ISSN 2279-9362

Collegio Carlo Alberto

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No. 311
November 2013

Carlo Alberto Notebooks

www.carloalberto.org/research/working-papers

Big Data, Big Profits?
Understanding the Role of Targeting Technologies as Part of a Mixed Online Advertisement Strategy[1]

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Abstract

The rapid rise of online sales has introduced technologies that promise better targeting of consumers for specific ads. Thus far the literature has not differentiated between online advertising strategies and, instead, explores whether one strategy is more effective than another in identifying a consumer with a propensity to buy a particular product, in the belief that a higher transaction rate is better. This paper empirically explores what firms truly gain when they use behavioral targeting (BT) rather than traditional online advertising and the outcomes of different mixes of online advertising strategies. We use a novel dataset to analyze each stage of the transaction process for multiple online advertising strategies of multiple firms in twenty different industrial sectors over six years. We find that BT is effective in reducing costs and enabling better price discrimination, however, beyond the initial investment, traditional online advertising is much more effective in generating revenues.

[1] **Acknowledgments:** the authors would like to thank Syemour Goodman, Shari l Pfleeger, Jerry Thursby, Avi Goldfarb, Catherine Tucker, Chris Forman, and German Retana for comments on numerous versions of this paper. In addition, the comments we got from participants at the 2013 NBER Summer Meeting (Digitization Group), and the Institute for Information Infrastructure Protection (I3P) Privacy Project meetings in Indiana University and Washington D.C. during 2012 helped us to hone on the main questions. Last but not least, we want to thank EC and IO for their generosity in giving us access to data and helping us to understand the internal working of online advertising. This research was supported by a grant from the I3P through its Privacy Project and the NBER through its Economics of Digitization and Copyright Initiative. This paper was partly written while Breznitz was a visiting professorial fellow of the Collegio Carlo Alberto and the University of Turin Department of Economics S. Cognetti de Martiis, Moncialieri and Torino, Italia. The views presented in this paper are solely those of the authors, and so are all the mistakes

Introduction

Online sales have become a critical and rapidly growing revenue stream for many businesses. In the United States alone, annual online sales were estimated at $57 billion in the third quarter of 2012 (U.S. Department of Commerce, 2012). Not surprisingly, online spending accounted for 18% of advertising expenditures in 2012, and its share of total sales is only expected to grow thanks to new technologies and the spread of mobile devices such as smartphones and tablets (Hallerman, 2008). Accordingly, devising an effective online advertising strategy has become one of the most important managerial decisions.

Knowledge has supposedly become the new "gold" in our "age of big data" (Nissenbaum, 2004; World Economic Forum, 2012).[2] This analogy should remind us that data, like gold, requires mining and processing before it can be a valuable and usable asset. In the context of online advertising, the low (sometime free) cost and easy availability of finely refined personal data that can be analyzed allows for a new investment strategy that has been called "behavioral targeting" (BT). This strategy allows advertisers to precisely tailor their online advertising 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 advertising spending by focusing on profitable consumers interested in purchasing a specific product, instead of being distributed to a broad and generic audience. Companies that access user information can gain a competitive advantage over competitors by using this knowledge to define customers, markets, and product characteristics at lower cost.

Accordingly, using a BT strategy entails approaching a specific, preselected, smaller subset of consumers with the expectation of higher rates of conversion to transactions and the ability to charge higher prices on average vis-à-vis more traditional strategies. Understanding the differences between strategies is an important aspect of strategy implementation: BT differs substantially from traditional advertising strategy in the focus on customers and the level of personalization. These two opposite

[2] Perry Rotella, "Is Data the New Oil?" *Forbes,* April 2, 2012, http://www.forbes.com/sites/perryrotella/2012/04/02/is-data-the-new-oil/ (accessed May 16, 2012).

mechanisms are not mutually exclusive, but they require different types of implementation, thus it is of the utmost importance to specify the underlying mechanisms of each strategy and their impact on firm performance.

While a growing steam of literature has significantly advanced our understanding of the impact of different online advertising strategies on consumer behavior and intent to buy, we still have little knowledge about BT's profitability, competitive advantage, and, at least as important, interaction with other strategies within a comprehensive online marketing campaign. Existing literature on BT has used either survey data or single-firm cases to analyze individual user preferences and to address privacy concerns related to the collection of personal data online (Goldfarb and Tucker, 2011a; Goldfarb and Tucker, 2011c; Lambrecht and Tucker, 2011; Manchanda et al., 2006). Furthermore, the individual consumer was always studied either as a generic consumer or as a group. In the former case, costumers are exposed to a predetermined online advertising strategy (e.g., offers only available to a preselected subgroup) verify the efficiency of said treatment under different conditions. In the latter, the propensity to buy is fixed and the main effect of online technology is in better locating those who are already predisposed to buy and expose them to tailored ads.

Analyzing a novel proprietary dataset, we extended on the existing literature in order to provide new insights on how firms can benefit from targeted advertising. We examine BT's actual return to investment compared with other online advertising strategies as well as ability to allow more refined price discrimination and, hence, increase not only the conversion rate but also profit per sale. In addition, we explore the critical questions of using joint strategies and of whether, how, and when BT complements or substitutes for other online advertising strategies.

We compare the impact of BT and traditional strategies to highlight the importance and the impact they have on a firm performance. Companies face a trade-off between reaching large volumes of undifferentiated customers and the focus on a well-defined small segment, so the trade-off may translate in different pricing strategies and different sources of profitability. To our knowledge, this paper is the first in two important ways: (1) it analyzes the actual investment data of multiple firms that ran multiple

campaigns before and after the advent of BT; and (2) it assumes that each strategy operates on a different set of consumers and employs a different logic of revenue generation, each of which is more appropriate under different conditions. Our results directly analyze the impact of BT and traditional advertising investments from the point of view of the firm rather than the consumers, as previously done in existing literature.

