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The Effectiveness of Retargeting in Online Advertising

Master's Thesis

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AALTO UNIVERSITY SCHOOL OF SCIENCE Degree Programme in Industrial Engineering and Management	ABSTRACT OF THE MASTER´S THESIS

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Following the emergence of global online service and advertising platforms such as Facebook and Google, and the development of advanced tracking and targeting solutions including online retargeting, the advertising industry has experienced a major change during the past few years. However, not much research is yet done on these new advertising methods, and the existing literature is focused on investigating more general level phenomena. This research aims to fill a part of this research gap by studying the factors in retargeting advertisement that can increase advertising performance.

An empirical analysis is performed on data collected from two European e-commerce companies. Both companies created similar retargeting campaigns targeting their recent website visitors, who had not purchased or signed up for receiving newsletter, and presented them advertisements in which three research variables were manipulated: providing a discount, referral to previous visit and landing page. Performance was analyzed using variables measuring customer engagement, time spent on the website and conversion rates for performing a desired action.

The results suggest that mentioning a discount in the advertisement can improve performance, but the effect is industry-specific. Referring to customer's previous visit to the website and directing the customer to a more detailed landing page increase time spent on the website but do not otherwise improve advertisement performance. Additionally, too intrusive retargeting advertisement content is found to have a negative effect on performance in some cases. The results provide important managerial insights for online advertisers and also provide a basis for future research on retargeting in online advertising channels.

Keywords: retargeting, online advertising, behavioral targeting, direct response advertising	Publishing language: English

AALTO-YLIOPISTO
Perustieteiden korkeakoulu
Tuotantotalouden koulutusohjelma

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Globaalien online-palveluiden ja mainonta-alustojen, kuten Facebookin ja Googlen kasvun, sekä edistyksellisten seuranta- ja kohdentamisteknologioiden kehittymisen myötä markkinointiteollisuus on kokenut merkittäviä muutoksia viime vuosina. Kehitys on mahdollistanut myös uudelleenmarkkinoinnin, eli mainonnan kohdistamisen ihmisille jotka ovat vierailleet tietyllä verkkosivulla. Kirjallisuus näistä aiheista on vielä hyvin rajallista ja olemassa oleva tutkimus on pääosin keskittynyt ylemmän tason tarkasteluun. Tämä tutkimus pyrkii täyttämään tätä aukkoa tutkimalla muuttujia jotka parantavat uudelleenmarkkinoinnin tehokkuutta online-kanavissa.

Tutkimuksen empiirinen osa on tehty kahden eurooppalaisen verkkopalvelun kanssa kerätyllä datalla. Molemmat yritykset loivat samankaltaiset uudelleenmarkkinointikampanjat, joilla mainostettiin heidän sivuillaan viimeisen kuukauden aikana käyneille vierailijoille, jotka eivät kuitenkaan olleet ostaneet mitään tai tilanneet uutiskirjettä. Vierailijoille näytettiin mainoksia, joiden sisältöä vaihdeltiin eri kohderyhmille tutkimuksen tarpeiden mukaisesti. Mainosten toimivuutta analysoidaan useilla mainoksen vastaanottamaa interaktiomäärää, verkkosivuvierailujen kestoa sekä osto- ja rekisteröitymistodennäköisyyksiä tarkkailevilla mittareilla.

Tulokset osoittavat, että alennusten mainitseminen mainoksessa voi parantaa mainoksen tehokkuutta, mutta vaikutus on toimialakohtaista. Asiakkaan edelliseen vierailuun verkkosivulla viittaaminen ja räätälöidymmälle kohdesivulle ohjaaminen pidentävät sivuilla keskimäärin vietettyä aikaa mutta eivät muuten paranna mainoksen tehokkuutta. Lisäksi liian räätälöidyllä uudelleenmarkkinoinnilla huomataan olevan mahdollinen negatiivinen vaikutus mainosten tehokkuuteen.
Tulokset antavat tukea online-markkinointia työssään tekeville, sekä muodostavat monipuolisen pohjan online-kanavien uudelleenmarkkinoinnin jatkotutkimukselle.

Avainsanat: uudelleenmarkkinointi, online markkinointi, käyttäytymisperusteinen kohdentaminen, suoramarkkinointi	Julkaisukieli: Englanti

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Jose Kantola

Helsinki, November 19th 2014

Contents

1 Introduction

1.1 Motivation and background

Following the emergence and development of global social media networks, complementing mobile device applications and modern customer behavior tracking methods, advertising industry has experienced a major change during the past few years. Global social platform providers such as Facebook and Google have access to a remarkable amount of personal and behavior data of their users, which they have started to leverage in creating advertising targeting solutions that are more accurate than ever (Lambrecht & Tucker 2013). Modern online advertising technologies provide possibilities to target advertisement (referred to as "ad" from now on) to very focused groups of people. For example, a web store could target advertising to people who visited the store and browsed for shoes during last three days.

Simultaneously, websites and mobile applications have become common channels to advertise and sell products online or to acquire new customers for offline services. Advertising results can be tracked almost in real-time by connecting the converting user, related purchase value and other attributes directly to the ads that the person has seen or clicked before visiting the website (Facebook.com 2014b).

While these new technologies are important for the entire advertising industry, research on behavioral retargeting is limited. General effectiveness of retargeting ads has been studied before (Lambrecht & Tucker 2013) but no research has been made on what kinds of appeals are the most effective in making the customer to return to the website. To fill this research gap, this research focuses on studying people who have visited and browsed online stores and thus showed interest towards their products, but have not converted to paying customers. The aim is to identify factors in the ad creative that improve retargeting performance and provide information of behaviors and reasons that drive these website visitors back to the website to finish their purchase process. The results contribute to existing literature about both customer acquisition and retention, and behavioral retargeting. Managerially, the results help advertisers design more effective remarketing ads for reaching customers, increasing customer retention and driving up sales and long term customer lifetime value.

To fill in the gap in the literature, I conducted a field experiment with two online businesses: an online motor vehicle marketplace and an online travel agency. The companies launched their own respective Facebook remarketing campaigns to consumers who had visited their websites but had not bought anything. In the campaigns, three variables were manipulated: whether an additional discount was offered, whether the ad referred to the person's previous visit and to which part of the website the ad directed the person. In total 3260 customer interactions with ads and 583 conversion events were accounted during the research period.

The scope of this research was limited to Facebook as the online advertising channel because of its vast retargeting opportunities. Facebook has grown to one of the major online advertising channels (eMarketer 2013) and provides advertisers display advertising possibilities in format of both banner and native advertising. Being a social networking platform where people share their personal information, discuss, share stories and "like" things, Facebook has an access to an enormous amount of data. That data is used to provide advertisers advanced targeting possibilities for reaching out very specific groups of potential customers, which is especially valuable for advertisers whose goal is to make customers act directly after seeing an ad (Hu 2004).

1.2 Research question

In case of a potential customer who has already visited a website but not converted, there are at least three variables to try in the retargeting ad when trying to attract the customer back to the website: mentioning a discount to make returning to website appear more attractive, referring to their previous visit to improve the effect of the call to action, and the landing page to which the customer is directed when clicking a link in the ad. Price is considered one of the main means of competition in marketing literature, particularly when used as a negotiation strategy to a hesitating customer (Lewis 2006a) while referral to a customer's previous visit to a store can be seen as a way of customizing ad content towards customers, which has been seen to be effective in direct marketing literature (Ansari & Mela 2003). Different landing pages are supposed to affect the customer's conversion process and easiness to convert, thus being integral part of optimizing the results towards more effective advertising (Ash et al. 2012).

Deriving from these variables and the research objective described above, the main question this research aims to answer is

"How do different means of retargeting influence the effectiveness of online advertising?"

The research question will be answered by altering three research variables: reference to customer's previous visit on a website, mentioning a discount in the ad and altering the landing page to which the customer is directed from the ad. Results are measured with various metrics measuring click-through rates (CTR), conversion rates (CR) and time spent on a website. More detailed description of variables and metrics is presented in data and methods chapter.

1.3 Key concepts

Direct response advertising is a focal part of online advertising because most of current online platforms are designed for responsive communication between its users, the platform and advertisers. Krugman et al. (1994, p. 490), have defined direct response advertising so that it "seeks an immediate response or action such as an order, an inquiry about the product or service, or a visit to a retail store." (Seitz 1998)

Native advertising is a rather new concept lacking standardized definition, but for example Khan (2013) has defined it as following: "Native ads are ads in a format that is native to the platform on which they are run, bought or sold. Native advertising is the activity of producing, buying and selling native ads." In other words, native advertising is a format of advertising that blends in to all other content on the platform, making it less disruptive for the customer.

Retargeting is a highly effective marketing method that is nowadays available in many online advertising channels. Goldfarb (2013) describes retargeting as a form of behavioral targeting, which "involves showing an ad to a user who searched for (or saw) a particular kind of content". This means that for example a user who has browsed shoes on an online retailer's website can be then targeted with ads showing similar, or even the same shoes.

Conversion event is a general term used to describe measureable user actions that are tracked and linked back to one or several advertising campaigns. Term converting is used in this study to refer to customer actions that lead to conversion, i.e. purchase, registration, contact request or other action the advertiser is aiming for with the advertising. (Marketingterms.com 2014)

2 Literature review

This chapter will present existing literature on topics that are relevant for understanding the concepts and assumptions of this research. First an introduction to online advertising will be made, also explaining the concept of direct response marketing and main differences between online and offline advertising channels. Then a more detailed discussion will follow on customer acquisition and retention processes and customer lifetime value, assessing how they support efficient advertising performance. After these, retargeting and its role in executing customer acquisition and retention campaigns in online advertising is presented, followed by discussion of potential privacy concerns that modern retargeting technologies may arise. Finally research hypotheses are derived from existing literature in order to answer the research question.

2.1 Online advertising

This chapter provides brief introduction into online advertising, why it is especially effective channel for direct response advertisers and what are the main factors contributing to its difference and advantages compared to more traditional advertising channels such as billboard and print media, radio and television.

