Profiting from Targeted Advertising: Exploring synergies among media channels

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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 the advantages associated with the adoption of behavioral targeting (BT) jointly to paid search advertising. Because of tracking technologies, firms may able to reduce information asymmetries about consumers and define a better advertising strategy which exploits synergies across different media channels. We use a novel dataset to analyze classic advertising measures (Click-through-rate and Conversion Rate) for multiple online advertising strategies of multiple firms in twenty different industrial sectors over six years. We find that BT complements the adoption of sponsored advertising, thus offering new insights on marketing strategies implementation. We also find that there exist asymmetric spillovers across media channels that, ultimately, benefit the overall firm performance.

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, NOVEMBER 17, 2011). 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). Accordingly, devising an online advertising strategy that combines multiple media channels has become one of the most important managerial decisions.

Knowledge has supposedly become the new "gold" in our "age of big data" (Nissenbaum, World Economic Forum).¹ 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 tailor their online advertising to buyers' needs and preferences. On the face of it, BT advertising should increase the ability to identify consumer preferences to offer enhanced and personalized services (Acquisti and Varian). Accordingly, BT can be seen as a mechanism to reduce asymmetric information about online users (Acquisti and Varian, Chen and Iyer) and it entails approaching a specific smaller subset of consumers defined by their past online activity.

Understanding how media channels are interconnected and whether they complement each other is an important aspect of strategy implementation: while the difference between targeted and untargeted advertising may be clear and it is based on the focus on customers and the level of personalization, the implementation and adoption of BT advertising with other media channels (we focus on paid search advertising, hereafter PS) is still overlooked. In other words, we focus on the mechanism and spillovers

¹ 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 Feb 01, 2015).

that may connect targeted ads and search engine advertising. These two 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. PS and BT advertising are driven by different sources of data, users' behavior and query input respectively, and it becomes crucial to understand the potential spillover between them to maximize the benefits from online advertising.

By analyzing a novel proprietary dataset, we extended on the existing literature in order to provide new insights on how firms can benefit from the adoption of targeted technologies in a multi-channel strategy context. We examine BT's effect on classic performance measures (Click-through-Rate and Conversion Rate) when it is adopted jointly with PS advertising. We compare the impact of BT and PS to highlight the importance and the impact on the overall firm performance and we study the possible spillovers that may exist between these two media channels. 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.

The paper proceeds as follows. The next section reviews existing literature, then, we define our data and methodology. We proceed to describe the empirical results and then offer a conclusion.

Theory development

Although there are mechanisms and strategies to tailor advertising on television (Gal-Or et al., May 1, 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., February 1, 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., 2006/11/01, Zhang and Wedel, 2009/04/01).

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). 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. Second, firms have better knowledge on advancements in technology which have facilitated online tracking. Goldfarb and Tucker (Jan) identify these technological advancements as web bugs, cookies, and clickstream data.² Internet and tracking technologies allow advertisers to gain detailed knowledge of Internet users. Third, a rapidly growing number of firms now specialize in the collection and analysis of user data on large scale.³

BT advertising can be studied as an example of how firms use and exploit user data collected through new information and communication technologies. 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. The data collected can be used to target advertisements to people based on their behavior, ergo the name "behavioral targeting." The use of personal and behavioral information should promote market efficiency (e.g. offers are

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 of the promised higher sale conversion rates. For instance, H. Beales. 2010. *The value of behavioral targeting*. finds that the price of targeted advertising is 2.68 times the price of untargeted advertising.

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² 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.

customized based on individual characteristics), thus reducing asymmetric information and increasing both users' utility in terms of better offers and firms' benefits in terms of higher revenues. Consequently, by looking at BT and PS, we quickly realize that these two channels rely on different mechanisms, one based on large volumes and customization derived by keyword matching while the other exploits small volumes and high customization. It follows that in order to understand firm performance; it becomes crucial to study the underlying mechanism of each strategy as well as their spillovers.

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 impact on 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, Goldfarb and Tucker, Manchanda et al.). Defined as a generic variable (e.g. ratio of transaction per impression), ads effectiveness has been the focus of recent research, for example, Goldfarb and Tucker (have shown the trade-off between online and offline media, and Manchanda, Dubé, Goh and Chintagunta (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) and how search results affect advertising (Yang and Ghose). Also, Tucker (finds that personalized ads are effective in boosting product demand, however, their effect is negatively mediated by privacy concerns. Similarly, Goldfarb and Tucker (study how targeting can affect purchasers' intention to buy: when advertising matches the website content, it is very effective in increasing the purchase intent.

Following earlier studies, we focus on evaluating how firms can benefit from the use of personal data to achieve higher performance. We advance our knowledge about BT adoption by looking at its effect when combined with PS advertising and the spillovers generated between the two strategies. The information collected through targeting technologies may represent a source of competitive advantage for companies that: (i) are able to reduce the amount of "wasted" advertising by targeting specific users; and

(ii) increase profitability. First, 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 (Acquisti and Varian). Second, advertisers may exploit targeted ads as an informative mechanism to increase the visibility of their products thus favoring other forms of advertising. Therefore, we suggest that spillovers may exist both from BT advertising to PS. Spillovers may exists in the opposite direction as well (from PS to BT): online users expose their personal preferences by querying search engines (e.g. a user may search for a Broadway show in New York), thus providing new information that may enrich the online profile of the user used by companies in targeted ads. In other words, firms can gather new information and reduce their information asymmetries by exploiting users' behavior through PS advertising: the new data allows creating a better taxonomy of users and advertisers can exploit it to better refine their level of segmentation.

It follows that firms should consider the benefits, and costs, associated with each strategy to successfully implement a successful mix. Firms face a trade-off between a large consumer reach and a narrow, but well-defined, 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). 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.). As noted by Athey, Calvano and Gans (, multi-homing customers have an impact on the investment decision in multiple webpages and search engines: 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 PS) in order to exploit their interactions requires effective media planning, the exploitation of internal capabilities, and understanding

market needs (Schultz et al.). 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 performance by implementing an efficient combination of BT and PS advertising to potentially reach the majority of customers and the most profitable ones simultaneously.