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 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 clarify how the availability of users' private information can shape and affect portfolios of advertising investment; 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 follows. The next section defines BT as investment strategy. We then review existing literature, describe the on-line purchasing process, introduce our arguments, and define our data and methodology. We proceed to describe the empirical results and then offer a conclusion.

Definition of behavioral targeting strategy

Online advertising 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 users complete anonymity and freedom from identification, the opposite has happened. Nowadays, it is possible to collect more data on people's activities than ever before by collecting detailed histories of their online behaviors, including web research, activities on visited web sites, and even product purchases.

Although there are mechanisms and strategies to tailor advertising on television (Gal-Or et al., 2006), the level of personalization and the richness of data collected online cannot be offered by any other media outlet, since the ability to increase the specificity of advertising content for these outlets is limited

by logistical costs (Bertrand et al., 2010). The advent of Internet and tracking technologies has made the data collection easier and its use cheaper. It follows that the ability to precisely target users can be imagined as a reduction in search and identification costs for advertisers. The Internet has made it easier for firms to offer personalized products and promotions (Ghosh 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 advertising 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 visit a website, search keywords on search engines (e.g., those of Google, Bing, or Yahoo), or purchase a 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 that firms have better knowledge is that advancements in technology have facilitated online tracking. Goldfarb and Tucker (2011d) identify these technological advancements as web bugs, cookies, and clickstream data.[3] Internet and tracking technologies allow advertisers to gain detailed knowledge of Internet users and to target advertising to specific segments of a market. Third, a rapidly growing number of firms now specialize in the collection and analysis of user data on large scale.[4]

The power of BT depends on the ability to parse data from online users. It represents an incredible reduction in segmentation and feedback costs, and companies can even exploit personal information to refine their products and personalize their offers. This strategy has benefits for firms, which should reduce

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[3] Web bugs are often used to monitor activity of customers on webpages. Cookies are stored in users' web browsers and track previous activity on a website. Clickstreams record users' clicks and store them to analyze specific patterns and behaviors.

[4] 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 of the promised higher sale conversion rates. For instance, Beales (2010) finds that the price of targeted advertising is 2.68 times the price of untargeted advertising.

the number of inefficient advertising, 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 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 will see advertisements about computers and computer accessories. While those ads may prove useful for a potential buyer and, therefore, may increase the chance of a purchase by this user, she has not granted permission to collect and use her information. Clearly, privacy concerns could limit the adoption of BT. Turow 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 (2011b) point out that use of this information needs to be divided between "targetability" and "measurability." In the first case, consumer data is used to determine the likelihood of being influenced by an ad. Measurability, by contrast, refers to the ability to evaluate the advertisement's 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 of those who saw the ad with those who did not.

Theory Development

In order to understand how different online advertising technologies work, it is essential to understand the online purchasing process. The investment decision for an online campaign is determined by the number of advertisements displayed on the Internet. As in the real world, companies pay to advertise their product. In order to buy a specific product, Internet users follow a process that begins with

viewing an advertisement and ends with an actual product purchase. Figure 1 summarizes the online purchasing process and shows the linear progression of the different stages.

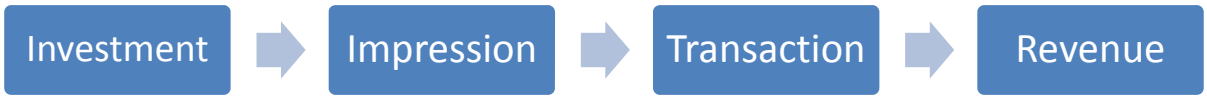

Figure 1 Online Advertising Purchasing Process

First, firms buy online advertising space to increase the visibility of their products and campaigns. Investment flows mainly to two advertising channels: traditional advertising and BT. The former reaches a large set of Internet users with low differentiation, while the latter targets a small, specific group of customers defined by precise characteristics.

Second, after users are exposed to an advertising campaign through ads in the form of pop-ups, links, and banners (also known as "impressions"); either they decide to buy the product, thus generating a transaction, or they ignore the ads. The number of transactions is influenced by the original advertising investment choice: In BT, the assumption is that using this format increases the probability of a purchase because it promotes a product that is in line with the preferences of a specific subset of customers. Traditional advertising generates transaction by being exposed to a larger volume of users in the hope of reaching 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, after transactions are completed, they generate revenue for the company; however, the source of revenue 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 (WTP). Customers that are exposed to targeted advertisements are also offered a product that better matches users' preferences, as a consequence, their willingness to pay should higher given the higher perceived quality of the products. In other words, companies can price discriminate among their customers thanks to the detailed data availability: online data facilitate the creation of very narrow and detailed individual profiles that can

be used to segment the market and reduce information asymmetries. Conversely, general advertising is directed at large undifferentiated audiences, who tend to have a lower WTP so companies are not able to charge higher prices and thus have less ability to price differentiate. When firms adopt general advertising, they segment customers based on broad characteristics (e.g., male vs. female). These broad segments may include very heterogeneous customers thus reducing the ability to offer a tailored product.

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 customization. It follows that in order to understand firm performance, it becomes crucial to study the effectiveness of each strategy as well as their joint effect and, hence, the managerial implications of different choices. Nonetheless, even with the great advancements in the ability to determine the effectiveness of online advertising, this question was considered rarely, if at all. Instead, effectiveness defined as a generic variable (ratio of transaction per impression) has been the focus of research, for example, a recent paper by Goldfarb and Tucker (2011c) has shown the trade-off between online and offline media, and Manchanda 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 impression of an ad (Danaher and Mullarkey, 2003) and how search results affect advertising (Yang and Ghose, 2010). Moreover, 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 (2011a) study how targeting can affect purchasers' 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 who refuse to share their personal data.

