) to target appropriate ad positions. Such conflicting results are even more troubling for advertisers who rely on paid search to induce local store purchases as they need to know ad positioning's impact on online as well as offline benefits. Yet, current research on ad positioning effects is limited to the online environment. We therefore seek to augment current research by investigating ad position effects in the online as well as the offline environment. In particular, we pose the following research question:

Does the targeting of a less prominent ad position pay off for bricks-and-mortar retailers?

To answer this research question, we teamed up with a well-known bricks-and-mortar business-to-consumer (B2C) furniture retailer operating in Germany. To quantify the impact of a less prominently positioned ad on the subsequent consumer behavior we conducted a field experiment. Developing an experimental research setup based on random assignment to conditions and combined with a pre-test/test design, allows to address common endogeneity concerns of marketing campaigns (Blake *et al.*, 2015) and particularly those associated with ad positioning effects (Narayanan and Kalyanam, 2015).

The experiment commenced in October 2016 and was executed over 42 days in which more than 450,000 consumers were exposed to paid ads and more than 11,000 reached the website via those ads. On the website, we offered every paid search consumer a €20 coupon (online conversion) which, when downloaded, could be redeemed in any one of the retailer's local stores (offline conversion). Our preliminary results reveal that targeting a less prominent ad position might benefit bricks-and-mortar retailers in several ways. First, results indicate that consumers who reach the website via a less prominent ad position might be more interested as they tend to visit more webpages compared to consumers who were acquired via more prominent ad positions. Second, when targeting a less prominent ad position, costs-per-click decrease significantly whereas online as well as offline conversions remain quantitatively unchanged. Hence, for a limited advertising budget, more consumers convert when a less prominent ad position is chosen. Third, our findings illustrate that search theory continues to be applicable in the realm of paid search and different consumer types are likely to click on differently positioned ads. Put differently, a more sophisticated approach to paid search would enable advertisers to bid for specific ad positions if they wanted to reach specific customer types. In our case, at least, targeting the less prominent (and cheaper) ad position 4 instead of 3 enhances the reach of the marketing campaign by exposing more potential buyers to the firm's offerings (ad impressions), getting more interested consumers to visit the firms' webpages (more webpages viewed) and, not least, increasing online conversions. In sum, our results indicate that paid search advertising budgets might be allocated more efficiently when targeting a less prominent ad position.

2 Ad Positioning in the Context of Paid Search

Currently all major search engines such as Google, Bing or Yahoo place up to four ads in the most prominent slots directly below the search query (see Figure 1). In scholarly research the top positioned ad on the first SERP is referenced as *ad position* 1 and the assigned number increases with position on the SERP. Advertisers have to define keywords for which they want to be listed on the SERP. Whenever a consumer enters a search term (e.g. "buy furniture") into a search engine, this will be linked to contextually matching keywords and displays ads of marketers who bought those *keywords*. Accordingly, the number of ads shown on a SERP depends on how many advertisers have placed their bid for a keyword (e.g. Figure 1, Keyword: "buy furniture" was bought by four different advertisers). Paid ads on ad position 1-4 are placed *above the fold* (area which is directly viewable by the consumer without the need to scroll down) followed by organic entries which are determined by the search engines ranking mechanism and cannot be bought by the advertiser.

