Life Is But an Online Shopping Journey?
Exploring the Dynamic Interactions Between Targeted and Paid Search Advertisement Mix

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Introduction

The rapid rise of online sales has led to the development of technologies promising better targeting of consumers with specific ads.[1] These technologies now enable firms to employ different strategic combinations to optimize advertising performance. However, currently the literature suffers from two limitations. First, the focus has been on whether a specific technology is more effective than another in identifying a consumer with a propensity to buy a particular product. As a result, we know very little about the potential interactions and spillovers generated by combining multiple strategies at the same time. The second limitation regards the way outcomes are measured. Currently, the literature on the effects of online advertisement solely looks on immediate response: that is only action that the user has taken directly after being exposed to a specific ad are measured and analyzed (Acquisti, 2006; Goldfarb and Tucker, 2011; Zhang and Wedel, 2009). While this allows for simplicity, much, if not most, of the effects of marketing are not immediate but happen in a significantly longer timeframe (Putsis and Srinivasan, 1994).

As a consequence, while research has significantly advanced our understanding of the effectiveness and outcomes of online advertisement, it leaves us with two significant knowledge gaps. First, we know very little about the interactions between different online strategies when used together as a strategic mix in a campaign. Secondly, we do not know what are the dynamic overtime overall impacts of the usage of these different technological mixes, throughout an online marketing campaign.

To develop a framework that mitigate both of these limitation we develop a framework that views online shopping as a journey. Thus, instead of seeing the interaction of ads and users as immediate cause and effect, we analyze online shopping is a continuous process in which users develop preferences and gather information before culminating in a purchase. In so doing we draw on the work first developed by

[1] In the United States alone, annual online sales were estimated at $57 billion in the third quarter of 2012, with online spending accounted for 18% of advertising expenditures in 2012 (U.S. Department of Commerce, 2012). Furthermore, online 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).

Moe (2003). In our view, the sale action is the end of process that starts with the first exposure to any form of advertising which trigger a desire, it continues through the utilization of the internet as an effective tool to collect information and compare products characteristics (e.g. quality, reviews, and prices) across different sellers, and only then ends with a sale. Thus, different kind of ads should, if effective, trigger different responses from the users, depending on where they are in the progression through their shopping journey. For example, in the early stages of a shopping journey a successful ad to trigger a process of information gathering, while at a later stage a successful ad would indeed trigger a sale. It therefore follows that different technologies should be utilized to identify and approach users differently depending on where the users is along her online shopping journey with regards to the specific product the advertiser aims to promote.

Following these insights we proceed to look at spillover mechanisms between two of the most widely used channels over the life cycle of an advertisement campaign: Paid Search (PS) and Behavioral Targeting (BT). PS refers to ads that are shown when users' uses specific keyword queries on search engines. Therefore, this strategy aims to locate users that are well advanced in their shopping journey and are actively searching for a specific product category to buy (e.g., airline tickets) and then prod them to buy a specific product (e.g., Turkish Airline).[2] BT refers to technologies used to determine a well-defined set of users by their propensity to buy specific products, whether or not they have currently demonstrated active desire to buy. As a consequence advertisers can use BT to "prospect," that is precisely tailor ads based on analysis of costumers' preferences, in the hope of triggering a "shopping journey." As such, the PS can be seen as a reactive strategy, an ad is released in reaction to a specific action by the user (e.g. search engine query) that supposedly reveals the user aim to buy, while BT is an active strategy; it aims to prod a specific pre-defined set of customer into action.

[2] By definition, therefore, paid search is highly susceptible to activity bias, since it aims to identify these users already engaged in specific online shopping activities. Thus, many of the successful conversions from ads to sale originating from paid search are of people that already decided to buy such a product (if not that specific one) before being exposed to the ad (Lewis et al., 2011).

We adopt a novel dataset to study the effect of the two media channels (PS and BT) on traditional performance measures such as Click-through-Rate and Conversion Rate to demonstrate these multidirectional interactions over the lifetime of an overall online campaign. Using an online campaign timeframe of up to five weeks, we find that spillovers across media channels exist, but they are effective only up to two weeks in advance. Unlike the current thinking which view the impact of ads as immediate our finding suggest that online shopping is indeed a journey. On average, before final transition, users tend to be exposed to targeted ads two weeks prior, exploit search engines one week before and only then complete the transition. Secondary findings suggest that (1) users exposed to BT ads are price insensitive (that is average sale price of the same product is higher) and that (2) a more aggressive strategy in terms of Cost-per-Click offers a better performance for BT, but may harm the conversion rate of both strategies (higher CPC means higher impressions that may not translate into conversions).

The paper proceeds as follows. The next section reviews the literature, after which we define our data and methodology, before proceeding to describe the empirical results and then conclude.

Literature review

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. [3] The Internet has made it easier for firms to offer personalized products and promotions (Ghosh et al., 2006; Zhang and Wedel, 2009).

Despite the growing interest in online advertising, there is still a lack of empirical research on the interaction between different media channels along the existence of a marketing campaign. In particular,

[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, Beales (2010) finds that the price of targeted advertising is 2.68 times the price of untargeted advertising.

the role of targeted ads and their impact on other marketing strategies is greatly overlooked. Recent work on targeted advertising finds that personalized ads are effective in boosting product demand, however, their effect is negatively mediated by privacy concerns (Tucker, 2011). Similarly, Goldfarb and Tucker (2011) 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.

