Is it Always Best to be on Top?
The Effect of Ad Positioning on Key Performance Indicators in Search Engine Advertising

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Abstract

Search Engine Advertising is one of the fastest growing instruments in online marketing and a major source of costs for online advertisers. In this research, we empirically and experimentally investigate the impact of ad positioning on key performance indicators in search engine advertising namely click-through-rates, cost-per-click, conversion-rates, and cost-per-conversion. We answer our research question by using a unique and very rich dataset provided by an online marketing agency as well as by conducting a field experiment on a major web search engine. Our analysis of the provided dataset shows that click-through-rates and cost-per-click are negatively correlated with the ad position i.e., the topmost ad position has higher click-through-rates and cost-per-click than, for example, positions two and three. In contrast, we do not find a significant negative correlation, and in the majority of cases no correlation, between ad positions and conversion-rates. Thus, due to the high cost-per-click for the top ad positions and the non-existent negative correlation between ad positions and conversion-rates, lower ad positions are also correlated with lower costs-per-conversion compared to the top positions. In particular, we find a decrease in the costs-per-conversion of approximately 40% if ads are not listed at the top position but, for example, on the less prominent position four. Validating these results, our field experiment shows a significant and substantial negative relationship between ad-position and click-through-rates, cost-per-click, and costs-per-conversion and no significant relationship between ad position and conversion-rates.

Keywords: *Search Engine Advertising, Advertisement Position, Click-through-Rates, Conversion-Rates, Cost-per-Click, Cost-per-Conversion, Field Experiment.*

1. Introduction

US digital ad spending accounted for $36.8 billion in 2012 and is projected to grow to $61.4 billion in 2017. Sponsored search results ('ads' in the following) accounted for $17.3 billion or 47% of this market and are estimated to grow to $25.6 billion in 2017 (emarketer.com, 2013). On most search engines, ads are sold via an auction mechanism for specific search keywords. For each keyword, advertisers place bids based on their maximum willingness to pay for a click by a consumer on an ad for a specified keyword. After an auction, the search engine operator ranks the bidders by their willingness to pay, combined with their ads past click performance. Subsequently, the search engine operator makes a decision about the positioning of the ad on the search website based on this ranking. Typically, there are up to three slots for sponsored search results above and up to eight slots on the right hand side of the organic search results, with the top positions invariably the most costly. But do these top positions offer the best value for the advertiser?

While several studies find that click-through rates (number of clicks divided by the number of impressions of a specific keyword) decrease for less prominent ad positions (Brooks, 2004; Ghose and Yang, 2009; Agarwal et al., 2011, Animesh et al., 2011), there is an ongoing discussion as to which ad position leads to the highest conversion of clicks to actual purchases (Brooks, 2004; Chakravarti et al., 2006; Ghose and Yang, 2009; Agarwal et al., 2011). In particular, experimental results of Chakravarti et al. (2006) suggest that prescreening information is irrelevant in subsequent search behavior, which in turn suggests that conversion-rates (conversions divided by clicks on a specific keyword) should be independent of the ad position whereas Ghose and Yang (2009) and Brooks (2004) find a significant negative relationship between less prominent ad positions and conversion-rates. Contrasting with these results, Agarwal et al. (2011) find a positive relationship between less prominent ad positions and conversion-rates. Brooks (2004) reports the same relationship for unpopular keywords with low search volumes.

With this paper we want to add to this literature. In particular, we answer the following research question: *How does the ad position of a sponsored search result affect its click-through-rate, conversion-rate, and cost-per-conversion?* We answer our research question by analyzing a unique and very rich dataset provided by a big German online marketing agency for several customer projects on Google AdWords, as well as by conducting a field experiment where we display a group randomly selected keywords from one of these customers on less prominent ad positions and compare their performance to a control group which is displayed on more prominent positions. Our dataset contains detailed click and transaction data for the ads for 7,048 keywords from 5 different companies over a 5 month period. The field experiment was conducted for 198 keywords over an eight week period. The results of our analyses are as follows: In our empirical study, we find a significant negative correlation between an ad's position, its click-through-rate, and its cost-per-click and no significant negative correlation between an ad's position and its conversion-rate. As ad-positions are negatively correlated with costs-per-click and uncorrelated or even positively correlated with conversion-rates, costs-per-conversion are also negatively correlated with ad-position. In particular, we find a decrease in the costs-per-conversion of approximately 40% if ads are not listed at the top position but, for example, on the less prominent position four. Validating these results, our field experiment shows a significant and substantial negative relationship between ad-position and click-through-rates, cost-per-click, and costs-per-conversion and no significant relationship between ad position and conversion-rates.

Our paper contributes to the existing literature for several reasons: First, our study provides additional empirical and field experimental evidence for the negative effect of an ad's position on click-through-rates and costs-per-click. By introducing a new dataset consisting of more than 500,000 observations for German retailers from five different categories, our work contributes to the internationalization as well as to the generalization of the previous research on the effects of ad-positioning on key performance indicators in search-engine-advertising. Moreover, our field experiment addresses potential endogeneity concerns regarding the relationship between keywords' ad positions, click-through-rates, costs-per-click, and conversion-rates. Second, there is no consensus about the effect of ad positioning on conversion-rates. With our research, we provide empirical and (field-) experimental evidence that conversion-rates are not negatively and most often even unrelated with ad-positions. Third, recent studies have been able to show that advertisers can substantially increase their profits by not bidding for the top positions for their keywords (Skiera and Abou Nabout, 2013). By empirically and experimentally showing that costs-per-conversion decrease with less prominent ad-positions, our paper provides additional evidence for the potential higher profitability of these ad-positions.

2. Literature

In recent years, a broad literature on search engine advertising has emerged analyzing the design of keyword auctions (e.g., Varian, 2007), optimal bidding behavior in keyword auctions (e.g., Yao and Mela, 2011), spillover effects from generic to branded search (e.g., Rutz and Bucklin, 2011), differences in prices per click among different countries (e.g., Abou Nabout et al. 2014) and the substitution between online and offline advertising (e.g., Goldfarb and Tucker, 2011). Most closely related to our paper is the empirical literature on the effect of ad positioning on consumer behavior (Brooks, 2004; Ghose and Yang, 2009; Agarwal et al., 2011; Animesh et al., 2011).

Brooks (2004) investigates the effect of a change in the keyword position on the conversion-rate. In particular, he analyzes 408.000 keywords that move among ranks. Based on the analysis of average values and without controlling for keyword attributes or other sources of heterogeneity, he finds that conversion-rates fall with increasing ad position for the majority of keywords. For ads that usually generate only a small number of clicks, he finds a small increase in conversion-rates if ads are displayed on less prominent positions.