2.1.1 Brief introduction

Online advertising consists of a wide spectrum of digital advertising channels, also defined by Evans (2009) as "advertising delivered over the Internet". Goldfarb (2013) has divided it into three general categories: search advertising, classified advertising, and display advertising. Based on his definitions search advertising is the advertising that appears along with the results on search engines such as Google or Bing. Online classified advertising is simply a modern version of the classified ads in newspapers and magazines. Usually they are used in websites focused on some certain topics such as job sites and online market places. Display advertising includes for example simple banner ads, plain text ads, video ads and other similar ad formats found on websites. Display advertising is also the main revenue generator for online media advertising platforms outside search engines and the main focus of this study. (Goldfarb 2013)

Since its emergence in 1994 (Evans 2009) online advertising has evolved quickly during the last 20 years, experiencing many technological leaps and founding of new advertising and tracking methods. Tucker (2012b) has explained two major developments, which are improvement of targeting and development of more obtrusive ad formats. With more obtrusive ad formats Tucker refers to advertisers starting to use video and audio content and ads that take over the website content, forcing the user to see and click on the ad. Targeting of ads was first improved by starting to match the ads to the content of the website but more importantly to search keywords that people used. As Goldfarb (2013) has stated: “Because each search is a statement of intent, advertisers can get their ads in front of people at the exact moment that the latter are looking for something”. More recently emergence of tracking cookies and retargeting through them has created even more effective targeting possibilities (Lambrecht & Tucker 2013).

Evans (2009) argues that these innovative developments of online advertising methods are leading to significant reductions in transactions costs between merchants and consumers, and are thus disrupting the whole marketing industry by rechanneling significant amounts of marketing spend from traditional medias to online platforms. Also Reinartz et al. (2005) have said that firms must start to evaluate different channels to interact with their customers, especially related to cost differences between traditional communications media and online channels.

As was already stated, advertising channel scope of this study is on Facebook that is currently one of the leading digital marketing channels globally (eMarketer 2013). Facebook is logical choice as the studied platform because it provides advertisers all the possibilities mentioned above: advanced targeting methods such as retargeting, conversion tracking across desktop and mobile devices, many ad formats and a global inventory of potential customers.

2.1.2 Direct response advertising

As was defined in key concepts, direct response marketing is an interactive form of marketing that aims to trigger immediate customer actions. Compared to more traditional advertising mediums where accurate tracking of advertising results is very challenging, the two-way information flow and improved possibilities to track customers’ actions with various metrics make online advertising channels good platforms for direct response advertising (Hu 2004).

Improved tracking has also lead to the emergence of performance-based advertising pricing models (Hu 2004). Compared to the cost-per-mille (CPM) pricing model that has been the industry standard in more traditional advertising channels and brand advertising (Evans 2009), performance-based advertising makes it possible to pay only for the desired customer actions instead of impressions. It is especially the performance-based measurability and pricing that makes online advertising channels so attractive for direct response advertisers, because they make it possible to control advertising spend and prices paid more efficiently by allocating more resources for well performing ads and customer segments (Hu 2004).

Even as Facebook is providing advertising solutions for both branding and direct response advertisers, its greatest benefits compared to other advertising channels are still seen in direct response advertising (McDermott 2014a, 2014b; EMarketer 2014). Facebook's key competences for direct response marketing include its various ad formats with call-to-action buttons, advanced tracking technology that works across mobile and desktop devices, and a large active user base that can be targeted using combination of data from Facebook, advertiser and 3rd party data partners, (McDermott 2014a).

2.1.3 Special characteristics compared to other advertising channels

Online advertising channels differ from other advertising channels in several ways. The main benefits are related to its agility, measurability, low fixed costs for setting up advertisements and ability to gather and process large amounts of customer data that can be leveraged in advertising.

Evans (2009) has listed some of these benefits compared to print, radio and television advertising. For tracking purposes he mentions that in online channels it is possible to know if the user is actually looking or listening to the ad or not, and also to know the exact location of that user based on IP address. This possibility is completely different compared to for example newspaper advertising where it is only possible to know the spread and geographical distribution area without any exact information of how many people actually see the ad and act based on it. In addition to these, in online channels it is also possible to know which device the user is using to access the content (Facebook.com 2014e), how big part of an video ad the user has viewed (Facebook.com 2014b) and what actions user has taken after seeing the ad (Facebook.com 2014c).

On data processing side, which also represents the agility of online channels, Evans mentions that online advertising platforms and publishers are able to consider information of registered users and their behavior such as search keywords used and websites visited. All that data can be processed almost in real time to define which ads are most relevant for a specific user, thus improving the match between advertiser and customer. (Evans 2009; Rushton 2012) Accurate targeting, improved measurability and fast data processing are main examples of the differences between online and offline channels, illustrating the benefits created by modern online advertising technologies.

2.2 Customer acquisition, retention and lifetime value

This study is focused on retargeting; advertising to people with whom there has already been a point of contact in the advertiser's website. In order to understand the whole power of retargeting, I will next introduce customer lifetime value theory that helps to understand the broader picture of the value of a continuous customer relationship and how advertising can be used to enhance it. Later in this chapter I will go through concepts of customer acquisition and retention, both of which are important for successful advertising and retargeting. In the end of the chapter I will also introduce concept of shopping cart abandonment that is highly relevant to customer acquisition process and estimating customer lifetime value.

2.2.1 Customer lifetime value

In the end of the day, customers of all businesses are always individuals, which means that they also behave in a unique manner and are willing to use varying amounts of money to purchase products or services that are offered to them. For this reason Kotler and Armstrong (1996) have stated that not every customer, even inside company's main target group, is always profitable and worth pursuing for the company (Berger & Nasr 1998). By definition a profitable customer is one whose revenues over time exceed, by an acceptable amount, all costs derived from attracting, selling, and serving that customer (Ahmad & Buttle 2001; Berger & Nasr 1998). This implies that also marketers should consider customer lifetime value (CLV) and leverage it to optimize advertising in order to maximize CLV for existing customers.

When sufficient amount of information is available, calculating CLV is a simple process. CLV is the net present value of expected cash flows generated by customer during the whole customer relationship (Berger & Nasr 1998). Kumar and Reinartz (2003) and Rust et al. (2004) have proposed that CLV should be used as the main metric to model expected financial return of marketing efforts. For example Getz and Thomas (2001) have incorporated acquisition, retention and cross buying, i.e. all stages of customer relationship, into a model of customer lifetime value in their book (Reinartz et al. 2005). With models using CLV, strategic marketing investments can be designed to focus on most profitable individual customers or customer segments (Kumar & Reinartz 2003). These points direct to a conclusion that for example website visitors should be evaluated by their expected CLV based on their earlier behavior, such as what kind of products they have been browsing on the website. Customers with different expected CLV can then be targeted with different acquisition price targets, optimizing the advertising results separately within each sub-category. Important fact to consider with CLV is that as advertising to potential and existing customers affects their behavior, those advertising actions alter the expected CLV making it a dynamic variable. Thus the CLV both affects and is affected by the allocation of advertising resources. (Berger et al. 2002)

Widespread belief in customer relationship management is that retaining existing customers is always cheaper than replacing them by acquiring new customers (Ahmad & Buttle 2001). Jain and Singh (2002) support this belief by arguing that cost of acquiring is even higher on internet, making profitable customer relationship even more dependent on loyalty and repeating purchase behavior of customer.

However, also contrary arguments exist. Reinartz and Kumar (2000) have presented that maximizing CLV does not necessarily require long-lasting customer relationship, but that both long-term and short-term customers can be profitable. However there is a difference between these customers and thus it is important to consider that in designing marketing efforts. For example customer satisfaction appears to affect more short-term customers while long-term relationships become more profitable when more focus is put on building trust and commitment between customer and the company (Garbarino & Johnson 1999). Similarly Villanueva et al. (2007) have presented that customers attracted with advertising usually create more short-term value compared to customers acquired through word-of-mouth who are more valuable in long term. For these reasons maximizing CLV requires understanding of how specific relationship factors have different effects on short- and long-term performance metrics (Reinartz & Kumar 2003).

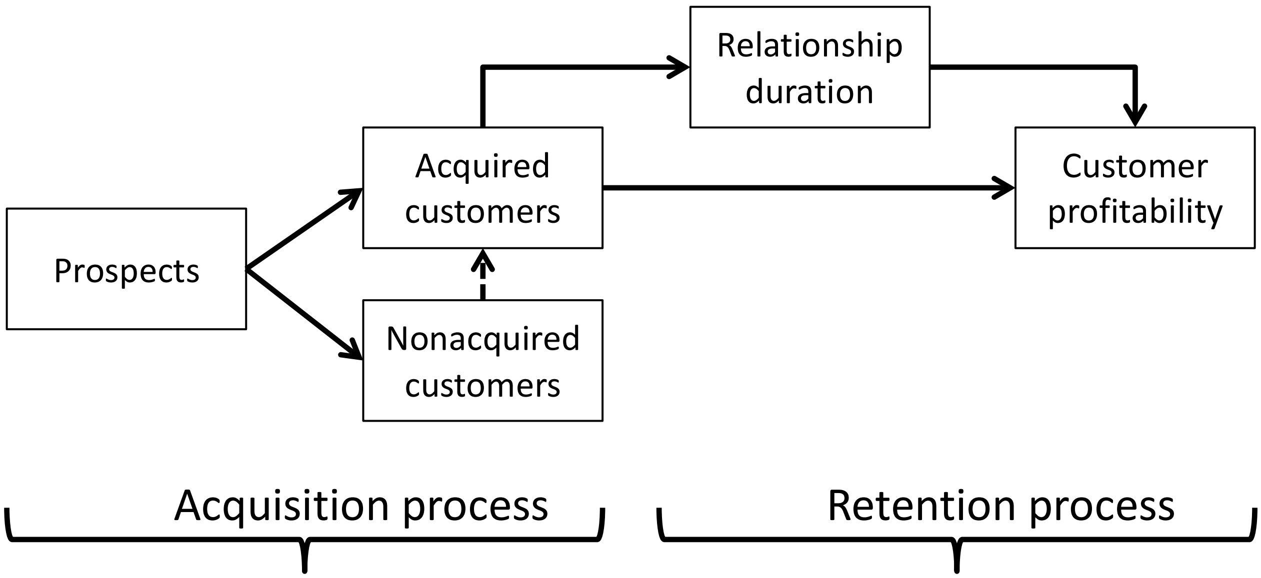
Together with development of customer behavior measurement technologies, CLV methods are becoming more common ways to plan and control advertising efforts and customer relationships. Jain and Singh (2002) argue that firms have started to take more customer-centric approach to their marketing strategies. This approach is explained to mean treating customers as assets and focusing the marketing to both acquiring and retaining customers, making the retained customers the basis of sustained competitive advantage. This view emphasizes the importance of using marketing also in retaining existing customers, which is discussed in the next chapter, and also highlights the role of retargeting as integral part of marketing strategy, which is discussed in the later chapters.