Data

Our analysis focuses on understanding the mechanisms that affect advertisers' performance after they invested in both BT and PS advertising. The data generation process differs among these two forms of advertising. In particular the bidding process and the display of ads differ between these two channels. Displayed ads are denoted as impressions. In case of BT, advertisers bid on the placement of impressions (e.g. a banner, pop-up) on specific websites. Advertisers enter the bidding process if, upon visiting a website, a user shows specific characteristics, such as age, race, geographic location and personal interests. This information is available through data collected via cookies, web bugs and other tracking technologies.⁴ If the user represents a positive match based on the preselected characteristics, a targeted ad is displayed. Figure 1 represents an example on how firms are able to specifically target only selected users.

⁴ Complex tracking algorithms are adopted by the company that provided the data. These algorithms exploit third party data to increase the traceability of online users. Unfortunately, we were not able to access more specific information on how this mechanism works since it represents a proprietary source of competitive advantage for the company.



Figure 1. Example of targeting characteristics

In case of PS, firms compete based on keywords. Advertisers bid on keywords and, based on their offer, they are assigned a rank. An ad rank represents the physical position of the ad on the search engine: low ranking refers to ads displayed on the top of the page while higher ranking is linked to ads displayed in the middle and bottom of the page. Opposite to BT, the PS bidding process starts with a user query on a search engine (e.g. Google.com, Bing.com, Yahoo.com): based on the keywords used by the user, several ads are ranked on the left or right side of the page. No matter if an impression is displayed through BT or PS, users can click on the ad to be redirected to the advertiser's page, this is recorded as a click. Conditional on clicking, the number of conversion (or transaction) is defined as the number of times a user buys the advertised product.

It is important to notice a crucial difference on how the match user-impression is determined under these the advertising channels: advertisers select the targeting criteria prior to the beginning of BT campaign, the section may occur based on product characteristics and the specificity of market segmentation. Conversely, PS impressions are display as a consequence of a user query based on specific keywords; it is the user target herself through the use of keywords. As a consequence of these two mechanisms, the effect and the underlying dynamics of PS and BT in increasing a firm's performance may be different.

Our data contains weekly information on both PS and BT on 3786 different advertisers that invest through our data provider between November 2010 and November 2012, thus our unit of analysis is at the advertiser/week level. Our firms represent a total of 20 different industries: Computers is the largest industry with almost 12% of the observations and Hotels, Retails and Telecom are the second largest with almost 10% of the observations each⁵. The weekly data for each firm (identified by a unique ID) includes information on number of impressions, clicks, conversion and revenues for both PS and BT. 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.

Our dataset is novel and unique; it offers the possibility to study the adoption of BT and its joint effect with PS advertising. However, it is far from being perfect and it presents some limitations due to privacy and corporate restriction imposed by our data provider. The optimal dataset would be at the product/campaign level in order to clearly identify the impact of different advertising modes on a single campaign. Aggregation at the firm level may not be perfect because any differences may be due to differences in a firm's strategy, the life cycle a product, or product market share. Given to our data limitations, we try to reduce any potential bias induced by the level of aggregation by introducing industry dummies to account for product and market characteristics. We also include firm fixed effects to control for unobserved firm's strategy characteristics.

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

The raw data includes information on number of impressions, number of clicks, number of conversions, total cost and revenues generated by all transactions for both PS and BT. We report descriptive statistics and correlations in Table 1 and Table 2, respectively.

<Insert Table 1 and Table 2 here>

We exploit the information available to compute two common measure of advertising performance: *Click-through-Rate* (CTR) and *Conversion Rate* (CR).

CTR is computed as the ration between the number of clicks and the number of impressions (CTR=Clicks/Impressions). This variable shows how often users actually click on an impression after they are exposed to it. It is a measure to evaluate the performance of keywords and targeted impressions: higher values of CTR indicate a better keywords and targeted performance. Our average firm has a CTR of 4%, thus suggesting that users actually click 4 times for every 100 impressions displayed. By looking at the single strategies, BT shows a low CTR of only 0.6% which contrast with the 4% CTR of PS impressions. The difference between the CTR of these two channels is statistically significant as reported in Table 3 and it suggests two possible preliminary interpretations. First, PS may experience a higher CTR because of the existence of "activity biases" (Lewis et al.): users that specifically search for keywords may be more likely to click on an ad given their pre-determined intention to search for a specific product or service. Second, it may be possible that the level of targeting of BT impressions is not fully exploited by advertisers such that targeted ads do not create bigger incentives for internet users.

CR rate is defined as the ratio between the number of transactions and the number of clicks (CR=Transactions/Clicks). It is a common measure to evaluate if a click transforms into a purchase. On average, our firms experience a CR of 6.4%: for every 100 clicks, 6 of them translate into a final transaction. Opposite to CTR, BT shows almost triple the percentage of CR when compared to PS. BT has a CR of 16.4% while PS is only about 6%, this difference is statistically significant at the 1% level

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(Table 3). This results are in line with those of Beales (, and they suggest that BT is more successful than PS.

<Insert Table 3 here>

Our set of independent variables includes the *Cost-per-Click* (CPC), the *Average Revenue per Transaction* and the number of *Impressions*.

CPC is measured as the ratio between total advertising cost and the number of clicks (CPC=Cost/Clicks). It represents the strategic behavior of firms: advertisers decided how much to bid to display their ads via PS and BT. Higher CPC favors better placement of the impressions and a higher frequency. Our average firm pays about \$1.63 per click; however we find a large difference in CPC between the two media channels (PS and BT). In line with Beales' findings , our data supports that the CPC for targeted ads is higher than other media. Our test in Table 3 shows that the average CPC for BT is about \$2.01 and \$0.4 more expensive than PS advertising.

The second independent variable is the *Average Revenue per Transaction*. It is defined as the ratio between total revenues for firm *i* during week *t* divided by the number of transaction occurred in the same period (=Revenues/Transactions). This variable can be interpreted as a proxy for the average selling price of the product.⁶ Surprisingly, we find a difference between the average revenue per transaction generated through BT and PS. The former is significantly higher than the latter: the average revenue per transaction through BT advertising is about \$264 while the same measure for PS advertising is about \$232. This

⁶ Our interpretation is based on two bases: first, economic theory suggests that Revenues=Price*Quantity. Our data includes information about both revenues and quantity in terms of transactions, thus price can be approximated as the ratio between revenues and quantity. Second, the same company that provided the data adopts this measure as proxy for price.

result would suggest that firms are able to generate on average about \$31 more revenues per transaction via BT than PS.