Ghose and Yang (2009) analyze consumer search and purchase behavior using a hierarchical Bayesian modeling framework. They quantify the effects of various keyword characteristics, as well as ad position and landing page quality score on consumer search and purchase behavior. They find that click-through-rates are highest for the most prominent ad positions. With regard to an ad's conversion-rate they find that this rate decreases with less prominent positions of an ad. In addition, they show that the top positions are not necessarily the most profitable ones. Profits on the most prominent positions as well as on the least prominent ones are often lower than those for the middle positions.

Agarwal et al. (2011) evaluate the impact of ad position on revenues and profits in search engine advertising. In line with Ghose and Yang (2009) they use a hierarchical Bayesian model to investigate the effect of ad placement on several performance indicators and find that click-through-rates decrease for less prominent ad positions. In contrast to Ghose and Yang, they show an increase in conversion-rates if ads move from top to bottom. Still, they can confirm the results of Ghose and Yang (2009) with regard to the impact of ad positions on profitability. The topmost position in their study generates comparably less profit than lower and, therefore, less expensive positions.

Finally, Animesh et al. (2011) study the joint impact of a seller's positioning strategy, its rank in sponsored search listings, and by the nature of competition around the firm's listing. Amongst other results, they confirm the prior finding that click-through-rates decrease for less prominent ad positions.

3. Research Setup

We use two distinct approaches to investigate the effect of ad positioning on click-through-rates, cost-per-click, conversion-rates, and costs-per-conversion. First, we analyze a unique and very rich dataset consisting of observational data to investigate the relationship between an ad's position and click-through-rates, costs-per-click, and conversion-rates. Second, we conduct a field experiment to further ensure that the reported correlations are not caused by unobserved variables, simultaneity, or selection-issues but may indicate a causal relationship. We describe the empirical study and the field experiment in sections 3.1. and 3.2. respectively.

3.1. Empirical Study

3.1.1. Data

Our dataset is provided by a large German Online Marketing Agency. It contains data for customer projects of five different retailers on Google AdWords for the German market and spans a period of five months (April 1, 2012 to August 31, 2012, 153 days), providing keyword-specific information for 12,211 distinct keywords. The retailers in our sample come from five different categories namely travel, clothing, garden-sheds, sports, and electrical equipment. We have data for 2,338 keywords for the first retailer, 6,483 keywords for the second, 575 for the third, 2,298 for the fourth, and 517 keywords for the fifth retailer. For each keyword, we have daily information about the number of impressions of an ad for this keyword, the number of clicks on the ad, the number of conversions generated by these clicks, the average ad position, the paid cost-per-click, and ad revenues. In line with Agarwal et al. (2011), we limit our data to the first seven ad positions. This ensures that all of our ads are displayed on the first search page. Because not all companies in our dataset advertised during the whole observation period, the final dataset has an unbalanced panel structure and consists of 544,282 observations for 12,152 unique keywords over a period of 5 months.

3.1.2. Main Variables

An ad generates an impression if somebody uses Google to search for a keyword associated with an ad and the ad is displayed on the search results page for this user. The variable *Impressions* captures the number of impressions of an ad for a specific keyword on a given day. The variable *Clicks* captures the number of clicks on an ad for a specific keyword on a given day. Dividing the number of clicks by the number of impression gives the *Click-Through-Rate* which measures the rate by which an ad for a keyword converts impressions into clicks. *Conversions* are defined as daily purchases which are directly generated through a consumer’s click on an ad for a keyword. Dividing the number of daily conversions by the number of daily clicks gives the *Conversion-Rate* of a keyword. This variable measures the rate by which clicks are converted into actual purchases. The *Cost-per-Click* variable is defined as the average payment per click on an ad for a given keyword on a given day. These cost-per-click depend on an advertisers maximal bid for a click on an ad for a specific keyword and, as the ad-positions are auctioned in a form of a second price auction, on the bids of other advertisers for this keyword.[1] Figure 1 illustrates the relationship between these variables.

[1] The so-called quality score of the landing page to which an ad is linked also affects the positioning and the cost-per-click for an ad for a specific keyword. Higher quality scores lead to better positions for lower costs-per-click. Unfortunately, we do not have

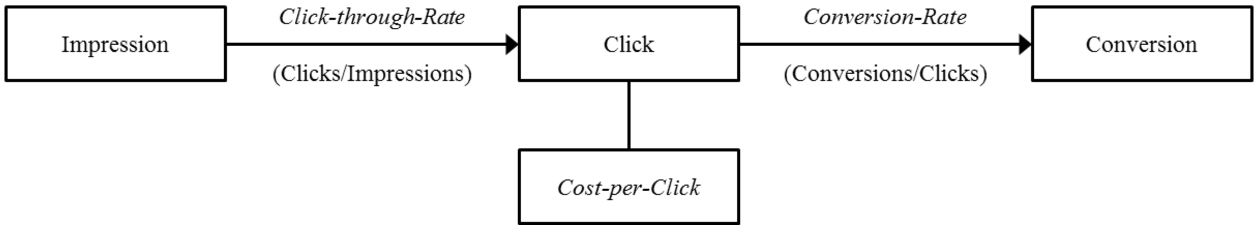

Figure 1: Relationship between Impressions, Click-through-Rates, Clicks, Costs-per-Click, Conversion-Rates, and Conversions

As we want to investigate the effect of ad positioning on click-through-rates, cost-per-click, conversion-rates, and costs-per-conversion, our main variable of interest is the position of an ad for a specific keyword. We measure this position with the variable *Position.* In line with prior works (e.g., Agarwal et al. 2011) and because of the unavailability of intraday changes of ad positions, we define this variable as the average ad position for a given keyword on a given day.

Prior studies (e.g., Ghose and Yang 2009, Agarwal et al. 2011) have identified several keyword characteristics as important variables when analyzing the effects of ad-positioning on different performance measures in search-engine-advertising. First, keywords can be classified into generic keywords, brand specific keywords, and retailer specific keywords. A generic keyword relates to a specific product but does not contain brand or retailer information. One example for such a keyword is *Red Shoe* which relates to a red shoe but does not contain information about the shoe brand or a specific retailer where one could buy such a shoe. The keyword *Red Shoe Adidas* would be an example for a branded keyword. This keyword would relate to a red Adidas shoe but does not contain information about a specific retailer where one could buy this shoe. Finally, *Red Shoe Zappos* would be an example for a retailer specific keyword. This keyword does not contain information about the brand of the shoe but relates to a specific shoe retailer. To consider the effects of this keyword specific information, we assigned each keyword to one of these categories and use the dummy variables *Generic*, *Brand*, and *Retailer* to capture these characteristics. In line with Ghose and Yang (2009), we also consider the number of distinct words that form a specific keyword. For example *Shoe* would be a keyword consisting of one word, *Red Shoe* a keyword consisting of two words, and *Red Sport Shoe* a keyword consisting of three words.