2.2.2 Customer acquisition and retention

As expressed by Kotler and Armstrong (1996) "marketing is the art of attracting and keeping profitable customers" (Berger & Nasr 1998). Generally in the marketing literature the first is referred to as customer acquisition and the latter as customer retention. For example Thomas (2001) has defined customer acquisition as "part of the customer-firm relationship that begins with the consumers' first interaction with the firm and proceeds through the first purchase until the first repeat purchase" and retention so that it begins from the first repeat purchase, i.e. continuing from acquisition process, and continues until the end of the relationship.

Reinartz et al. (2005) have introduced a conceptualization presented in Figure 1 of different stages of customer-firm relationship and how they are divided to acquisition and retention processes. In line with what has been discussed earlier, the model shows that, in the end, customer profitability is the result of both acquisition and retention processes and the value of all the purchases that the customer makes.

Figure 1 Linking customer acquisition, retention and value



Importance of customer retention processes and their impact, in addition to customer acquisition, on advertising profitability have gained more attention as use of customer lifetime value has become more common. Significance of customer retention has been studied by Dawkins and Reichheld (1990), who claim that a 5% increase in retention rate can lead to 25-85% increase in average customer lifetime value, which can attribute to remarkable improvement in profitability (Ahmad & Buttle 2001). Ahmad and Buttle (2001) have listed a number of factors that contribute to this increase. Among them are loyal customers' tendency to purchase on more regular basis, which leads to a stable minimum spend per period and higher likelihood of price premiums and increasing revenue per customer since regular customers do not usually wait for promotions before purchasing. According to them loyal customers are cheaper to keep than attracting new customers and also give free referrals to their contacts.

From this higher-level view it is then logical to move into more practical operationalization of customer acquisition and retention actions. As discussed earlier with CLV theories, one part of optimizing advertising effectiveness is to divide customers into segments based on their expected CLV and customize maximum acquisition prices accordingly (Kumar & Reinartz 2003). Probably most optimal results would be achieved by estimating CLV of every potential customer individually and use that to define the maximum price to pay for acquisition or retention. However that is not feasible with current technology and thus customers should be divided into larger segments instead. In addition to expected CLV

Berger et al. (2002) have suggested that the segments should also be built to contain customers with similar interests, needs, purchase power and purchase frequency.

To maximize advertising effectiveness, advertising content can be customized for each segment based on whether customers are still in acquisition or retention phase of customer life cycle. Lewis (2006b) has demonstrated effect of customization by showing that when providing different order size incentives and shipping fees, customer acquisition performance is more sensitive to order size incentives and customer retention performance to shipping fees. Thus the customer attraction methods used in advertising should be customized separately based on customer relationship stage. It is important to notice that even though non-acquired customers, the focus group of this research, are still in acquisition phase of customer relationship, a contact with them has already been established and thus some retargeting methods can be applied.

As already mentioned earlier, means of customizing ad content to maximize performance are various. Offering discounts is an example of such method and is commonly used to improve advertising effectiveness. According to Lewis (2006a), discounts can help in acquiring a larger customer base by making it cheaper and thus easier for new customers to make their first order or try the service for the first time. However, discounts also attract more low-value customers, leading to lower expected CLV of the acquired customers. As potential explanations for this Lewis has presented that acquisition discounts may attract increasing numbers of customers who buy only during deal periods and that offering discounts of around 35% can decrease the expected lifetime value of new customers by 50% compared to customers acquired without discounts. Similarly Donkers and Verhoef (2005) have stated that customers acquired with attractive pricing offers are probably also inclined to switch to competitors when receiving offers from them.

However, also research with opposite results exists. For example, Anderson and Simester (2004) have found that customers acquired through catalogs with more discounted items have higher long-term value. The findings are explained by high repeat-purchase rates of new customers that overcome the discounts' negative effect on revenue in the longer run. However, all studies in their research are focused on mail catalogs posted to households, which is why the results cannot be generalized without further research and this study is relying on the findings of Lewis when formulating the hypotheses.

2.2.3 Shopping cart abandonment

Shopping cart abandonment is a behavior related to online shopping activities of consumers. Kukar-Kinney and Close (2009) have defined it as "consumers' placement of item(s) in their online shopping cart without making a purchase of any item(s) during that online shopping session". Thus cart abandoners are a subgroup of all non-converted website visitors in acquisition phase and subgroup of existing customers in retention phase, making it is closely related to both customer acquisition and retention activities of companies.

This behavior is important due to its high frequency in online shopping. For example Forrester Research (2005) has reported that 88% of online shoppers have abandoned their electronic shopping cart before and that in general carts are abandoned at 25% of times (Kukar-Kinney & Close 2009). Similar results have also been found by Fenech (2002), who stated that approximately 25–75% of shopping carts are abandoned. Based on these findings it can be derived that shopping cart abandonment is an important phenomena affecting online customer acquisition and retention processes.

Opposing to general believes, Kukar-Kinney and Close (2009) argue that shopping cart abandonment is not a sign of consumer dissatisfaction but rather a way for consumer to save a list of desired items or to track prices of something they are willing to buy later. As implications from this they suggest that companies should present discounts or free shipping to attract these customers to finish their purchase process. To avoid optimism related to this behavior they have also found (Kukar-Kinney & Close 2010) that despite of signals of willingness to buy, the final purchase may also take place in other channels such as in competitor's web store or in an offline retail channel. Placing items in the cart may also provide some entertainment value for the customer, meaning that just putting the items to shopping cart without buying them provides satisfaction similar to actual buying. (Kukar-Kinney & Close 2009)

2.3 Retargeting

In this chapter I will present earlier literature on retargeting and behavioral advertising, discuss how it can be leveraged in online marketing and how online retargeting differs from more traditional offline version of it.

2.3.1 Online retargeting in general

Well-designed use of retargeting can help advertisers overcome the classic challenge of advertisers, as stated in a popular saying, "Half the money I spend on advertising is wasted; the trouble is I don't know which half" by Lord Lever (Hu 2004). Retargeting can be used to target customers who already showed interest in a product, with ad content that is highly relevant for them.

Retargeting is often referred to as remarketing, but the two are actually considered to have slightly different meanings. Remarketing is a more traditional term referring to process where information collected of a customer is used in marketing to them via mail or email. Retargeting is a more recent term for online advertising methods, where the customers are tagged with cookies when visiting a website and those cookies are then later used for targeting the customer again on online advertising channels. (Arsenault 2012; Cooan 2013) Retargeting is a very efficient method for reaching website visitors and shopping cart abandoners as target audiences for advertising.

Large web platforms such as Facebook have recently introduced retargeted ads into its members' newsfeeds as a central plank in their advertising strategy (Lambrecht & Tucker 2013; Rusli 2013). And there is a reason for it. For example Ansari and Mela (2003) have found that customized products and communications attract customer attention and foster customer loyalty and lock-in, and also that customized ad design is one of the key features that differentiates online marketing from more traditional media. Similarly Lambrech and Tucker (2013) have stated that existing marketing literature has emphasized that greater specificity of a firm's interactions with consumers should increase relevance and consumer response.

Retargeting platforms and tools, such as Adroll and Merchenta, support the literature in their case studies which prove that retargeting can improve click through rates, conversion rates, conversion value and customer retention (Insidefacebook.com 2014; Merchenta 2014). Due to these increased performance indicators the website visitors can be considered more likely to convert and thus the advertiser should be willing to pay higher advertising price to reach these customers.

The latest step in technological development of retargeting has been dynamic ad creation that uses the same technical solutions as parsing individual-level browsing data to the use of making product recommendations to the customers inside a web store. This data can be used in retargeting by creating dynamic retargeting ads that present the exact products the customer had earlier browsed on the website. (Lambrecht & Tucker 2013)

Despite enabling highly targeted and customized ad content, dynamic retargeting still has its downsides. Lambrecht and Tucker (2013) have also found that in order to be more effective than regular retargeting ads, dynamic retargeting requires specific information of customers' behavior and level of purchase intention. These are discussed in next chapter. Another downside is that in order to achieve a high degree of personalization in the ads the advertisers have to give up the control over some ad parameters that are customized using automated algorithms (Meyer et al. 2011).

Another downside is that as retargeting can be an extremely accurate and effective advertising method, it can also be frightening towards the customers if they are afraid that their privacy is being violated or feel that they are being stalked by the ads (Helft & Vega 2010). This raises the question of how retargeting ads should be designed and targeted in order to find an optimal compromise between ad personalization and accuracy and avoiding a too intrusive appearance.