Our study focuses on two issues. First, following earlier studies, it focuses on evaluating how firms can benefit from the use of personal data to achieve higher performance. User information may represent

a source of competitive advantage for companies that: (i) are able to reduce the amount of "wasted" advertising by targeting specific and more profitable users; and (ii) offer differential pricing so as to maximize the revenue of each transaction from different customers. The ability to tailor advertising to user preferences and needs should increase both the probability of a purchase and the ability to price at the maximum that the customer would be willing to pay. Second, our study highlights the problems of defining effectiveness—and, hence, better performance—based solely on the ability to identify more precisely a very small subset of consumers who are already predisposed to make a purchase. Consequently, we offer a first step in rekindling the debate on the proper strategic mix of different online advertising technologies, each of which employs a different logic of extracting surplus from consumers.

Several mechanisms support the argument that BT is associated with better performance. First, advancements in tracking technologies reduce the cost of gathering information on 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 associated 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 segment the market with precision; as a result, consumers may pay a higher price for a product that better meets their needs. For example, Athey and Gans (2010) model the impact of targeted advertising from a demand and supply perspective. In their model, they point out that when advertising has no limits (e.g., advertising space, a firm's investment constraints) most of the inefficiencies related to their heterogeneous audience can be mitigated by nontargeted messages, thus reducing the importance of targeting. In other words, in the unrealistic situation in which the firm's ability to pay for advertising space is unlimited, the nature of nontargeted messaging to a heterogeneous audience is less problematic. Under the more realistic condition of potential constraints, targeting improves the efficiency of the allocation of messages and leads to positive changes in demand and prices. Based on these mechanisms,

our empirical analysis should find BT a more effective strategy than traditional online advertising with regard to both sale generation per display (conversion rate) and price discrimination.

In addition, BT represents an innovative new strategy for companies engaged in online advertising, and it is important to understand how companies manage their new strategy choices to obtain the greatest benefit from their investment. Apart from our central argument about the divergence in customer group exposure and a different logic of value extraction, interaction between BT and other strategies is unclear, and empirical research on this subject is not plentiful.

Firms should consider the benefits, and costs, associated with each strategy to successfully implement a successful strategy mix. Firms face a trade-off between a large consumer reach and a narrow, but loyal, set of customers. Internet technologies have reduced customer loyalty: for example, while customers used to spend 25 minutes reading the newspaper, they now spend only 90 seconds reading web articles (Varian, 2010). In a broader context, internet users can exploit web pages, search engines, and social networks to access the information they are looking for, thus increasing the probability that customers will switch between advertising outlets (Athey et al., 2012). Traditional advertising promotes product indiscriminately: an ad can either reach a new customer, and increase the visibility of a product, or be shown to already informed users and have no effect, hence increasing the amount of "wasted" advertising. Tracking technologies may reduce the reduction in loyalty because they are able to follow customers across websites and offer a personalized advertising experience, thus reducing advertising duplication. As noted by Athey et al. (2012), switching customers have an impact on the investment decision in multiple webpages and search engines. The authors conclude that high-value advertiser invest in multiple outlets to reach a larger number of non-informed customers, while low-value advertisers prefer investing in single outlets to capture customers who are already loyal and those who are switching from other websites.

Given the complexity of the internet environment introduced by tracking technologies, switching customers, and multiple advertising outlets, advertisers often adopt several advertising strategies simultaneously. The ability to integrate different strategies (e.g., BT and traditional advertising) in order

to exploit their interactions requires effective media planning, the exploitation of internal capabilities, and understanding market needs (Schultz et al., 1993). Firms may struggle in developing an effective media strategy because either they are unable to identify consumer segments or their ads reach the same customers too many times. Therefore, firms can benefit and increase their profits by implementing an efficient combination of BT and traditional advertising to potentially reach the majority of customers and the most profitable ones simultaneously. For instance, consumers who do not have strong preferences may choose to buy a competing product; it follows that in the absence of a more general advertising effort, these consumers may be lost: the implementation of a broader untargeted advertising may potentially reach the entire demand of undecided users. However, if consumers have already strong preferences, targeted advertising may provide a cost-effective incentive to buy a specific product (Esteban et al., 2001).

The joint effect of BT and traditional advertising investments depends on the type of customers that the firms want to reach. Firms have higher incentives to invest in tailored advertising and to reduce their investment in of "wasted" advertising but at the same time they need to traditional advertising to reach new users that may not be aware of their products. Companies can focus predominantly on profitable customers through user-specific offers and, simultaneously, exploit a broad and undefined strategy (e.g., traditional advertising) to increase online product awareness and visibility.

Data and Methodology

Empirical Strategy

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 consists of a total of 237,911 weekly observations.[5] The data includes online advertising investment

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

decisions divided among several strategies (traditional advertising, BT, and organic search) and different measures of firm performance (e.g., clicks, impressions, conversions, and revenues). To deal with observations equal to zero, we compute our variables as ln(1 + *x*), thus the estimated marginal effects can be interpreted as elasticities.

We use a straightforward panel specification to test for the effect of BT and traditional advertising across the online purchasing process. Equation 1 reflects our empirical model for firm *i* at time *t*:

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

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 effects (X_i).

For each specification of Equation (1), we estimate the first derivatives with respect to BT and traditional advertising to estimate the marginal effect of each strategy. Equations (2) and (3) show the derivative of Equation (1) with respect to BT and traditional advertising, respectively.

$$\frac{dPerf_{it}}{dTraditional\_ads_{it}} = \alpha_2 + \alpha_3 BT_{it} \quad (2)$$

$$\frac{dPerf_{it}}{dBT_{it}} = \alpha_1 + \alpha_3 Traditional\_ads_{it} \quad (3)$$

The difference between the estimates of Equations (2) and (3) tells us whether behavioral targeting is more efficient than traditional advertising. In other words, we study the impact of the two strategies at each step of the purchasing process to determine which underlying mechanism has a bigger impact.