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detailed information on the quality scores for all keywords in our dataset. However, as these quality scores typically change only seldom, the effects of these quality scores should be captured in the keyword specific fixed effects in our econometric models. Confirming this assumption, we observe a constant quality score for 7,956 out of 8,219 keywords where we have information about the quality score during the whole observation period. All of our results are not affected by excluding the keywords with varying quality score from our dataset.

Table 1 shows summary statistics for our key-variables. The ads for the keywords in our dataset generated on average 87.39 impressions each day. These impression lead to an average of 1.034 clicks and 0.019 conversions per keyword per day. The average click-through-rate in our sample is 0.050 and the average conversion-rate 0.017[2]. The average ad position is 3.13 inducing cost-per-click of 0.452€.[3] 65.5% of the observations in our sample are for generic keywords, 30.1% for branded keywords and 4.4% for retailer specific keywords. On average, each keyword consists of 2.3 distinct words.

Variable	N	Mean	Std. dev.	Min	Max
Impressions	544,282	87.39	1,502.15	1	632,242
Clicks	544,282	1.03	7.59	0	727
Click-Through-Rate	544,282	0.050	0.160	0	1
Conversions	544,282	0.019	0.215	0	25
Conversion-Rate	128,848	0.017	0.106	0	1
Position	544,282	3.13	1.564	1	7
Cost-per-Click (in Euro)	128,848	0.452	0.352	0.01	8.02
Generic	544,282	0.655	0.475	0	1
Brand	544,282	0.301	0.459	0	1
Retailer	544,282	0.044	0.206	0	1
Word Count	544,282	2.324	0.721	1	7

Table 1. Summary statistics for the daily aggregated data

3.1.3. Basic Models

The panel structure of our dataset allows us to control for time constant heterogeneity on a keyword level (Hsiao 2003). For example, there may be some keywords which tend to generate higher conversion or click-through-rates independently of the actual ad position, while ads for other keywords might on average generate lower conversion or click-through-rates. If advertisers target to place ads with a higher inherent conversion-rate on more prominent positions, we would wrongly conclude that more prominent ad positions lead to higher conversion-rates. By estimating fixed effects models we can address this

[2] Note that we can only compute the conversion rate if a keyword generated at least one click on a given day.
[3] Note that we only have information on the cost per click if a keyword generated at least one click on a given day.

important source of endogeneity.[4] Fixed effects models use only within-keyword variation such that our coefficients are estimated only from changes of the ad-positions within specific keywords and not from difference of the ad-positions between different keywords. Thus, we can rule out any keyword specific, time-constant heterogeneity (e.g., keywords with a particular good fit to an ad may generate more clicks and more conversions), as explanation for our results.

In the following, we estimate several models for investigating the effects of ad positioning on the click-through rate, the cost-per-clicks, as well as on the conversion-rate. Our basic econometric models are:

$$Y_{i,t} = \beta_1 Position_{i,t} + \beta_2 Position_{i,t}^2 + \zeta_i \boldsymbol{D_i'} + \delta_t \boldsymbol{W_t'} + \varepsilon_{i,t}$$

where $Y_{i,t}$ denotes the *Click-Through-Rate, Cost-per-Click*, or the *Conversion-Rate* respectively, $\boldsymbol{D_i}$ is a vector of keyword specific fixed effects, and $\boldsymbol{W_t}$ is a vector of company day specific fixed effects. The error term ε_{it} captures all omitted influences, including any deviations from linearity. In all models, β_1 and β_2 are the main coefficients of interest. These coefficients measure the potential impact of a change in the positioning of an ad on our dependent variables. We include the square of *Position* into our models to allow for increasing or decreasing marginal-effects of *Position* on our dependent variables. To account for potential company specific time effects $\boldsymbol{W_t}$ contains 572 company day dummy variables (one for each company for each day where the company advertised except for the first company and the first day). These variables control for any potential weekday or holiday effects, company specific time effects such as advertising campaigns or media exposure, or general time trends. Our models will consistently estimate the effects of changes in the positioning of an ad on our dependent variables if $Cov\left(Position_{i,t}, \varepsilon_{i,t}\right) = 0$.

3.1.4. Results Click-through-Rate

Table 2 presents the estimates of our regression models with *Click-through-Rate* as dependent variable. Throughout, all standard errors are robust against arbitrary heteroscedasticity and are clustered on the keyword level. Column (1) shows estimated coefficients of -0.0263 (s.e.=0.00106) and 0.00183 (s.e.=0.000119) for the impacts of *Position* and *Position²* respectively on the *Click-through-Rate.* The coefficient on *Position* suggests that an increase of the average ad-position by one i.e., a change of the average ad-position from one to two reduces the *Click-through-Rate* by 2.63 percentage points. The coefficient on *Position²* indicates that an increase of the squared ad-position by one increases the *Click-*

[4] The significant Sargan-Hansen statistics (*Click-through-Rate:* $X^2 =$ 2010.858, p-value = 0.0000, *Cost-per-Click:* $X^2 =$ 2717.784, p-value = 0.0000, *Conversion-Rates:* $X^2 =$ 963.793, p-value = 0.0000) from the artificial regression approach described by Arellano (1993) and Wooldridge (2002) supports our choice of models.

through-Rate by 0.183 percentage points. Combining these two effects gives us the total effect of a change of an ad's position on the *Click-through-Rate*. This total effect is negative and decreases with increasing ad positions i.e., a change of an ad's position from one to two has a stronger negative effect (-2.08 percentage points) on the *Click-through-Rate* than a change of an ad's position from positions five to six (-0.62 percentage points). Such a primacy effect has also been reported for a recipient's likelihood to click on a link in an email (e.g., Ansari and Mela 2003) or for the likelihood that a shopper clicks on a link in a shopping search engine (e.g., Baye et al. 2009).

By considering the average value of the fixed effects (which we report in the row labeled *Intercept* for this and all following models) and the average of the coefficients on the significant company day dummies (-0.0195), we can also compute the average *Click-through-Rate* for all seven ad positions. These average click-through-rates are illustrated in Figure 1 and range from 8.60% on position one to 1.61% on position seven.