While existing literature has broaden our understanding about online advertising and consumer behavior, it is mostly limited to outcomes (e.g. clicks or final transactions) that are directly related to a single exposure. As a consequence, there is a lack of research addressing the importance of the duration of customers' purchasing process: in the context of online advertising, it is important to understand the factors affecting the purchasing decision, the path and timing from the first exposure to the final transaction. Advertisers may learn how to distinguish between customers based on how close they are to a purchase and treat them differently to improve their online performance in terms of clicks or revenues. In a different context, Putsis and Srinivasan (1994) model the deliberation process of customers in the process of buying a new car and they suggest that differences between browsing for information and buying depend on the duration of the purchasing deliberation.

Consumers' behavior may be one reason of cross-channel behavior: some users may be far from a purchase decision and they are simply looking for product information, while other users may have already developed specific preferences and they may be more product-oriented. Moe (2003) describes four different types of shoppers based on the combinations of two determinants: search behavior (directed or exploratory) and purchasing horizon (immediate or future). In particular, consumers can be classified as direct buyers when they express a directed search behavior and they intend to finalize the purchase in the immediate future. On the opposite end, there are customers that are distant from a transaction and their search behavior is merely exploratory (e.g. gather information). Finally, Moe (2003) introduces two intermediate types of customers: the first has a distant purchasing horizon but she has already formed preferences on the product, while the second type is still in the exploratory phase of gathering information but she has an immediate purchasing horizon.

We rely on this typology as starting point to study the impact of media channels along the purchase process: different type of users may be more affected by different ads (e.g. PS) than other (e.g. BT) based on how close they are to the final purchase. For example, findings by Jerath et al. (2014) suggest that, in the case of sponsored and organic search keyword popularity (in terms of search volume) is related to users' behavior. More precisely, popular keywords are associated with lower clicks on sponsored ads. This suggests that, compared to more popular keywords, less popular keywords are queried by users that have already invested efforts in their searches and are now closer to a purchase. We advance this stream of research by analyzing the effect of two distinct channels, namely PS and BT, on the purchasing process and the possible information spillovers between them.

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). Looking at switching customers Athey et al. (2012) found they 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.

By looking at online shopping from this vantage point we can clearly see what might be the different mechanisms in which ads generated by different online strategy help the user along her shopping journey. This then allows us theorize on the multidirectional interactions between the two strategies we focus in this paper. Paid Search strategy works by identifying users who are already well into the process of looking (and hence buying) a specific product. It aims to figure out which search words might indicates that the user is actively looking to buy the product category the advertiser aims to sell, and then interject with an ad to that particular user, so she will be the specific product of the advertiser as she is already well into his shopping journey. Accordingly, what PS does is specifically look for and exploit an activity bias

– recognizing that the user is online because she already decided to buy and moving her to choose a specific product (Lewis et al., 2011). For example, if a user has already decided to buy a new Swiss watch, one of the options she has is go online and search for information (e.g. reviews, available prices). While on a search engine, this user will be exposed to ads for specific Swiss watches (e.g., Tissot) because of her online query. As noted by Jerath et al. (2014), the likelihood of clicking on a sponsored ad is higher for users that have already developed clear preferences and are far along the purchasing process. On the other hand, behavioral targeting can focus on users that are on different stages of the purchasing process and have two different effects. First, more broadly defined, BT can start the shopping journey by targeting prospecting users. After the first exposure, users may have more incentive to gather information about the advertised product and move one step closer to the final transaction. Users exposed to prospective targeting may increase their queries on search engines to collect information about the product. Going back to our example, advertisers may select a generic user as a prospective buyer of Swiss watches because of her income (e.g. wealthier users may be more likely to buy high-end Swiss watches) and target her with prospecting ads. Since the user is still in the early stages of purchasing process, we should not expect a successful the ad to translate into an immediate sale, but instead to trigger interest towards the product and accordingly actions to collect more information, for example an increase in search queries on Swiss watches. These actions may then create potential spillovers towards paid search advertising.

Second, BT can be used to re-target users with a higher propensity to buy. Here BT is using extra data based on the new data collected after the search engine queries. The advertiser then expose such users to an ad, in the assumption that the ad already answers an articulated need of the user and saves her time and effort, presenting her with the deal she already decided to commence. In our example, the user has been exposed to a BT ad which triggered a process of search, which then allow the adversities to analyze her new preferences as she expressed them via keywords queries (e.g. specific watch model, price range). At that stage BT can be used to retarget (e.g. re-engage the user) the user exploiting the new enriched data to advertise a specifically tailored offer which should increase the chances of a conversion.

These two very different mechanisms of transaction mean that the spillovers from PS and BT and vice versa are quite different, and dynamically change with time, but might be of critical importance in both sides. We argue that there may be spillovers effect between PS and BT based on the users and their progression in the purchasing decision process. Our argument relies on broader vision of BT. We contend that even when successfully identifying users with a high propensity to buy a product, many times BT ads do not act is an immediate trigger for buying, but instead play the role of "shopping reminders," increasing the willingness to buy (Goldfarb and Tucker, 2011). Thus, BT can be an extremely effective way to trigger a shopping journey ending with a sale, even if exposure does not translate into an immediate transaction. Further, by triggering the shopping process, the user may actively search for information on the product, thus BT ads not only lead to higher exposure to PS ads, but also increase the probability that she will click on them.