The sign of the coefficient α_3 in Equation (1) represents the joint relationship between BT and traditional advertising. If the sign is positive, it suggests that these two mechanisms reinforce each other, in the sense that firms can experience synergies from the adoption of multiple online channels. Conversely, a negative sign provides support for the idea that firms can experience higher gains by focusing on only one of the two strategies studied in this paper.

Because the data on BT begin in 2009, we have to limit our estimation to a subsample of our dataset. Our main statistical method is the Coarsened Exact Matching (CEM) procedure (Blackwell et al., 2009; Iacus et al., 2012). We consider firms that adopt BT at any point starting from 2009 as treated, while those that rely exclusively on traditional advertising as controls. As described in previous literature on matching, the object of matching treated and control firms is to reduce the endogeneity problem (Ho et al., 2007) as shown in recent papers that adopt the CEM approach to improve the identification of control groups (Azoulay et al., 2012; Furman et al., 2012). Iacus et al. (2012) describe several advantages of the CEM procedure. 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 assumptions of exogenous treatments.

The aim of this empirical procedure is to create a set of control and treated firms whose advertising performance would mirror each other if the treated firms did not invest in BT. The main idea behind CEM is to temporarily create several strata (e.g., groups) based on predefined matching parameters and then to generate and exact match between treated and control observations (Blackwell et al., 2009). The CEM procedure is a nonparametric approach that does not require the estimation of propensity scores through parametric methods. The nonparametric approach is very useful in our setting because we have limited information that would predict the likelihood of adoption of BT as advertising strategy. Since exact matching is nearly impossible in observational data, we also include firm fixed effects to reduce the concern over potential omitted variables.

In our dataset, we match firms based on eight attributes: (1) the investment in traditional advertising, (2) the number of impressions derived from traditional advertising, (3) the number of weekly campaigns, (4) the number of search engines used, (5) firm size, (6) industry, (7) month, and (8) year of the observation. We define this set of matching variables as CEM1 procedure. We impose an exact match for the industry, month, and year of observation while we use different cutoffs points for the remaining variables. Traditional advertising costs, impressions, and firm size are divided in strata that each includes 5% of the sample. Number of weekly campaigns is divided into 10 strata while the number of search engines is coarsed based on 4 different groups.[6]

Our aim is to create a comparable control group to estimate the benefit gained by the adoption of BT and reducing possible distortion introduced by potential endogeneity. To further corroborate our estimations, we adopt a less restrictive matching that does not include the two variables on traditional advertising, cost and impressions. Our CEM2 match includes six variables: (1) the number of weekly campaigns, (2) the number of search engines used, (3) firm size, (4) industry, (5) month, and (6) year of the observation.[7] In both procedures, treated observations for which a control was not identified were dropped from the regression sample. Table 1 reports a summary of the variables used in each matching procedure and the number of treated used in the empirical regressions.

<Insert Table 1 here>

Data Description

Main Variables

[6] Based on the distribution of the CEM variables, multiple combinations of cut-off points have been tested and the results are unchanged. Empirical estimations are available from the authors upon request.

[7] Likewise for the CEM1 procedure, multiple cut-off points were tested and the results were unchanged. Empirical estimations are available from the authors upon request.

Four variables are used to measure the performance or the investment decisions: total firm costs, total firm transactions, total firm revenues, and the average price of the products. Firm costs are defined as the total weekly investment in online advertising. This variable includes investments in both BT and traditional advertising. Our average firm invests about $40,000 per week in online advertising; about 55% of the total advertising cost is allocated in traditional advertising, and the remaining is spent in targeted ads.

Transactions are defined as the actual number of online purchases made by online users. Our variable reflects the quantity of products sold weekly through all the online advertising strategies (BT, traditional advertising, and organic search). We would expect that investments in online advertising increase a firm's transactions: traditional advertising relies on large volumes to increase transactions while BT exploits a narrow segment of the demand with higher probability of purchase. Our third variable reflects the total revenues generated by online campaigns: the variable *revenues* represents the dollar amount generated by online transactions at the firm level. It equals the sum of revenues generated through BT and traditional advertising, on average, a firm generates about $4 million of revenues per week. Finally, we define our last variable, *price*, as revenues divided by transactions. Unfortunately, our data does not include the actual price charged to customers for each advertising campaign, but our measure represents the average price charge by a company in a specific week.[8]

We focus on two different investment strategies: paid search and BT. Paid search advertising matches keywords entered on search engines: Companies pay to facilitate the display of their ads on search engines when their chosen keywords are searched on. BT refers to the strategy of selecting specific market segments and tailoring advertising campaigns to consumers' preferences.

[8] The company that provided us with access to the data adopts the same price measure to track changes in pricing strategies. We acknowledge that this measure may not be perfect but it represents a good approximation of the price charged to internet buyers.

To measure consumer demand, we use two different proxies. First, *impressions* are defined as the number of ad views on websites used by the focal firms during their campaigns. Our measure reflects the number of total ads displayed per week. Second, we include the total number of *clicks* that ads receive each week. When firms invest in a paid search strategy, clicks on average number more than 30,000 per week, compared to 5,700 for BT, which is in line with the idea that traditional advertising relies on larger volumes than does BT.

