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A Strategic Advantage with Behavioral Targeting? How can (and what) firms benefit from personal data-based online marketing strategies

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Abstract

To benefit from the constant increase of on-line sales, firms have been deploying an ever changing set of novel technologies to target specific consumers on-line. The logic behind targeting suggests that in reality there should be different strategies are in effect operating on different sets of consumers in varied ways. For example, the adoption of Behavioral Targeting relies on approaching a low number of potential customers with the aim of achieving high transaction rate and high profitability per transaction. This paper explores: i) whether firms gain a strategic advantage using Behavioral Targeting; ii) how they devise their advertising strategy mix, and; iii) what are the outcomes of their different choices. Our main theoretical insight is that BT and paid search strategies operate on different set of consumers utilizing different logics of revenues generation. We utilize a novel dataset, which allows us to analyze each stage of the transaction process from initial ad viewing to final transaction for multiple advertisement strategies of multiple firms over a period of six years. We find that targeted investments are indeed more effective than traditional advertising investment in reducing costs and enabling better price discrimination, as they exploit better knowledge of a much smaller subset of potential consumers. However, there are two opposite effects when the two strategies are combined: complementarities in reducing overall investment and substitution in transactions generation. These results suggest that the decision of the proper on-line ad strategy mix using ?old? and ?new? technologies is much more important than previously identified.

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Abstract
In order to benefit from the constant rapid increase of on-line sales, firms have been increasing their on-line advertising effort and deploy an ever changing set of novel technologies to better target specific consumers. While more refined targeting has been the holy grail of the industry, the strategic logic behind targeting suggests that in reality there should be different strategies are in effect operating on different sets of consumers in varied ways. For example, the adoption of Behavioral Targeting allows firms to track and identify user preferences and characteristics, supposedly enabling the offering of better match and increasing purchase's probability. Accordingly, this strategy relies on approaching a low number of potential customers with the aim of achieving high transaction rate and high profitability per transaction. Nonetheless, this also, by definition, means that other strategies could usefully be employed to engage the rest (in effect over 99%) of the customer population. Nonetheless, the literature so far has not differentiated between different logics employed by different on-line advertisement strategies and instead checked whether each strategy is more or less effective assuming a linear logic of higher transaction rate always equal better, and disregarding the simple fact that the better the targeting the more potential customers are not even engaged. As a first step in broadening our understanding of the impact of on-line advertisement strategies on the new digital economy this paper explores: i) whether firms gain a strategic advantage using Behavioral Targeting; ii) how they devise their advertising strategy mix, and; iii) what are the outcomes of their different choices. Our main theoretical insight is that BT and paid search strategies operate on different set of consumers utilizing different logics of revenues generation. To do so we utilize a novel dataset, which allows us to analyze each stage of the transaction process from initial ad viewing to final transaction for multiple online advertisement strategies of multiple firms in twenty different industrial sectors over a period of six years. We find that targeted investments are indeed more effective than traditional advertising investment in reducing costs and enabling better price discrimination, as they exploit better knowledge of a much smaller subset of potential consumers. However, there are two opposite effects when behavioral and traditional investments are combined: complementarities in reducing overall investment and substitution in transactions generation, these occurs since the logic of generating revenues in traditional advertisement relies on reaching a much larger subset of consumers, assuming lower rate of conversion to transaction at a lower product price. These results suggest that the strategic crafting of the proper on-line ad strategy mix using "old" and "new" technologies is much more important than previously identified.

Introduction

Online sales have become an essential and rapidly growing revenue stream for many businesses. In the United States alone annual online sales are estimated to be $57 billion (U.S. Department of Commerce 2012). Not surprisingly online spending accounted for 18% of all advertising expenditure in 2012, and its share of total sales is only expected to grow thanks to new technologies and the spread of 'smart' mobile devices (Hallerman 2008).[1] Accordingly, devising an online advertising strategy has become one of the most important managerial decisions.

Online marketing promises to solve one of the biggest challenges faced by marketers – ensuring that they target the correct set of consumers in the most cost effective ways. Using several techniques, commonly referred to as Behavioral Targeting (hereafter BT), companies can now use online tracking technologies, and various other sources of personal data, not only to target their products' advertisement to an ever more precise set of potential customers, but also to measure, almost instantly and more accurately than ever before, the impact of their various online strategies..

Knowledge has supposedly become the new "gold" in our so-called "age of big data" (Nissenbaum 2004; World Economic Forum 2012).[2] This analogy should remind us that data, similarly to gold, requires mining and processing before it becomes a valuable and usable asset. In the context of online advertising, the low (sometime free) cost and easy availability of finely refined personal data, which can be analyzed, allows for a new investment strategy which has been defined as "behavioral targeting". This strategy allows advertisers to precisely tailor their online advertisements to buyers' needs and preferences. On the face of it BT should be more effective than traditional online advertising since targeted media should reduce wasted advertisement by focusing on profitable consumers interested in purchasing a specific product, instead of reaching a broad and generic audience. Companies that access user information can gain a competitive advantage against competitors by using this knowledge to define customers, markets and product characteristics at lower costs. Accordingly, utilizing a BT strategy entails approaching a

[1] http://www.zenithoptimedia.com/zenith/ (last access 12/09/2012).
[2] Perry Rotella, "Is data the new oil?". Forbes 04/02/2012.
http://www.forbes.com/sites/perryrotella/2012/04/02/is-data-the-new-oil/ (last accessed 05/16/2012)

specific, preselected, smaller, subset of consumers, with the expectation of higher rates of conversion to transactions, and the ability to extract higher prices on average vis-à-vis more traditional strategies that relies on approaching a larger number of consumers assuming lower transaction conversion rates at lower prices.

While a growing steam of literature has significantly advanced our understanding of the impact of different online advertisement strategies on consumer behavior and their intent to buy, we still have little knowledge regarding BT's profitability, competitive advantage, and, at least as important, its interaction with other strategies within a comprehensive online marketing campaign. Analyzing a novel proprietary dataset we examine BT's actual return of investment compared with other online advertising strategies, as well as ability to allow more refined price discrimination, and hence, not only increase conversion rate but also profits per sale. In addition, we inquire into the critical question of using joint strategies and offer answers as to whether, how, and when BT complements or substitutes other online advertisement strategies.