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, which the algorithms they use shows as predictive. This information is available through data collected via cookies, web bugs and other tracking technologies.[4] If the user represents a positive match (e.g., score higher than a benchmark devised by a specific algorithm) 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 seen the core proprietary source of competitive advantage of different advertising companies. These algorithms represent their unique ability to analyze effectively the date combine by using their own resources as well as third party data as they trace online users through extended period of time.

<Insert Figure 1 Here>

In case of PS, firms compete 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 selection 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 that 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 75 different advertisers between November 2010 and November 2012, thus our unit of analysis is at the advertiser/week level. Our firms represent a total of 15 different industries: Computers is the largest industry with almost 12% of the observations and Hotels is the second largest with 11% of the observations.[5] The weekly data for each firm (identified by a unique ID) includes information on number of impressions, clicks, conversion and

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

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 direct effect of BT and its potential spillovers on other advertising channels like PS. 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 a firm's strategy.

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, in this case the fact 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, 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 study. In terms of mitigating the activity biases, we first include lagged effects of our main variables to capture possible effect that occur across different weeks. 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) may complete the transaction in the first days of the following week (e.g. Saturday). The inclusion of lagged variables allows capturing this effect and reducing possible bias. 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.

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 ratio 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 0.6%, thus suggesting that on average users click six times for every 1000 impressions displayed. The low CTR is driven by the low performance of BT impressions that show an average CTR of only 0.01% which contrast with the 2.9% 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., 2011): 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 about 11%: that is for every 100 clicks, eleven translate into a final transaction. Here, in direct opposition to CTR, BT shows almost double the percentage of CR when compared to PS. BT has a CR of 15% while PS is only about 8%, this difference is statistically significant at the 1% level (Table 3). This results are in line with those of Beales (2010), and they suggest that BT is more successful than PS when effectiveness is defines as immediate transaction.

After we combine our preliminary results on CTR with those of our CR variable, we believe that the difference in CTR is predominately driven by activity biases. In fact, users are exposed to BT impressions while vising different websites (e.g. ESPN.com, economist.com) thus the probability on clicking on an impression depends not only on the level of targeting but also on the consumer's internet behavior.[6] However, while users tend to click less on a targeted ad, the users that do are very likely to purchase the offered product or service.

<Insert Table 3 here>

Our set of independent variables includes the number of *Impressions* and the *Cost-per-Click* (CPC) for the estimations with *CTR* as dependent variable while we use *CTR*, the *Average Revenue per Transaction* and the *Cost-per-Click* (CPC) to study the impact on *Conversion Rate* (CR).

Our first independent variable is the number of *Impressions*. This measure 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.

[6] For example, users may not click because they delay their purchase and gather more information about the product.

Second, we measure CPC 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 $0.98 per click; however we find a large difference in CPC between the two media channels (PS and BT). In line with Beales' findings (2010) , we find that the average CPC for BT is about $2.22 which is more than double the CPC for PS advertising at $0.94.

We recognize that CPC may introduce an endogeneity problem since firms can strategically decide how to bid on keywords and impressions in order to maximize their performance. To deal with this problem we use instrumental variable estimations. Specifically, we assume that the current CPC is a function of the performance in the past periods. We use the lagged variable up to 3 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 three weeks lag of the *Rank* of PS impressions. *Rank* refers to the physical location of each PS impression, a rank value equal to one indicates that the impressions was placed on top of the page while higher values suggests that the impressions were displayed towards the bottom of the page. Similarly to ROI, the lagged *Rank* variables are a measure of performance although it only refers to PS impressions. 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[7].

Finally, in our CR models we also include 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.[8] Surprisingly, we find a marked difference between the average revenue per

[7] We tried using the lag variables up to one week, two weeks and four weeks and the results are consistent across specifications.

[8] 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

transaction generated through BT and PS. The former is significantly higher than the latter: the average revenue per transaction through BT advertising is about $370 while the same measure for PS advertising is about $342. This result would suggest that firms are able to generate on average about $28 more revenues per transaction via BT than PS.

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. 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.

Results

We report the results of our estimations in Table 4 and Table 5. In Table 4, we adopt CTR as our dependent variable. Models 1 to 3 adopt the overall CTR of the firm to estimate the mechanism of BT and PS on firm performance. We use the CTR of PS and BT as dependent variable in Models 4 to 6 and Models 7 to 9, respectively. We study the CTR of our two media channels in order to understand the potential spillover and cross-effects between BT and PS. Models without the CPC variables are estimated adopting a Panel FE model. Model 3, Model6 and Model 6 are estimated instrumenting the two CPC variables. Since our set of instrument is constant across models (only the dependent variable changes) the F-statistics of the first stages and the under-identification test (Kleibergen-Paap rk LM statistic) are

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the ratio between revenues and quantity. Second, the same company that provided the data adopts this measure as proxy for price.

constant across models. As reported in the table footnote, the F-statistics of the first stages are significant and the under-identification test rejects the null hypothesis, thus the model is identified. In addition, our models also pass the over-identification test (Hansen J Statistics), thus suggesting that the instruments are valid.