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

Controls

We control for several other factors. First, we include variables on *Natural search* results, also called organic search. *Natural search* refers to listings on search engines that appear simply because of their relevance to the search keywords; in contrast to other forms of advertising investment, *Natural results* have no cost to companies. The number of impressions and costs are missing for natural search because of the intrinsic characteristics of this advertising strategy. In addition, we include the total *number of campaigns* run by each company per week. Firms rely on several websites to implement their advertising campaigns, and search engines are crucial in redirecting customers to specific pages. Accordingly, we include the *number of search engines* used by each company. Search engines rank their advertising links based on where they appear on the webpage; therefore we include the *rank* variable in

our regressions. We include *dummy behavioral targeting* to identify firms that invest in BT. We use this variable to identify our treated group in contrast to the control group.[9]

We control for industry sector. Of the 20 different industries in our study, the largest is "computer products" (about 10% of our sample), "automotive" (9%), "telecommunications" (8%), and "retail" (7%). We include an industry dummy variable to control for possible product-specific characteristics. Certain products may be easier (e.g., automobiles and vacation packages) than others (e.g., fresh produce and soda) to sell online. Finally, to take into consideration possible time effects, we include both year and month dummies, and by doing so we also control for the impact of major events such as Christmas, Thanksgiving, and sporting events. Table 2 lists summary statistics, and Table 3 reports the correlation matrix.

< Insert Table 2 and 3 here>

[9] We fully acknowledge that due to our use of observational data, our results may show an upward bias due to the effect of "activity biases" (Lewis et al., 2011). Activity biases are the effect of a classic intervening variable, namely, in this case that consumers that spend more time online and perform multiple activities have a higher correlation to be exposed to different advertising campaigns. While our usage of observational data does not allow us to control for users' activity, we believe that due to our specific line of inquiry (even assuming that after mitigation our results lead us to believe that online ads are more effective than they truly are), it does not change the diversity of mechanisms and logic of revenue extraction between the different online advertising technologies that are the focus of our inquiry. In terms of mitigating the activity biases, we first study the effect of paid search and behavioral targeting over a long period of time (years versus weeks) and over thousands of different campaigns. Second, since in their paper, Lewis et al. (2011) specifically show how ads that were shown only in one website correlate with high activity biases, we made sure to include multiple search engines, several advertising campaigns, and different industries.

Results

We report the results of our estimations and the marginal effects of our variable of interests in several 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 4 regresses advertising costs on the number of clicks and the number of impressions. By definition, higher levels of impressions and clicks increase total advertising costs, 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 investment. Investment costs are determined by two factors: number of impressions and number of clicks. Firms bid on the number 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 who clicks on the advertised link. Our results confirm that the marginal effect of both strategies increases the total advertising cost; however, the cost increase due to BT is lower than that of paid search. These results confirm that BT increases costs less than a traditional strategy does. Thanks to advancements 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 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 supports the idea that BT and paid search focus on different sets of customers, and their combination reduces costs by increasing the efficiency of the overall advertising strategy.

<Insert Table 4 here>

Table 5 reports our estimation of the next step of the purchasing process, so we regress the total number of transactions on clicks, investments costs, and product prices. We adopt three measures as independent variables to describe three different mechanisms. First, we focus on the relation between final purchases (transactions) and clicks: Users who are exposed to advertising campaigns need to click on the ad in order to buy the advertised products. We try to understand whether an increase in the number of clicks is associated with a higher level of transactions. Second, we describe the same mechanism by focusing on the relation between transactions and the amount of advertising investment per strategy. Third, the final purchasing decision may be affected by the price of the product. Using BT, companies are able to personalize their offers and adopt price discrimination; hence, companies might be able to charge higher prices and increase customers' willingness to pay. However, high prices may also discourage users from completing the online transaction.

Model 1 adopts clicks as a 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 the main independent variables. An increase in paid search investment generates more transactions than does an increase in BT investment. Those results corroborate our argument about the advantages *and limitations* of BT. BT is much more effective in generating revenues from a small, well-defined group. However, attempts to enlarge the group have rapidly declining marginal effects. Paid search is not as effective in generating revenues from larger, less-defined groups, but its declining marginal effect if investment is increased is much smaller.

To further test the differences in the customer base and 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 found only for paid search price. Conversely, we do not find that the BT price has a significant effect on the number of transactions. These results also support our argument about the different logic of surplus extraction between the two strategies. BT allows the firm to focus on generating the maximum number of transactions for the highest possible price from a small, well-defined subset of

consumers. Traditional advertising allows firms to approach a significantly larger set of consumers with the aim of generating a low ratio of transactions for lower prices, but on a much larger scale.

As described in the methodology section, we estimate the interaction term between our main independent variables, BT and traditional advertising. We find support for a substitution effect between BT and paid search. It suggests that companies try to reach customers with a higher willingness to pay through BT in order to maximize the opportunity for a transaction, while paid search is used to focus on a broader group of users that excludes those targeted by BT. As our results on prices demonstrate, 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 may increase the ability to reach a larger customer base but consumers prefer to buy the final product only through one media channel.

<Insert Table 5 here>

The next set of analyses focuses on the revenue generation process; in particular, it studies the impact of transactions and price on total firm revenues (Table 6). The marginal effects in Model 1 show that BT transactions generate more revenues than traditional advertising, although the difference between the two strategies is only marginal. As in the previous regressions, this result can be explained by the different strategy implementation mechanisms: Traditional advertising generates a high volume of transactions because of the larger customer base, and it relies on a large number to generate revenues with a lower probability per transaction. However, BT relies on a 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 in 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 in traditional advertising, the price has no effect on revenues, in BT the price has a strong and positive impact on revenues. Combined with previous results on the impact of

prices on the number of transactions, these results emphasize how firms are able to exploit user information to extract greater consumer surplus through the adoption of a BT strategy.