Finally, our last group of independent variables is represented by the number of *Impressions* and the number of *Clicks. Impressions* counts the number of ads displayed as a consequence of a user's query on search engine or as targeted advertising. Impressions are important because they start the entire advertising process, in fact, users can potentially click an ad and buy the product only after they are exposed to impressions. In our estimates, we include both the number of impressions for the current week and the lagged variable up to three weeks before. The reason to include lagged variable of *Impressions* is to account for possible effects generated from being exposed to ads in periods before a user click or complete a transaction. It may be possible that after being exposed to a PS or BT impression, users may delay their activity because of their browsing behavior (e.g. intention to buy in later periods) thus creating potential spillovers across weeks. *Clicks* records the number of users that have clicked on the ads (either BT or PS) after being exposed.

We control for several other factors. 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. A value equal to 1 indicates that the ad was placed on top of the page while higher values suggest that the impressions were displayed towards the bottom of the page. We also control for industry sector. 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 major sport events.

Identification strategy

We adopt a model that accounts for the sequential correlation between CTR and CR: CR is defined only if CTR is >0. In other words, it is possible to have conversions only if consumers have previously clicked on an ad. We first model the CTR function:

1. $CTR_{itj} = \beta_0 + \beta_1 PS_I mpression_{it} + \beta_2 BT_I mpression_{it} + \beta_3 BT_I mpression_{it} * PS_I mpression_{it} + \beta_4 K_{it} + I_i + T_t + \varepsilon_{it}$

CTR_{itj} is the click-through-rate for firm *i* at time *t* and *j* represent the level of analysis (=firm level, PS or BT). Our main independent variables are represented by the number of impressions for PS and BT their joint effect. K_{it} is the set of controls, I_i and T_i represent the Industry fixed effects and the time fixed effects, respectively. Our focus is on the estimates of the β_3 parameter, the benchmark results are given by the firm level dependent variable, while we use the strategy level variables (PS and BT) to estimates potential spillovers generated across media channels. Similarly, we model the CR function with the same notation as the Equation (1):

2.
$$CR_{itj} = \beta_0 + \beta_1 PS_Click_{it} + \beta_2 BT_Click_{it} + \beta_3 BT_Click_{it} * PS_Click_{it} + \beta_4 K_{it} + I_i + T_t + \varepsilon_{it}$$

We seek to estimate a model with Equations 1 and 2 for two dependent variables (CTR and CR) simultaneously. Given the nature of CR, the two equations present inter-equation correlation, therefore, the seemingly unrelated regression (SUR) is an appropriate estimation mechanism. In addition, to account for heteroskedasticity, we estimate robust clustered standard errors.⁷ Finally, we recognize that *CPC* and *PS Rank* may introduce an endogeneity problem since firms can strategically decide how to bid on

⁷ We also replicated our estimates by bootstrapping the standard errors over 1000 repetitions and the results are unchanged.

keywords and impressions in order to maximize their performance. To deal with this problem, we model these two variables as endogenous. Specifically, we assume that the current CPC and Rank are a function of the performance in the past periods. We use the lagged variable up to 2 weeks before the current period of the *Return of Investment* (ROI) of both PS and BT; based on past performance, firms have higher incentives to invest in each advertising channel thus affecting the current CPC decision. In addition we also include the 2 weeks lag of the *CTR* to account for the search engine algorithm that assigns ads ranking. We decided to use multiple lags for our instruments to account for the duration of a generic campaign: while our unit of observation is at the week level, campaign may run across several weeks and firms can adjust their bidding strategy accordingly based on the ongoing performance.

To identify our model and the possible spillovers between strategies we exploit the variation between firms that adopt only PS, only BT or both strategies. Figure 2 reports the average CTR, CR and Revenue for firms that adopt both BT and PS and firms that rely only on sponsored advertising. The vertical line represent the first week since BT was available as investment strategy with our data provider.⁸ It is possible to identify a positive effect of adopting BT and Ps simultaneously compared to PS alone.

<Insert Fig.2 Here>

Results

We report the results of our estimations in Table 4. Model 1 and Model 2 refer to the estimates with the dependent variables at the firm level, Model 3 and Model 4 use the dependent variables for PS advertising while Model 5 and Model 6 use BT advertising. The first two models are estimated to test whether BT and PS are complements at the firm level, while the other four models estimated the potential

⁸ While there is no precise date on the availability of BT, we exploit the variation in our data provider offers to distinguish between firms that adopt both BT and PS or only PS.

spillovers across media channels. We study the CTR of our two media channels in order to understand the potential spillover and cross-effects between BT and PS. All models are estimated instrumenting both the *Rank* and the *CPC* variables. We believe that these two variables represent the strategic decision of the firm. Higher level of investments lead to better ad placements, therefore lower ranking on search engines. Since we don't have data available on ads placement for BT advertising we directly model the investment decision in terms of CPC.

By looking at the CTR equation first, in Model 1 we find that PS Impressions has a negative impact on the overall CTR of the firm, while an increase in BT Impressions generates a positive effect. However, once we control for the interaction between the two strategies, we find evidence that the positive effect on CTR is driven by synergies generated by the simultaneous adoption of BT and PS. Based on our results; advertisers have a higher incentive to invest in both BT and PS to favor higher CTR. A similar positive effect is shown in Model 4 and Model 6, where we use the PS and BT CTR respectively. These models are estimated to capture possible spillover across media channels. The positive interaction would confirmed the existence of positive spillovers across media channels and that a firm's strategy (e.g. PS) may benefit by investing in a different channel like targeted ads.

The negative effect shown in Model 1 to 4 for the linear variables (PS impressions and BT Impressions) may have two potential explanations: first, despite a firm's strategic behavior, the layout of the impressions (e.g. images, discounts, length of the text) may create incentive to click on an ad, unfortunately we cannot control for this characteristics due to our data restrictions. Second, it may suggest that firms may bid on ineffective keywords; it is possible that the product offered is only loosely related to the user's query thus reducing the probability of a click.⁹ Surprisingly, the linear variables in Model 5 and Model 6 are both positive. First, it is possible that BT Impressions are able to attract users thanks to

⁹ While we don't have specific data on keywords, discussion with our data provider confirmed that advertisers bid on thousands of keywords (and combinations of keywords) but very few are actually effective and related to the product offered.

tracking technologies, thus increasing CTR. Second, PS Impressions are the outcomes of search queries which provide novel information to advertisers that can use in refine their targeting strategy.