Across our models, we don't find any impact of PS impressions and its lagged variable but we identify an interesting trend relative to BT impressions. BT impressions suggest a delayed effect on CTR: ads displayed in the concurrent week reduce the probability of a click; however, impressions from the week before have a significant positive effect. It appears that users exposed to BT advertising delay their action (in this case the click on the advertisement), past impressions act like a reminder of advertised products. The lack of results relative to PS impressions may be due to our aggregate dependent variables: significant variance at the firm level appears to be predominantly driven by impressions via BT advertising and CPC (Model 3). Once we focus on the CTR generated only by PS advertising (Models 4 to 6) we find that PS impressions show a significant impact. Results suggest a positive impact up to two weeks before the current period of analysis, thus suggesting a potential delay. This delay may be due either to a postponement in the users' action (clicking on an ad) because of their browsing behavior or to the possibility that after being exposed to an ad they purchase the product via different channels (either online or offline). The effects of BT impressions PS CTR (Models 4 to 6) corroborate our idea that this type of ads may have an informative function: the concurrent BT impressions increases the PS CTR, users exposed to targeted ads may not click on the ad and use search engines to gather more information. This mechanism would also explain the higher CTR for PS advertising. In other words, after a BT ad is displayed, a user may search for more information about the product like characteristics, price, and availability thus increasing the chance of a click via PS than BT.

By looking at Model 3, we find that PS CPC has no statistical impact on the overall CTR of the firm, while an increase in BT CPC generates a positive effect. A 1% increase of BT CTR leads to a 0.14% increase on the overall firm CTR. Based on our results; advertisers have a higher incentive to increase their investments in BT to favor higher CTR. A similar positive effect is shown in Model 9 where we use only the CTR generated by BT advertising as dependent variable. Conversely, the PS CPC has a negative impact on the CTR of both PS and BT (Model 6 and Model 9). The negative effect shown in Model 2 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]

<Insert Table 4 here>

To further understand the impact of PS and BT advertising we report our estimations using the conversion rate as dependent variable in Table 5. Similar to our empirics on CTR (Table 4), we estimate our conversion rate models on the overall firm performance (Models 1 to 3) and the CR of PS (Models 4 to 6) and BT (Models 7 to 9). Our inclusion of the regressions on the single media channel is important to understand the impact one advertising media (e.g. PS) has on the performance of the other channel (e.g. BT). We estimate the models that include PS and BT CPC using our set of instrumental variables. Across our IV estimations, only the dependent variable changes while the instrumental variables are constant across models, thus the F-statistics of the first stages and the under-identification test (Kleibergen-Paap rk LM statistic) are the same between the three models. As shown in Table 5, the F-statistics of the first stages are significant and the validity of our instruments is confirmed by the over-identification test (Hansen J Statistic). The under-identification test also rejects the null hypothesis, thus the model is identified.

The specification used to estimate the regressions in Table 5 includes our CPC variable, the average revenue per transaction and the lag variables of the CTR for both PS and BT.

[9] Discussions 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.

Both our CPC variables negatively impact the conversion rate of the firm (Model 1). This result should not be surprising: adopting a more strategic behavior via CPC favors a higher frequency of impressions. Everything else being equal, by increasing the number of impressions, the likelihood that a user completes a transaction is reduced. As shown in Table 4, a larger number of impressions do not automatically translate into higher CTR, thus reducing the possibility of a transaction. Investing in CPC in the current week may increase the number of ads displayed but those impressions are likely to be a "reminder" of products. In other words, a larger number of impressions due to a more aggressive strategy should increase the visibility of the product, but users tend to delay their internet activity (either clicks or conversions).

The effect of PS and BT CTR on the conversion rate supports this explanation: the concurrent variable of both BT and PS CTR has a significant negative effect on conversion rate in all three specifications. Users that click on an ad and land on the advertised webpage are less likely to conclude a transaction in the same week. However, the lagged variable of PS CTR at time *t-1* has a positive effect in all three models, thus suggesting that users exposed to PS advertising delay their conversions by one week. It is likely that this activity delay represents users gathering information about a product prior to finalize a transaction. A similar discussion can be done for the CTR via BT advertising; however there is a two weeks lag between the current week and the positive impact of past CTR. In Model 2, the persistent negative effect of BT CTR and its lagged variables on PS CR, further supports the preliminary results that the conversion rate of BT is almost double than the CR of PS. In other words, conditional on clicking, users exposed to targeted advertising are more likely to purchase via the same media channel.

<Insert Table 5 here>

Finally, the final purchasing decision may be affected by the price of the product. 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. As shown previously in Table 3, 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. Model 2 and Model 3 suggest that there is a substitute relationship between BT and PS: the conversion rate of once channel (e.g. PS) is negatively affected by its own average revenue per transaction (e.g. PS) while there is a positive relationship with respect of the same variable of the opposite advertising channel (e.g. BT).

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 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. PS 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.

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 (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 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.

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.[10] 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 forty 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."[11]

The Orbitz example shows how companies can take advantage of the high availability of customer data and exploit it in their favor.