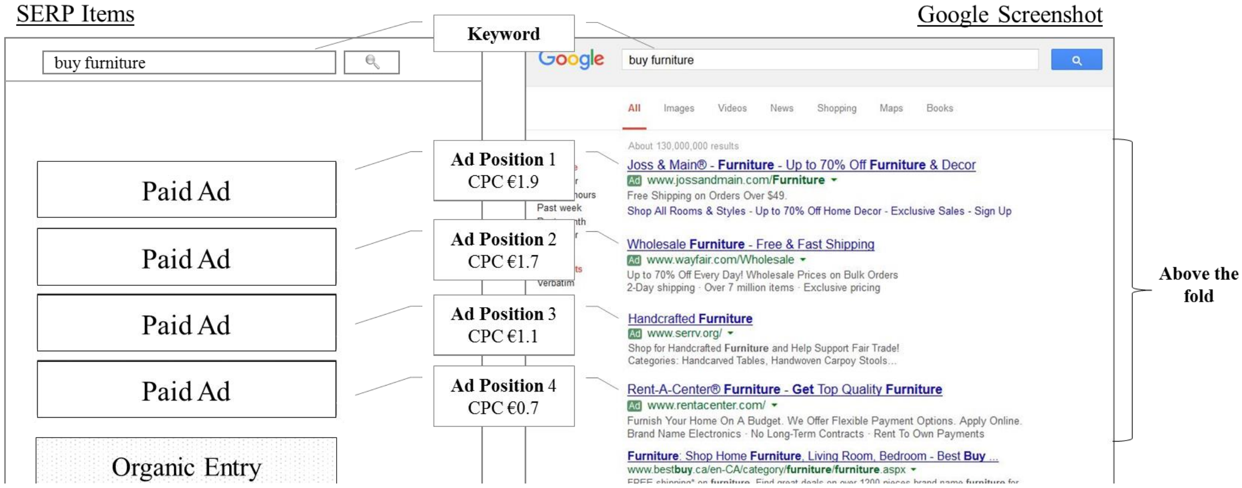

Figure 1. Paid ads on a SERP

Various eye-tracking studies (Phillips *et al.*, 2013; Mediative, 2014) have established that consumers tend to browse through SERPs in a sequential order and scan paid ads from the top down to lower positioned ads. This *sequential scanning* process leads to a decrease in attention for lower positioned ads for mainly two reasons. First, some consumers will be attracted by better positioned ads and click on those and therefore never reach less prominently positioned ads. Second, consumers' *search intensity* is likely to differ based on the ad position (Animesh *et al.*, 2010) due to individually perceived search costs and the potential benefits of the search (Stigler, 1961; Nelson, 1970). The individual consumer characteristics such as education and income (Ratchford, 1982; Ratchford and Srinivasan, 1993) shape the interrelation between perceived search costs and benefits. Consumers who experience low opportunity costs of time are likely to show an increased search intensity as opposed to consumers who experience high opportunity costs of time (Schmidt and Spreng, 1996). Conceptually speaking, consumers tend to investigate paid ads in a sequential order and those who show an increased search intensity might be especially likely to investigate less prominently placed ads further down. Accordingly, as can be seen in Figure 2, with an increasing ad position paid ads become less prominent as they are likely to receive far less attention due to the interplay of sequential scanning and search intensity.