<Insert Table 6 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 7, we use the average firm price as a dependent variable. We do not find any joint effect between our strategies in any of our models, suggesting that each strategy has a linear effect on prices. In Models 1 and 2, we assume that transactions and clicks proxy for product demand, while costs (Model 3) represent the investment to implement 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 7 and 8 here>

The ability to set higher prices using BT allows firms to extract higher value from online users. Companies exploit higher willingness to pay when customers are offered a product that matches their needs. In Table 8 we perform three different means 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 significantly lower than the average cost of targeted advertising, which is $243. Second, we include our control group and obtain similar results: The price of paid search is $27 lower than that of BT. Finally, we run the same

means test without restricting the sample, and the difference between the two prices increases; in fact, the price using BT is about $50 higher than that of traditional advertising.[10]

These results should not come as a surprise to anyone who followed the pricing strategies adopted by websites such as Orbitz.com, which charges Apple Computer users higher prices.[11] 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."[12]

The Orbitz example shows how companies can take advantage of the high availability of customer data and exploit it in their favor. By targeting specific consumers, companies are able to reduce their costs and extract consumer surplus by charging higher prices, significantly increasing their profit margins. We summarize our main findings in Table 9.

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[10] We acknowledge that our price mean tests include industries and products with different levels of personalization. We therefore, ran multiple tests by splitting the sample in industry-level subgroups, and the results are still consistent with those in Table 7.

[11] "On Orbitz, Mac Users Steered to Pricier Hotels," *Wall Street Journal,* August 23, 2012 http://online.wsj.com/article/SB10001424052702304458604577488822667325882.html (accessed on July 25, 2012).

[12] "Mac Users May See Pricier Options on Orbitz," ABC News, June 26, 2012 http://abcnews.go.com/Travel/mac-users-higher-hotel-prices-orbitz/story?id=16650014#.UBCJHaNdeSo/ (accessed on July 25, 2012).

<Insert Table 9 here>

The adoption of BT has a clear and positive impact on firm performance across different measures; however, it has two limitations. First, it can be used only among a small subset of consumers. Second, its implementation depends upon the availability of detailed data on consumers collected using several tracking technologies. Data is often collected without the explicit consent of online users, raising important privacy concerns (Turow et al., 2009). Users tend to reject ads that exploit their data through context-based advertising and when they are obtrusive because customers manifest privacy concerns (Goldfarb and Tucker, 2011a).[13]

Conclusion

While there is growing theoretical literature discussing BT and its effects on privacy (Acquisti and Varian, 2005; Fudenberg and Villas-Boas, 2006; Goldfarb and Tucker, 2011a), empirical results on BT, specifically its interactions with other strategies, are still scarce. We attempt to fill this gap by conducting a focused comparison of two different strategies—paid search and behavioral targeting—analyzing both at the different stages of and the complete online purchasing process.

Our results confirm that BT generates a higher conversion rate than traditional advertising and allows price discrimination. These results support the argument that BT can be seen as a profitable and innovative strategy that can reduce "wasted" advertising by tailoring online campaigns to consumer preferences and needs and increase the profit margins of firms by allowing refined price discrimination.

[13] The recent events regarding the National Security Agency (NSA) are a perfect example of the use of users' data without explicit consent. However, it is utmost important to clarify that the NSA didn't directly gathered data but they access information previously collected by other companies (e.g., Microsoft, Apple, and Google).

In that vein, we also find that BT increases costs less than paid search does. The power of BT relies on the ability to parse data from online users. It represents an incredible reduction in segmentation and feedback costs. The ability to track and identify costumers reduces segmentation cost and information asymmetries, so firms can easily identify more profitable customers and target their ads based on their characteristics.

However, our results also show the limits of BT, namely, the fact that, inherently, it works only on a small, very well defined subgroup of total potential consumers. In addition, our results suggest that when companies invest in both BT and traditional advertising, they can exploit potential economies of scope in reducing their cost. Firms can focus on customers with a 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 segments associated with their ads. Using BT, firms have another way to expand their audience; this feature may complement more traditional advertising strategies based on keywords, especially when keywords are not well defined and ad placement is limited. However, our empirical regressions show that the two strategies have a jointly negative effect in generating transactions. This result is not surprising, since firms focus on different user segments. On the one hand, customers exposed to BT advertising have a higher willingness to pay, and they are more lucrative customers because companies can adopt price discrimination. On the other hand, traditional advertising reaches a broad but generic group of customers distinct from BT users, thus substituting for BT advertising.

These results have important managerial implications as they show that building a comprehensive multifaceted online advertising strategy is much more important, and more complex, than analyzing technology based solely on its perceived effectiveness in terms of transaction conversion ratio per impression. In addition, our research adds to the growing literature showing that companies can exploit the detailed information gathered through BT; private data may provide useful feedback to improve their products and their traditional advertising strategy. However, as profitable and efficient as BT strategy seems, there may also be some disadvantages that companies should not underestimate. In particular, privacy concerns should not be taken lightly, as previous studies have shown that if online consumers

start to see ads show up in unexpected or unwanted places, they may consider them obtrusive or invasive (Goldfarb and Tucker, 2011a). 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 of focusing on market niches too small to be profitable.

This paper contributes to the existing literature on online advertising and BT (Acquisti and Varian, 2005; Goldfarb and Tucker, 2011a; Iyer et al., 2005). While there is extensive theoretical literature on BT and its implications for privacy and performance (Acquisti and Varian, 2005; Fudenburg and Villas-Boas, 2006; Hermalin and Katz, 2006), empirical research on BT 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 on the ability to arrive at a strategic mix of both strategies to reach superior results. Because we view our inquiry as an exploratory attempt to rekindle the debate over the interactions of different online advertising strategies, and the way in which we define which of them is "better," we hope that our paper will inspire future research.