Existing literature on behavioral targeting has either used survey data or single firm cases to analyze individual user preferences and to address privacy concerns related to the collection of personal data online (Manchanda, Dubé et al. 2006; Goldfarb and Tucker 2011; Goldfarb and Tucker 2011; Lambrecht and Tucker 2011). Further, the individual consumer was always treated as a generic consumer to which either a different treatment (that is particular online advertisement strategy) was given in order to check the efficiency of said treatment under different conditions, or as a group where the propensity to buy is set and the main effect of on-line technology is in better locating those who are already pre-disposed to buy. To our knowledge this paper is the first in two important ways, analyzing the actual investment data of multiple firms running multiple campaigns before and after the advent of BT, as well as the first in assuming that each strategy operates on a different set of consumers and employs a different logic of revenue generation, each of which more appropriate under different conditions. We analyze the data at the firm per week level to estimate the impact of BT on different performance measures such as purchase conversions and revenues. We also study the joint effect of BT and traditional advertising in order to estimate the simultaneous impact of both investments. Our contribution speaks not only to academics but to managers and policy makers. On the one hand, it helps the understanding of how the availability of users' private information can shape and affect portfolios of advertisement investments; on the other hand, it allows a refined empirically-based discussion of the issues regarding privacy and the use of individualized data.

The paper proceeds as follow: the next section defines BT as investment strategy. We then review existing literature, introduce our hypotheses, and define our data and methodology. We proceed to describe the empirical results before concluding.

Definition of behavioral targeting strategy

Online advertisement is less than twenty years old. Its origins can be traced to 1994 when HotWired, a web magazine, sold the first online banner to AT&T (Kaye and Medoff 2001). However, in less than two decades the field has changed tremendously. If in 1994 the public illusion was that the Internet will offer complete anonymity and freedom from identification to users, the opposite has happened. Nowadays, it is possible to collect more data on peoples' activities than ever before by collecting detailed histories of their online activities including web research, activities on visited web sites, and even product purchases.

Although there are mechanism and strategies to tailor advertisement on television (Gal-Or, Gal-Or et al. 2006), the level of personalization and the richness of data collected online cannot be offered by any other media outlet, such as TV or newspaper, since the ability to increase the specificity of advertising content for these outlets is limited by logistic costs (Bertrand, Karlan et al. 2010). The advent of internet and tracking technologies has made both the data collection easier and its use cheaper, for companies that intend to personalize their advertisements. It follows that the ability to precisely target users can be imagined as a reduction in searching and identification costs for advertisers. The internet has made it easier for firms to offer personalized products and promotions (Ghosh, Dutta et al. 2006; Zhang and Wedel 2009).

The data collected can be used to target advertisements to people based on their behavior, ergo the name behavioral targeting. The ability to tailor online advertisement is possible thanks to three important changes. First, firms today have much better knowledge on users and their preferences (The Economist 2011). Every time individuals browse a website, search keywords on web engines (e.g. Google, Bing and Yahoo) or purchase any product online, they leave traces of their activity, and professional data miners use this information to create precise profiles based on past purchases and individual characteristics. The second reason why firms have better knowledge is the advancements in technologies facilitating online tracking. Goldfarb and Tucker (2011) identify these technologies as web bugs, cookies, and clickstream data. Internet and tracking technologies allow advertisers to have a detailed knowledge of internet users and to target advertisement to specific segments within a market. Third, there are now a fast growing number of firms, specializing in the collection and analysis of user data on large scale.[3]

The power of BT relies on the ability to parse data from online users. It represents an incredible reduction in segmentation and feedback costs and in fact, companies can even exploit personal information to refine their products and personalize their offers. This strategy has benefits for both firms, which should reduce their inefficient advertisements, and for users, who should receive more attractive offers. While data collection has been made easy thanks to advancements in technology, processing and analyzing this data require internal capabilities to correctly identify and segment customers, tailor the most relevant content to them, and deliver these targeted advertisements across a range of digital channels and devices.

However, the use of this data raises privacy concerns and it may generate a possible tension between profit-seeking strategies and the protection of user privacy. For example, if a user is searching for a new laptop, there is a higher probability that she might be displayed advertisements about computers and their accessories. While those ads may prove useful for a potential buyer, and therefore, may increase

[3] From the point of view of advertisers BT has already proved profitable, since companies pay a premium price over standard online advertising strategies to implement a BT strategy because the promised higher conversion rates from ad into a sale. For instance, Beales (2010) finds that the price of targeted advertising is 2.68 times the price of untargeted advertising.

the chance of purchasing by said user; she has never granted permission to collect and use her information. Clearly, privacy concerns could limit the adoption of BT. Turow, King et al. (2009) and Wathieu and Friedman (2009) document that customers are concerned about their privacy, and they are more likely to resist tailored advertisements.

BT advertising can be studied as an example of how firms use and exploit user data collected through new information and communication technologies. Goldfarb and Tucker (2011) point out that the use of this information needs to be distinguished between “targetability” and “measurability.” In the first case, consumer data is used to determine the likelihood of being influenced by an ad. Measurability, instead, refers to the ability to evaluate the advertisement success and efficiency through the collection of browsing activity data. The recombination of this information allows online advertisers to perform market experiments that expose only some customers to a specific ad, and then compare the behavior between those who saw the ad and those who did not.

Literature review and hypotheses

Our paper relates primarily to the stream of literature on the effectiveness of online advertising and targeting. Here there has been great advancement in the last few years, for example, a recent paper by Goldfarb and Tucker (2011) has shown the trade-off between online and offline media, and Manchanda, Dubé et al. (2006) show how ad placement affects the repetition of purchases. In addition, we know much more on how the length of exposure affects the impressiveness of an ad (Danaher and Mullarkey 2003) and how search results affect advertising (Yang and Ghose 2010). Despite the interest in online advertising, there is still a lack of empirical research on the effectiveness of BT on firm performance. For instance, Tucker (2011) finds that personalized ads are effective in boosting product demand, however, their effect is negatively mediated by privacy concerns. Similarly, Goldfarb and Tucker (2011) study how targeting can affect buyers’ intention to buy. Their results confirm that when advertising matches the website content it is very effective in increasing the purchase intent. However, when ads match the website content and, simultaneously, are obtrusive, they reduce the willingness to buy. This limitation is probably related to privacy concerns, since the negative effect is stronger for people that refuse to share their personal data.