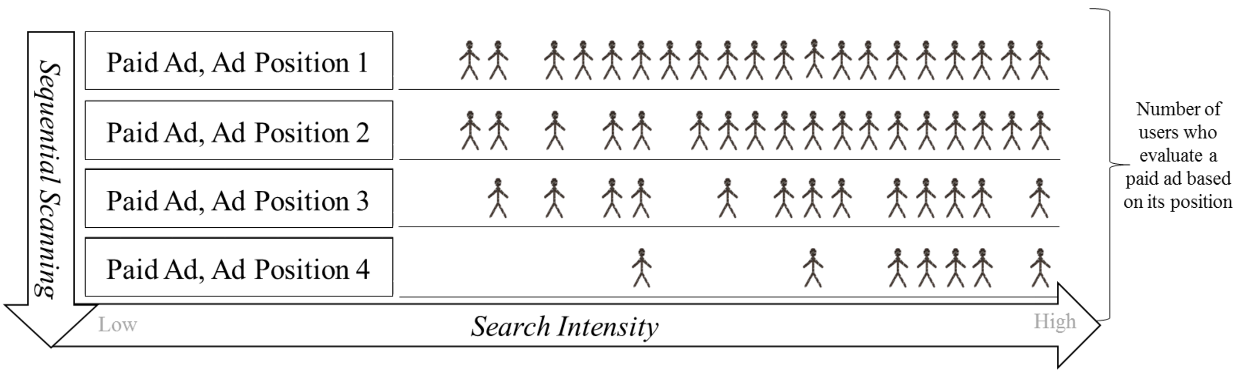

Figure 2. Visual Prominence of a Paid Ad

3 Conceptual Basis & Hypotheses

As an emerging technology, paid search has spawned numerous avenues for research, especially in the fields of Information Systems and Marketing (Rutz and Bucklin, 2013). The current literature comprises analytical studies which focus on the paid search market as a whole, and empirical studies which address the benefits of paid search for advertisers (Desai *et al.*, 2014). In the empirical stream of literature, which is the one we are concerned with here, it is a well-established fact that at least advertising *costs* decrease substantially with an increasing ad position (see Table 1, Costs). However, the interrelation between ad position and advertising benefits commonly measured as a desired action (*conversion*) a consumer engages in after clicking on an ad such as buying a product is subject to a lively debate as contradictory results persist (see Table 1, Conversions - Online). From an advertiser's perspective understanding the ad positioning impact on conversions is of crucial importance to allocate marketing budgets efficiently. With our research, we therefore seek to shed light on the question of whether ad positioning affects conversion rates, and if so, how. Furthermore, the current body of research is limited to the benefits of ad positioning in the online environment and does not account for potential spillover effects from the online to the offline environment (see Table 1, Conversions – Offline). However, broadening the scope might be beneficial as many retailers rely on paid search as an advertising channel to induce offline purchases (Abraham, 2008) and several studies indicate that paid search might to be highly effective in fostering offline conversions (Wiesel *et al.*, 2011; Dinner *et al.*, 2014). Accordingly, we broaden the general research scope by analyzing the conversion impact of ad positioning in the online as well as the offline environment.

<table>
<tr><th rowspan="3">Source</th><th colspan="3">Increase in Ad Position: Effect on</th><th colspan="2" rowspan="2">Purchase Channels</th><th rowspan="3">Branch</th></tr>
<tr><th rowspan="2">Costs</th><th colspan="2">Conversions</th></tr>
<tr><th>Online</th><th>Offline</th><th>Online</th><th>Offline</th></tr>
<tr><td>Ghose and Yang (2009)</td><td>-</td><td>-</td><td>n.a.</td><td rowspan="4">✓</td><td rowspan="4">n.a.</td><td>B2C, Retailer</td></tr>
<tr><td>Agarwal et al. (2011)</td><td>-</td><td>+</td><td>n.a.</td><td>B2C, Pet Products</td></tr>
<tr><td>Rutz et al. (2012)</td><td></td><td>-</td><td>n.a.</td><td>B2C, Lodging</td></tr>
<tr><td>Narayanan and Kalyanam (2015)</td><td></td><td>0</td><td>n.a.</td><td>B2C, Retailer</td></tr>
<tr><td>Jansen et al. (2013)</td><td>-</td><td>(-)</td><td></td><td>✓</td><td>✓</td><td>B2C, Retailer</td></tr>
<tr><td>Our Study</td><td>?</td><td>?</td><td>?</td><td>n.a.</td><td>✓</td><td>B2C, Furniture</td></tr>
<tr><td colspan="7">Effect Direction: - = negative, (-) = partially negative, 0 = none, + = positive</td></tr>
</table>

Table 1. Current State of the Literature

3.1 Ad Positioning Effects on Costs

In research on paid search, advertising costs are calculated as the product of clicks on a paid ad multiplied by the costs-per-click (CPC). In paid search, advertisers are only charged for clicks on their advertisements and ad positions are assigned via an auctioning mechanism. Today, all major search engines assign ad positions in accordance to the generalized second-price auctioning mechanism (Varian, 2007). In this auction mechanism, the advertiser in position *i* pays the bid of advertiser *i+1* as CPC; the advertiser in position *i+1* pays the bid of advertiser *i+2* as CPC, and so on. When a consumer enters a search query, paid ads will be shown of all advertisers who placed a bid in descending order of their bid amount (Edelman *et al.*, 2007) and advertisers have to pay the assigned CPC for each click on their ads. Accordingly, when an advertiser targets a less prominent ad position the corresponding CPC will decline (see example in Figure 1: with the transition from ad position 3 to ad position 4 CPC declines by €0.3).

As can be seen in Table 1 there is a consensus among researchers that advertising costs decline with an increasing ad position. However, the decline in advertising costs is not necessarily uniform as competition is highest for top positioned ad slots (Jansen *et al.*, 2013) and costs tend to rapidly decrease with an increasing ad position (Agarwal *et al.*, 2011). Furthermore, the decrease in advertising costs depends on the keyword type. Ghose and Yang (2009) report that more targeted keywords (e.g. "buy furniture of manufacturer X) generally incur higher CPC values. In accordance, with current research we would expect to see that advertising costs (measured on a CPC basis) will decline when the ad position increases. Hence, we formulate our first hypothesis:

H1. An increase in the position of a paid ad leads to a decrease in CPC.

3.2 Ad Positioning Effects on Conversions

In paid search research, advertising benefits are commonly measured on the basis of conversion-rates (CVR). CVR is defined as the number of consumers who carry out a desired action such as buying a product out of the total number of people who clicked the ad.