	Click-through-Rate		
	(1)	(2)	(3)
Position	-0.0263***	-0.0234***	-0.0152***
	(0.00106)	(0.00125)	(0.00362)
Position²	0.00183***	0.00155***	0.00125***
	(0.000119)	(0.000141)	(0.000401)
*Brand*Position*		-0.00330	-0.00348
		(0.00221)	(0.00222)
*Retailer*Position*		-0.0481***	-0.0507***
		(0.00861)	(0.00862)
Brand Position²*		0.000180	0.000233
		(0.000251)	(0.000253)
Retailer Position²*		0.00508***	0.00529***
		(0.000923)	(0.000923)
*Number Words * Position*			-0.00339**
			(0.00154)
*Number Words * Position²*			0.000111
			(0.000172)
Keyword Fixed Effects	✓	✓	✓
Company Day Fixed Effects	✓	✓	✓

Intercept[5]	0.130***	0.131***	0.133***
	(0.00972)	(0.00973)	(0.00958)
N	544,282	544,282	544,282
R^2	0.316	0.316	0.316
Number of Keywords	12,152	12,152	12,152
Cluster Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1			

Table 2. Fixed Effects Regression Results Click-Through-Rate

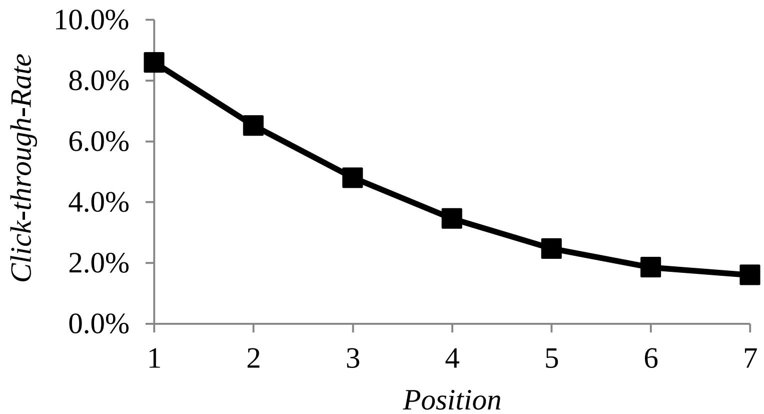

Figure 1: Average Estimated Click-Through-Rates for Ad-Positions One to Seven

To allow for different effects of the ad position on the *Click-through-Rate* for generic, branded, and retailer specific keywords, we include the interactions of the *Brand* and *Retailer* variables with *Position* and *Position²* in our model.[6] Column (2) of Table 2 shows the estimated coefficients for this extended model. As the model contains interactions of *Brand* and *Retailer* variables and *Position* and *Position²,* the coefficients on *Position* (-0.0234 s.e.=0.00125) and *Position²* (0.00155 s.e.=0.000141) indicate the effect of an ad's position on the *Click-through-Rate* only for generic keywords. This effect is slightly less negative than the combined effect for all keywords in column (1). Combining the direct effects and the interaction terms allows us to calculate the effect of an ad's position on the *Click-through-Rate* for branded and for retailer specific keywords. In particular, we need to add up the coefficients on (1) *Position* and *Brand * Position,* (2) *Position* and *Generic * Position,* (3) *Position²* and *Brand * Position²,* and (4) *Position²* and *Generic * Position²* to get these effects. The effect of an ad's position on the *Click-through-Rate* for branded keywords is not significantly different from the effect for generic keywords. However,

[5] Throughout the paper, we report the average value of the fixed effects as intercept.
[6] The direct effects of *Brand* and *Retailer* are already included in the keyword fixed effects as these variables do not change over time.

for retailer specific keywords, the negative effect is significantly more negative than for branded and for generic keywords. These results show that the negative effect of an ad's position on the *Click-through-Rate* in our main model is not caused by the keyword type, but does hold for generic, branded, and retailer specific keywords.

To further allow for different effects of the ad position on the *Click-through-Rate* depending on the length of a keyword, we include the interactions of the *Word Count* variable, *Position* and *Position²* into our model.[7] Column (3) of table 2 shows the estimated coefficients for this extended model. We still see a highly significant negative coefficient for *Position* (-0.0152 s.e.=0.00362) which is significantly smaller than the coefficient on this variable in columns (1) and (2). However, as we also included the interaction between *Number of Words* and *Position*, this effect can only be interpreted as the effect of *Position* on the *Click-through-Rate* conditional on *Number of Words* being equal to zero. If we compute the effect of *Position* on the *Click-through-Rate* for the average number of Words of a keyword (2.324 words), we get $-0.0152 + 2.324 * (-0.00339) = -0.023078$ which is a very similar magnitude compared to the coefficients in columns (1) and (2). The significant negative coefficient on the interaction between *Number of Words* and *Position* further indicates that the decrease of the *Click-through-Rate* with increasing position is more emphasized for longer keywords. To summarize, the results from presented in columns (2) and (3) show that the negative correlation between an ad's position and the *Click-through-Rate* in our main model is neither caused by keyword type nor by the length of a specific keyword but does hold for all types of keywords and all length of keywords in our sample.

3.1.5. Results Cost-per-Click

Column (1) of Table 3 shows the estimates for our main model with *Cost-per-Click* as dependent variable. We have estimated coefficients of -0.124 (s.e.=0.00784) for *Position* and of 0.00930 (s.e.=0.000884) for *Position²* where the first suggests a decrease of 12.4 Cent in *Cost-per-Click* for each one unit increase of *Position* and the latter a 0.93 Cent increase for each one unit increase of *Position²*. Combining these two coefficient results in a negative total effect of an ad's position on the *Cost-per-Click* an advertiser needs to pay. This negative effect decreases with increasing ad positions i.e., a change of an ad's position from one to two has a stronger negative effect (-9.61 Cent) on the *Cost-per-Click* than a change of an ad's position from positions five to six (-2.17 Cent). As for the *Click-through-Rate*, we can also compute the average *Cost-per-Click* for all seven ad positions by considering the average value of the fixed effects as well as

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[7] The direct effect of *Word Count* is already included in the keyword fixed effects as these variables do not change over time.

the average of the coefficients on the day dummies. These average *Cost-per-Click* are illustrated in Figure 2 and range from 61.85 Cent on position one to 32.09 Cent on position seven.