In contrast to prior research, our study focused on two issues, first, it focuses on evaluating how firms can benefit from the use of personal data in terms of higher performance. User information may represent the source of competitive advantage for companies that are: i) able to reduce the amount of "wasted" advertisement by targeting specific and more profitable users; ii) offer differentiate pricing so as to maximize the revenues of each transaction from different customers. The ability to tailor advertising on user preferences and needs should increase both the probability of a purchase, and the ability to price at the maximum said customer would be willing to pay. Secondly, our study highlights the problems of defining effectiveness, and hence, better performance, solely on the ability to identify ever more precisely a very small subset of consumers who are highly pre-disposed toward purchase. Consequently, we offer a first step in rekindling the debate on the proper strategic mix of different on-line advertisement technologies, each of which employ a different logic of extracting surplus from consumers.

There are several mechanisms in support of the argument that BT has higher effectiveness. First, advancements in new tracking technologies reduce the cost of gathering information regarding product and consumer characteristics. Firms are able to access a vast amount of data on consumers at a very low cost, almost zero, therefore reducing the uncertainty associate with new markets, products and strategies. Second, the availability of information reduces market uncertainty on consumer's needs and product characteristics necessary to achieve a dominant market position. Finally, companies may adopt price discrimination as result of the new targeted strategy. Firms are able to precisely segment the market; as a result, consumers may pay a higher price for a product that better meets their needs. Based on these mechanisms, our empirical analysis should find BT to be a more effective strategy compared with traditional online advertising with regards to both sale generations per display (conversion rate) and price discrimination.

Additionally, BT represents a new innovative strategy available to companies involved in online advertising and it is important to understand how companies manage their new set of strategy choices to obtain the highest benefit from their investments. However, the interaction between BT and other strategies is unclear and we have a dearth of empirical research on this subject. On the one hand, BT may complement and reinforce traditional advertising by increasing consumer awareness; on the other hand, it may have a substitute effect since it increases the ability to focus on very narrow and specific market segments and it may reduce the amount of unsuccessful advertising. While substitutability is certainly plausible, complementary relations may be expected as well since advertisers often adopt several advertising strategies simultaneously. The ability to integrate different strategies in order to exploit their interactions requires an effective media planning, the exploitation of internal capabilities and understanding market needs (Schultz, Tannenbaum et al. 1993)

Firms may struggle in developing an effective media strategy because they are unable to identify consumer segments, therefore, they could benefit from BT thanks to its targeted focus and the ability to offer specific products to particular consumers. On the one hand, consumers who are already predisposed towards a specific product have a higher probability of buying; therefore targeting a specific segment can be more profitable than targeting a generic one. For instance, monopolistic firms are better off by targeting consumers which already want its product. In addition it was found that the level of general advertising falls with targeting, and this result implies that BT can substitute for general advertisement (Esteban, Gil et al. 2001).On the other hand, consumers who do not have strong preferences may choose to buy a competing product; it follows that without a more general advertising effort these consumers may be lost.

Based on existing results on product information and pricing, BT may substitute for traditional advertising investment: firms have higher incentives to invest in tailored advertisement and reduce their investment in traditional advertisements. The underlying reason is the reduction of “wasted” advertisement: companies can focus predominantly on profitable customers through user specific offers instead of relying on a broad and undefined strategy like traditional advertising.

Conversely, traditional advertising can benefit from feedbacks and information generated by the targeted strategy. The deeper knowledge on users generated by BT should favor the redefinition of traditional advertising. In other words, the recombination of knowledge generated by targeting advertisement should increase the understanding of existing and potential users. It follows that BT may complement traditional advertising by providing information feedbacks from users. Through the adoption of targeted advertisement, firms have new ways to reach their desired audience. This feature can complement traditional advertising which are often based on placement (e.g. web-site banners) and keywords. Under this view, BT may reinforce existing advertising strategies and enhance their effect; therefore, targeted ads may be complementary to traditional advertising.

To see which of these logics prove stronger in reality we set to check if, and under what conditions, BT complement and/or substitute traditional online advertisement strategies.

Data and Methodology

The online purchasing process

To understand the impact of advertising strategies on firm performance, it is important to understand and study the online purchasing process. The investment decision for an online campaign is determined by the number of advertisement displayed throughout the internet. As in the real world, companies pay to advertise their products, the strategic choice is whether to use a BT approach or not. In the former case, advertisements are displayed in specific websites and only to a subset of users who were identified as already having stronger preferences for the advertised product. In order to buy a specific product; internet users follow a process spanning from viewing of an advertisement to actual product purchase. Fig.1 summarizes the online purchasing process and shows the linear relation between the different stages.

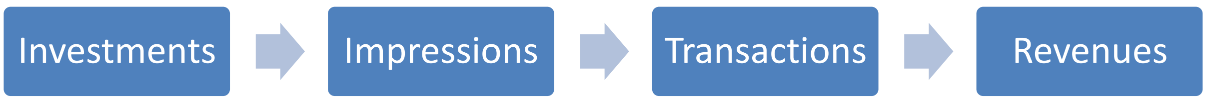

Fig.1. Online advertising purchasing process

First, firms buy online advertising space to increase the visibility of their products and campaigns. Investments mainly focus on two advertising channels: traditional advertising and behavioral targeting. The former reaches a large set of internet users without differentiating among them, while the latter targets a small specific group of customers defined by precise characteristics.