<Insert Table 4 here>

The second half of Table 4 reports our estimations using the conversion rate as dependent variable. Similarly to our empirics on CTR, the interaction variables in all models are significant and positive, thus confirming even further that firms can benefit greatly by investing in both BT and PS compared to either one or the other strategy. Everything else being equal, by increasing the number of impressions, the likelihood that a user completes a transaction is increased when a firm exploits targeted ads and sponsored advertising. The negative signs associated with the linear coefficient of our Click variables may be explained by a possible delay in the transaction: there is no certainty that users that click on an ad and land on the advertised webpage will conclude a transaction. It is likely that this activity delay represents users gathering information about a product prior to finalize a transaction.

Finally, the final purchasing decision may be affected by the price of the product, thus we include the average transaction variable in the CR equations. We again acknowledge that our data doesn't include the actual price of the transaction but we proxy price through the average revenue per transaction. Through the use of BT, companies are able to personalize their offers and may adopt price discrimination; hence, companies might be able to charge higher prices and to exploit customers' willingness to pay. However, high prices may also discourage users from completing the online transaction.

Economic theory suggests that an increase in price would reduce quantity sold. However, when we look at the overall firm CR the predicted negative effect is found only for PS advertising. Conversely, we do not find that BT has a significant effect. These results may suggest that BT allows firms to focus on generating the maximum number of transactions for the highest possible price from a subset of consumers.

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Companies may adopt price discrimination as result of the new targeted strategy. Firms are able to segment the market with higher level of precision; as a result, consumers may pay a higher price for a product that better meets their needs. For example, Athey and Gans (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 non-targeted 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 non-targeted 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

Robust analyses

To test the robustness of our results we performed a series of additional estimates. We first include lagged effects of our main variables to capture possible effect that occur across different weeks (Table 5). For example, our time variable *Week* spans from Saturday to Friday, users that are exposed to an impression in the last days of the week (e.g. Friday) they may complete the transaction in the first days of the following week (e.g. Saturday). The inclusion of lagged variables should capture this effect and reducing possible bias. Table 5 reports the SUR estimates for the models with interaction terms. Model 1 confirms the posit synergies between BT and PS at the firm level CTR, however, the positive variation is driven by the effect on the PS CTR only as shown in Model 2. In fact, once we control for past exposure, the coefficient of the interaction term in the BT model (Model 3) is it positive but not significant. Regarding CR, the robust estimates confirm the positive interaction in all our models, thus supporting our previous findings.

<Insert Table 5 Here>

It is possible that users from different geographic area react differently to different types of advertising, thus affecting the possibility to create synergies and spillovers across media channels. To account for potential geographic preferences we split our sample based on the geographic exposure of the ads. We define three dummies variables to identify campaigns in *Europe*, *USA* and *Other*. While Europe and US represents the majority of our sample (Europe represents about 33% of our observations and US represents about 43%), *Other* represent about 23% of our sample and it mostly includes Japan and China).

<Insert Table 6 Here>

As expected, the geographic results are mixed supporting the idea that consumer preferences have an impact on performance and that these preferences vary across different geographic locations. For the CTR equations, the positive effect is confirmed only for Europe and Other countries but not for the US. A result in line with the fact that Americans reject tailored advertising (Beales). The estimates on CR emphasize the role of individual prefers as well. The results on the European sub-sample support the idea of a positive effect in investing in both BT and PS, however the variation is driven by the preference on sponsored search rather than targeted ads. The regressions on the US sub-sample confirms our benchmark estimates while the *Other* subsample shows that, on average, the two strategies are not complements.

Finally, in Table 7, we explore differences across our two major industries (Computer and Retails). As for the geographic differences, different sectors may experience different effect when targeted ads are combined with sponsored advertising. For example, it is possible that the level of product personalization may favor synergies between BT and PS. All our results in Table 7 confirm our benchmark results, thus suggesting that firms in the computer and retail industries are better off when they combine BT and PS.

<Insert Table 7 Here>

Conclusion

While there is growing theoretical literature discussing BT and its effects on privacy (Acquisti and Varian, Fudenberg and Villas-Boas, Goldfarb and Tucker), empirical results on BT, specifically its adoption and interactions with other strategies, are still scarce. We attempt to fill this gap by conducting a focused comparison of paid search and behavioral targeting. Our study describes how these two media channels contribute to advertising performance (defined in terms of Click-through-Rate and Conversion Rate) and it documents the existence of spillovers across them. This paper contributes to the existing literature on online advertising and BT (Acquisti and Varian, Goldfarb and Tucker, Iyer et al., Summer 2005). While there is extensive theoretical literature on BT and its implications for privacy and performance (Acquisti and Varian, Fudenburg and Villas-Boas, Hermalin and Katz), empirical research on BT is still limited. We offer an empirical estimation on the effect of BT on the overall firm performance and we study the potential spillovers that targeted ads have on PS advertising.

Our results confirm the idea that PS can be source of information to be used in BT advertising, in fact past PS advertising positively increases the performance of targeted ads. Surprisingly, we find that BT impressions and clicks have an impact on the performance of PS. We believe that customers exposed to BT ads exploits sponsored advertising to gather more information about the product offered (e.g. product reviews, availability, price), as such targeted advertising plays the informative role of a "reminder". If customers do not click on a targeted ad, they will remember it and exploit PS to find product characteristics. In other words, users are less likely to click on a targeted ad but when they do, the chances of a transaction are very high while those that do not click on a targeted ad may use search engines to collect information and they delay the final transaction.

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 PS advertising. Companies can leverage the synergies 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 and inform their audience, the role played by targeted ads is twofold: first, BT can play an informative role and incentive users to search for their product through search engines, therefore creating positive spillovers towards PS. Second, despite the low CTR, targeted ads offer a remarkable conversion rate and the opportunity to extract more value from customers through higher revenues per transaction.

While this study offers a new prospective on how PS and BT affect each other, there are several limitations we acknowledge. First, our limitations are primarily due to the inability to access a more detailed dataset due to restrictions imposed by the company that provided the data. For example, the level of analysis (advertiser/week) may not be optimal because it abstracts from within firm variation (e.g. different marketing mix for different product based on popularity, product life cycle, etc.). Unfortunately, our dataset does not include information at the product level; to compensate for this limitation we study only firms that invest in both BT and PS simultaneously. We believe that our results are informative in describing potential effects across media channels and they offer a broad view of the impact of targeted ads on a firm' marketing mix decision. A product level of analysis would be more informative and it is still an open question for future research. Second, we are not able to control for the level of targeting. In our dataset, all firms access the same targeting options (e.g. geographic targeting, re-targeting, age, etc.), but we are unable to distinguish between them.