	Cost-per-Click		
	(1)	(2)	(3)
Position	-0.124***	-0.165***	-0.118***
	(0.00784)	(0.0110)	(0.0292)
Position²	0.00930***	0.0138***	0.00774**
	(0.000884)	(0.00121)	(0.00330)
*Brand*Position*		0.102***	0.104***
		(0.0137)	(0.0136)
*Retailer*Position*		0.159***	0.155***
		(0.0225)	(0.0230)
Brand Position²*		-0.0112***	-0.0115***
		(0.00162)	(0.00160)
Retailer Position²*		-0.0179***	-0.0175***
		(0.00261)	(0.00265)
*Number Words * Position*			-0.0216*
			(0.0117)
*Number Words * Position²*			0.00279**
			(0.00133)
Keyword Fixed Effects	✓	✓	✓
Company Day Fixed	✓	✓	✓
Intercept	0.839***	0.829***	0.829***
	(0.0288)	(0.0269)	(0.0270)
N	128,848	128,848	128,848
R^2	0.761	0.763	0.763
Number of Keywords	8,290	8,290	8,290
Cluster Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$			

Table 3. Fixed Effects Regression Results Cost-per-Click

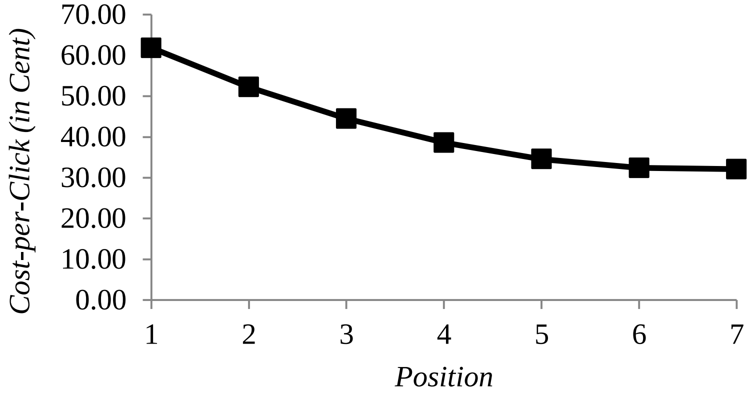

Figure 2: Average Estimated Cost-per-Click for Ad-Positions One to Seven

Columns (2) and (3) of Table 3 emulate columns (2) and (3) of Table 2. Again, we allow for varying effects of an ad's position on the *Cost-per-Click* depending on the keyword type and length. These further analyses show that the negative effect of an ad's position on the *Cost-per-Click* is strongest for generic keywords, second strongest for branded, and insignificant for retailer-specific keywords. Moreover, the estimates presented in column (3) show that the negative effect of an ad's position on the *Cost-per-Click* is more pronounced for longer keywords. As for the models with *Click-through-Rate* as dependent variable, the results from our main model hold for both extended models validating that the correlations reported for the main model are not driven by keyword type or length.

3.1.6. Results Conversion-Rate and Cost-per-Conversion

Table 4 shows the estimates for our main model (column (1)) and for the extended models (columns (2) and (3)) with *Conversion-Rate* as dependent variable. All coefficients in this table are insignificant on the 5% level. Thus, we conclude that there is no significant correlation between the position of an ad and the *Conversion-Rate*. Combining this result with the significant negative correlation between *Position* and *Cost-per-Click* suggests that the *Cost-per-Conversion* are significantly negatively correlated with ad position. While the number of clicks needed for one conversion does not change with increasing or decreasing ad positions, the costs for one click significantly decrease with increasing ad position. This relationship is illustrated in Figure 3. Estimated costs-per-conversion range from 45.13€ on position one, over 28.16€ on position four, to 23.41€ on position seven. Thus, if an advertiser decides not to bid for the top position but, for example, for the less prominent position four, the reported correlations suggest that costs-per-conversion decrease by approximately 40%

	Conversions Rate			
	(1)	(2)	(3)	(4)
Position	0.00269*	0.00224	0.00709	-0.000971
	(0.00141)	(0.00164)	(0.00469)	(0.00206)
Position²	-8.35e-05	-7.74e-06	-0.000659	0.000111
	(0.000180)	(0.000208)	(0.000591)	(0.000244)
*Brand*Position*		0.00207	0.00224	-0.000382
		(0.00331)	(0.00331)	(0.00135)
*Retailer*Position*		-0.00215	-0.00253	-0.00295
		(0.00751)	(0.00755)	(0.00301)
Brand Position²*		-0.000241	-0.000266	0.000109
		(0.000436)	(0.000437)	(0.000175)
Retailer Position²*		-0.000346	-0.000311	0.000237
		(0.000925)	(0.000927)	(0.000348)
*Number Words * Position*			-0.00224	0.000403
			(0.00212)	(0.000883)
*Number Words * Position²*			0.000303	-5.35e-05
			(0.000276)	(0.000106)
Keyword Fixed Effects	✓	✓	✓	✓
Company Day Fixed	✓	✓	✓	✓
Intercept	0.0289**	0.0288**	0.0288**	0.0113***
	(0.0115)	(0.0115)	(0.0115)	(0.00317)
N	128,848	128,848	128,848	127,693
R^2	0.086	0.086	0.086	0.067
Number of Keywords	8,290	8,290	8,290	8,271
Cluster Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1				

Table 4. Fixed Effects Regression Results Conversion-rate

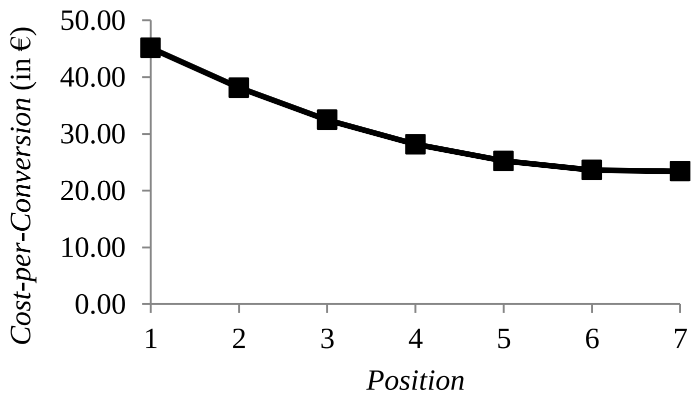

Figure 3: Average Estimated Cost-per-Conversion for Ad-Positions One to Seven

3.1.7. Retailer Specific Results

One might argue that the reported correlations are not general effects, but substantially differ in sign and magnitude depending on retailer specific characteristics. For example, there may be retailer types where conversion-rates increase with less prominent ad positions while conversion-rates decrease for other types of retailers. It is, therefore, an important step in the generalization of the research on search engine advertising to show that the reported correlations hold across different types of retailers. To allow for retailer specific relationships between ad positioning, *Click-through-Rate*, *Cost-per-Click*, and *Conversion-Rate*, we re-estimate our main models separately for each retailer in our dataset. Tables 5, 6, and 7 show the estimation results for the models with *Click-through-Rate*, *Cost-per-Click*, and *Cost-per-Conversion* as dependent variables and Figures 4, 5, and 6 illustrate the respective correlations. As for our main models, we find a negative correlation between *Position*, *Click-through-Rate*, and *Cost-per-Click* for each individual retailer. With regard to the *Conversion-Rate*, we find no significant correlation for retailers 1, 3, and 5 and a positive correlation for retailers 2 and 4 (significant on the 5% level). Further investigations show that this positive correlation is caused by observations with a *Conversion-Rate* of exactly one i.e., observation where each click on an ad generated a conversion. If we exclude these observations from our dataset (507 observations for retailer 1, 368 observations for retailer 2, 20 observations for retailer 3, 255 observations for retailer 4, and 5 observations for retailer 5) and re-estimate our models, all coefficients are insignificant on the 5% level and the magnitude of the coefficients substantially decreases (the estimation results for this analysis are displayed in Table 8 and ad illustrated in Figure 7 respectively). Thus, we conclude that the positive correlation between *Conversion-rate* and *Position* for retailers 2 and 4 is solely attributable to observations with conversion-rates of exactly one. If we do not consider these observations, *Position* and *Conversion-Rate* are uncorrelated.