Conclusion

While there is growing theoretical literature discussing the role of online advertising such as PS and BT, its effectiveness and its impact on privacy (Acquisti and Varian, 2005; Fudenberg and Villas-Boas, 2006; Goldfarb and Tucker, 2011; Hermalin and Katz, 2006), empirical results on dynamic interactions of BT with other strategies, are still scarce. We attempt to fill this gap by describing how these two media channels contribute to advertising performance (defined in terms of Click-through-Rate and Conversion Rate) and we document the existence of temporal spillovers across them. We assume that these two media channels operate and focus on different type of users: both PS and BT impact performance of online campaigns but their effects vary based on consumers' behavior and how close they are in finalizing a

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[10] "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).

[11] "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).

transaction. Our vision of a potential shopping process is in line with the taxonomy described by Moe (2003) and the results expands Jerath et al. (2014) findings by looking at the joint effects of both PS and BT.

Our results confirm the idea that PS can be an important source of information to be used in BT advertising. In fact, past exposure to PS positively increases the performance of targeted ads. Surprisingly, we also find that BT impressions and clicks have an impact on the performance of PS. This effect shows a delayed action by internet users up to two weeks before their final purchase. We believe that customers postpone their transactions to gather more information about the product offered (e.g. product reviews, availability, price), under these circumstances, targeted advertising plays the informative role of a "reminder". If customers do not click on a targeted ad, they will remember the advertised product and exploit PS to find product characteristics and to gather more information.

Descriptive and empirical analyses also suggest that BT generates a higher conversion rate than PS advertising and it should favor the adoption of 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. However, we also find that BT advertising has a much higher cost than PS, thus confirming Beales (2010) results. The power of BT relies on the ability to exploit data collected from online users' activity. It represents an incredible source of information that increases the ability to track and identify costumers, so firms can easily identify more profitable customers and target their ads based on their characteristics.

According to our results, it is important to offer the right type of advertising to each user based on how far she is from a purchase and the amount of information she has collected. Online customers go through several stages of a shopping journey, they move along from being undecided to have a clear idea of what to buy. Because of targeting technologies, firms can learn consumers' behavior and focus on customers with a higher propensity to buy through BT, and, simultaneously, they can reach users in search of information by investing in PS 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 and inform their audience, the role played by targeted ads is twofold: first, BT can play an informative role and it creates incentive to search for products 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 traditional advertising 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, 2011). When targeting is in place, companies need to be vigilant in protecting their brand equity by being transparent to their audience and reducing the risk 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.

We argue that our results open future research possibilities about targeted advertising and its interaction with other media channels. First, a comparison across products would enrich our understanding of the shopping journey (e.g. is the interaction between median channels the same for different products? How does a user's purchasing decision differ across products?) and it would validate our findings in different context. Second, our results on price differences between BT and PS open the discussion on the ability to adopt price discrimination across users based on their purchasing behavior. Third, the implementation of BT 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).[12] It is important to study how privacy concerns may generate possible tensions between profit-seeking strategies such as BT advertising and the protection of users' privacy.

[12] 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).

References

Acquisti, A. 2006. Ubiquitous computing, customer tracking, and price discrimination, ***Ubiquitous and Pervasive Commerce***: 115-132: Springer.

Acquisti, A., & Varian, H. R. 2005. Conditioning Prices on Purchase History. ***Marketing Science***, 24(3): 367-381.

Athey, S., Calvano, E., & Gans, J. 2012. The impact of the internet on advertising markets for news media. ***Available at SSRN 2180851***.

Athey, S., & Gans, J. 2010. The Impact of Targeting Technology on Advertising Markets and Media Competition. ***American Economic Review***, 100(2): 608-613.

Beales, H. 2010. The value of behavioral targeting, ***Network Advertising Initiative***.

Bertrand, M., Karlan, D., Mullainathan, S., Shafir, E., & Zinman, J. 2010. What's Advertising Content Worth? Evidence from a Consumer Credit Marketing Field Experiment. ***The Quarterly Journal of Economics***, 125(1): 263-306.

Fudenberg, D., & Villas-Boas, J. M. 2006. Behavior-based price discrimination and customer recognition, ***Handbooks in Information Systems, Vol. 1: Economics and Information Systems***: 377-436: Terrence Hendershott.

Ghosh, M., Dutta, S., & Stremersch, S. 2006. Customizing Complex Products: When Should the Vendor Take Control? ***Journal of Marketing Research***, 43(4): 664-679.

Goldfarb, A., & Tucker, C. 2011. Online Display Advertising: Targeting and Obtrusiveness. ***Marketing Science***, 30(3): 389-404.

Hallerman, D. 2008. US Online Advertising: Resilient in a Rough Economy: Summary. http://www.emarketer.com/Reports/Viewer.aspx?R=2000488&page=1.

Hermalin, B., & Katz, M. 2006. Privacy, property rights and efficiency: The economics of privacy as secrecy. ***Quantitative Marketing and Economics***, 4(3): 209-239.

Jerath, K., Ma, L., & Park, Y.-H. 2014. Consumer Click Behavior at a Search Engine: The Role of Keyword Popularity. ***Journal of Marketing Research***.

Lewis, R. A., Rao, J. M., & Reiley, D. H. 2011. ***Here, there, and everywhere: correlated online behaviors can lead to overestimates of the effects of advertising***. Paper presented at the Proceedings of the 20th international conference on World wide web.

