Native Advertising, Sponsorship Disclosure and Consumer Deception: Evidence from Mobile Search-Ad Experiments*

Navdeep S. Sahni
Asst. Prof. of Marketing
Stanford GSB

Harikesh S. Nair
Prof. of Marketing
Stanford GSB

This draft: Feb 23, 2016

Abstract

Recent advances in advertising technology have lead to the development of "native advertising", which is a format of advertising that mimics the other non-sponsored content on the medium. While advertisers have rapidly embraced the format on a variety of digital media, regulators have expressed serious concerns about whether this format materially deceives consumers when the advertising disclosure is incomplete or inappropriate. This has reignited a longstanding debate about the distinction between advertising and content, and how it affects consumers. This paper contributes to this debate by providing empirical evidence from randomized experiments conducted on native advertising at a mobile restaurant-search platform. We experimentally vary the format of paid-search advertising, the extent to which ads are disclosed to over 200,000 users, and track their anonymized browsing behavior including clicks and conversions. Our research design uses comparisons of revealed preferences under experimentally manipulated treatment and control conditions to assess the potential for consumer confusion and deception. A design based on revealed preference is important to speaking to the "material" standard of regulators, and to assessing "confusion" while avoiding direct questioning of consumers. We find that native advertising benefits advertisers, and detect *no evidence* of deception under typically used formats of disclosure currently used in the paid-search marketplace. Further investigation shows that the incremental conversions due to advertising are not driven by users clicking on the native ads. Rather, the benefits from advertising are driven by users seeing the ads and later clicking on the advertiser's "organic" listings. Thus, we find little support of typical native advertising "tricking" users and driving them to advertisers. Users seem to view ads and deliberately evaluate the advertisers. Overall, our results imply the incentives of the platform, advertisers and regulators with respect to disclosure are aligned: consumers value the clear disclosure regulators demand, and it benefits advertisers and improves monetization for the platform.

Keywords: native advertising, disclosure, consumer deception, field-experiments, restaurants, mobile, paid-search, platforms, media.

*The views discussed here represent that of the authors and not of Stanford University or Zomato. The usual disclaimer applies. We thank Dan Edelman, Puneet Manchanda, participants at the 2015 Marketing Science conference and in seminars at HBS, MIT-Sloan and the University of Michigan for helpful comments and suggestions. Please contact Sahni (navdeep.sahni@stanford.edu) or Nair (harikesh.nair@stanford.edu) for correspondence. The authors declare they have no commercial relationship with Zomato, and the research is conducted with no restrictions on the publishability of the findings from the field experiment. The authors thank Shuo Xie and Charles Zhang for excellent research assistance.

1 Introduction

Ever since its earliest days, the separation of content from advertising has been an important issue for media. Clear separation is seen as essential for the credibility of the media's content, and for sustaining an ad-supported business (Carlson, 2014, Coddington, 2015). However, this separation is increasingly becoming blurred in modern digital settings. There are several reasons for this development. On the demand-side of the market, the effectiveness of online banner advertising is unclear, and consumers are increasingly using technology such as ad-blockers to avoid ads. On the media-side, revenues from traditional forms of advertising are declining, forcing media companies to explore new avenues for monetization. Further, shifting media consumption to small-screen mobile devices has pushed platforms to develop new schemes for delivering ads that capture consumer attention (Sonderman and Tran, 2013, Mitchell, 2015). Consequently, publishers have responded to these marketplace pressures by introducing "native ads" – advertising that matches the form, style and layout of the media content into which it is integrated.

The Interactive Advertising Bureau (IAB), the main trade group of the digital advertising industry in the US, classifies digital native ads into six types: in-feed units, paid search units, recommendation widgets, promoted listings, IAB standard ads with "native" elements, and custom ad-units [IAB, 2013]. The appendix shows examples. Reports in the trade-press suggest that US spending on such native ads may grow as high as $21 billion in 2018, rising from just $4.7 billion in 2013 (Hoetzel, 2015).

The proliferation of native advertising has ignited a vociferous policy debate about its effect on consumers. On the one side are regulators, who are concerned that consumers are harmed when the commercial nature of content is not properly disclosed. On the other side is the advertising industry that is worried that overly prescriptive and onerous regulatory guidelines will hamper the efficiency and growth of well functioning ad-markets.