For strategic management, in particular, we think it is important to understand how firms decide to allocate their media budgets among different strategies. The strategic investment in BT advertising may be affected by differences among industrial sectors: Firms that operate in different industries face different product characteristics, product awareness, and consumer propensity to buy, which can affect the decision to invest in BT. Moreover, privacy concerns generate 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 exist. Instead, the impact might be more nuanced where different kinds of privacy protection leads to different usage of online advertising strategies and, even more importantly, to different online technology development trajectories. Sadly, this line of research has been, for the time being, unexplored. We hope that the availability of new data and the longer history of online technology development will allow researchers to start exploring these questions in the near future.

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Table 1. CEM Matching Definition

		Variables used in the matching procedure							
	Matched treated observations	Traditional advertising cost	Traditional advertising impressions	N. of campaigns	N. of search engines	Firm size	Year	Month	Industry
CEM1	1053	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEM2	1086	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Table 2. Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max
Firm level				
Total cost	40,085.72	172,154.3	0	4,333,594
Total transactions	36,965.24	288,250.3	0	8,280,926
Total Revenues	40,70515	2.33E+07	0	3.15E+08
Average Price	1,214.058	17,968.75	0	577,373.4
Strategy level				
Paid search				
PS – Impressions	1,843,027	6,390,229	0	1.38E+08
PS – Clicks	30,481.49	92,944.52	0	2,115,229
PS – Cost	22,288.53	63,777.38	0	1,064,008
PS – Transaction	24,423.52	269,498	0	8,280,722
Behavioral targeting				
BT – Impressions	8,034,857	2.32E+07	0	3.36E+08
BT – Clicks	5,722.388	17,995.5	0	255,442
BT – Cost	17,797.2	15,9714.2	0	4,333,594
BT – Transaction	1,077.576	9,078.841	0	184,383
Controls				
Organic Search – Click	24,739.31	68,340.62	0	1,471,296
Organic Search – Transaction	10,304.35	58,579.32	0	554,685
Number of campaigns	38.649	52.441	0	353
Number of search engines	2.201	1.681	0	11
Ads rank	2.744	1.982	0	14.207

Table 3. 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 4. Panel Regressions on Costs

	CEM1		CEM2	
	(1)	(2)	(3)	(4)
	Cost	Cost	Cost	Cost
Traditional (Impressions)	0.637***		0.664***	
	(0.036)		(0.035)	
BT (Impressions)	0.632***		0.645***	
	(0.047)		(0.041)	
Traditional * BT (Impressions)	-0.042***		-0.042***	
	(0.003)		(0.003)	
Traditional (clicks)		0.886***		0.847***
		(0.056)		(0.053)
BT (clicks)		0.801***		0.788***
		(0.147)		(0.145)
Traditional * BT (clicks)		-0.078***		-0.074***
		(0.013)		(0.013)
Organic search (clicks)	0.070*	0.019	0.078**	0.044
	(0.036)	(0.066)	(0.034)	(0.061)
No. of campaigns	0.005**	0.002	0.004**	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Search engines	-0.041	-0.056	0.019	-0.001
	(0.059)	(0.059)	(0.058)	(0.066)
Rank	-0.013	-0.072	-0.067	-0.019
	(0.043)	(0.068)	(0.055)	(0.065)
BT dummy	1.256	1.713	0.843	1.179
	(1.210)	(1.128)	(0.864)	(0.824)
Constant	-0.429	0.668	-0.533	0.783
	(0.664)	(0.711)	(0.537)	(0.600)
N	2106	2106	2172	2172
No. of clusters	779	779	771	771
R-square	0.843	0.841	0.828	0.817
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Marginal effects				
Traditional advertising	0.325***	0.596***	0.352***	0.569***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Behavioral targeting	0.190***	0.238***	0.193***	0.239***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The marginal effects of *Traditional Advertising* and *Behavioral Targeting* are estimated based on Equations (2) and (3), respectively. Both the dependent and the independent variables are transformed using the natural logarithm.

Table 5. Panel Regressions on Transactions

	CEM1			CEM2		
	(1) Transactions	(2) Transactions	(3) Transactions	(4) Transactions	(5) Transactions	(6) Transactions
Traditional (clicks)	0.326***			0.439***		
	(0.072)			(0.063)		
BT (clicks)	0.347***			0.376***		
	(0.125)			(0.114)		
Traditional * BT (clicks)	-0.027***			-0.035***		
	(0.010)			(0.009)		
Traditional (cost)		0.258***			0.348***	
		(0.056)			(0.057)	
BT (cost)		0.153***			0.193***	
		(0.058)			(0.054)	
Traditional * BT (cost)		-0.011**			-0.015**	
		(0.005)			(0.006)	
Traditional (price)			-0.367			-0.819***
			(0.277)			(0.114)
BT (price)			0.421**			0.144
			(0.173)			(0.147)
Traditional * BT (price)			-0.073*			-0.017
			(0.040)			(0.020)
Organic search	0.330***	0.370***	0.252***	0.291***	0.297***	0.237***
	(0.070)	(0.063)	(0.073)	(0.055)	(0.063)	(0.069)
No. of campaigns	0.003	0.003*	0.001	0.004	0.004	0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Search engines	-0.009	-0.020	0.043	-0.047	-0.054	0.067**
	(0.053)	(0.048)	(0.030)	(0.092)	(0.089)	(0.027)
Rank	-0.105	-0.056	-0.019	-0.113	-0.064	-0.024
	(0.076)	(0.057)	(0.040)	(0.076)	(0.063)	(0.043)
BT dummy	-0.189	-0.247	0.160	-0.127	-0.573*	0.028
	(0.251)	(0.295)	(0.105)	(0.259)	(0.346)	(0.123)
Constant	2.007***	2.447***	6.893***	1.409**	2.244***	9.245***
	(0.526)	(0.447)	(1.190)	(0.667)	(0.668)	(0.877)
N	2,106	2,106	877	2,172	2,172	912
No. of clusters	779	779	46	771	771	44
R-square	0.488	0.399	0.165	0.534	0.462	0.238
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Marginal effects						
Traditional advertising	0.224***	0.214***	-0.712***	0.308***	0.289***	-0.900***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Behavioral targeting	0.150***	0.074***	0.103	0.118***	0.086***	0.070
	(0.009)	(0.005)	(0.198)	(0.056)	(0.006)	(0.302)

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The marginal effects of *Traditional Advertising* and *Behavioral Targeting* are estimated based on Equations (2) and (3), respectively. Both the dependent and the independent variables are transformed using the natural logarithm.