2.3.2 Behavioral targeting

Behavioral targeting is an advertisement targeting format that leverages data of customer's past online, and possibly even offline behavior (Facebook.com 2013). Online behavioral data can include for example information of user's visited websites, search keywords, pages liked or articles shared in social media channels (Goldfarb 2013). Offline behavior data can include information of customer's living area, credit card use and shopping habits. Both online and offline behavioral data can for example in Facebook's advertising platforms be used in combination with other targeting methods like retargeting. (Facebook.com 2014e)

Importance of targeting has been studied and found very important, since targeting wrong people usually equals wasted money. For example Iyer et al. (2005) have found that companies are able to reach higher profits when they are able to customize advertising levels for different consumer groups. As an example they have found that proper ad targeting has more influence on the profits than ability of setting customized prices to customers.

Important part of retargeting effectiveness is also timing of the ad impressions. To maximize ad effectiveness the ad should be designed to match the customer's interest and commitment to purchase at the moment of impression, which can only be predicted by examining signals given by past behavior. As mentioned in previous chapter, Lambrecht and Tucker (2013) have found that more generic ads work better for customers who are still exploring a wider range of products, while very customized dynamic ads work better for customers who have already narrowed their possible alternatives.

One example of a situation where retargeting at right time could be effective is the shopping cart abandonment event described in earlier chapters. Since shopping cart abandonment is a sign of a purchase intention (Kukar-Kinney & Close 2009), it should also be an important signal for triggering retargeting campaigns that aim to attract the customer back to finish the purchase and turn into an acquired customer instead of doing that in competitors' sales channels.

One suggested theoretical solution for improving the understanding customer behavior and its impact on advertising effectiveness is to create set of metrics that are unobservable in regular advertising performance measuring. For example customer satisfaction is a metric that could explain much of the variation of advertising effectiveness inside a group of otherwise similar customers. (Gupta & Zeithaml 2006)

2.3.3 Targeted marketing in offline channels

Online advertising methods are in many ways much alike their offline versions, most likely because online advertising has evolved from offline advertising as an extension to new advertising channels created by technological innovations. Despite sharing similar methods, the two have some fundamental differences in how and on which level data is collected and used.

Market segmentation and on more detailed level targeting is generally seen as one of the most important marketing concepts (Smith & Cooper-Martin 1997). Also Iyer et al. (2005) have stated that proper ad targeting has more influence on the profits than ability of setting customized prices to customers. Thus differences in targeting methods of online and offline advertising have major role in advertising effectiveness.

A good example of offline targeting is a study by Laroche et al. (2001). They have studied a case of finding target customer segments that are willing to pay more for environmentally friendly products. They presented numerous survey results of how customers' gender, age, income, education, relationship status and number of children living at home affected their willingness to pay more for environmentally friendly products. As a result they came up with attributes that did or did not correlate with customers' willingness to pay more for green products, thus providing advertisers better possibilities to specifically target the people matching those criteria. One could argue that these same data points are used in online advertising, but there are fundamental differences derived from how all that data can be collected, how long the collection and processing takes time and how that data can be used in the actual targeting. (Goldfarb 2013)

More related to retargeting purposes Marinova et al. (2002) argue that a common way to create targeted advertising lists is to analyze customers' preferences, purchasing histories and future purchasing intentions using data from company's customer-information databases. Main difference to online channels like Facebook is that the data is mainly collected by the company itself after which it is analyzed and then used to create retargeting lists. Facebook collects data of customers' preferences, web browsing behavior and purchasing history globally regardless of which companies are interested to target them (Facebook.com 2014e). Thus advertisers are able to leverage significantly larger amount of data that is provided to them in real time.

Continuing on differences from data perspective, Prins and Verhoef (2007) have stated that generally mass advertising data are only available at an aggregate weekly or monthly level and thus cannot be directly combined with actions in customer databases. Thus also customer behavior data must be aggregated to weekly or monthly level to match it with advertising data. Resulting from this, analyzing advertising performance can only be done after some weeks of running advertising campaigns, and still on aggregate level instead of analyzing individuals or small customer segments. Here is also a major difference to online advertising, where the results can be tracked in almost real time and on very specific level down to user segments of only some thousands of users.

To conclude, the main difference between online and offline channels is that all internet traffic is communication between identifiable computers that can be tracked and recorded. Ability to track the traffic in real time and combine it with accurate targeting possibilities presented before also leads to substantial reductions in the cost of targeting. (Goldfarb 2013)

2.4 Privacy

Following advanced tracking and retargeting methods that are widely used by advertisers, data mining companies and global online platforms like Google, users' privacy has become a major concern for many people today. As Tucker (2012b) has noted, overly obtrusive advertising can lead to decreased ad effectiveness. Especially privacy-focused consumers react negatively to advertisements that are both targeted and obtrusive (Goldfarb & Tucker 2011a). This can have major impact on the effectiveness of retargeting ads if the customers feel that advertiser is violating their privacy and using information they should not have.

Even as generally all data that company collects about a customer can be considered to be its property and thus available for any advertising actions until customer asks to be removed from targeting lists, using that data for any actions is not always recommended (Goldfarb 2013). Customers have started to acknowledge the privacy issues more, which is partly due to increasing number of contexts in which they feel privacy concerns to be relevant (Goldfarb & Tucker 2011b). Existing literature suggests that advertising companies can mitigate customers' privacy concerns by giving them more control over how data of them is collected and used for marketing purposes (Marinova et al. 2002; Tucker 2011). In more detail, clear control and understanding of data usage process can make the ads feel less intrusive for customers. Tucker (2012) also argues that although privacy concerns can reduce the effectiveness of certain ads, on balance the use of data substantially increases the effectiveness of online advertising.

Deeper understanding of the actual reasons for customers' privacy concerns can be acquired with more controlled laboratory studies and surveys. Consumer discomfort with targeted advertising has been proven in existing literature, and Tucker (2011) has found similar results also for advertising in social networks. (Goldfarb 2013)

2.5 Hypotheses

As discussed in the literature section, retargeting ads are supposed to have higher effectiveness compared to regular advertising on general audience (Insidefacebook.com 2014; Merchenta 2014). In addition, Lambrecht and Tucker (2013) have studied how the effectiveness of dynamic retargeting changes depending on customers' existing knowledge of the product and commitment to purchase. However, there are no studies on how the specific variables on different kinds of retargeting ads affect the performance.

In order to answer the research question "How do different means of retargeting ads influence the effectiveness of online advertising?" the following hypotheses were created based on existing literature and the ad content variables presented with the research question. Figure 2 provides a visualization of the hypotheses, presenting the relationships of research variables and advertising performance.

Existing literature argues that discounts are supposed to increase the probability of customer coming to website and convert (Lewis 2006a). Also Kukar-Kinney and Close (2009) have suggested that shopping cart abandoners, who are a subgroup of all non-acquired website visitors, should be attracted back to website by providing discounts and free shipping of products. Mentioning a discount is also a value proposition for the customer, which is listed as one of the best practices to use for improving Facebook advertising performance (Slagen 2012).

Chapter 2.2.2 Customer acquisition and retention discussed that the effectiveness of different methods for attracting customers varies between customer segments and life cycle stages (Lewis 2006b). Thus the effect of discounts must be studied separately for website visitors in different industries. The first hypothesis is formulated based on these findings:

> *H_1: When a discount is mentioned in an ad, the performance of Facebook retargeting ads is higher than without discount.*

Website visitors have already expressed their interest of some level towards the products offered, meaning that the purpose of retargeting ad is to gain back customer's attention. Previous visit referral is one way to make the ad more customized towards the customer, which has been recognized to attract higher customer attention (Ansari & Mela 2003) and increase ad's relevance and customer response (Lambrecht & Tucker 2013). Slagen (2012) has similarly presented examples of personalized content in the ad as potential 'disruption factors' that draw the attention and interest of the customer.

In addition to gaining more attention from the customer, improvements in click-through and conversion rates can be achieved by more customized and personal ad content (Ansari & Mela 2003; Iyer et al. 2005). Thus referring to previous visit is expected to improve the content relevance, effect of ad's call to action and get engaged customers to click and convert, leading to second hypothesis:

H_2: When ad refers to customer's previous visit on the website, the performance of Facebook retargeting ads is higher than without reference.

Landing page of an ad affects the path and the length of the path a customer has to follow in order to eventually convert. Thus it can have an effect on the conversion rates and time spent on the website. By common sense, the shorter the path from seeing an ad to converting, the higher the probability of customer being engaged enough to go through all the steps. Ash et al. (2012) state in their book that a website main page is often quite generic because it has to serve audiences with many interests. Different category pages are then designed to serve better the more exact needs of those various audiences.

These findings of website structure can be combined with findings of Lambrecht and Tucker (2013), who have found that retargeting advertising performance depends on how specific the ad is in relation to how ready to purchase the customer actually is. Thus it can be argued that a more general landing page suits better for customers who are still in the beginning of their selection process, while more detailed landing page suits better for customers who are already more aware of what they are looking for. In this study the customers who visited the website earlier are assumed to already have more detailed knowledge of what they are looking for and thus should benefit of a landing page that is more customized based on their previous behavior. These assumptions provide third hypothesis:

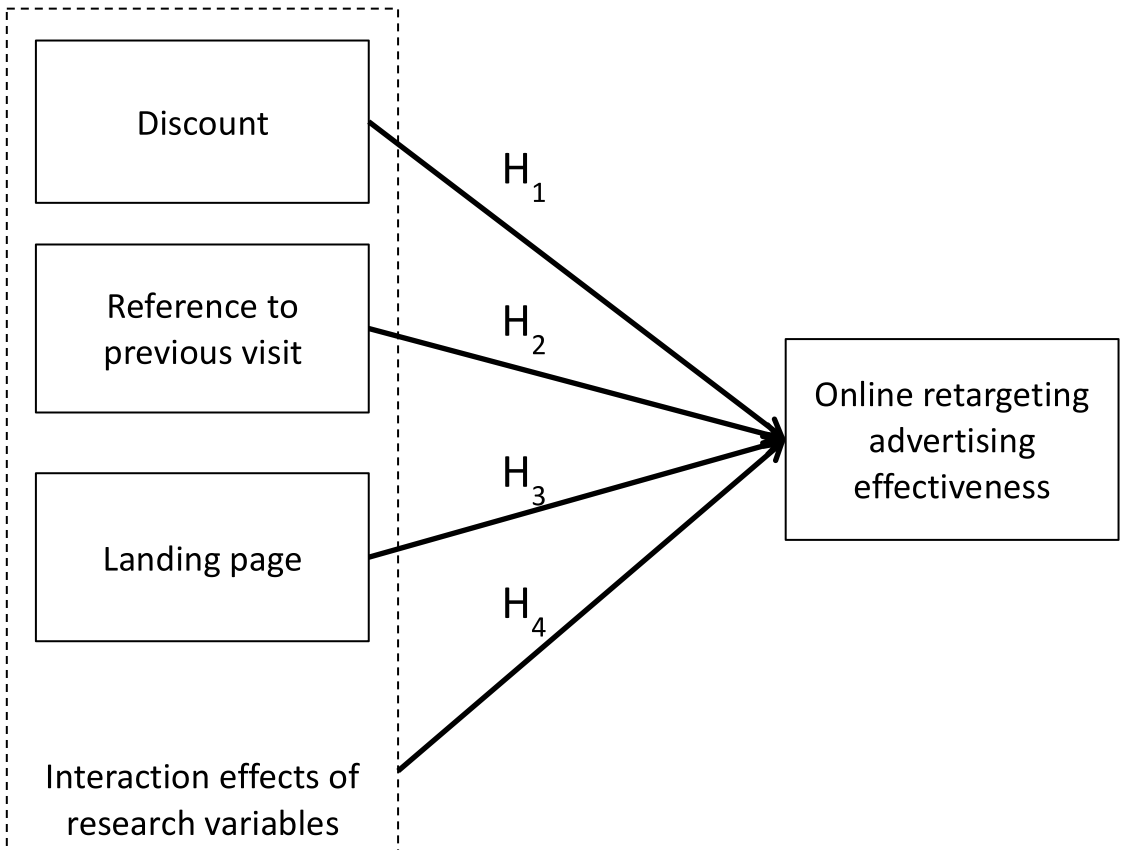
H_3: When ad directs customers to specific product category page they have visited before, the performance of Facebook retargeting ads is higher than when customer is directed to front page of a website.

In addition to testing effect of individual variables it is also interesting to test the interaction effect of them. For example Tucker (2012b) has found in her study that while accurate targeting and more obtrusive ad design increased ad effectiveness, using them in combination nullified these benefits. Variables tested here are different from the ones Tucker studied but her results provide good reasoning for testing if similar effects appear also here. Drawing from the previous hypotheses all research variables are assumed to have positive effect on retargeting ad performance. Thus in fourth hypothesis I assume this positive effect to be at least as big when multiple variables are used together in same ad creative.

H_4: Interaction effect of previous visit referral, mentioning a discount in the ad and using product category level landing page improves the performance of Facebook retargeting ads compared to individual effects of the variables.

These four hypotheses are next tested with real advertising data of companies who participated in this study.

Figure 2 Formation of hypotheses from research variables



3 Data and methods

Data for this study was collected from two European e-commerce companies who are working internationally in many countries. Companies were selected based on their fit to the study's requirements, their willingness to cooperate and so that they operated in different industries which improved the applicability of the results.

3.1 Variable and company selection

Research variables were selected based on existing knowledge of e-commerce companies' most common current marketing methods, existing literature on the field of online marketing, and the practical possibilities and restrictions derived from the selected participant companies' operations. Main research variables were mentioning discount in the ad, referring to customer's previous visit to the website and alternating the landing page to which the customer was directed after clicking the ad.

Companies' fit for the study was assessed by checking that the companies were already doing retargeting in Facebook, had collected sufficient target audiences of website visitors in some of their market areas, and their business model and website design made it possible to create comparable advertising campaigns.

3.1.1 Company A

The first company the study was conducted with (Company A) is an international online marketplace for motor vehicles, operating in over 10 countries in South America, Africa, Asia and Middle East. On seller side the marketplace is used by both private individuals and local dealers selling their vehicles, and on buying side mostly private persons buying vehicles for their use, although also companies might use the platform to purchase vehicles.

The online marketplace is structured so that it has a front page from which customer may navigate to browse only certain vehicle types, e.g. cars, and then even further to more detailed categorizations based on the model, manufacturer etc. Main actions the customers can perform on the website are creating new listings of vehicles they want to sell, search and browse existing listings and contact the sellers by sending them a message or contact request. In general the main Facebook advertising goal of Company A is to generate more traffic and contact requests to the listings which then makes the platform more attractive place to make a listing. This leads to virtuous cycle where increasing amount of listings makes the platform more attractive place to visit, driving more traffic.

In terms of this study, the target audience was customers from the target country who had visited the website and had been looking at products in the cars section of the website. Company A had already been advertising to their website visitors and thus had sufficient target audiences available. The advertising goal of their campaigns is to attract traffic and potential buyers to existing listings so that they make contact requests with the sellers. Thus in the context of this study and Company A, term “conversion” is used to refer to contact requests made in the website of Company A. Indirect goal of advertising is also to increase the amount of listings, but that was out of scope of this study and thus not measured.

The website structure and advertising goals of Company A lead to use of all three research variables: mentioning discounted prices of listings, referring to customers’ previous visit to the marketplace, and having two landing page variations: the front page of marketplace and main page of cars category. All permutations of these variables were tested, resulting in eight different ad variations with a between-subject factorial design. Company A also had access to restricted feature on Facebook’s advertising platform which made it possible to randomly divide the target audience into eight unique user segments, each of them being served only one variation of the ad.

3.1.2 Company B

The second company (Company B) is an international online travel agent offering daily discounted traveling opportunities to their customers. They operate in 18 countries all around Europe. The discounted travel opportunities are offered by third party travel service providers and are available for the customers 24 hours at a time. Company’s country specific websites and emails sent to registered customers are the main channels for spreading information of the daily offers.

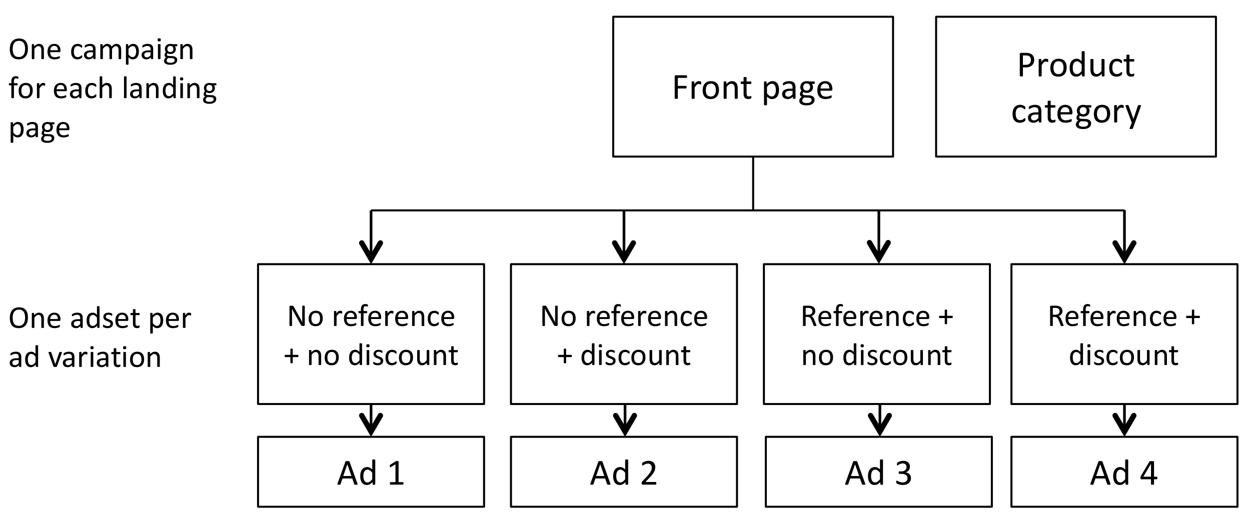
The website of the company is designed so that the customer can easily browse through the offers of the day on a single page, proceed to getting more detailed information of an individual deal, after which it is possible to book the vacation directly from the same website. For new visitors the website also launches a popup window which aims to make the customer subscribe for receiving emails of daily offers.

In this study, the target audience for Company B was all visitors of their website in the selected target country, excluding customers who had already subscribed to their newsletter. Also Company B had already been advertising to their website visitors and thus had existing target audiences. Advertising goal was to gain new newsletter subscriptions through a landing page that was focused to provide the user this possibility. Thus when discussing about Company B, the term "conversion" refers to newsletter subscription made in the website of Company B. Research variables were the same as for Company A, except that only one landing page, the newsletter subscription page, was used due to the selected advertising goal. Thus for Company B only four ad variations were tested.

3.2 Advertising campaign design and creation

For both companies the advertising campaigns were designed with a similar collaboration process. The campaign structure was first designed to meet the requirements of this research, which are to provide as equal delivery of all ad variations as possible. Following the campaign structure, the companies designed the ad creatives using their own materials and guidelines. Content of the ad creatives was then checked and approved to guarantee sufficient quality and comparability of the performance data collected from the ads. Figure 3 presents the design of campaign structure.

Figure 3 Advertising campaign structure



To guarantee equal delivery of ad variations, each ad was placed into individual ad set inside the campaign. This way the delivery allocation algorithms of Facebook did not have an effect on the spread of impressions between the ads. Also the daily budget and bidding method and amount were set equal for all the ad sets to guarantee stable and predictable delivery of ad impressions for all variations.