Current research is based on the assumption that different consumer types are likely to click on differently positioned ads (see Figure 2). However, it is unclear whether consumer heterogeneity affects conversion behavior. As can be seen in Table 1 scholarly results differ widely in regard to ad positioning's impact on conversions and range from a negative (Ghose and Yang, 2009) to a positive effect (Agarwal *et al.*, 2011). One set of empirical findings indicate that conversions depend on ad position and CVR decrease with an increasing ad position. In their empirical analysis Ghose and Yang (2009) show that from the lowest ad position (131) to the best (1), the conversion rate can increase by as much as 92.5%. These findings are consistent with Rutz et al. (2012) who state that elasticity of conversions with respect to ad position is actually higher than the elasticity of clicks in respect of its position. In their investigation for a better position 35% of the increased conversions are due to the increase in clicks and 65% are rooted in a higher CVR. Ghose and Yang (2009) argue that the ad position serves as a quality signal and consumers associate higher quality and trust with the best ranked ads. This quality signal would appear to translate into conversions. In support of this view, Jansen et al. (2013) report that ad positions' impact on CVR is limited to the top three positions.[1] Their empirical findings indicate that less prominent ad positions do not seem to affect CVRs. A second set of empirical findings indicate that conversions depend on ad position but CVR increase with an increasing ad position (Agarwal *et al.*, 2011). The scholars argue that especially non-serious buyers might prefer ads in top positions and do not make a purchase compared with serious buyers, who buy from the middle and lower ad positions. However, a recent study by Narayanan and Kalyanam (2015) questions the relationship between ad position and conversion behavior in general. The researchers argue that measuring causal effects of ad position is generally challenging due to endogeneity concerns. Endogeneity problems are rooted in the ad position allocation mechanism which is based on dynamic auctions where competing advertisers place bids. In their point of view, past research fails to sufficiently address endogeneity. They argue that Ghose and Yang (2009) who rely on observational data failed to use sufficient parametrization techniques and Agarwal et al. (2011) did not use an appropriate randomization mechanism in their field experiment. Agarwal et al.'s approach towards randomizing advertisers' bid values to estimate ad positioning's causal impact is viewed as insufficient as it does not account for the bidding behavior of competing firms which might systematically bias results. In their own study, Narayanan and Kalyanam use a quasi-experimental setting and address endogeneity problems by applying a regression discontinuity approach. Results indicate that ad positions – except when comparing positions five to six – do not significantly affect CVRs. They conclude that consumers might not distinguish between prominently positioned ads directly below the

[1] Results were obtained for SERPs where only up to three ads were shown above the organic results. More recently, 4 ads are shown above the organic results (see Figure 1).

search query[2]. Accordingly, ads placed directly below the search query on a SERP (see Figure 1) might not serve as a quality signal. Conceptually, the observed differences might be rooted in consumer heterogeneity as different consumer types are likely to click on differently positioned ads (see Figure 2). This consumer heterogeneity might result in differing conversion behavior (Rutz *et al.*, 2012). However, recent findings by Narayanan and Kalyanam (2015) indicate that at least for ads placed directly below the search query, consumer heterogeneity might not translate into differing conversion behavior (measured on a CVR basis). As we do not expect ad positioning effects to affect online conversions we won't expect to find any differences in terms of offline conversions either. Accordingly, we formulate our second set of hypotheses:

H2a. For a paid ad placed above the fold an increase in the position does not affect online CVR.

H2b. For a paid ad placed above the fold an increase in the position does not affect offline CVR.

4 Field Experiment

To estimate the impact of a less prominently positioned paid ad on consumer behavior in the online as well as the offline environment we teamed up with a well-known B2C bricks-and-mortar furniture retailer in Germany. Quantifying ad positioning's impact on consumer behavior is a challenging task as researchers need to sufficiently address endogeneity concerns regarding the ad position (Narayanan and Kalyanam, 2015). As suggested by Bandiera et al. (2011) we take advantage of experimental methods and design a well-controlled field experiment to address potential endogeneity biases. Our field experiment consists of a pre-test/test-design and is based on random assignment to conditions to enhance reliability (Shadish *et al.*, 2002).