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 available online; private data may provide useful feedback to improve their products and their PS strategy. However, as profitable as BT strategy appears to be, 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). The use of this data raises privacy concerns, and it may generate tension between profit-seeking strategies and the protection of user privacy. Clearly, privacy

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concerns could limit the adoption of BT. Turow et al. (and Wathieu and Friedman (Jan) document that customers are concerned about their privacy, and they are more likely to resist tailored advertisements. 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. For strategic management, in particular, we think it is important to understand how firms decide to allocate their media budgets among different advertising channels. First, 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. Second, managers should consider the temporal interaction between media channels in order to maximize firm performance. Finally, privacy concerns generate possible tension between profit-seeking strategies such as BT advertising and the protection of users' privacy.

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Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
PS				
Impression	1386791.000	6821316	0	4.92E+08
Clicks	22987.730	105851.8	0	6613146
Transaction	2132.474	22318.35	0	1825592
Revenue	252664.100	2281278	-605	1.87E+08
CTR	0.040	0.05378	0.000014	1
СРС	1.616	4.84318	0.003082	55.998
CR	0.064	0.131775	0	1
ROI	23.424	160.0564	-1.62679	21257.65
Rank	1.054	1.594284	0	38.77143
Average Transaction	232.353	480.1372	0	6837.258
ВТ				
Impression	400061.400	5857862	0	4.21E+08
Clicks	441.318	7209.603	0	626512
Transaction	53.455	1255.414	0	154850
Revenue	4874.402	93188.14	0	1.09E+07
CTR	0.006	0.046475	0	1
CPC	2.016	17.9615	0	660.6721
CR	0.164	0.228004	0	1
ROI	50.957	204.6086	-1	2442.493
Average Transaction	264.154	550.3881	0	12016.44
Firm level				
СРС	1.624	5.130661	0	430.7222
CTR	0.040	0.053791	0	1
CR	0.064	0.132139	0	1
Revenue	257531.500	2289480	-605	1.87E+08
ROI	23.478	160.0486	-1.62679	21257.65
Num. of Campaigns	31.836	42.69025	1	1364
Num. of Search Engines	1.963	1.105242	0	23
Num. of Competitors	176.265	130.4407	0	483

Table 2. Correlation Table

	1	2	3	4	5	6	7	8	9	10	11	12
1.PS Impression	1											
2.PS Clicks	0.955	1										
3.PS Transaction	0.845	0.915	1									
4.PS Revenue	0.758	0.712	0.607	1								
5.PS CTR	-0.104	-0.039	-0.033	0.041	1							
6.PS CPC	-0.165	-0.163	-0.134	-0.190	-0.242	1						
7.PS CR	0.040	0.059	0.149	-0.009	-0.018	0.243	1					
8.PS ROI	-0.044	-0.037	-0.051	0.313	0.369	-0.204	-0.096	1				
9.PS Rank	-0.071	-0.097	-0.090	-0.055	-0.195	-0.147	-0.121	-0.055	1			
10.PS Average Transaction	-0.043	-0.090	-0.119	0.290	0.234	-0.111	-0.286	0.489	-0.088	1		
11.BT Impression	0.520	0.533	0.465	0.406	-0.154	0.000	0.025	-0.046	-0.163	-0.155	1	
12.BT Clicks	0.607	0.608	0.514	0.495	-0.075	-0.155	0.085	-0.054	-0.187	-0.101	0.767	1
13.BT Transaction	0.780	0.829	0.830	0.617	-0.037	-0.180	0.173	-0.039	-0.096	-0.148	0.612	0.622
14.BT Revenue	0.597	0.594	0.496	0.657	-0.053	-0.217	0.021	0.086	-0.042	-0.005	0.594	0.554
15.BT CTR	-0.001	-0.007	0.006	0.004	0.008	-0.051	0.160	-0.033	-0.017	-0.043	-0.079	0.141
16.BT CPC	-0.004	-0.007	-0.006	-0.017	-0.031	0.021	-0.022	-0.026	0.092	-0.018	-0.062	-0.059
17.BT CR	0.223	0.243	0.266	0.150	0.006	-0.219	0.195	-0.019	0.161	-0.237	0.004	-0.011
18.BT ROI	0.002	-0.015	-0.028	0.120	-0.025	-0.132	0.015	0.085	-0.019	0.011	0.127	0.094
19.BT Average Transaction	-0.077	-0.092	-0.102	0.081	0.247	-0.080	-0.231	0.195	-0.090	0.759	-0.150	-0.113
20.Firm CPC	-0.073	-0.071	-0.059	-0.084	-0.041	0.277	0.026	-0.086	0.009	-0.029	-0.090	-0.110
21.Firm CTR	0.127	0.169	0.169	0.140	0.219	-0.196	0.200	0.079	0.032	-0.038	-0.192	0.002
22.Firm CR	0.066	0.082	0.167	0.026	0.031	0.013	0.863	-0.058	-0.070	-0.288	-0.001	0.060
23.Firm Revenue	0.769	0.731	0.620	0.980	0.019	-0.210	-0.002	0.276	-0.055	0.233	0.484	0.545
24.Firm ROI	-0.034	-0.043	-0.060	0.356	0.341	-0.268	-0.085	0.902	-0.030	0.457	0.019	-0.012
25.Firm Num. of Campaigns	0.637	0.649	0.523	0.444	-0.126	-0.199	0.033	-0.039	-0.188	-0.028	0.526	0.601
26.Firm Num. of Search Engines	0.208	0.205	0.190	0.204	-0.026	-0.252	0.135	0.124	0.039	0.021	0.095	0.109
27.Firm Num. of Competitors	0.219	0.221	0.218	0.123	-0.215	-0.218	0.031	-0.112	-0.219	-0.027	0.115	0.235