Table 6. Panel Regressions on Revenues

	CEM1		CEM2	
	(1) Revenues	(2) Revenues	(3) Revenues	(4) Revenues
Traditional (transaction)	0.287**		0.514***	
	(0.131)		(0.152)	
BT (transaction)	0.328*		0.518**	
	(0.176)		(0.215)	
Traditional * BT (transaction)	-0.012		-0.043**	
	(0.016)		(0.019)	
Traditional (price)		0.381		-0.409
		(0.343)		(0.472)
BT (price)		0.581***		-0.098
		(0.195)		(0.403)
Traditional * BT (price)		-0.065		0.057
		(0.042)		(0.079)
Organic search (transaction)	0.392		0.216	
	(0.266)		(0.216)	
Organic search (price)		0.521***		0.405***
		(0.124)		(0.133)
No. of campaigns	-0.010***	0.001	-0.007*	0.001
	(0.003)	(0.002)	(0.004)	(0.002)
Search engines	0.246*	0.048	0.196*	0.059*
	(0.134)	(0.035)	(0.114)	(0.034)
Rank	0.055	-0.020	-0.094	-0.025
	(0.090)	(0.045)	(0.079)	(0.052)
BT dummy	0.183	-0.131***	-0.564	0.185
	(0.716)	(0.004)	(0.504)	(0.234)
Constant	4.700***	6.622***	4.847***	11.066***
	(1.194)	(1.823)	(1.037)	(2.585)
N	2,106	649	2,172	662
No. of clusters	779	31	771	29
R-square	0.524	0.321	0.564	0.229
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Marginal effects				
Traditional advertising	0.256**	0.048	0.400***	-0.114
	(0.029)	(0.806)	(0.005)	(0.455)
Behavioral targeting	0.269**	0.267***	0.301**	0.180**
	(0.017)	(0.000)	(0.023)	(0.019)

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The marginal effects of *Traditional Advertising* and *Behavioral Targeting* are estimated based on Equations (2) and (3), respectively. Both the dependent and the independent variables are transformed using the natural logarithm.

Table 7. Panel Regressions on Prices

	CEM1			CEM2		
	(1) Price	(2) Price	(1) Price	(2) Price	(3) Price	(3) Price
Traditional (transaction)	-0.199*			-0.309*		
	(0.107)			(0.171)		
BT (transaction)	0.080**			0.364**		
	(0.041)			(0.145)		
Traditional * BT (transaction)	-0.002			-0.032**		
	(0.003)			(0.012)		
Traditional (clicks)		-0.010			0.033	
		(0.022)			(0.034)	
BT (clicks)		0.017			0.084*	
		(0.044)			(0.044)	
Traditional * BT (clicks)		0.003			-0.006	
		(0.005)			(0.005)	
Traditional (cost)			-0.006			0.037
			(0.020)			(0.034)
BT (cost)			0.010			0.043
			(0.020)			(0.030)
Traditional * BT (cost)			0.001			-0.006
			(0.002)			(0.005)
Organic search (transaction)	0.090			0.001		
	(0.070)			(0.046)		
Organic search (clicks)		0.050*	0.052		0.012	0.027
		(0.027)	(0.033)		(0.042)	(0.047)
No. of campaigns	0.0001	-0.001*	-0.001*	0.001	-0.003	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Search engines	0.052*	0.057*	0.056*	0.095**	0.130	0.134
	(0.028)	(0.033)	(0.032)	(0.044)	(0.099)	(0.096)
Rank	0.002	-0.037*	-0.033	0.013	-0.042	-0.036
	(0.036)	(0.020)	(0.021)	(0.055)	(0.034)	(0.036)
BT dummy	0.183	0.186	0.249	-0.391*	-0.224***	-0.047
	(0.161)	(0.152)	(0.246)	(0.209)	(0.084)	(0.198)
Constant	4.443***	3.560***	3.511***	5.253***	3.462***	3.357***
	(0.435)	(0.296)	(0.320)	(0.669)	(0.603)	(0.715)
N	1,814	1,814	1,814	1,877	1,877	1,877
No. of clusters	613	613	613	601	601	601
R-square	0.056	0.064	0.070	0.008	0.001	0.007
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Marginal effects						
Traditional advertising	-0.206*	0.002	0.000	-0.407	0.005	0.011
	(0.056)	(0.905)	(0.998)	(0.041)	(0.868)	(0.674)
Behavioral targeting	0.068**	0.040**	0.021***	0.178**	0.030*	-0.007
	(0.014)	(0.012)	(0.005)	(0.022)	(0.077)	(0.775)

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The marginal effects of *Traditional Advertising* and *Behavioral Targeting* are estimated based on Equations (2) and (3), respectively. Both the dependent and the independent variables are transformed using the natural logarithm.

Table 8. Test of the Mean between Behavioral Targeting and Paid Search Prices

	Entire dataset	CEM1	CEM2
Paid search price	193.013	207.015	232.112
Behavioral targeting price	240.431	234.189	249.729
Difference	-47.418	-27.174	-17.616
Standard error	9.853	6.728	9.528
t-statistic	-4.812***	-4.038***	-1.848**

* $t < 0.10$, ** $t < 0.05$, *** $t < 0.01$ The difference is computed as Paid Search Price – BT Price.

Table 9. Summary of Results

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