Ad design was standardized by clear guidelines. Creative image, description, link caption and call to action button were identical between all ads. The link URL changed for Company A’s ads depending on the landing page used. Other variables were varied in the message field so that the message text was otherwise identical, only varying depending on if the previous visit or discount was to be mentioned. Below in Figure 4 two generic examples of the ads are presented, one of which does not refer to previous visit nor to any discount and the other one mentioning both in its message text. Table 1 provides concrete examples of how discounts and previous visit references were varied in the four different message parts of the ads.

Table 1 Examples of ad text variations

Ad variation	Ad message text
No discount and no reference to previous visit	New assortment of delicious iced tea flavors now in our web store, check it out!
Discount mentioned but no reference to previous visit	New assortment of delicious iced tea flavors **today with -20% discount** in our web store, check it out!
No discount but reference to previous visit	**Visited our web store but didn’t find what you were looking for?** New assortment of delicious iced tea flavors now in our web store, check it out!
Discount mentioned and reference to previous visit	Visited our web store but didn’t find what you were looking for? New assortment of delicious iced tea flavors today with -20% discount in our web store, check it out!

Figure 4 Examples of complete ad design

3.3 Data collection

Data was collected by running the ad campaigns continuously until a sufficient amount of data had been collected to all ad variations and after that until the Companies themselves decided when to stop the campaigns due to declined performance. As for all advertising, the performance of these ads started to decrease after reaching certain saturation point of being seen too many times by the same customers.

To maximize the amount of available performance metrics, both Facebook and Google Analytics data reports were used to analyze ad performance. Both of them have advantages and disadvantages, due to which certain parts of data were selected from each system.

Facebook's tracking pixel and user-based conversion attribution methods make it possible to attribute conversions made within 28 days after seeing or clicking on the ad. User-based attribution also enables conversion tracking across devices, meaning that person seeing the ad when using a desktop access to Facebook may later make the conversion on his or her mobile device and the conversion is still attributed to the ad seen on desktop device. Google's click tag tracking is only able to attribute conversions based on last click model, meaning that the conversion must happen directly after the customer has clicked the ad and landed on the website. For this reason the click and conversion amounts, rates and prices analyzed in this study are collected with Facebook conversion pixel. Facebook's default attribution model is to track all conversions within 28 days after clicking the ad or one day after seeing it. To decrease the time required to wait for all conversion data to be tracked, this study uses attribution model of seven days after clicking and one day after seeing the ad.

Advantages of Google Analytics were leveraged by also using the metrics available there but not in Facebook. These metrics include amount of bounces, bounce rate, amount of sessions, average session duration and average number of pages visited per session. These metrics describe the quality of clicks made on the ads and the level of engagement of customers who visited the website, thus providing valuable information on top of the conversion rates.

3.4 Performance metrics used

Metrics presented in Figure 5 are used for measuring the performance of each ad variation. Some metrics are calculated from other metrics that were used in data collection phase.

Figure 5 Performance metrics used in the study

	Metric	Explanation
Facebook metrics	Impressions	Total amount of views that each ad collected.
	Post Engagement rate	Official Facebook term is CTR. Measures amount of click-based actions (likes, shares, link clicks etc.) taken by users on the ad
	Link clicks	Amount of clicks on the link in each ad
	Click through rate (CTR)	Amount of link clicks per impressions
	Conversions	Amount of target conversion actions attributed to each ad
	Conversion rate (CR)	Amount of target conversions divided by amount of impressions
	Conversion rate (CR) from clicks	Amount of target conversions divided by amount of link clicks
	Cost per action (CPA)	Average price paid per target conversion
Google metrics	Bounce rate	Percentage of users who only visited on the landing page before leaving the website
	Pages per session	Average number of pages visited by a user during one session
	Average session time	Average time spent on the website per one user session

4 Results

4.1 Data summary and correlations

The data analysis was started by investigating the summary statistics of main metrics and correlations between individual variables and metrics. Main purpose of this was to gain better understanding of the variables and thus also better basis for the more complex analyses later.

Summary statistics presented in Table 3 show the main differences between datasets of Companies A and B. Amount of impressions, i.e. data observations within each control group are smaller for Company A, which explains the larger standard deviations on their data. Other major differences are in the performance metrics and are attributable to different advertising goals and website designs of the companies. For example conversion rate after clicking link to website is on average higher for Company B which can be explained by customers' direct landing to a page where they can convert compared to landing page of Company A from which the customer still has to navigate further to some product page before being able to make a conversion. Higher bounce rate, less pages visited and less time spent per session on website of Company B are results of more flat website structure that allows user to register on one page and browse through all daily deals on another page, compared to Company A whose website contains a larger variety of items and actions that can be browsed on multiple levels. Due to these differences both data sets are later standardized before performing analyses for combined data set.

Table 2 presents the correlations between the research variables used and the main performance metrics. We can see some numbers supporting each other in both cases, but also some differences. First, it appears that for Company A mentioning discount and referring to previous visit correlate positively with the probability of user clicking the ad. For Company B the effect is the opposite, implying that there are differences in how customers react to ads of different industries. This implies that an online marketplace reminding a user to return to their site and providing discounts attracts the user to return and see if there is something new and affordable they might be interested in. On the contrary the visit referrals and discounts of travel agency do not seem to appear as effective compared to more neutral advertisements.

Second, for Company A referring to previous visit correlates negatively with conversion rates but mentioning discount in the ad has positive correlation. For Company B both of these correlations are negative.

Third, for both companies referring to previous visit on the website correlates positively with the amount of time spent and pages visited on the website. Also mentioning discount has positive correlation with these metrics for company B, but for Company A the correlation is not very strong.

Table 2 Correlations of research variables and key performance metrics

	Company A			Company B		Combined data		
	Landing	Discount	Reference	Discount	Reference	Landing	Discount	Reference
Engagement rate		0,52	0,24	-0,52	-0,82		0,19	-0,09
CTR		0,59	0,28	-0,33	-0,89		0,3	-0,09
CR impressions	-0,13	0,81	-0,17	-0,77	-0,52	-0,09	0,31	-0,28
CR clicks	-0,39	0,37	-0,41	-0,76	-0,14	-0,28	0,01	-0,32
Bounce rate	0,09	-0,24	0,15	-0,4	-0,54	0,07	-0,29	-0,07
Pages per session	0,21	-0,06	0,82	0,86	0,5	0,15	0,23	0,72
Average session time	-0,25	0,26	0,44	0,63	0,76	-0,18	0,38	0,54

Table 3 Summary statistics of key metrics

	Variable	Impressions	Post engagement rate	Link clicks	CTR	Conversions
Company A	Min	13808	0,0046	68	0,0026	12
	Mean	26776	0,0064	107	0,0042	28
	Max	38019	0,0077	159	0,0051	51
	Std. Deviation	9201	0,0011	34	0,0008	15
Company B	Min	60039	0,0062	204	0,0034	58
	Mean	71262	0,0068	257	0,0036	90
	Max	77351	0,0071	303	0,0039	108
	Std. Deviation	7673	0,0004	42	0,0002	22

		Conversion rate	Conversion rate from clicks	Bounce rate	Pages per session	Average session time
Company A	Min	0,0005	0,1008	0,2255	6,62	286
	Mean	0,0011	0,2608	0,3138	8,14	364
	Max	0,0016	0,4457	0,3833	9,79	482
	Std. Deviation	0,0004	0,1091	0,0494	1,12	70
Company B	Min	0,0010	0,2843	0,6478	2,69	108
	Mean	0,0012	0,3459	0,6703	3,24	128
	Max	0,0014	0,3960	0,6821	3,90	153
	Std. Deviation	0,0002	0,0462	0,0155	0,52	19

The effect of landing page was tested for Company A and the correlations imply that using product category level landing page actually decreases the conversion rate compared to using the platform front page as the landing page. There is also weak positive correlation with number of pages visited and weak negative correlation with average time spent on the website, which implies that when directed to product category page users are more actively clicking on different alternatives, but leave the website faster.

4.2 Analysis of variance

The main analysis of the data was to study if the different configurations of research variables have different impacts on key performance metrics of the advertising campaigns. Data values of treatment groups from the whole time period are simply means of their values from shorter time periods within the study. Thus the differences of those means were studied to identify potential differences in the impact of research variables. ANOVA was selected as the analysis method because it is designed for this kind of analysis of variance, and compared to Student's t-test it requires significantly lower amount of individual tests in a study of multiple variations like this (Armstrong et al. 2000).

The null hypothesis tested for each linear model was: "There is no difference between the means of dependent performance variables across the treatment groups". Tables in Appendices 1-4 present results of ANOVA analyses for Companies A and B and their combined data. It is clearly visible that according to p-values there are not many statistically significant differences between the treatment groups. Analysis results are next discussed in the order of the hypotheses, going first through the effects of discount and previous visit referral variables, then the effect of landing page variations for Company A and finally the interaction effects of all three variables. Results are analyzed for combined data of both companies and also individually for each company to identify the underlying differences between industries.

4.2.1 Mentioning a discount in the ad

Based on the results of the study, mentioning a discount in the ad had a statistically significant effect only in terms of bounce rate ($F=5.1373$, $p < .1$) and average pages visited per session ($F=8.9997$, $p < .05$). This implies that mentioning a discount in the ad only increases the average amount of pages a customer goes through when visiting the website but does not improve the ad performance in other ways. Table 1 shows that the correlation between discount and bounce rate is negative, meaning that bounce rate decreases when a discount is mentioned in the ad.

Looking into company level data the results differ for the companies. For Company A providing a discount had a statistically significant impact on conversion rate ($F=8.7992$, $p < .05$). Also impact on engagement rate ($F=1.9855$, $p < .3$) and click through rate ($F=3.0014$, $p < .2$) had slightly higher F-values, though results were not statistically significant. For Company B it had significant effect on average number of pages per session ($F=44.251$, $p < .1$) and quite high F-values on average time per session ($F=13.893$, $p < .2$), engagement rate ($F=4.7852$, $p < .3$) and conversion rate ($F=4.1521$, $p < .3$).