Moe, W. W. 2003. Buying, Searching, or Browsing: Differentiating Between Online Shoppers Using In-Store Navigational Clickstream. ***Journal of Consumer Psychology (Lawrence Erlbaum Associates)***, 13(1/2): 29.

Putsis, W. P., Jr., & Srinivasan, N. 1994. Buying or just browsing? The duration of purchase deliberation. ***JMR, Journal of Marketing Research***, 31(3): 393.

Tucker, C. 2011. Social Networks, Personalized Advertising, and Privacy Controls. ***SSRN eLibrary***.

Turow, J., King, J., Hoofnagle, C. J., Bleakley, A., & Hennessy, M. 2009. Americans Reject Tailored Advertising and Three Activities that Enable It. ***SSRN eLibrary***.

U.S. Department of Commerce. 2012. Quarterly Retail E-Commerce Sales 3rd Quarter ***Press Release (Novemeber, 16, 2012)***.

Zhang, J., & Wedel, M. 2009. The Effectiveness of Customized Promotions in Online and Offline Stores. ***Journal of Marketing Research***, 46(2): 190-206.

Figure 1. Example of targeting characteristics

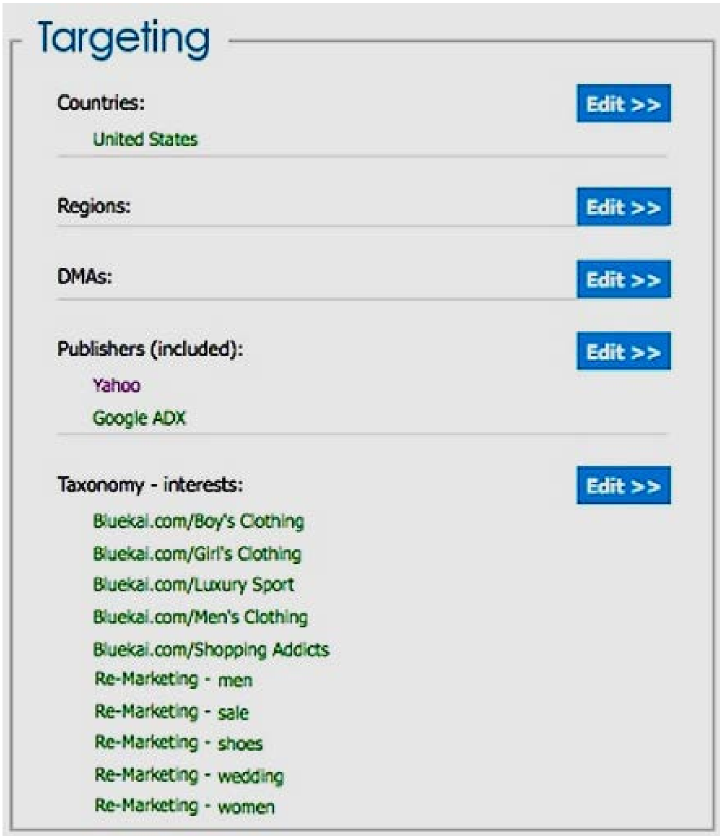

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Paid Search					
Impressions	1794	8764571	2.84E+07	5828	3.19E+08
Click-through-Rate	1794	0.029	0.031	0.0004	0.174
Cost-per-Click	1794	0.942	0.832	0.081	6.224
Conversion Rate	1794	0.081	0.109	0	0.973
ROI	1794	17.545	31.124	-1	288.032
Rank	1794	1.340	1.866	.0004	8.152
Average Transaction	1789	338.057	565.599	0	4979.336
BT					
Impressions	1794	2.78E+07	4.55E+07	279	4.21E+08
Click-through-Rate	1794	0.001	0.004	0.0001	0.139
Cost-per-Click	1794	2.228	2.870	1.57E-07	24.280
Conversion Rate	1794	0.153	0.206	0	0.999
ROI	1794	68.983	296.185	-1	3558.46
Average Transaction	1738	372.398	680.095	0	12016.44
Firm Level					
Click-through-Rate	1794	0.006	0.008	0.0001	0.137
Conversion Rate	1794	0.117	0.126	0	0.812
Other variables					
Number of Search Engines	1794	88.651	106.190	1	875
Number of Campaigns	1794	2.905	1.430	1	10
Number of Competitors	1794	2.601	2.652	0	8