4.1 Measurement

In October 2016, the field experiment was conducted over the course of 42 days. We chose a time span of six weeks to collect sufficient data to increase the validity of our findings and claims made. Our marketing initiative advertised a €20 coupon which customers could redeem in every local store of the chain. The coupon is advertised via paid ads on Google (see Figure 3, (1)). Consumers who click on the paid ad will be taken to the retailers' website on which they can inspect to find current offers as well as the coupon itself (see Figure 3, (2)). If consumers choose to download the coupon it is counted as an online conversion (see Figure 3, (3)). Local-store purchases paid via coupons trigger an offline conversion (see Figure 3, (4)).

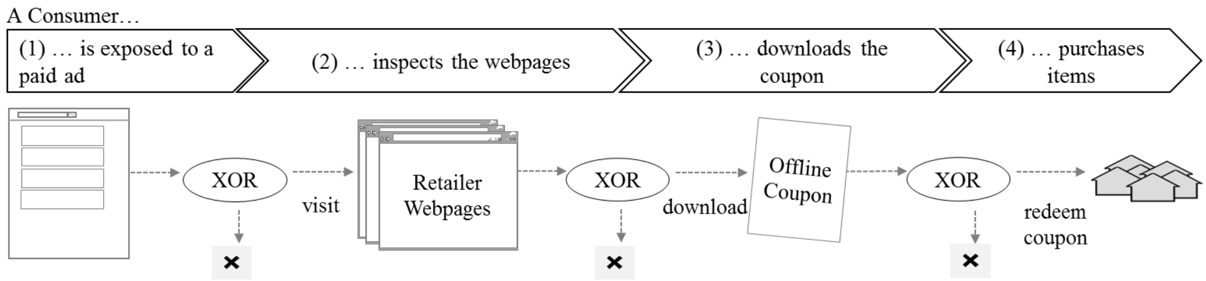

Figure 3. Marketing Initiative

Costs and benefits are measured as CPC and online/offline CVR. In addition, we use the average number of webpages visited (WV) as a proxy to determine a consumer's search intensity and the click-through-

[2] Results were obtained for SERPs where up to five ads were shown above the organic results. In their research environment consumers have to scroll down the SERP to view ad position six. More recently, only four ads are shown directly below the search query (see Figure 1) and four additional ads might be placed at the end of the SERP.

rate (CTR) to measure their likelihood to click on a paid ad. An explanation of the key metrics on which our analysis is built can be found in Table 2.

Variable	Description
CPC	Costs-per-click (CPC) measures the average cost for a click on a paid ad.
CTR	Click-through-rate (CTR) measures the percentage of consumers who click on an ad out of those who were exposed to it.
WV	Webpages visited (WV) measures the average number of webpages viewed by consumers who clicked on a paid ad.
Online CVR	Online conversion-rate (CVR) measures the percentage of consumers who download a coupon out of those who clicked on a paid ad.
Offline CVR	Offline conversion-rate (CVR) measures the percentage of consumers who redeem a coupon out of those who downloaded the coupon.

Table 2. Main Variables

4.2 Research Design

In a 14 day-long *pre-test phase*, we assigned 304 keywords to a Google bidding strategy which targeted ad position 3. In line with Rutz et al. (2012) we introduced generic keywords (e.g., "buying a sofa") as well as brand-specific ones (e.g., "buying a Rolf Benz sofa"). To prevent the common endogeneity problem of shifting marketing budgets due to endogenous events, the paid search advertising budget was fixed on a daily basis and held constant throughout the experiment. Within this phase more than 110,000 consumers were exposed to the crafted ad; 2,681 reached the website and 176 downloaded the coupon. After the pre-test we randomly assigned all keywords which received any clicks during the pre-test (176 Keywords) to either a control or a treatment group. Two-group mean comparison tests for assigned control and treatment keywords did not yield any significant differences for any of the main variables.[3] In a 28-day *test phase* the fixed daily advertising budget was split equally between control group keywords and treatment group keywords. All keywords belonging to the control group used the pre-test bidding strategy and targeted ad position 3. Keywords assigned to the treatment group used a less aggressive bidding strategy and targeted ad position 4. Throughout the test phase, more than 345,000 consumers were reached either via the bidding strategy which targeted ad position 3 (Control) or the less aggressive strategy which targeted ad position 4 (Treatment). Figure 4 depicts the overall research setup.