Combining these findings with earlier correlation analysis implies that in the case of Company A mentioning discount in the ad increases the ad performance. For Company B the effect is the opposite but not statistically significant. Thus hypothesis 1 is accepted for Company A but not for Company B and the combined data set. Difference in results of the two companies explains why the combined data set does not support the hypothesis.

4.2.2 Referring to previous visit on the website

Previous visit referral has statistically significant effect only on average time spent on the website ($F=13.4383$, $p < .05$) and pages visited per session ($F=11.6676$, $p < .05$), implying that it encourages more engaged customers to return to the website. Results for Company A are similar, average pages per session being only metric with significant results ($F=9.4343$, $p < .05$). For Company B the results are not as strong but still support the same findings. Also some effect can be seen on ad engagement ($F=11.8164$, $p < .2$) and click through rate ($F=8.5564$, $p < .3$) of Company B.

Based on these findings and the correlations between variables explained before it appears that referring to previous visit on the website has positive impact on the session duration and number of pages visited per session, but not on the conversion rates. Thus referring to previous visit does not seem to improve ad effectiveness and hypothesis 2 must be rejected.

4.2.3 Landing page

Two landing page versions were tested for Company A. As the results in Appendix 1 present, no statistically significant effects are found for the effect of landing page. Thus hypothesis 3 is rejected. Based only on correlation analysis a slight positive correlation (0.2) can be found between landing directly to product category and number of pages visited per session. A negative correlation can be found between landing to product category page and conversion rates (-0.39) and average time spent on the website (-0.25). Thus it appears that more detailed landing page may cause customers to browse through many pages faster than otherwise, but often with poor results.

4.2.4 Interaction effects

To test hypothesis 4 also interaction effects of the variables were tested. Sample size of Company B was too small to test them and analysis of Company A did not show any significant results, so this chapter focuses on analyzing the results of combined data set, which are presented in Appendix 4.

All interaction effects between variables have statistically significant impact on the bounce rate ($F > 7.4781$, $p < .1$). Earlier I found that mentioning a discount decreases bounce rate but previous visit referral and using a landing page on product category level do not. However this interaction effect implies that when a discount is mentioned in the ad, previous visit referral and product category level landing page used together with discount further decrease the bounce rate.

Second statistically significant interaction effect is combined effect of discount and landing page to average pages visited per session ($F=8.2107$, $p < .05$). Same effect is also present for the interaction effect of all three research variables ($F=20.4623$, $p < .05$). These findings imply that when a discount is mentioned in the ad, having the landing page on product category level further increases the average number of pages visited per session. These results together with effect on bounce rates are linked and thus support each other. However any other interaction effects do not present any significant results of increased advertising performance and thus hypothesis 4 is rejected.

5 Discussion

5.1 Results

Based on the results, the effectiveness of different kinds of retargeting ads varies between industries and thus requires different approaches in different contexts. Only one of the three variables, mentioning discount in the ad, contributed to improved effectiveness of retargeting ads. However, all of the studied variables appeared to have an effect on the amount of time the customers spent on the website after clicking on the ad.

The results show that mentioning a discount in the ad increased the probability of customer clicking the ad and converting to Company A, which is in line with existing literature that suggests that discounts attract more customers and transactions (Lewis 2006a; Kukar-Kinney & Close 2009). This also links to the framework presented in Figure 1, showing that with discounts non-acquired customers can be turned into acquired customers in a greater extent. After that next step is to optimize customer retention process so that eventually maximum CLV is achieved.

However, contradicting with literature the results of Company B did not show any improvements in advertising effectiveness when discounts were mentioned in the ad, but customers spent on average more time on the website. Since the results differ between companies and the ad design was similar for both of them, I assume that the difference is derived from the different industries where the companies operate. This adds to the existing literature by showing that, first, discounts do not always improve ad performance and, second, before drawing any managerial implications from general theories, some industry or company specific tests should always be performed.

Potential explanation for these results could be that as the business model of Company B is based on offering discounted travel packages, customers familiar with the company take discounts as granted, which decreases the attention of any additional discount. This is different for Company A whose business model is not based on discounts that can thus be used as an additional value proposition for the customer. Reason for longer average time spent on the website of Company B after seeing the discount mentioned in the ad could be that it made the customers clicking on the ad more motivated to explore the website trying to find best deals compared to other users on average.

As a general level note, the non-significance on the effect of all research variables on conversion rates could be assumed to derive from much bigger impact of the website design and content. While ads are used to drive traffic to a website, the specific content of the website in the end defines how interested customers are to convert. Thus the effect of ad design on conversion rates is more limited to attracting qualified potential customers to visit the website by providing reliable information of the website content and value proposition. This would also mean that the variables did not have significant effect on affecting which users clicked on the ad. Second probable cause for the similar conversion rates between all ad variations is the very targeted audience segment they all shared. Existing literature argues that one of the biggest factors in ad performance is the effectiveness of targeting (Iyer et al. 2005), meaning that in this customer segment all customers were on average as likely to convert through all ad variations.

Referring to the customer's previous visit to the website did not have statistically significant effects on ad performance. Thus, it seems that at least in these conditions that kind of reference does not improve marketing performance for neither industry. This contradicts existing literature, which argues that more customized and personal ad content should increase ad performance (Ansari & Mela 2003; Slagen 2012). A probable cause for this result is that referring to customers' earlier personal behavior violates their privacy and thus does not encourage them to take actions. Similar results have been presented by Tucker (2013) who found that customers' increased control over the use of their private data increases the effectiveness of personalized ads. Neither of the companies in this study ask permission for or inform about possible use of customers' browsing data for advertising purposes, which can be interpreted as customers having low control over their private data in this case. This is an interesting insight because retargeting technologies are becoming available to an increased number of advertisers (Facebook.com 2014d). Thus, it is important to acknowledge that privacy concerns can be a significant factor in defining ad performance.

Another possible cause for previous visit referral not having a significant effect on ad performance is that the website visitors do acknowledge that they are being retargeted as soon as they see the ad, regardless of its specific content. Thus adding previous visit referral to the ad does not provide any new information to the customer and does not make the ad gain any further attention or make it more appealing.

Previous visit referral did however increase the average time spent on the website for both companies, which is a sign of more engaged and motivated customers (Panalysis.com 2014). A possible explanation for this could be that since the ads were targeted to users who already had visited the website and thus were familiar with its content, only those customers who were genuinely interested in the content clicked on the ad.

Interestingly, the interaction effects of mentioning a discount and previous visit referral as well as mentioning a discount and the type of the landing page had a significant impact on bounce rates and average number of pages visited per session even though previous visit referral and the type of the landing page did not have any main effects. As these interaction effects do not have a significant effect on click through rates or conversion rates, the reason for lower bounce rates cannot be a stricter qualification of customers who clicked on the ad. Thus, it could be assumed that when used together with mentioning discounts, previous visit referral and a more specific landing page increased customers' commitment to browse through more available alternatives on the website.

Specific reasons for the finding must be studied in a more controlled experimental setting where participants can be analyzed in more detail, but one potential explanation is that when referring to customer's previous visit while also mentioning discounts, the customer feels that the advertiser knows about the last visit that did not lead to conversion and is now willing to offer better deals with discounts. This feeling then makes the customer more committed to use more time to browse through multiple alternatives, which decreases bounce rate and increases number of pages visited. These kinds of interaction effects have not been studied in previous literature, meaning that the results provide a basis and motivation for further research.

5.2 Managerial recommendations

The results have several implications that should be considered when designing online retargeting campaigns. First and probably strongest implication is that as retargeting can be a very specific targeting format, also the different ways to improve ad effectiveness can have varying effects and work well in some specific cases but not in others. Thus industry, business model and audience segment specific testing for ad effectiveness with different variables is encouraged. Testing framework used in this study can be used as basis for designing similar tests for any variations in ad content.

Mentioning discounts in the ads can be used to increase ad effectiveness for click trough rates and conversion rates, i.e. attracting larger customer base. However it is important to note that effectiveness can be industry specific, and this study does not consider discounts' effect on CLV. Previous visit referrals can be used to increase engagement level of retargeted customers who return to the website. To translate this engagement into improved conversion rates and profitable actions, the offering on the website must be designed so that returning customers become more interested to convert.

For industries and companies where no improvements in ad performance can be seen when using these variables, it is recommended to not use them. Reason for this is that in this kind of situations mentioning a discount in the ad can only decrease expected CLV of acquired customers, or create frustration if the customer does not find any interesting discounts from the website.

Another important recommendation is that customers should be provided control over how their information can be used for marketing purposes. Without such control or information retargeting ads, especially ones with customized content such as previous visit referral, can be perceived to violate one's privacy, which decreases the effectiveness. Nowadays it is becoming more common for websites to ask permission for, or at least inform visitors about use of cookies, which can help in mitigating this challenge.

6 Limitations and future research

6.1 Limitations

This study focuses on online retargeting on social media platforms, specifically Facebook. Retargeting and native advertising platforms like Facebook are still rather new and developing phenomena on which there is still not much existing scientific research. Due to this, much of the literature used in this study is discussing the important themes from rather general perspective or based on industries and advertising channels different from the ones in this study. This can also affect why many of the hypotheses were rejected, since they were originally formulated based on existing literature. However this situation provides this study a good possibility to provide very up to date results on these new technologies and thus form basis for further research.

Second limitation is also related to research scope. This study is focusing on Facebook as online advertising channel and on two countries in two industries, which limits the generalizability of the results and amount of data available. Results of this study cannot be fully generalized to apply on other market areas, industries or online channels without further research, but on the contrary results from more specific markets provide valuable information of their differences and help identifying that the theories presented in existing literature do not necessarily apply to all cases.

Third, strict industry and market focus due to having only two companies participating in this study restricted the amount of data available. Number of ad variations and thus number of data sets was eight for Company A and four for Company B, providing combined sample size of 12 variations. This set some limits to analysis since for example interaction effects could not be analyzed for Company B due to low amount of data sets. Small sample size may also have decreased statistical significance of results and thus affect the outcomes of the study. However some statistically significant results were found for both companies, indicating that the amount of data was sufficient.