Second, once users are exposed to an advertising campaign through ads impressions (e.g. pop-ups, links and banners) they either decide to buy the product, thus generating a transaction, or they can ignore the ads. The number of transactions is influenced by the original advertising investment choice: in BT the assumption is that impressions have an increase probability of leading to a purchase because they offer a product that meets the preferences of a specific subset of customers. Traditional advertising generates transaction by reaching out to a larger volume of users in the hope of catching a few. The main difference between the two advertising strategies is the reliance either on a small but well defined niche of customers or on a broader and less defined group of internet users.

Third, once transactions are completed they generate revenues for the company; however the source of revenues highly depends on the advertising strategy adopted. BT advertising focuses on a smaller number of transactions, but allows companies to exploit higher willingness to pay. In other words, companies can price discriminate among their customers thanks to the detailed data availability. Conversely, general advertising is directed to large audiences without precise characteristics, for this reason, companies are not able to charge higher prices, thus reducing their ability to price differentiate.

Consequently, by looking at the purchasing process, we quickly realize that the two advertising strategies rely on two different mechanisms, one based on large volumes and low customization while the other exploits small volumes and high level of tailoring. It follows that in order to understand firm performance it becomes crucial to understand both the effectiveness of each strategy as well as their joint effect, and hence, the managerial implications of different choices.

Data

Our dataset consist of data on 3,889 firms, active in 20 different industrial sectors, which invested in multiple online advertising campaigns between 2006 and 2011. This proprietary database is unique and contains a total of 237,911 weekly observations.[4] The data includes online advertising investment decisions among several strategies (namely traditional advertising, BT, and organic search) and different measures of firm performance (e.g. clicks, impressions, conversions and revenues).

Since data on behavioral targeting starts from 2009, we have to limit our estimation to a sub-sample of our dataset. First, we identify all the firms that have invested at least once in BT between 2009 and 2011; second, we create a control group which consists of companies without targeted investments to account for potential endogeneity. Our main statistical method is the Coarsened Exact Matching (CEM) (Iacus, King et al. 2012). This methodology assumes that after stratifying the data to account for the distribution of observed exogenous variables, the endogenous treatment (investment in BT) behaves as randomly assigned. Iacus, King et al. (2012) describe several advantages of CEM. First, it is easier to implement than propensity score balancing. Second, CEM does not rely on any modeling assumptions to estimate regression parameters. Finally, Monte Carlo tests and comparisons to experimental data suggest that CEM outperforms alternative matching estimators that rely on the same assumption of exogenous treatment conditional on observables.

In our dataset, we match firms that invest in BT with companies that have only focused on traditional advertising. Our aim is to create a comparable control group to estimate the benefit gained by the adoption of the new strategy. This allows comparing companies that only differ in the adoption of BT advertising. The matched observations show comparable values in advertising costs, number of impressions, number of weekly campaigns, number of search engines and firm size. We also impose an exact match on the industry and the month and year of investment to control for possible time and product effects. Our empirical strategy allow us to study the process of online advertising from the consumers'

[4] Access to this database has been generously provided by a well-established online marketing company with worldwide operations.

clicks to the revenues generated, both at its entirety and at each stage. By doing so, we can study the impact of BT in details and compare its effects to traditional advertising. To deal with observations equal to zero, we compute our investment variables as ln(1+x), thus the estimated marginal effects can be interpreted as elasticities.

We use a straightforward panel specification to test for our hypotheses across the online purchasing process. Equation 1 reflects our empirical model for firm i at time t:

(1) $$Perf_{it} = \alpha_1 BT_{it} + \alpha_2 Traditional\_ads_{it} + \alpha_3 BT_{it} * Traditional_{ads_{it}} + \alpha_4 Controls_{it} + \alpha_5 X_i + \varepsilon_{it}$$

Where $Perf_{it}$ represents one of the measures of firm performance described below, BT_{it} and $Traditional\_ads_{it}$ proxy for our variables on behavioral targeting and traditional advertising. We also include several controls and firm level fixed effect (X_i).

In each specification of Equation (1), the difference between the coefficients α_1 and α_2 tells us whether behavioral targeting is more efficient than traditional advertising. In other words, we study the impact of the two strategies in each step of the purchasing process to determine which underlying mechanism has a bigger impact.

The sign of the coefficient α_3 reflect the joint relationship between BT and traditional advertising. If the sign is positive, it suggests that these two mechanism complement for each other, in the sense that firms can experience synergies from the adoption of multiple online channels. Conversely, a negative sign provides support for a substitute relation; firms can experience higher gains by focusing only on one of the two strategies studies in this paper.

Main Variables

We focus on two different investment strategies to test our hypotheses: paid search and BT. Paid search advertisement matches keywords entered on search engines: companies pay to facilitate the display of their ads on web engines when their chosen keywords are searched for. BT refers to the strategy of selecting specific market segment and tailoring advertising campaigns to consumers' preference.

To measure consumers' demand, we use two different proxies. First, impressions are defined as the numbers of ad views on websites used by the focal firm during their campaigns. Our measure reflects the count of total ads displayed per week. Second, we include the total number of clicks that ads receive during each week. When firms invest in paid search strategy, clicks are on average more than 30000 per week compared to the 5700 of BT, which is in line with the idea that traditional advertising relies on larger volumes than BT

We proxy investment decisions by using the weekly expenditure for advertising cost. Our variable equals the amount of dollars paid to display an ad on a website. It is important to notice that in our dataset, cost represents the actual cost the intermediate marketers pay to display the ads, not the total cost to the firm. The average weekly cost for paid search strategy is about $22,000, while the investment in BT is just below $18,000. The difference in investment between the two strategies is not statistically significant, suggesting that there is no systematic investment pattern in favor of one of the strategies.

Three variables are used to measure the performance or the investment decisions: transactions, revenues and price. Transactions are defined as the actual number of online purchases made by internet users. Our variable reflects the quantity of products sold weekly through internet advertising. Our second variable reflects the total income generated by online campaigns, the variable revenues represents the dollar amount generated by online transactions. Finally, we define our last variable, price, as revenues divided by transactions.