Table 2. Correlation Table

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1.PS Impressions	1																	
2.PS Click-through-Rate	-0.104	1																
3.PS Cost-per-Click	-0.167	-0.240	1															
4.PS Conversion Rate	0.038	-0.019	0.274	1														
5.PS ROI	-0.056	0.476	-0.305	-0.168	1													
6.PS Rank	-0.071	-0.192	-0.139	-0.129	-0.069	1												
7.PS Average Transaction	-0.035	0.211	-0.104	-0.300	0.439	-0.077	1											
8.BT Impressions	0.518	-0.160	0.016	0.025	-0.064	-0.164	-0.164	1										
9.BT Click-through-Rate	-0.001	0.009	-0.051	0.160	-0.042	-0.016	-0.039	-0.081	1									
10.BT Cost-per-Click	0.025	0.037	-0.007	-0.141	-0.012	0.202	0.113	-0.170	-0.099	1								
11.BT Conversion Rate	0.233	0.007	-0.255	0.199	-0.106	0.161	-0.265	0.015	-0.031	0.356	1							
12.BT ROI	0.015	-0.027	-0.124	-0.010	0.123	-0.032	0.054	0.104	0.018	-0.152	0.083	1						
13.BT Average Transaction	-0.073	0.248	-0.074	-0.232	0.335	-0.082	0.804	-0.156	-0.042	0.139	-0.228	0.043	1					
14.Firm Cost-per-Click	0.128	0.232	-0.225	0.202	0.156	0.033	-0.029	-0.190	0.274	0.022	0.144	0.046	-0.005	1				
15.Firm Conversion Rate	0.066	0.027	0.028	0.863	-0.143	-0.079	-0.312	0.001	0.113	-0.067	0.484	0.052	-0.245	0.216	1			
16. Number of Search Engines	0.640	-0.120	-0.246	0.034	-0.035	-0.190	-0.022	0.534	0.015	-0.104	0.116	0.198	-0.036	0.117	0.102	1		
17. Number of Campaigns	0.218	-0.041	-0.263	0.120	0.115	0.018	0.009	0.115	-0.022	-0.064	0.192	0.156	-0.026	0.242	0.225	0.323	1	
18. Number of Competitors	0.210	-0.225	-0.121	0.068	-0.208	-0.195	-0.074	0.102	0.108	-0.166	-0.025	0.118	-0.058	0.044	0.144	0.379	0.122	1

Table 3. Mean comparison test

	Average Revenue per Transaction	Conversion Rate	Cost per Click	Click through Rate	ROI
PS advertising	342.63	0.081	0.942	0.029	17.545
BT Advertising	370.69	0.153	2.228	0.002	68.983
Difference	-28.06***	-0.072***	-1.286***	0.027	-51.437***

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.

Table 4. Regressions on Click-through-Rate (CTR)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	LF_ctr	LF_ctr	LF_ctr	LPSctr	LPSctr	LPSctr	LDSPctr	LDSPctr	LDSPctr
PS Impressions	0.0002	-0.0000	-0.0003	-0.0148***	-0.0146***	-0.0109***	-0.0000	-0.0000	-0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0028)	(0.0030)	(0.0014)	(0.0001)	(0.0001)	(0.0001)
t-1	-0.0003	-0.0003	0.0002	-0.0010	-0.0010	-0.0009	0.0001	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0010)	(0.0009)	(0.0007)	(0.0001)	(0.0001)	(0.0001)
t-2	0.0001	0.0000	-0.0002	0.0014**	0.0017**	0.0013**	-0.0001	-0.0001	-0.0002**
	(0.0002)	(0.0002)	(0.0002)	(0.0006)	(0.0008)	(0.0006)	(0.0001)	(0.0001)	(0.0001)
t-3	0.0000	0.0000	0.0002	0.0009	0.0010	0.0006	-0.0000	-0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0009)	(0.0010)	(0.0009)	(0.0001)	(0.0001)	(0.0001)
BT Impressions	-0.0045***	-0.0046***	-0.0026***	0.0021**	0.0023***	0.0016***	-0.0003***	-0.0003***	-0.0001*
	(0.0014)	(0.0014)	(0.0007)	(0.0009)	(0.0007)	(0.0006)	(0.0001)	(0.0001)	(0.0001)
t-1	0.0013***	0.0013***	0.0009***	-0.0013***	-0.0013***	-0.0009**	0.0001	0.0001	0.0001
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0005)	(0.0003)	(0.0001)	(0.0001)	(0.0001)
t-2	0.0001	0.0001	-0.0000	0.0001	0.0002	0.0006**	0.0000	0.0001	0.0001**
	(0.0002)	(0.0002)	(0.0001)	(0.0004)	(0.0003)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
t-3	0.0003**	0.0004**	0.0002	-0.0010**	-0.0012**	-0.0009**	-0.0001	-0.0000	-0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0005)	(0.0006)	(0.0004)	(0.0001)	(0.0000)	(0.0000)
PS CPC			-0.0001			-0.0205**			-0.0017*
			(0.0027)			(0.0103)			(0.0009)
BT CPC			0.0014***			-0.0001			0.0004***
			(0.0004)			(0.0021)			(0.0001)
PS Rank		-0.0016	-0.0013		0.0039	-0.0066		-0.0002	-0.0005**
		(0.0015)	(0.0011)		(0.0070)	(0.0051)		(0.0001)	(0.0002)
Num. of Campaigns		0.0008*	0.0006*		0.0001	0.0015		-0.0002	0.0001
		(0.0004)	(0.0003)		(0.0022)	(0.0019)		(0.0002)	(0.0001)
Num. of Competitors		-0.0003	0.0002		-0.0044	-0.0013		0.0003***	0.0003***
		(0.0007)	(0.0004)		(0.0037)	(0.0018)		(0.0001)	(0.0001)
Num. of Websites		0.0003	0.0011		-0.0001	-0.0050		0.0003	-0.0001
		(0.0007)	(0.0008)		(0.0059)	(0.0033)		(0.0005)	(0.0003)
Obs.	1,285	1,285	1,283	1,285	1,285	1,283	1,285	1,285	1,283
Firm fixed effect	Yes	Yes	Yes	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
Hansen test			8.076			7.762			8.766
Hansen p-value			0.621			0.652			0.554
KP test			14.398			14.398			14.398
KP test p-value			0.212			0.212			0.212

Standard errors clustered by firms in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We use the lagged variables of *BT Roi, PS Roi and PS Rank* as instruments for *BT and PS CPC*. Auxiliary first-stage regressions (OLS linear regressions "within" firm) suggest that the instruments have power. Indeed, the F-test of the joint effect of the instruments on each endogenous variable are 4.186*** and 10.899*** for *PS CPC* and *BT CPC* respectively. Both the dependent and the independent variables are transformed using the natural logarithm.