On the regulator side, the main concern concern is the possibility of consumer deception. Under section 5 of the US Federal Trade Commission act, "an action or practice is deceptive if it's likely to mislead consumers who are acting reasonably under the circumstances, and if it would be material to their decision to buy or use the product." The FTC judges a misrepresentation as *material* if it is likely to affect consumers' choices or conduct regarding an advertised product or the advertising for the product, irrespective of the medium. Therefore, under these criteria, native ads raise the possibility of deception when the nature of sponsorship disclosure is (a) insufficient to help reasonable consumers recognize it as paid for by a third-party, *and* (b) this lack of recognition affects the consumers' decisions. On account of its dominant influence on digital advertising spending, concerns about disclosure in paid search – on which this paper focuses – have been particularly dominant. Reflecting these concerns, in letters sent to search engines in 2013, the FTC observed that,

> "*Consumers ordinarily expect that natural search results are included and ranked based on relevance to a search inquiry, not based on payment from a third party. Including or ranking a search result,*

> *in whole or in part, based on payment is a form of advertising. To avoid the potential for deception, consumers should be able to easily distinguish a natural search result from the advertising that a search engine delivers.*" (Engle 2013, FTC 2013)

Concerns over disclosure practices related to native advertising have since then accumulated, eventually culminating in the recent release of enforceable guidelines in December 2015 ([FTC, 2015]). In it, the FTC stipulates any disclosure used must be "sufficiently prominent and unambiguous to change the apparent meaning of the claims and to leave an accurate impression."

On the other side of the debate are advertisers and publishers who have embraced native advertising while voicing concern over increased regulatory oversight ([IAB, 2015]). The digital advertising industry bemoans the inability to enforce and monitor disclosure protocols in all scenarios; worries about the potential for some guidelines (for example, about the types of text that are understandable by consumers) to clash with platform look and style; is skeptical about government intervention in the "creative process", and feels that current levels of self-regulation are sufficient. Reflecting these considerations, Brad Weltman, Vice President of Public Policy at the IAB, notes in its official response to the FTC's guidelines,

> "*While guidance serves great benefit to industry, it must also be technically feasible, creatively relevant, and not stifle innovation. To that end, we have reservations about some elements of the Commission's Guidance. In particular, the section on 'clarity of meaning' in native advertising disclosures is overly prescriptive, especially absent any compelling evidence to justify some terms over others.*" (IAB, 2015)

As the quote illustrates, what complicates the debate is the absence of formal studies that explore the effect of native advertising on consumer behavior. Most studies in the area (reviewed later) have been survey-based, querying consumers about whether they were able to distinguish between the content and paid-ads they saw in the past, and assessing their attitudes towards native advertising. The survey evidence to date has been contradictory, with some suggesting consumer confusion about sponsorship status, and others the opposite. A significant lacuna has been that these studies cannot speak to the "material" impact of native advertising, because they lack data on actual consumer actions after been exposed to the native ads. Further, the results are subject to the typical concerns with inference based on stated preference data (like imperfect recall, framing effects and small sample sizes).

The contribution of this paper to this debate is the development of a field-experiment implemented on a restaurant-search platform to assess consumer response to native search advertising. The field experiment is implemented on the mobile search app of Zomato, one of the largest restaurant-search platforms in the world. Users of the platform search for restaurants to visit, and are shown listings of restaurants that match their search criteria. The app environment enables us to randomize users into conditions in which they are or are not exposed to advertised listings of differing formats. It also allows us to track their subsequent search and conversion activity using detailed click-stream data. The ability to randomize enables us to avoid the usual confounds of user self-selection into exposure plaguing inference in search settings, wherein advertising is served in response to user's search interest (Blake et al. [2015], Sahni [2015]). The opportunity to run an experiment at a large scale helps us obtain the sample sizes required to measure ad-effects precisely, and to assess the mechanism behind the effects we find by exploring heterogeneity across advertisers and consumers of differing profiles. Finally, the availability of data on consumer behavior post ad-exposure helps us assess whether the exposure produces effects that materially affect the exposed consumers. The experiment involves 622 advertising restaurants and 265,975 individuals and is implemented over a period of about six weeks in 2014.