Controls

We control for several other factors. First we include variables on Natural search results, also called organic search. Natural search refers to those listings on search engines that appear simply because of their relevance to the search keywords; in contrast to other forms of advertising investments, Natural results are of no cost for companies. It is important to notice that the number of impressions and costs are missing for natural search due to the intrinsic characteristic of this advertising strategy. In addition, we include the total number of campaigns run by each company per week. Firms relay on several websites to implement their advertising campaigns, of which search engines are crucial to redirect customers to specific pages. Accordingly, we include the number of search engines used by each company. Search engines rank their advertisement links based on their position on which they appear on the webpage; as such we include the rank variable in our regressions. We include dummy behavioral targeting to identify those firms that invest in targeting advertising. We use this variable to identify our treated group compared to the control one.

We control for industry sector, our firms operate in twenty different industries. The largest industry is "computer products" which represents about 10% of our sample, "automotive" follows with 9% and "telecommunication" and "retail" represent 8% and 7% of our observations, respectively. We include industry dummy variable to control for possible product specific characteristics: certain products may be easier to sell online (e.g. automobile and vacation packages) compared to others (e.g. fresh product and sodas). Finally, to take into consideration possible time effects we include both year and monthly dummies, by doing so we also control for the impact of major event such as Christmas, Thanksgiving and sport events. Table 1 reports summary statistics while Table 2 reports the correlation matrix.

< Insert Table 1 and 2 here>

Results

We report the results of our estimations and the marginal effects of our variable of interests in the following tables.

First, we analyze the first step of the online purchasing process; we focus on the impact of clicks and impressions on the firms' investment decision. Table 3 regress advertising costs on number of clicks and number of impressions. By definition higher levels of impressions and clicks increase total advertising cost, however firms are able to gather consumer information at a lower cost when they rely on targeted advertising. The aim of these regressions is to understand the drivers of advertising cost investments. Investment costs are determined by two factors: number of impressions and number of clicks. Firms bid on numbers of impressions to display their campaigns on specific websites, therefore the number of impressions a company is able to secure reflects the investment in advertising. Similarly, total costs are determined by the number of clicks: firms pay for every user that clicks on the advertised link. Our results confirm that the marginal effect of both strategies increases the advertisement total cost; however the cost increase due to BT is lower than that of paid search. Specifically, 1% increase in paid search impressions leads to a 32% increase in total cost while behavioral targeting impressions increase cost by 20%. Similarly, total cost increases by about 60% after a 1% increase in paid search clicks while behavioral targeting clicks lead to a 24% cost increase. These results confirm that BT increases costs less than traditional strategies. Thanks to advancement in tracking technologies, customers are precisely identified thus reducing market segmentation costs.

In addition, we focus on the interaction between our two main variables. The object is to study potential complementarities and scope economies between BT and traditional advertising. The negative interaction term suggests that both strategies are able to create economies of scope in reducing costs. Companies investing in both strategies can exploit the wide reach of traditional advertising and the precision of BT to find an optimal balance in their investment portfolio. This result suggests that BT and paid search are complementary strategies in reducing costs.

<Insert Table 3 here>

Table 4 reports our estimation of the next step of the purchasing process, we regress the total number transactions on clicks, investments costs and product prices. We adopt three measures as independent variable to describe three different mechanisms. First, we focus on the relation between final purchases (transactions) and clicks: users that are exposed to advertising campaigns need to click on the ad in order to buy the advertised products. We try to understand if an increase in the number of clicks is associated with higher level of transactions. Second, we describe the same mechanism by focusing on the relation between transactions and the advertising investment per strategy. Third, the final purchasing decision may be affected by the price of the product. Through BT, companies are able to personalize their offer and adopt price discrimination: companies are able to charge higher prices and appropriate customers' willingness to pay. However, high prices may also discourage users from completing the online transaction.

Model 1 adopts clicks as proxy for paid search and BT strategies; the marginal effect of traditional advertising is higher than that of BT, suggesting that paid search is able to generate more transactions than BT. Similar results are confirmed in Model 2 in which we use the cost for each strategy as main independent variables. An increase in paid search investment generates more transactions than an increase in BT investment. Those results corroborate our argument about the advantages and limitation of BT. While BT is much more effective in generating revenues from a small well defined group, any attempt to enlarge the group suffers from rapidly declining marginal effects. On the other hand paid search has a much lower efficiency but much less declining marginal effect if investment is increased.

To further test the difference in customers' base and their characteristics we study the impact of price on transactions; economic theory suggests that an increase in price would reduce quantity sold. The predicted negative effect is only found for paid search price, transaction reduces by 70% when price increases by 1%. Conversely, we do not find a significant effect of the BT price on transaction. These results again support our argument about the different logic of surplus extraction behind the two strategies. BT allows the firm to focus on generating the maximum number of transaction for the highest possible price from a small, well defined in advance, subset of consumers. Traditional advertisement, allows firms to approach a significantly larger set of consumers with the aim of generating small ratio of transaction for lower price, but on much larger scale.

As described in the method section, we estimate the interaction term between our main independent variables, BT and traditional advertising. We find support of a substitution effect between BT and paid search. It suggests that companies try to reach customers with higher willingness to pay through BT in order to maximize the opportunities of a transaction while paid search is used to focus on a broader group of users that excludes those targeted by BT. As show by our results on prices, the BT strategy can charge higher prices than traditional advertising and adopt price discrimination among different customers, thus the importance of separating the two different groups of users. it follows that our analysis supports the argument that BT and paid search are substitute strategies in generating transactions.

<Insert Table 4 here>

The next set of analysis focuses on the revenue generation process; in particular it studies the impact of transactions and price on total firm revenues (Table 5). The marginal effects in Model 1 show that BT transactions generate more revenues than traditional, although the difference between the two strategies is only marginal. In fact, the difference between BT and paid search represents only a revenue increase of 1.3%. Similarly to the previous regressions, this result can be explained by the different strategy implementation mechanisms: traditional advertising generates high volume of transactions because of the larger customer base and it relies on large number to generate revenues with lower probability per transaction. On the other hand, BT relies on higher level of efficiency in both conversion and price. This mechanism is reflected by the average rate of conversion per strategy: only 2% of paid search impressions transform into a purchase while 32% of targeted impressions result into a final purchase. In Model 2 we use prices as independent variable proxy for our strategies to further understand and analyze the efficiency of BT. While tradition advertising price has no effect on revenues, BT price has a strong and positive impact on revenues, an increase of 1% in price leads to a 26% increase in revenues, everything being equal. Combined with previous results of the impact of price on transaction, these results emphasize how firms are able to exploit users' information to extract consumer's surplus through the adoption of BT strategy.