Table 5. IV regressions on Conversion Rate (CR)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	LF_cr	LF_cr	LF_cr	LPScr	LPScr	LPScr	LDSPcr	LDSPcr	LDSPcr
PS Click-through-Rate	-0.037	-0.061	-0.240***	0.000	-0.008	-0.344***	-0.455	-0.487*	-0.399**
	(0.074)	(0.060)	(0.061)	(0.065)	(0.053)	(0.131)	(0.345)	(0.290)	(0.194)
t-1	0.096	0.091	0.216**	0.090	0.065	0.179**	0.663	0.610	0.610**
	(0.103)	(0.111)	(0.096)	(0.077)	(0.080)	(0.074)	(0.425)	(0.387)	(0.305)
t-2	-0.120	-0.179	-0.124	-0.031	-0.066	-0.075	-0.227	-0.300	-0.483**
	(0.096)	(0.123)	(0.098)	(0.060)	(0.072)	(0.064)	(0.232)	(0.239)	(0.194)
t-3	-0.101	-0.140**	-0.117***	0.035	0.025	-0.024	-0.170	-0.209	-0.324**
	(0.061)	(0.058)	(0.045)	(0.067)	(0.052)	(0.050)	(0.179)	(0.188)	(0.136)
BT Click-through-Rate	-7.513***	-7.369***	-9.003***	-1.321***	-1.214**	-3.233***	-14.700***	-14.814***	-18.78***
	(1.552)	(1.422)	(1.000)	(0.482)	(0.529)	(0.734)	(3.987)	(4.061)	(3.987)
t-1	-0.367	-0.428	-0.436	-1.473***	-0.940**	-1.642***	-1.380	-2.225**	-0.775
	(0.294)	(0.377)	(0.450)	(0.147)	(0.397)	(0.555)	(1.223)	(1.059)	(0.894)
t-2	0.902**	0.727*	0.821***	-1.758***	-1.435***	-1.636***	0.757	0.223	1.302*
	(0.382)	(0.392)	(0.306)	(0.330)	(0.261)	(0.257)	(0.811)	(0.852)	(0.739)
t-3	1.954***	1.975***	1.175***	-3.572***	-2.997***	-2.627***	3.855**	3.904***	3.224***
	(0.569)	(0.534)	(0.397)	(1.032)	(0.545)	(0.549)	(1.724)	(1.201)	(0.929)
PS CPC			-0.115***			-0.163**			0.035
			(0.028)			(0.070)			(0.062)
BT CPC			-0.017***			-0.004			-0.060***
			(0.004)			(0.008)			(0.020)
PS Price		-0.031***	-0.021***		-0.037***	-0.036***		0.017*	0.020**
		(0.010)	(0.007)		(0.013)	(0.007)		(0.010)	(0.010)
BT Price		-0.016*	-0.007		0.005	0.011***		-0.044**	-0.048***
		(0.008)	(0.005)		(0.005)	(0.003)		(0.017)	(0.012)
PS Rank		0.017***	-0.007		-0.014	-0.041**		0.019	0.016
		(0.006)	(0.006)		(0.011)	(0.019)		(0.020)	(0.019)
Num. of Campaigns		-0.007*	-0.006*		0.007	-0.001		-0.029	-0.016
		(0.004)	(0.003)		(0.006)	(0.005)		(0.019)	(0.020)
Num. of Competitors		0.002	-0.007		-0.005	-0.008***		0.003	-0.007
		(0.006)	(0.004)		(0.006)	(0.003)		(0.013)	(0.010)
Num. of Websites		-0.002	-0.004		0.002	-0.004		0.015	-0.040
		(0.007)	(0.009)		(0.008)	(0.009)		(0.031)	(0.030)
Obs.	1,285	1,285	1,283	1,285	1,285	1,283	1,285	1,285	1,283
Firm fixed effect	Yes	Yes	Yes	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
Hansen test			12.948			8.400			14.194
Hansen p-value			0.227			0.590			0.164
KP test			16.848			16.848			16.848
KP test p-value			0.112			0.112			0.112

Standard errors clustered by firms in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We use the lagged variables of *BT Roi*, *PS Roi and PS Rank* as instruments for *BT and PS CPC*. Auxiliary first-stage regressions (OLS linear regressions "within" firm) suggest that the instruments have power. Indeed, the F-test of the joint effect of the instruments on each endogenous variable are 4.650*** and 9.803*** for *PS CPC* and *BT CPC* respectively. Both the dependent and the independent variables are transformed using the natural logarithm.