	Click-Through-Rate				
	Retailer 1	Retailer 2	Retailer 3	Retailer 4	Retailer 5
Position	-0.0712***	-0.0103***	-0.0651***	-0.0196***	-0.0132**
	(0.00279)	(0.000997)	(0.00777)	(0.00173)	(0.00517)
Position²	0.00563***	0.000752***	0.00565***	0.00164***	0.000496
	(0.000293)	(0.000119)	(0.000926)	(0.000197)	(0.000637)
Keyword Fixed Effects	✓	✓	✓	✓	✓
Day Fixed Effects	✓	✓	✓	✓	✓
Intercept	0.287***	0.00407	0.217***	0.0766***	0.0718***
	(0.00924)	(0.00999)	(0.0159)	(0.00627)	(0.0117)
N	133,663	277,733	16,603	106,064	10,219
R^2	0.312	0.217	0.410	0.243	0.173
Number of Keywords					
Cluster Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1					

Table 5. Fixed Effects Regression Results Click-Through-Rate Company Level

	Cost-per-Click				
	Company 1	Company 2	Company 3	Company 4	Company 5
Position	-0.196***	-0.0629***	0.0177**	-0.0611***	-0.0294**
	(0.0136)	(0.00903)	(0.00892)	(0.00935)	(0.0140)
Position²	0.0155***	0.00424***	-0.00484***	0.00323***	0.000898
	(0.00154)	(0.00105)	(0.00135)	(0.00104)	(0.00168)
Keyword Fixed Effects	✓	✓	✓	✓	✓
Day Fixed Effects	✓	✓	✓	✓	✓
Intercept	1.157***	0.868***	0.268***	0.378***	0.348***
	(0.0291)	(0.00707)	(0.0178)	(0.0293)	(0.0287)
N	48,885	53,427	6,340	17,984	2,212
R^2	0.698	0.609	0.898	0.725	0.461
Number of Keywords					
Cluster Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1					

Table 6. Fixed Effects Regression Results Cost-per-Click Company Level

	Conversion-Rate				
	Company 1	Company 2	Company 3	Company 4	Company 5
Position	-0.000718	0.00538**	-0.00447*	0.00944**	0.00609
	(0.00218)	(0.00220)	(0.00268)	(0.00433)	(0.00478)
Position²	0.000359	-0.000421	0.000680	-0.000926	-0.000693
	(0.000287)	(0.000264)	(0.000414)	(0.000576)	(0.000503)
Keyword Fixed Effects	✓	✓	✓	✓	✓
Day Fixed Effects	✓	✓	✓	✓	✓
Intercept	0.0247***	-0.0429***	0.0148**	-0.00790	-0.00925
	(0.00690)	(0.00209)	(0.00733)	(0.0268)	(0.00899)
N	48,885	53,427	6,340	17,984	2,212
R^2	0.056	0.084	0.102	0.144	0.115
Number of Keywords					
Cluster Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1					

Table 7. Fixed Effects Regression Results Conversion-Rate Company Level

	Conversion-Rate (Except Observations with Conversion-Rate = 1)				
	Company 1	Company 2	Company 3	Company 4	Company 5
Position	-0.00180*	0.00147*	-0.00156	0.000855	0.00244
	(0.000966)	(0.000882)	(0.00144)	(0.00144)	(0.00204)
Position²	0.000170	-0.000132	0.000162	-7.94e-05	-0.000458
	(0.000115)	(0.000107)	(0.000187)	(0.000204)	(0.000332)
Keyword Fixed Effects	✓	✓	✓	✓	✓
Day Fixed Effects	✓	✓	✓	✓	✓
Intercept	0.0125***	-0.00655***	0.0124**	-0.00306	-0.00294
	(0.00286)	(0.000829)	(0.00609)	(0.00491)	(0.00262)
N	48,378	53,059	6,320	17,729	2,207
R^2	0.053	0.059	0.083	0.105	0.106
Number of Keywords					
Cluster Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1					

Table 8. Fixed Effects Regression Results Conversion-Rate Company Level[8]