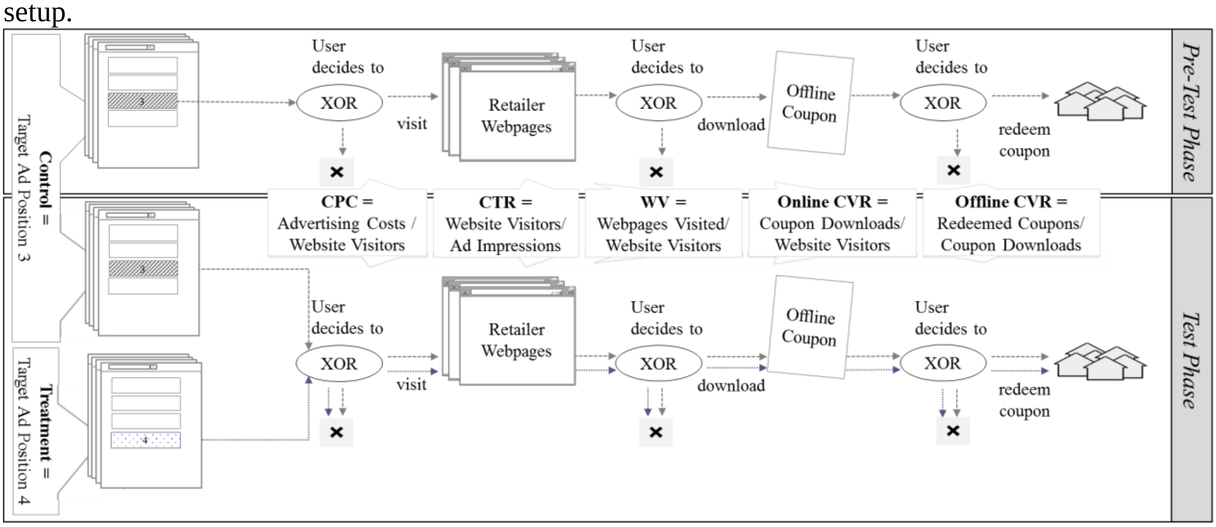

Figure 4. Research Design

3 Group differences tests and further information are provided as part of our online appendix: http://go.upb.de/AdPositioning

5 Preliminary Results

As can be seen in Table 3, during experiment execution 3,787 consumers visited the website via the control bidding strategy and downloaded 301 coupons (i.e. online conversions). In the treatment group 4,996 consumers visited the website and downloaded 312 coupons. The increase in websites visits is caused by a steep decline in CPC values which decreased from €1 to €0.7 when targeting ad position 4 instead of 3 (see Table 4, CPC). In turn, due to the equal allocation of advertising budgets, targeting ad position 4 increased the number of website visitors by over 30% and increased online conversions.

	Control	**Treatment**	**Sum**
Keywords (*)	*60*	*67*	*127*
Ad Impressions	128.457	220.930	349.387
Website Visits	3.787	4.996	8.783
Online Conversions	301	312	613
Offline Conversions	16	14	30

Note: (*) Keywords which received clicks during the test phase

Table 3. Test Phase: Summary statistics

Table 4 depicts two-group mean comparison tests used to estimate differences between the control and the treatment group on a keyword basis. During experiment execution, paid ads assigned to the less aggressive bidding strategy were on average placed in ad position 4 which is significantly higher than the control bidding strategy which on average reached ad position 3. As hypothesized (H1) CPC values declined significantly, i.e. by 30%, as well as CTR value which declined by 20% when using a less aggressive bidding strategy. However, analyzing the subsequent consumer behavior on the website, WV values increase significantly. Consumers acquired via the less aggressive bidding strategy seem to be more interested as they tend to inspect on average 0.7 more webpages. Yet, as expected (Hypotheses H2a and H2b), online as well as offline CVR differences remained insignificant when comparing control and treatment group.

Variable	**Control**	**Treatment**	**Pr(|T|>|t|)**
Ad Position	3	4	0,000
CPC	1,0	0,7	0,000
CTR	2,9%	2,3%	0,475
WV	3,0	3,7	0,000
Online CVR	7,9%	6,2%	0,164
Offline CVR	5.3%.	4.5%.	0.108

Table 4. Test Phase: Two-group mean-comparisons

6 Next Steps

Reported results are only of a preliminary nature and should be viewed as an outline. When data collection is completed we will deepen the analysis by investigating ad positioning's impact in respect of the different keyword characteristics, namely generic as well as brand-specific keywords. Increasing the depth of the analysis might also lead to more nuanced insights on ad positioning's impact on consumer behavior in the online as well as the offline environment.

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