13	14	15	16	17	18	19	20	21	22	23	24
1											
0.732	1										
0.046	-0.013	1									
-0.023	-0.035	-0.023	1								
0.371	0.243	-0.033	0.139	1							
0.108	0.401	0.010	-0.040	0.107	1						
-0.134	0.010	-0.044	-0.010	-0.228	0.013	1					
-0.078	-0.089	-0.029	0.490	0.018	-0.082	-0.010	1				
0.088	0.001	0.271	0.022	0.150	0.046	-0.008	-0.082	1			
0.265	0.120	0.112	-0.001	0.478	0.088	-0.245	0.040	0.211	1		
0.691	0.793	0.000	-0.023	0.185	0.202	0.068	-0.091	0.113	0.052	1	
0.016	0.276	-0.033	-0.051	0.046	0.328	0.224	-0.134	0.074	-0.004	0.360	1
0.517	0.549	0.015	-0.026	0.101	0.176	-0.036	-0.090	0.119	0.096	0.503	0.033
0.204	0.261	-0.024	0.089	0.203	0.141	-0.034	-0.066	0.231	0.238	0.233	0.166
0.235	0.253	0.102	-0.073	-0.019	0.119	-0.014	-0.049	-0.018	0.132	0.166	-0.052
	13 0.732 0.046 -0.023 0.371 0.108 -0.134 -0.078 0.265 0.691 0.016 0.517 0.204 0.235	13 14 1 1 0.732 1 0.046 -0.013 -0.023 -0.035 0.371 0.243 0.108 0.401 -0.134 0.010 -0.078 -0.089 0.088 0.001 0.265 0.120 0.691 0.793 0.016 0.276 0.517 0.549 0.204 0.261 0.235 0.253	13141510.73210.046-0.0131-0.023-0.035-0.0230.3710.243-0.0330.1080.4010.010-0.1340.010-0.044-0.078-0.089-0.0290.0880.0010.2710.2650.1200.1120.6910.7930.0000.0160.276-0.0330.5170.5490.0150.2040.261-0.0240.2350.2530.102	13 14 15 16 1	131415161710.73210.046-0.0131-0.023-0.035-0.02310.3710.243-0.0330.13910.1080.4010.010-0.0400.107-0.1340.010-0.044-0.010-0.228-0.078-0.089-0.0290.4900.0180.2650.1200.112-0.0010.4780.6910.7930.000-0.0230.1850.0160.276-0.033-0.0510.0460.5170.5490.015-0.0260.1010.2040.261-0.0240.0890.2030.2350.2530.102-0.073-0.019	13 14 15 16 17 18 1 0.732 1	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				

	25	26	27	
25.Firm Num. of Campaigns	1			
26.Firm Num. of Search Engines	0.289	1		
27.Firm Num. of Competitors	0.379	0.097	1	

Table 3. Mean comparison test

	CTR	CR	Average Revenue per Transaction	CPC	ROI
PS advertising	0.040	0.063	232.35	1.615	23.424
BT Advertising	0.006	0.163	264.15	2.015	50.956
Difference	0.033***	-0.099***	-31.80***	-0.399***	-27.532***

The table compares several measures (columns) across advertising channels (PS and BT). A negative difference suggests that BT advertising shows higher level of the specific measure.

***, **, * indicate that the difference is < 0 at the 0.01, 0.05 and 0.1 confidence levels, respectively. In case of Click-through-Rate the difference is >0 at the 0.01 confidence level.





I abit 7. Deneminar & SUN Commany	Table 4.	Benchmark	SUR	estimates	
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	(1)	$\langle 0 \rangle$	(2)	(4)	(5)	
	(1) Eirre	(2) Eirre	(3) DC	(4) DC	(5) DT	(0) DT
	Firm	F1rm Laval	PS Lovel	PS Lovel	BI	BI
CTD	Level	Level	Level	Level	Level	Level
DS Improviona	0.006***	0.007***	0.007***	0.007***	0.001***	0.001**
PS impressions	-0.000	-0.007	-0.007	-0.007	(0.001)	(0.001)
DT Improviona	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
B1 Impressions	(0.007)	-0.010	(0.009)	-0.002	(0.001)	(0.001)
DS Improvious*PT Improvious	(0.001)	(0.003)	(0.001)	(0.003)	(0.000)	(0.000)
FS impressions B1 impressions		(0.001)		(0.001)		(0.001)
Donk	0 1 80***	(0.000) 0.171 ^{***}	0 100***	(0.000) 0.176 ^{***}	0.001**	(0.000)
Kalik	-0.109	-0.1/1	-0.190	-0.170	-0.001	(0.000)
DT CDC	(0.003)	(0.003)	(0.000)	(0.003)	(0.000)	(0.000)
BICFC	-0.033	-0.007	-0.039	-0.020	-0.002	-0.002
Number Of Compaigne	(0.003)	(0.004)	(0.003)	(0.004)	(0.000)	(0.000)
Number Of Campaigns	(0.002)	(0.002)	(0.002)	(0.002)	-0.000	-0.000
Competitor	(0.001) 0.244***	(0.001) 0.217***	(0.001) 0.245***	(0.001) 0.225 ^{***}	(0.000)	(0.000)
Competitor	(0.244)	(0.217)	(0.243)	(0.223)	(0,001)	(0.001)
Number Of Search Engines	(0.009)	(0.007)	(0.009)	(0.008)	(0.000)	(0.000)
Number Of Search Englies	(0.027)	(0.020)	(0.020)	(0.020)	(0,001)	(0,001)
Firm size	(0.003)	(0.003)	(0.00+)	(0.003)	(0.000)	(0.000)
T IIIII SIZC	(0.00+	(0.00+	(0.004)	(0.004)	(0,000)	(0,000)
CP	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PS Click	-0.014***	-0.014***	-0.014***	-0.014***	0.001	-0.001**
15 CHER	(0.014)	(0.014)	(0,000)	(0,000)	(0,001)	(0,000)
BT Click	(0.000)	-0.010^{***}	(0.000)	-0.000	(0.000)	-0.011^{***}
DI Chek	(0.001)	(0.010)	(0.002)	(0.000)	(0,000)	(0,000)
PS Click *BT Click	(0.000)	0.001***	(0.000)	$(0.001)^{**}$	(0.000)	(0.000)
To check DT check		(0,000)		(0,000)		(0.002)
BT Price	0.000	0.001^{**}	-0.002**	-0.001^*	0.018***	(0.000)
DITINC	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
PS Price	-0.028***	-0.028***	-0.028***	-0.028***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number Of Campaigns	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{***}	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Competitor	0.005***	0.005***	0.005***	0.005***	0.001***	0.001***
<u>F</u>	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)
Firm Size	0.017^{***}	0.017***	0.017***	0.017***	(11000)	(
	(0.000)	(0.000)	(0.000)	(0.000)		
N	105445	105445	105442	105442	108322	108322
	* *		-			

Clustered robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01All models include: Industry Fixed effect, Year fixed effects and Month fixed effects