[8] Except Observations with Conversion-Rate = 1

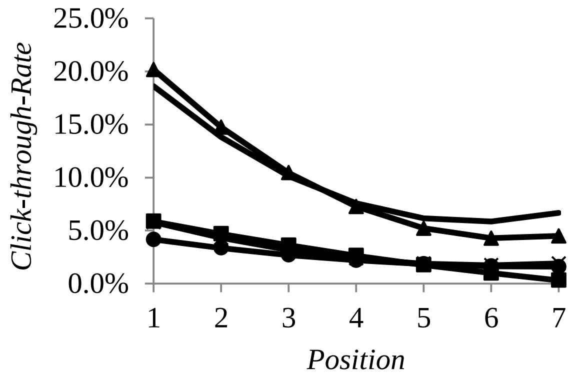

Figure 4: Average Estimated Click-through-Rate for Ad-Positions One to Seven

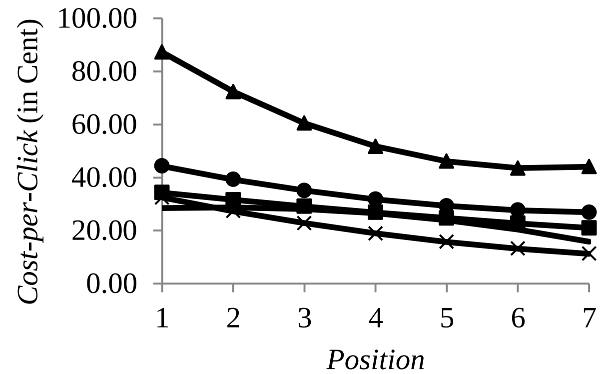

Figure 5: Average Estimated Cost-per-Click for Ad-Positions One to Seven

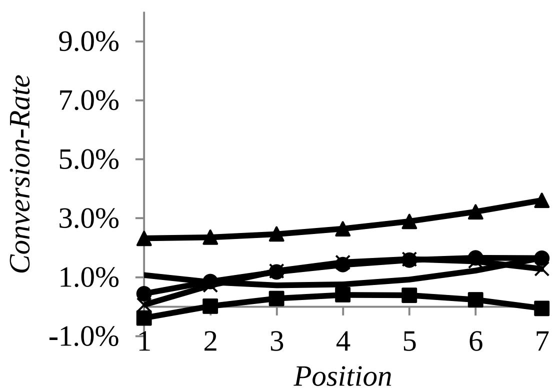

Figure 6: Average Estimated Conversion-Rate for Ad-Positions One to Seven

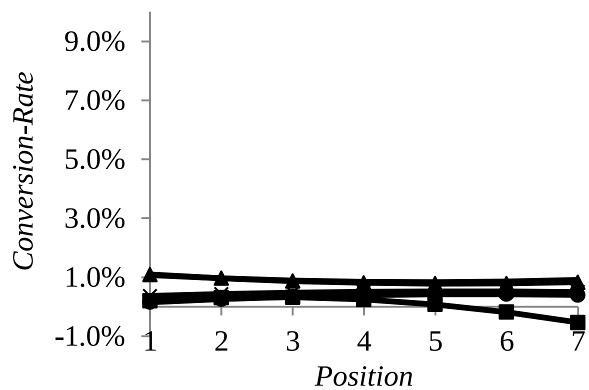

Figure 7: Average Estimated Conversion-Rate for Ad-Positions One to Seven[9]

3.1.8. Discussion of Empirical Results

To summarize, we show that the *Click-through-Rate* and the *Cost-per-Click* are negatively correlated with an ad's position. At the same time, we find that *Conversion-Rate* is uncorrelated (or even positively correlated for some retailers) with keywords' ad positions while there is a significant negative correlation between keywords' ad positions and *Cost-per-Conversion*. Moreover, we show that keyword-level

[9] Except Observations with Conversion-Rate = 1

covariates such as keyword-type (*Generic*, *Brand*, *Retailer*) or the length of a keyword – measured by the variable *Word Count* – or retailer specific effects are not responsible for the reported correlations.

Our first two results provide additional evidence for the results of Ghose and Yang (2009) and Agarwal et al. (2011) who also find that the *Click-through-Rate* and *Cost-per-Click* decrease with less prominent ad positions. In contrast, our finding that *Conversion-Rate* is not negatively, or even uncorrelated with keywords' ad position seems to contradict with the results of Ghose and Yang (2009) who find a decrease and Agarwal et al. (2011) who find an increase of the conversion-rate when ads are displayed on less prominent positions. However, as Agarwal et al. (2011) also mention, Ghose and Yang analyze a broad range of positions (1-131) where ads could be displayed. Very low conversion-rates on the least prominent positions may be an explanation for the negative effect they report. A combination of a low total number of conversions[10] in Agarwal et al. (2011) and a strong effect of observations with conversion-rates of exactly one may be a potential explanation for the difference between our result and the positive effect in their study. For our study, the estimated coefficient on *Position* in column (1) of Table 3 is also positive (0.0269 s.e.=0.00141) but not significant on the 5% level. Moreover, we also find a significant positive correlation between *Position* and *Conversion-rate* for retailers 2 and 4 in our dataset. However, if we exclude the observations with conversion-rates of exactly one (i.e., observations where the number of clicks received is equal to the number of conversions) from our dataset and re-estimate our main model as well as our company specific models on the remaining observation all coefficients substantially reduce in magnitude and become insignificant.[11] This additional finding indicates that observations with conversion-rates of exactly one also account for the largest part of the magnitude of the coefficient on *Position* in our main model as well as in our company specific models. If the dataset in Agarwal et al. (2011) contains only a few more observations with conversion-rates of one on lower ad positions, this small difference might explain why Agarwal et al. find that conversion-rates increase for less prominent ad positions, while most of our results suggest that conversion-rates and ad positions are uncorrelated.

3.2. Field Experiment

Between February 5th, 2013 and April 6th, 2013, we conducted a field experiment to address further potential concerns regarding the endogeneity of a keyword's ad position with regard to its *Click-through Rate*, *Cost-per-Click*, *Conversion-Rate*, and *Cost-per-Conversion*. In particular, one may argue that advertisers bid for the topmost ad positions for a specific keyword or that search engine operators display

[10] According to Table 1 in Agarwal et al. the authors base their estimates on around 65 conversions i.e., 3,187 observations with an average of 0.02 conversions.
[11] The full results of this regression models are displayed in column (4) of Table 4 and columns (1) to (5) in Table 8.

ads on favorable positions in times when they expect particularly high click-through and conversion-rates or particularly low costs-per-conversion. Our experiment involved 198 keywords belonging to one customer (retailer 4) of the online marketing agency. The keywords for our experiment were selected based on their performance in January 2013. We selected keywords with *Cost-per-Click* of above 30 Cents and with average ad positions between 1 and 2.9 in this period. These selection criteria left us with 198 keywords which we randomly assigned to a treatment group (99 keywords) and a control group (99 keywords). The average ad-position for the keywords in our treatment group is 1.716, the keywords generated average *Cost-per-Click* of 42.86 Cent, had an average *Click-through-Rate* of 5.9%, a *Conversion-Rate* of 2.2%, and *Costs-per-Conversion* of 6.928€. For the control group, we have an average ad-position of 1.727, average *Cost-per-Click* of 44.62 Cent, a *Click-through-Rate* of 5.6%, a *Conversion-Rate* of 3.3%, and *Cost-per-Conversion* of 7.048€. After the random assignment, we conducted two-group mean-comparison tests to ensure that the treatment and control group do not significantly differ in any key variable. Table 5 shows the results of the two-group mean comparison tests. These results confirm that there is no significant difference for any of our key-variables. Note that the group size for the first four variables (*Position*, *Cost-per-Click*, *Click-through-Rate*, *Conversion-Rate*) is 99 while it is 13 for the treatment group and 22 for the control group for the *Cost-per-Conversion* as this variable is only defined if the keyword generated at least one conversion in January 2013.

Variable	Treatment	Control	t	Pr(|T| > |t|)
Position	1.716 (0.062)	1.727 (.058)	-0.1299	0.90
Cost-per-Click	42.859 (1.08)	44.616 (1.39)	-0.9980	0.32
Click-through-Rate	0.059 (0.013)	0.056 (0.011)	0.1648	0.87
Conversion-Rate	0.022 (0.008)	0.033 (0.011)	-0.7856	0.43
Cost-per-Conversion	6.928 (2.066)	7.048 (1.212)	-0.0540	0.96

Table 9. Summary Statistics Treatment and Control Group before Treatment

During the course of the experiment, we kept the ad-position of the keywords in the control group unchanged, while we changed the positions of the keywords in the treatment group such that they were finally displayed on position four as this position promises lower costs-per-conversion compared to positions one to three. To achieve the targeted positioning for the treatment group, we implemented a bidding algorithm which checked the average ad-position for each keyword once a day. If the absolute difference between this position and position 4 is larger than 1, our algorithm adjusted the maximal bid for this keyword by 10%, if this difference is larger than 0.5 and smaller than 1 by 5%, and if it is smaller than 0.5 by 2%. After the experiment, we conducted a second set of mean-comparison tests for our key-variables in the treatment and control group. The results of these tests are displayed in Table 3. Note again that the group size for the first four variables (*Position*, *Cost-per-Click*, *Click-through-Rate*, *Conversion-Rate*) is 99 while it is 14 for the treatment group and 20 for the control group for the *Cost-per-Conversion* as this variable is only defined if the keyword generated at least one conversion during the course of the experiment.