To understand our research design, note that deception as defined by the regulators, occurs when the consumer's behavior differs from what it would have been if the consumer were best informed. Thus, the assessment of deception has to explore changes in behavior relative to a benchmark in which the ad is presented in a clear and conspicuous manner. These considerations require the research design to satisfy the following two criteria. First, the design needs to simulate relevant "counterfactual" situations such that user behavior across the situations can be studied to assess deception. Second, the design needs to track actual user behavior subsequent to ad exposure across the scenarios. One would prefer the assessment relied on revealed, as opposed to stated consumer data, because the change in behavior relative to a benchmark situation is difficult for a survey questionnaire to convey and for a respondent to imagine and articulate. The main innovation in our study is to present a research design that satisfies both these criteria, by basing assessment on (1) revealed behavior, that is, (2) linked to clearly-posed counterfactual comparisons. Specifically, we randomly allocate individuals to different experimental conditions with varying formats of advertising, and track their anonymized behavior.

Our choice of experimental conditions is motivated by the following rationale. We note that two factors could lead to deception. First, a consumer may be deceived if she does not *notice* that the product is advertised, perhaps because she does not see the ad-label. Second, the consumer may be deceived if she *misinterprets* the ad-label, perhaps because she does not understand that the label used by the platform signifies an ad. Our experiment aims to vary the two factors: noticability and content of the ad-labels. It allocates consumers into two extreme conditions: one, where advertisements are shown *without any* indication that they are sponsored by a paying restaurant (the "no-disclosure" condition), and the other extreme, where ads are shown with a clear and prominent disclosure that they are sponsored by a paying restaurant (the "prominent-disclosure" condition). If observed behavior under typical disclosure looks closer to the "no-disclosure" condition, we will infer that consumers are indeed deceived by typical disclosure protocols; if on the other hand, observed behavior under typical disclosure looks closer to the "prominent-disclosure" condition, we will infer that there is no evidence in the data for such deception. In this set-up, the "prominent-disclosure" conditions serves as the counterfactual world with "no deception". To assess the sensitivity of the consumers' behavior to the ad-label, our experiment also varies the content of the label, allowing a comparison of the clearest labels with the potentially more ambiguous ones.

Analyzing the data from our experiment, we first find that natively formatted advertising is beneficial to advertising restaurants on the platform: relative to a no-advertising control condition, visits to an advertising restaurant's information page hosted on the Zomato platform go up by 41% in conditions in which native advertising is served. Further, calls to the restaurant − the measure of conversion activity − go up by 67%. These results support the widely held belief amongst advertisers about the efficacy of the native advertising format. Establishing this is important because any potential for material harm is contingent on the existence of a measurably significant causal effect of such advertising on consumer behavior.

To assess the role of disclosure and deception, we then test two typical ad formats used widely in the industry. The first uses a yellow label with the word "Ad" disclosing the paid nature of the listing, which is commonly used by search engines like Google and Yelp. The second uses the text "Sponsored", which is commonly used by platforms such as Facebook. To create the "prominent-disclosure" conditions, we display these formats with a bold yellow highlight that makes such listings stand out in the users' search-results feed, denoting their special status as paid-ads. Comparing conversion outcomes in the typical versus prominent-disclosure formats, we find that calls to advertised restaurants are statistically *indistinguishable* between these conditions, suggesting no evidence of systematic deception under typical disclosure, based on the criteria above. Further, we find that outcomes are also statistically *indistinguishable* between the "Ad" and the "Sponsored" text formats, suggesting no evidence of systematic confusion between these two ways of wording disclosure. Finally, comparing conversion outcomes in the typical-disclosure condition to the no-disclosure condition, we find that calls to advertised restaurants are *higher* under typical-disclosure, suggesting that consumers value advertising.[1]

Delving deeper into the consumer behavior, we then assess whether there is any evidence for a commonly articulated viewpoint that unsuspecting consumers are "tricked" by native formatting into clicking on listings they would otherwise not consider, which then materially affects their restaurant choices. Whether this concern has support in the data depends on how consumers respond to ads. If consumers are naive, unable to recognize the ads and/or have low propensity to explore their options either because they are gullible or have a high "search-cost", ads disguised as non-advertised content can induce them to click on listings and make them buy the advertised product. On the other hand, if consumers are able to recognize ads and make their decision mindfully, ads can serve as additional options that improve consumer's decisions. Consumers would then know then that they are clicking on *ads*, and accordingly

[1] Note these contrasts are not due to the differences in the type of consumers or advertising restaurants, or the listing position or other content attributes of the ads. These factors are all held fixed in the comparisons due to randomization.

interpret the information they get from the exposure.