	(1)	(2)	(3)
	Firm Level	PS Level	BT Level
CTR			
PS Impressions	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)
BT Impressions	-0.009****	-0.001	0.001
	(0.003)	(0.003)	(0.001)
PS Impressions*BT Impressions	0.001^{***}	0.001^{**}	0.001
	(0.001)	(0.001)	(0.001)
Rank	-0.168***	-0.174***	-0.001
	(0.004)	(0.005)	(0.001)
BT CPC	-0.006^{*}	-0.014***	-0.001***
	(0.003)	(0.003)	(0.001)
Number Of Campaigns	0.003^{**}	0.003^{**}	0.001
	(0.001)	(0.001)	(0.001)
Competitor	0.214^{***}	0.221^{***}	0.001^{***}
	(0.007)	(0.008)	(0.001)
Number Of Search Engines	-0.024***	-0.024***	0.001^{*}
	(0.003)	(0.003)	(0.001)
Firm size	0.004^{***}	0.004^{***}	-0.001^{*}
	(0.001)	(0.001)	(0.001)
CR			
PS Click	-0.017***	-0.017***	-0.001****
	(0.001)	(0.001)	(0.001)
BT Click	-0.010****	-0.001	-0.015****
	(0.001)	(0.001)	(0.001)
PS Click *BT Click	0.001^{***}	0.001^{*}	0.002^{***}
	(0.001)	(0.001)	(0.001)
BT Price	0.001^{*}	-0.002**	0.020^{***}
	(0.001)	(0.001)	(0.001)
PS Price	-0.028****	-0.028***	-0.001****
	(0.001)	(0.001)	(0.001)
Number Of Campaigns	0.002^{***}	0.002^{***}	0.001^{***}
	(0.001)	(0.001)	(0.001)
Competitor	0.005^{***}	0.005^{***}	0.001
	(0.002)	(0.002)	(0.001)
Firm Size	0.017^{***}	0.017^{***}	0.001^{***}
	(0.001)	(0.001)	(0.001)
N	103892	103889	103895

Table 5. SUR estimates with past variables up to t-3

Clustered robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01All models include: PS and BT Impressions up to t-3, PS and BT Clicks up to t-3 Industry Fixed effect, Year fixed effects and Month fixed effects

	(1)	(2)	(3)
	Firm Level	PS Level	BT Level
CTR			
PS Impressions	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
BT Impressions	-0.014***	-0.003	0.001
	(0.004)	(0.004)	(0.001)
PS Impressions*BT Impressions	0.001^{***}	0.001	0.001^{*}
	(0.001)	(0.001)	(0.001)
Rank	-0.110***	-0.112***	-0.001
	(0.003)	(0.003)	(0.001)
BT CPC	0.005^{**}	0.002	-0.001***
	(0.002)	(0.002)	(0.001)
Number Of Campaigns	-0.021***	-0.022***	0.001
	(0.001)	(0.001)	(0.001)
Competitor	0.158^{***}	0.161^{***}	0.001^{***}
	(0.007)	(0.007)	(0.001)
Number Of Search Engines	0.007^{**}	0.008^{**}	0.001
	(0.003)	(0.003)	(0.001)
Firm size	-0.003***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)
CR			
PS Click	-0.019^{***}	-0.019***	-0.001***
	(0.001)	(0.001)	(0.001)
BT Click	-0.016***	-0.022***	0.025^{***}
	(0.003)	(0.003)	(0.001)
PS Click *BT Click	0.002^{***}	0.003***	-0.001***
	(0.001)	(0.001)	(0.001)
BT Price	-0.002	-0.003***	0.014^{***}
	(0.001)	(0.001)	(0.001)
PS Price	-0.033***	-0.033****	-0.001****
	(0.001)	(0.001)	(0.001)
Number Of Campaigns	-0.001*	-0.001	0.001
	(0.001)	(0.001)	(0.001)
Competitor	0.009^{***}	0.009^{***}	0.003****
	(0.003)	(0.003)	(0.001)
Firm Size	0.021^{***}	0.021^{***}	0.001^{***}
	(0.001)	(0.001)	(0.001)
N	33828	33827	33830

Table 6. SUR Regressions (Europe Only)

Clustered robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01All models include: Industry fixed effects, Year fixed effects and Month fixed effects

<u>-</u>	(1)	(2)	(3)
	Firm Level	PS Level	BT Level
CTR			
PS Impressions	-0.014***	-0.015***	0.001^{***}
Ĩ	(0.001)	(0.001)	(0.001)
BT Impressions	0.002	0.013***	0.001
	(0.003)	(0.004)	(0.001)
PS Impressions*BT Impressions	-0.001	-0.001***	0.001***
	(0.001)	(0.001)	(0.001)
Rank	-0.132***	-0.142***	0.001^{***}
	(0.005)	(0.006)	(0.001)
BT CPC	0.008	0.001	-0.001***
	(0.013)	(0.014)	(0.001)
Number Of Campaigns	0.013^{***}	0.014^{***}	-0.001***
	(0.001)	(0.001)	(0.001)
Competitor	0.143***	0.152^{***}	-0.001***
	(0.008)	(0.009)	(0.001)
Number Of Search Engines	-0.056^{***}	-0.061***	0.001^{***}
	(0.004)	(0.004)	(0.001)
Firm size	0.008^{***}	0.008^{***}	-0.001***
	(0.001)	(0.001)	(0.001)
CR			
PS Click	-0.015****	-0.015****	-0.001****
	(0.001)	(0.001)	(0.001)
BT Click	-0.010****	-0.002	-0.013****
	(0.002)	(0.002)	(0.001)
PS Click *BT Click	0.001^{***}	0.001^{**}	0.002^{***}
	(0.001)	(0.001)	(0.001)
BT Price	0.002^{**}	-0.001	0.025***
	(0.001)	(0.001)	(0.001)
PS Price	-0.027***	-0.027***	-0.002***
	(0.001)	(0.001)	(0.001)
Number Of Campaigns	0.002***	0.002***	0.001
	(0.001)	(0.001)	(0.001)
Competitor	0.002	0.002	-0.004
	(0.002)	(0.002)	(0.001)
Firm Size	0.017^{***}	0.017^{***}	0.001***
	(0.001)	(0.001)	(0.001)
Ν	47923	47921	47924

Table 6b. SUR Regressions (USA Only)

Clustered robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01All models include: Industry fixed effects, Year fixed effects and Month fixed effects