Variable	Treatment	Control	t	Pr(|T| > |t|)
Position	2.960 (0.096)	1.650 (0.099)	-9.5176	0.00
Cost-per-Click	26.300 (1.47)	37.620 (2.09)	4.4265	0.00
Click-through-Rate	0.052 (0.006)	0.075 (0.007)	2.572	0.01
Conversion-Rate	0.027 (0.011)	0.023 (0.007)	-0.2825	0.78
Cost-per-Conversion	5.774 (1.51)	11.894 (2.97)	1.618	0.12

Table 10. Summary Statistics Treatment and Control Group after Treatment

As can be seen from Table 10, our treatment significantly increased the average ad position (2.960 in the treatment versus 1.650 in the control group) and decreased the *Cost-per-Click* for the keywords in our treatment group. This is an expected result as our treatment was to reduce the maximum bid for the *Cost-per-Click* if an ad is displayed above position four which is directly related to the *Cost-per-Click* as well as to the position on which an ad is displayed. In line with the results from prior literature (e.g., Agarwal et al. 2011, Ghose and Yang 2009) and from our empirical study, we observe a decrease in the *Click-through-Rate* for the treatment group i.e., the keywords which are displayed on less prominent positions need more impressions to generate one click. In contrast, the conversion-rate was not significantly affected by our treatment i.e., changing the positions of the keywords in our treatment group to less prominent ones has not significantly affected the *Conversion-Rate* of these keywords. Combining this result with the lower costs-per-click in the treatment group suggests that the *Cost-per-Conversion* in the treatment group should also be lower than in the control group. The last row of Table 3 confirms this expectation. While the *Cost-per-Conversion* in the treatment and in the control group were not significantly different before we implemented our treatment, there is a substantial difference (which is also significant on the 12% level) after the treatment. In particular, a keyword that generated a conversion induced costs of 5.77€ (s.e.= 1.51€) in the treatment group while a keyword that generated a conversion in the control group induced costs of 11.89€ (s.e.= 2.97€). Note that these costs are only those that were induced by keywords that generated at least one conversion either in the treatment or in the control group during the course of the experiment and, therefore, are substantially lower than the estimated *Cost-per-Conversion* displayed in Figure 3. We can also consider the full costs that accrued in the treatment and in the control group and distribute these full costs to the total number of conversions in each group. After the treatment, the treatment group generated 24 conversions for a total cost of 398.04€ while the control group generated 30 conversions for 738.42€. This gives us total costs-per-conversion of 16.59€ in the treatment and 24.61€ in the control group. Before the treatment, we had 27 conversions and a total cost of 389.18 in the control group and 30 conversions for a total cost of 471.93 which correspond to total costs-per-conversion of 15.73€ in the treatment and 14.41€ in the control group.

Conclusion and Managerial Implications

There is a growing body of research which analyses the effects of ad positioning on different key performance indicators in search engine advertising. Several prior studies from this literature find that click-through-rates and costs-per-click decrease for less prominent ad-positions. By introducing a new dataset consisting of more than 500,000 observations for German retailers from five different categories, our work contributes to the internationalization as well as to the generalization of the research on the effects of ad-positioning on these key-performance-indicators in search-engine-advertising.

Regarding the effect of ad positioning on the conversion-rate of a keyword, there is no consensus in the literature. Some studies find that lower ad positions lead to higher conversion-rates (e.g., Agarwal et al, 2011) while other authors find that lower ad positions lead to lower conversion-rates (e.g., Ghose and

Yang, 2009) or that conversion-rates should be independent of ad positions (e.g. Chakravarti et al. 2006). By investigating the relationship between ad-positions and conversion-rates with a new dataset and with a field experiment, we contribute to the debate on this issue. Consistently, our analyses show that conversion-rates and ad positions are not negatively correlated or even – in most cases – uncorrelated.

The findings of our paper might have important managerial implications. Currently, advertisers are engaged in intense bidding wars for the top position in sponsored search results (Agarwal et al., 2011). Our findings emphasize that this strategy might be based on an incorrect assumption about the relationship between ad positions and costs-per-conversion. If an advertiser's main target is to generate a maximal number of conversions with a given daily budget and the daily budget is typically depleted at some point in time, or the monetary and non-monetary value of a conversion is lower than the cost-per-conversion on the most prominent ad position, she may generate a substantially higher value by not participating in these bidding wars. While conversion-rates do not decrease with increasing ad-positions, costs-per-click strongly decrease if advertisers do not compete for the top positions. Combining these two effects leads to diminishing costs-per-conversion for less prominent ad positions. In particular, we show that advertisers can reduce their cost-per-conversion by around 40% if they decide not to bid for the top ad position but, for example, target position four. Still, if an advertiser's main target is to generate as many clicks or conversions as possible, bidding for the top position in sponsored search results might be the best strategy. Higher click-through-rates and constant (or only slightly increasing) conversion-rates at the top positions promise the highest total number of clicks and conversions on these positions.

In reality, advertisers should neither minimize their cost-per-conversion nor maximize the total number of conversions without considering the costs and benefits of a conversion. In contrast, they should carefully analyze the monetary and non-monetary value of a conversion and maximize the product of the total number of conversions and the value of a conversion net of the cost-per-conversion as this optimization yields the highest profits from search-engine-advertising. One way to implement such an optimization is presented in Skiera and Abou Nabout (2013) and has been shown to significantly increase the profitability of search-engine-advertising.

Naturally, this paper also has some limitations. First, our data structure is based on daily aggregated values for our keyword set. This might lead to a small bias in our estimates as there might be significant intra-day variations in the ad positions (Abhishek et al., 2011). Furthermore, our analysis focuses on transactional activities within search engine marketing. Due to our available dataset and the main research question we do not consider non-transactional effects such as branding or awareness of a brand. Finally, we do not consider potential differences in conversions for different ad positions. It is an important question to investigate whether the ratio between conversions of new and returning customers is different for different ad-positions. It may be that consumers who convert after a click on ads on less-prominent ad-positions click on the lower ranked ad because they have a higher preference for a specific retailer because they already have a customer account at this retailer.

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