<Insert Table 5 here>

Finally, based on previous results, we question whether the adoption of paid search or BT has a significant impact on the average price of the product sold. In Table 6, we use the average firm price as dependent variable. In all our models we don't find any joint effect between our strategies, suggesting that each strategy has a linear effect on prices. In Model 1and 2 we assume that transactions and clicks proxy for the product demand while costs (Model 3) represent the investment of implementing a specific strategy. We find that there is an average significant impact of 4% upward on the average price per transaction across all the specifications. Traditional advertising is comparable to targeted advertising only in Model 2 when we proxy product demand by using clicks.

<Insert Table 6 and 7 here>

The ability to set higher prices using BT allows firms to extract higher value from internet users. Companies exploit higher willingness to pay when customers are offered a product that matches their needs. In Table 7 we perform three different mean tests to compare the average price for BT and paid search. We compare the averages with three different samples. First, we compare the prices only for those companies that invest in BT. Paid search price averages about $222 per product and it is significant lower than the average targeted advertising which equals $243. Second, we include our control group and we find similar results: paid search price is $27 lower than BT. Finally, we run the same mean test without restricting the sample and the difference between the two prices increases; in fact, price using BT is about $50 higher than traditional advertising price.

These results should not come as a surprise for anyone who followed the pricing strategies adopted by online websites such as Orbitz.com, who offers higher price to Apple users.[5] According to Orbitz.com worldwide CEO, Barney Harford:

> "Just as Mac users are willing to pay more for higher-end computers, at Orbitz we've seen that Mac users are 40 percent more likely to book four- or five-star hotels ... compared to PC users, and that's just one of many factors that determine which hotels to recommend a given customer as part of our efforts to show customers the most relevant hotels possible."[6]

The Orbitz example shows how companies can take advantage of the high availability of customers' data and exploit it in their favor. By targeting specific consumers, companies are able to reduce their costs and extract consumers' surplus by charging higher prices, significantly increasing their profit margins. We summarize our main finding in Table 8. The adoption of BT has a clear positive impact on firm performance across different measures; however, it has two limitations. First, it can be used only a small subset of all consumers. Secondly, its implementation depends upon the availability of detailed data on consumers collected through several tracking technologies. Very often, data is collected without an explicit consent of internet users, raising important privacy concerns (Turow, King et al. 2009). Users tend to reject ads that excessively exploit their data or when they are excessively obtrusive (Goldfarb and Tucker 2011).

<Insert Table 8 here>

Conclusion

While there is a growing theoretical literature that discusses BT and its effects on privacy (Acquisti and Varian 2005; Fudenberg and Villas-Boas 2006; Goldfarb and Tucker 2011), empirical results on the choice of implementing BT, and its interaction with other strategies are still scarce. We attempt to fill this

[5] "On Orbitz, Mac Users Steered to Pricier Hotels", The Wall Street Journal, http://online.wsj.com/article/SB10001424052702304458604577488822667325882.html (Last accessed on 07/25/2012).

[6] "Mac Users May See Pricier Options on Orbitz", ABC News, http://abcnews.go.com/Travel/mac-users-higher-hotel-prices-orbitz/story?id=16650014#.UBCJHaNdeSo (Last accessed on 07/25/2012)

gap by studying companies are able to benefit from the exploitation of consumer information. We are able to focus on different stages of the advertising process and compare two different strategies, paid search and behavioral targeting.

First, our results confirm that BT generates higher conversion rate than traditional advertising and it allows for price discrimination. These results support the logic that BT can be seen as a profitable and innovative strategy which can reduce “wasted” advertisements by tailoring online campaigns to consumer preferences and needs, and increase the profit margins of firms by allowing refined price discrimination. We also find that BT increases costs less than paid search. The power of behavioral targeting relies in the ability to parse data from online users, it represents an incredible reduction in segmentation and feedback costs, in fact, companies can exploit this information to refine their product and personalize their offers. The ability to track and identify costumers reduces segmentation cost and information asymmetries, firms can easily identify more profitable customers and target their ads on their characteristics.

However, our results also shows the limits of BT, namely the fact that by definition it works only on a very well defined in advance small subgroup of total potential consumers, and suffers from rapidly declined marginal effects if this group is enlarged. In addition, our results suggest that when companies invest in both BT and traditional advertising they can exploit potential complementarities in reducing their cost. The combination of both types of investments reduces advertising costs by generating possible economies of scope: firms can focus on customers with higher propensity to buy through BT and, simultaneously, they can reach a large number of generic customers by investing in traditional advertising. Companies can leverage the efficiency gained through the contemporaneous combination of these two strategies to choose market segment associated with their ads. Through BT, firms have another means to expand their audience; this feature may complement more traditional advertising strategies based on keywords, especially when keywords are not well defined and placements are limited. Based on our results, the two strategies show a substitute effect in generating transactions. This result is not surprising, since firms focus on different users segments. On the one hand, customers exposed to BT advertising have higher willingness to pay and they are more lucrative users because companies can adopt price discrimination. On the other hand, traditional advertising reaches a broad but generic group of customers well distinct from BT users, thus substituting for BT advertising.

These results have important managerial implications. Companies can exploit the detailed information gathered through BT; private data may provide useful feedbacks to improve their products and their traditional advertising strategy. However, as profitable and efficient targeting strategy seems, there may also be some disadvantages that companies cannot underestimate. In particular, privacy concerns should not be taken lightly, previous studies have shown that if online consumers start to see ads show up in unexpected or unwanted places, they may consider them as obtrusive and/or invasive (Goldfarb and Tucker 2011). When targeting is in place, companies need to be vigilant in protecting their brand equity by being transparent to their audience and reducing the risk to focus on market niches too small to be profitable.