Also since this study was executed by advertising in Facebook and measuring the results and customer behavior with measurement technologies of Facebook and Google, there was no possibility to do interviews or questionnaires of customers' individual perceptions of ads. This limits the possibilities to identify the exact behavioral reasons behind differences in ad performance. For example possible privacy concerns could only be measured by studying how individual customers feel about the ad content. However as the research subjects acted anonymously and naturally in their normal environment and were not aware that they were participating in this study when seeing the ads, the responses are truthful and data is reliable in that matter. From this point of view this study also provides valuable insights for designing further studies to cover these topics.

6.2 Future research

As discussed in previous chapter of limitations, this study provides results related to technologies that are still rather new and have not been studied that much. Due to this there are many topics on which this study provides basis for further research.

First of all to find if the results also apply to other industries, market areas and advertising channels, the tests in this study could be performed with other companies operating in different industries. Similarly other online advertising channels, such as Google or Twitter, could be tested.

Complementing the anonymity and way of users acting without knowing of this study, further research could be done by organizing more controlled studies where test subjects are aware that they are participating to the study and could be interviewed or otherwise tested for more detailed information of their perceptions of the ads. As discussed earlier this kind of studies could provide insights for underlying causes of interaction effects and potential privacy concerns related to using too detailed personal information. (Goldfarb 2013)

This research could also be extended by studying effect of variables that were not tested in this study. As Lambrecht and Tucker (2013) have proposed, important part of retargeting effectiveness is the suitable timing of ad impressions. This study only targeted customers who had visited the websites of the companies during last 30 days, but different retention times could be leveraged to test if ad effectiveness would be better for customers who visited more recently or longer time ago. There are also other attributes of the ads, such as the ad image and call-to-action button, that can affect the performance (Salagen 2012) but were not tested here to keep amount of ad variations feasible.

Since results provided support for discounts improving ad performance in some industries, that could be further studied by testing it with cases where it’s also possible to measure revenue generated by the conversions. That would provide deeper understanding of the effects on the CLV and profitability, which in most cases is the ultimate goal of direct response advertising. Another possibility to extend this result would be to apply customer lifetime approach to test what kind of ad content should be used in relation to items the customer has browsed on the website during last visit. Designing the ad content based on the items browsed before could be one way to increase the relevance of the ad towards the customer.

7 Conclusions

The development of more accurate online retargeting possibilities has improved online advertising effectiveness significantly (Insidefacebook.com 2014; Merchenta 2014). However, the existing research is focusing on online advertising and retargeting on a more general level and does not provide solutions for the actual ad design. To fill this research gap, main research question of this research was "What means of retargeting ads influence the effectiveness of online advertising?" Three variables of Facebook retargeting ad design were analyzed: mentioning a discount in the ad, referring to customer's previous visit on a website and varying the landing page between front page of the website and more specific front page of a certain product category. Especially three findings were highlighted from the results:

1) Of the three variables only mentioning a discount in the ad had an effect on ad performance, and this effect was found only for one of the two companies studied. Thus it was concluded that, supporting existing literature, mentioning discounts in retargeting ads can improve ad performance, but that effect is industry specific.

2) Interaction effects of the three variables, lead by mentioning a discount, were found to lead to more engaged website visitors who browsed through more pages when visiting the website. Thus the variables seem to affect the behavior of customers so that they were more interested in exploring available options, even as the conversion rates did not change. Need for future research was identified for understanding the deeper underlying causes of this behavior.

3) Previous visit referral was found to increase the average time spent on the website, indicating that it either made the customers more engaged or contributed to natural selection of more engaged customers. However, contrary to existing literature, customizing ads for customers with previous visit referral did not improve ad performance in other terms (Ansari & Mela 2003; Slagen 2012). Potential explanations were found from privacy concerns customers might have when ad content becomes too customized.

To conclude, retargeting methods in online advertising channels are still relatively recent innovations and thus not much research has been made on them. Also the methods and underlying platforms, together with their users, are still only adapting to these recent developments and thus more research is needed for understanding what kind of advertising methods work together with these technologies. Similarly more research is required for understanding the major differences between the online advertising methods and their offline predecessors. This study has provided insights for recommended advertising methods to use in online retargeting and basis for future research that can add to these findings and further contribute to general understanding of retargeting in online advertising channels.

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APPENDIX 1. ANOVA results of Company A

	Research variable								
	Reference			Discount			Landing page		
Dependent variable	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)
Engagement rate	1	0.4318	0.5401	1	1.9855	0.2179			
Click through rate	1	0.6956	0.4423	1	3.0014	0.1437			
Conversion rate	1	0.4109	0.55638	1	8.7992	0.04129 *	1	0.2167	0.66580
Conversion rate from link clicks	1	1.1901	0.3366	1	0.9665	0.3812	1	1.0953	0.3544
Bounce rate	1	0.1042	0.7631	1	0.2539	0.6408	1	0.0372	0.8565
Average pages per session	1	9.4343	0.03724 *	1	0.0545	0.82683	1	0.6105	0.47825
Average time per session	1	1.1096	0.3516	1	0.3866	0.5678	1	0.3511	0.5854

Signif. codes: *** 0.001 ** 0.01 * 0.05 ‘ 0.1

APPENDIX 2. ANOVA results of Company A, including interaction effects

	Research variable								
	Reference			Discount			Landing page		
Dependent variable	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)
Engagement rate	1	0.3470	0.5875	1	1.5953	0.2752			
Click through rate	1	0.5600	0.4959	1	2.4161	0.1951			
Conversion rate	1	0.9475	0.5086	1	20.2882	0.1391	1	0.4996	0.6083
Conversion rate from link clicks	1	4.8909	0.2703	1	3.9720	0.2961	1	4.5011	0.2804
Bounce rate	1	0.0438	0.8686	1	0.1069	0.7988	1	0.0156	0.9208
Average pages per session	1	3.6504	0.3070	1	0.0211	0.9082	1	0.2362	0.7120
Average time per session	1	0.8773	0.5208	1	0.3056	0.6785	1	0.2776	0.6913

	Reference*Discount			Reference*Landing			Discount*Landing		
Dependent variable	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)
Engagement rate	1	0.0174	0.9015	1					
Click through rate	1	0.0249	0.8823	1					
Conversion rate	1	7.8202	0.2186	1	0.0039	0.9601	1	0.3985	0.6415
Conversion rate from link clicks	1	9.3034	0.2017	1	2.7566	0.3451	1	3.3784	0.3172
Bounce rate	1	0.1051	0.8004	1	0.1302	0.7796	1	0.4486	0.6243
Average pages per session	1	0.2997	0.6811	1	0.1161	0.7909	1	0.1319	0.7783
Average time per session	1	0.3107	0.6763	1	0.6564	0.5665	1	1.1952	0.4717

Signif. codes: *** 0.001 ** 0.01 * 0.05 ‘ 0.1

APPENDIX 3. ANOVA results of Company B

	Research variable					
	Reference			Discount		
Dependent variable	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)
Engagement rate	1	11.8164	0.1802	1	4.7852	0.2730
Click through rate	1	8.5564	0.2097	1	1.1540	0.4772
Conversion rate	1	1.8813	0.4011	1	4.1521	0.2904
Conversion rate from link clicks	1	0.0507	0.8590	1	1.4101	0.4456
Bounce rate	1	0.5331	0.5985	1	0.2900	0.6855
Average pages per session	1	14.973	0.16100	1	44.251	0.09499 '
Average time per session	1	19.843	0.1406	1	13.893	0.1669

Signif. codes: *** 0.001 ** 0.01 * 0.05 ‘ 0.1

APPENDIX 4. ANOVA results of combined data

	Research variable								
	Reference			Discount			Landing page		
Dependent variable	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)
Engagement rate	1	0.0477	0.8377	1	0.1910	0.6847			
Click through rate	1	0.0455	0.8416	1	0.5031	0.5173			
Conversion rate	1	0.5820	0.4880	1	0.6983	0.4504	1	0,0615	0.8163
Conversion rate from link clicks	1	0.8502	0.4087	1	0.0008	0.9785	1	0,6497	0.4654
Bounce rate	1	0.2642	0.634335	1	5.1373	0.086054 '	1	0,2706	0.630386
Average pages per session	1	11.6676	0.02688 *	1	8.9997	0.03994 *	1	0,226	0.65928
Average time per session	1	13.4383	0.02147 *	1	1.3678	0.30712	1	0,5951	0.48350

	Reference*Discount			Reference*Landing			Discount*Landing		
Dependent variable	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)	Degrees of freedom	F value	Pr(>F)
Engagement rate	1	0.0677	0.8075	1	0.0061	0.9417			
Click through rate	1	0.0178	0.9004	1	0.0061	0.9414			
Conversion rate	1	0.3648	0.5784	1	0.0483	0.8367	1	1.4680	0.2923
Conversion rate from link clicks	1	0.2658	0.6334	1	0.1959	0.6810	1	2.0600	0.2245
Bounce rate	1	9.6072	0.036237 *	1	7.4781	0.052194 '	1	9.1714	0.038840 *
Average pages per session	1	1.4482	0.29517	1	0.2638	0.63460	1	8.2107	0.04568 *
Average time per session	1	1.0563	0.36215	1	0.9629	0.38202	1	2.6696	0.17762

Reference*Discount*Landing

Dependent variable	Degrees of freedom	F value	Pr(>F)
Engagement rate	1	0.1944	0.6820
Click through rate	1	0.3054	0.6100
Conversion rate	1	0.0414	0.8487
Conversion rate from link clicks	1	0.1717	0.6998
Bounce rate	1	25.0209	0.007479 **
Average pages per session	1	20.4623	0.01063 *
Average time per session	1	2.0879	0.22198

Signif. codes: *** 0.001 ** 0.01 * 0.05 ‘ 0.1