<u>-</u>	(1)	(2)	(3)
	Firm Level	PS Level	BT Level
CTR			
PS Impressions	-0.011***	-0.011***	-0.001
L	(0.001)	(0.001)	(0.001)
BT Impressions	-0.010***	0.001	-0.001***
L L	(0.002)	(0.002)	(0.001)
PS Impressions*BT Impressions	0.001^{***}	-0.001	0.001***
1 1	(0.001)	(0.001)	(0.001)
Rank	-0.011***	0.004^{**}	0.001^{***}
	(0.002)	(0.002)	(0.001)
BT CPC	0.003	0.010	0.007^{***}
	(0.009)	(0.008)	(0.001)
Number Of Campaigns	-0.001	-0.003***	-0.001***
	(0.001)	(0.001)	(0.001)
Competitor	0.031***	0.016^{***}	-0.001***
	(0.003)	(0.002)	(0.001)
Number Of Search Engines	0.011^{***}	0.012^{***}	0.001
	(0.001)	(0.001)	(0.001)
Firm size	0.005^{***}	0.005^{***}	-0.001****
	(0.001)	(0.001)	(0.001)
CR	***	***	***
PS Click	-0.006***	-0.006***	-0.001
	(0.001)	(0.001)	(0.001)
BT Click	-0.002	0.017^{***}	-0.034
	(0.003)	(0.003)	(0.001)
PS Click *BT Click	0.001	-0.001	0.004
	$(0.001)_{*}$	(0.001)	(0.001)
BT Price	-0.004	-0.007	0.025
	(0.002)	(0.002)	(0.001)
PS Price	-0.024	-0.023	-0.001
	(0.001)	(0.001)	(0.001)
Number Of Campaigns	0.007	0.007	0.001
	(0.001)	(0.001)	(0.001)
Competitor	0.006	0.006	0.001
T I C I	(0.003)	(0.003)	(0.001)
Firm Size	0.015	0.015	0.001
	(0.001)	(0.001)	(0.001)
Ν	24090	24090	24090

Table 6c. SUR Regressions (Other countries)

Clustered robust standard errors in parentheses. * p < 0.1, *** p < 0.05, **** p < 0.01All models include: Industry fixed effects, Year fixed effects and Month fixed effects

	(1)	(2)	(3)
	Firm Level	PS Level	BT Level
CTR			
PS Impressions	-0.010***	-0.011***	0.001
	(0.001)	(0.001)	(0.001)
BT Impressions	-0.006***	-0.001	0.001^{***}
	(0.001)	(0.002)	(0.001)
PS Impressions*BT Impressions	0.001^{***}	0.001	-0.001***
	(0.001)	(0.001)	(0.001)
Rank	0.007^{***}	0.015^{***}	-0.001*
	(0.002)	(0.002)	(0.001)
BT CPC	0.002	-0.001	0.001
	(0.005)	(0.005)	(0.001)
Number Of Campaigns	-0.006***	-0.005***	-0.001
	(0.001)	(0.001)	(0.001)
Competitor	-0.007***	-0.015***	0.001^{***}
	(0.003)	(0.004)	(0.001)
Number Of Search Engines	0.014^{***}	0.013^{***}	0.001
	(0.001)	(0.002)	(0.001)
Firm size	0.007^{***}	0.007^{***}	-0.001*
	(0.001)	(0.001)	(0.001)
CR			
PS Click	-0.010***	-0.010****	-0.001
	(0.001)	(0.001)	(0.001)
BT Click	-0.010***	-0.008^{**}	-0.026***
	(0.003)	(0.003)	(0.001)
PS Click *BT Click	0.001^{***}	0.001^{***}	0.002^{***}
	(0.001)	(0.001)	(0.001)
BT Price	-0.004**	-0.006***	0.029^{***}
	(0.002)	(0.002)	(0.001)
PS Price	-0.023***	-0.023***	-0.001***
	(0.001)	(0.001)	(0.001)
Number Of Campaigns	0.003***	0.004^{***}	0.002^{***}
	(0.001)	(0.001)	(0.001)
Competitor	0.012^{**}	0.013**	-0.003
-	(0.006)	(0.005)	(0.002)
Firm Size	0.013***	0.013***	-0.001
	(0.001)	(0.001)	(0.001)
N	9449	9448	9449

Table 7a. SUR Regressions (Retail Industry)

Clustered robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01All models include: Geographic fixed effects, Year fixed effects and Month fixed effects

	(1)	(2)	(3)
	Firm Level	PS Level	BT Level
CTR			
PS Impressions	-0.013***	-0.013***	-0.001*
-	(0.001)	(0.001)	(0.001)
BT Impressions	-0.024***	-0.012*	-0.001
-	(0.007)	(0.007)	(0.001)
PS Impressions*BT Impressions	0.001^{***}	0.001	0.001^{***}
	(0.001)	(0.001)	(0.001)
Rank	-0.072***	-0.072***	0.001^{***}
	(0.003)	(0.003)	(0.001)
BT CPC	0.031***	0.024^{***}	-0.001***
	(0.006)	(0.006)	(0.001)
Number Of Campaigns	-0.002^{*}	-0.002^{*}	-0.001
	(0.001)	(0.001)	(0.001)
Competitor	0.129***	0.129***	-0.001****
	(0.009)	(0.009)	(0.001)
Number Of Search Engines	0.046^{***}	0.046^{***}	-0.001****
	(0.003)	(0.003)	(0.001)
Firm size	0.006***	0.006***	-0.001*
	(0.001)	(0.001)	(0.001)
CR	***	***	***
PS Click	-0.019	-0.019	-0.001
	(0.001)	(0.001)	(0.001)
BT Click	-0.048	-0.039	-0.060
	(0.008)	(0.008)	(0.002)
PS Click *BT Click	0.005	0.004	0.007
	(0.001)	(0.001)	(0.001)
BT Price	0.004	0.002	0.010
	(0.003)	(0.003)	(0.001)
PS Price	-0.028	-0.028	-0.002
	(0.001)	(0.001)	(0.001)
Number Of Campaigns	0.015	0.015	-0.001
	(0.001)	(0.001)	(0.001)
Competitor	0.019	0.018	0.003
E' 0'	(0.007)	(0.007)	(0.002)
Firm Size	0.019	0.019	0.001
	(0.001)	(0.001)	(0.001)
Ν	12921	12921	12921

Table 7b. SUR Regressions (Computer Industry)

Clustered robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01All models include: Geographic fixed effects, Year fixed effects and Month fixed effects