While there are important implications for practitioners; our results also open important questions regarding privacy policies. In fact, there may be the risk of an excess data collection. Online users may raise concerns about the use of their personal data. While more relevant and personalized ads are offered through BT, people may feel uneasy about companies keeping tracks of their online behavior (Beales 2010; Goldfarb and Tucker 2011). However, while it is important to protect the information of individuals, policy makers should keep in mind that information is increasingly becoming ubiquitous and source of important streams of revenue for companies involved in online advertising. Goldfarb and Tucker (2011) have found that banner ads have experienced reduction in effectiveness in Europe where privacy laws have already been implemented; therefore privacy regulation may affect the development of innovation in the space of internet advertising. If privacy laws are too restrictive they may reduce the incentive to invest in innovative strategies such as behavioral targeting. Therefore, privacy laws are a trade-off between consumer privacy and firms' profits: on the one hand, policy makers need to regulate the right to privacy (Rubenfeld 1989) while on the other hand, they should also consider the economic impact on the online industry.

Concluding, we contribute to existing literature on online advertising and BT (Acquisti and Varian 2005; Iyer, Soberman et al. 2005; Goldfarb and Tucker 2011). While there is an extensive theoretical literature on behavioral targeting and its implications for privacy and performance (Acquisti and Varian 2005; Fudenburg and Villas-Boas 2006; Hermalin and Katz 2006), empirical research on behavioral targeting is still limited. We offer a rich empirical estimation on the efficiency of BT strategy compared to paid search advertising, as well as offering first insights into the ability to strategically mix the usage of both strategies to reach superior results. As we view our inquiry as an exploratory attempt to rekindle the debate about the interaction efforts of different online advertisement strategies, and the way in which we define which of them is "better." We hope our paper would serve to open an array of future research. For strategic management we specifically think it is important to understand how firms decide to allocate their media budgets between different strategies. The strategic investment in BT advertising may be affect by differences among industrial sectors: firms that operate in different industry face different product characteristics, product awareness and consumers' propensity to buy which can affect the decision to invest in BT. Additionally, privacy concerns generate a possible tension between profit-seeking strategies such as BT advertising, and the protection of users' privacy. However, our results suggest that the dichotomy displayed in the literature so far (more protection less innovation) might not be true. Instead the impact might be more nuanced where different kind of privacy protection leads to different usage of online advertisement strategy and even more importantly to different online technologies development trajectories. We hope that the availability of new data and the longer history would allow researchers to start answering these questions in the near future.

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Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Firm Level				
Total cost	40085.72	172154.3	0	4333594
Total transactions	36965.24	288250.3	0	8280926
Total Revenues	4070515	2.33E+07	0	3.15E+08
Average Price	1214.058	17968.75	0	577373.4
Strategy Level				
Paid Search				
PS – Impressions	1843027	6390229	0	1.38E+08
PS – Clicks	30481.49	92944.52	0	2115229
PS – Cost	22288.53	63777.38	0	1064008
PS – Transaction	24423.52	269498	0	8280722
Behavioral Targeting				
BT – Impressions	8034857	2.32E+07	0	3.36E+08
BT – Clicks	5722.388	17995.5	0	255442
BT – Cost	17797.2	159714.2	0	4333594
BT – Transaction	1077.576	9078.841	0	184383
Controls				
Organic Search – Click	24739.31	68340.62	0	1471296
Organic Search – Transaction	10304.35	58579.32	0	554685
Number of Campaigns	38.64957	52.4416	0	353
Number of Search Engines	2.20133	1.681623	0	11
Ads rank	2.744031	1.982916	0	14.2079

Table 2. Correlation Table

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1.Total cost	1																
2.Total transactions	0.108	1															
3.Total Revenues	0.096	0.294	1														
4.Average Price	0.106	-0.008	0.027	1													
5.PS - Impressions	0.182	0.512	0.014	-0.008	1												
6.PS - Clicks	0.224	0.255	0.090	-0.014	0.763	1											
7.PS - Cost	0.383	0.182	0.072	0.289	0.481	0.570	1										
8.PS - Transaction	0.088	0.977	0.154	-0.005	0.541	0.248	0.177	1									
9.BT - Impressions	0.097	0.158	0.282	-0.019	0.152	0.129	0.056	0.072	1								
10.BT - Clicks	0.106	0.178	0.196	-0.017	0.183	0.175	0.086	0.121	0.641	1							
11.BT - Cost	0.923	0.042	0.075	-0.007	-0.004	0.005	-0.003	0.021	0.081	0.079	1						
12.BT - Transaction	0.013	0.068	0.074	-0.007	-0.026	-0.021	-0.026	0.016	0.264	0.318	0.025	1					
13.Organic Search - Click	0.161	0.150	0.282	-0.017	0.489	0.551	0.312	0.061	0.372	0.341	0.044	0.014	1				
14.Organic Search - Transaction	0.115	0.397	0.700	-0.010	-0.001	0.077	0.061	0.196	0.361	0.235	0.099	0.107	0.394	1			
15.Number of Campaigns	0.079	0.060	-0.001	-0.013	0.377	0.435	0.312	0.067	0.199	0.225	-0.045	-0.074	0.253	-0.027	1		
16.Number of Search Engines	0.046	0.092	0.160	-0.012	0.194	0.265	0.208	0.054	0.107	0.083	-0.037	-0.101	0.198	0.208	0.451	1	
17.Ads rank	-0.016	0.099	0.103	-0.006	0.094	0.059	0.100	0.071	0.070	0.030	-0.059	-0.136	0.111	0.177	0.196	0.256	1

Table 3. Panel regressions on Costs

	(1) Cost	(2) Cost
Traditional (Impressions)	**0.637*****	
	(0.0358)	
BT (Impressions)	**0.632*****	
	(0.0474)	
Traditional * BT (Impressions)	**-0.043*****	
	(0.00272)	
Traditional (clicks)		**0.886*****
		(0.0562)
BT (clicks)		**0.801*****
		(0.147)
Traditional * BT (clicks)		**-0.078*****
		(0.012)
Organic Search (clicks)	**0.069***	0.019
	(0.035)	(0.066)
Num. of Campaigns	**0.005****	0.002
	(0.002)	(0.002)
Search Engines	-0.041	-0.055
	(0.058)	(0.058)
Rank	-0.013	-0.072
	(0.042)	(0.067)
BT dummy	1.256	1.713
	(1.210)	(1.128)
Constant	-0.429	0.668
	(0.664)	(0.711)
N	2106	2106
Marginal Effects		
Traditional Advertising	**0.325*****	**0.595*****
	(0.024)	(0.051)
Behavioral Targeting	**0.19*****	**0.237*****
	(0.037)	(0.073)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Panel regressions on Transaction

	(1) Transactions	(2) Transactions	(3) Transactions
Traditional (clicks)	**0.275*****		
	(0.075)		
BT (clicks)	**0.330*****		
	(0.124)		
Traditional * BT (clicks)	**-0.024****		
	(0.010)		
Traditional (cost)		**0.215*****	
		(0.073)	
BT (cost)		**0.141*****	
		(0.054)	
Traditional * BT (cost)		**-0.009***	
		(0.004)	
Traditional (price)			-0.374
			(0.264)
BT (price)			**0.414****
			(0.164)
Traditional * BT (price)			**-0.072***
			(0.038)
Organic Search (clicks)	**0.329*****	**0.360*****	**0.253*****
	(0.066)	(0.064)	(0.072)
Num. of Campaigns	**0.004***	**0.004****	0.001
	(0.002)	(0.002)	(0.001)
Search Engines	0.013	0.019	0.043
	(0.048)	(0.044)	(0.030)
Rank	-0.070	-0.021	-0.019
	(0.090)	(0.086)	(0.040)
BT dummy	-0.196	-0.333	-0.023
	(0.211)	(0.242)	(0.060)
Constant	**2.131*****	**2.560*****	**7.081*****
	(0.617)	(0.542)	(1.153)
N	2106	2106	874
Marginal Effects			
Traditional Advertising	**0.185*****	**0.179*****	**-0.711*****
	(0.062)	(0.064)	(0.129)
Behavioral Targeting	**0.156*****	**0.076*****	0.102
	(0.058)	(0.026)	(0.079)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Panel regressions on Revenues

	(1) Revenues	(2) Revenues
Traditional (transaction)	**0.259****	
	(0.131)	
BT (transaction)	**0.296***	
	(0.167)	
Traditional * BT (transaction)	-0.0104	
	(0.0161)	
Traditional (price)		**0.551****
		(0.258)
BT (price)		**0.542*****
		(0.200)
Traditional * BT (price)		**-0.078****
		(0.038)
Organic Search (transaction)	0.365	
	(0.256)	
Organic Search (price)		**0.519*****
		(0.123)
Num. of Campaigns	**-0.009*****	0.001
	(0.003)	(0.001)
Search Engines	**0.371*****	**0.042***
	(0.139)	(0.022)
Rank	0.108	-0.048
	(0.116)	(0.048)
BT dummy	0.010	-0.011
	(0.501)	(0.056)
Constant	**4.072*****	**6.605*****
	(1.188)	(1.154)
N	2106	874
Marginal Effects		
Traditional Advertising	**0.231*****	0.048
	(0.118)	(0.195)
Behavioral Targeting	**0.244*****	**0.265*****
	(0.105)	(0.062)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Panel regressions on Price

	(1) Price	(2) Price	(3) Price
Traditional (transaction)	-0.117		
	(0.098)		
BT (transaction)	**0.091***		
	(0.047)		
Traditional * BT (transaction)	-0.004		
	(0.003)		
Traditional (clicks)		0.044	
		(0.033)	
BT (clicks)		0.047	
		(0.035)	
Traditional * BT (clicks)		-0.001	
		(0.004)	
Traditional (cost)			0.041
			(0.031)
BT (cost)			0.019
			(0.021)
Traditional * BT (cost)			-0.001
			(0.002)
Organic Search (transaction)	0.095		
	(0.068)		
Organic Search (clicks)		**0.044****	**0.051****
		(0.020)	(0.024)
Num. of Campaigns	0.001	**-0.002***	-0.002**
	(0.001)	(0.001)	(0.001)
Search Engines	**0.071***	**0.064***	**0.065***
	(0.036)	(0.036)	(0.036)
Rank	0.013	-0.042	-0.033
	(0.035)	(0.028)	(0.028)
BT dummy	0.0735	0.0713	0.111
	(0.125)	(0.105)	(0.179)
Constant	**3.953*****	**3.194*****	**3.199*****
	(0.393)	(0.286)	(0.287)
N	1810	1810	1810
Marginal Effects			
Traditional Advertising	-0.131	**0.042***	0.041
	(0.099)	(0.025)	(0.025)
Behavioral Targeting	**0.063****	**0.041****	**0.018*****
	(0.03)	(0.016)	(0.006)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Mean test between behavioral targeting and paid search prices

	Behavioral Targeting firms only	Behavioral Targeting firms only + control group	Entire dataset
Paid Search Price	221.614	207.015	193.013
Behavioral Targeting Price	243.576	234.189	240.431
Difference	-21.961	-27.174	-47.418
Standard Error	7.885	6.728	9.853
t-statistic	-2.785***	-4.038***	-4.812***

* t < 0.10, ** t < 0.05, *** t < 0.01

Table 8. Summary of results

	Dependent Variable			
	Cost	**Transaction**	**Revenues**	**Price**
Marginal effects	BT increases costs less than paid search	No difference	BT generates more revenues than paid search	BT price is higher than paid search price.
Motivation	Behavioral targeting reduces information asymmetries	Paid search generates more transaction because of the larger customer base while behavioral targeting has higher rate of transactions	Behavioral targeting relies on higher prices and willingness to pay rather than large number of transactions	Firms can extract more consumer surplus because they can offer tailored products to users
Joint effect	Complements	Substitute	No joint effect	No joint effect
Motivation	Behavioral Targeting and Paid Search create economies of scope	Customers buy the product/service only through one mechanism		