We find that the naive consumer viewpoint has little support in our data. Analyzing consumer search patterns, we find that consumers continue to search significantly for other options on the app without calling, even after clicking on advertised listings, irrespective of disclosure. This implies that clicks on the ads *per se* are not the main channel by which the advertising translates to conversion on this medium. Further, there does not seem to exist high search-costs that constrain consumers from exploring new options conditional on clicking. We then explore in more detail the source of the increase in calls in the advertising condition relative to the no-advertising condition. We find the increase is not driven by users who click on advertised listings. Rather, the effect is almost entirely driven by consumers who call the restaurant after clicking on its organic listing after being exposed to the restaurant's advertisement. Thus, ads appear to work through exposure − individuals view the ads, update their impression of the advertiser, and continue to search. Eventually, if they decide to pick the advertised option, consumers reach it through search or organic clicks. Consequently, if a product is advertised, conveying clearly to the consumers that it is advertised benefits the firm. In our companion paper (Sahni and Nair [2016]) we show that such effects can be rationalized by canonical signaling theories of advertising.

These findings have two main implications. First, users in our data are sophisticated consumers of advertising. Advertising does change their behavior. But this change is not likely because they are being "tricked" into clicking on native ads. Second, the incentives of the platform, advertisers and regulators are aligned: consumers value the clear disclosure regulators demand, and it benefits advertisers and improves monetization for the platform. Further, currently used native formats in paid-search do not seem to confuse consumers, and there is no compelling evidence of deception.

To close the introduction, although our findings are consistent with beliefs in the industry (e.g., Sebastian [2014]), we caution the reader that we do not mean to imply that this finding generalizes across all scenarios found in the digital economy, especially in contexts where ads are annoying, out of context, or inappropriately disclosed (unlike the formats we have considered in this paper). A distinguishing feature of our setting is that ads are relevant to the search, and hence useful for consumers to make better decisions about restaurant choice. They are also not annoying because they are fluidly blended into the in-feed of the search listings. To thoughtful consumers in search-mode, ads thus serve as additional options that improve consumer decisions and reduce search costs. These seem like important considerations for the success of native advertising. In other settings, such as particular types of paid-advertorials on news websites, consumers may be more annoyed by native ads because they interfere with their goals from visiting and consuming the medium. In such scenarios, it is possible they respond differently. Further research and enquiry on these aspects is warranted to generalize beyond our context. Having said that, we believe that our results do warrant a rethinking of a default presumption that consumers are easily tricked and fooled by ads, and hence are highly susceptible to deception. At least in our setting, that does not appear to be the case, and this may be relevant in other settings as well.

The rest of the paper discusses the relevant literature, the empirical setting, the experimental design and the main results. The last section concludes.

2 Literature Review

As noted in the introduction, most studies on native advertising have been survey based, either querying consumers *ex post* about their attitudes and/or confusion regarding the distinction between paid and unpaid content, or asking them to imagine their actions in new situations with counterfactually posed native formatting. Summarizing the research in this area, Bakshi [2015] notes, "There are no published, empirical studies on the association between native advertising and consumer deception, but some in-progress research supports the intuitive notion that consumers often mistake native advertisements for independently created editorial content." In perhaps the most comprehensive survey research to date, Franklyn and Hyman [2013] run online surveys (N = 1,000) in three waves in 2010 and 2012, and report that only 42% of participants in their first survey understood the difference between sponsored and unsponsored search results (36% in second); and only 35% report they find it easy to distinguish between paid and unpaid search results. Both these suggest the possibility of confusion. They also report that a near-majority state they simply click on the first link for which they see the brand they are interested in, irrespective of whether the link is paid or unpaid, suggesting that clicks may drive consumers into subsequent conversion. In a similar vein, Hoofnagle and Meleshinsky [2015] showed (N = 598) internet users a labeled advertorial embedded in a blog and queried them open-ended and closed-ended questions about the articles' content. 27% of the users thought that the advertorial was written by a reporter or an editor even after displaying a label stating "sponsored content", again suggesting the possibility of consumer confusion.

Other studies expose users to native advertising in lab settings. Using responses from university participants (N = 56) to a lab-moderator who showed them the listings from six web searches, Jansen et al. [2007] report that online searchers prefer to click links that they believe are algorithmic results rather than advertisements. In another lab-experiment, Tutaj and van Reijmersdal [2012] report that (N = 99) participants find sponsored content more informative, more amusing, and less irritating than traditional banner ads, and that ad skepticism seems to be strongly related to perceived advertising value. Wojdynski and Evans [2015] recruited (N = 242) adult U.S. residents via Amazon Mechanical Turk, and exposed them to 12 versions of a news story web page with native formatting. Querying participants after they finished reading both stories, they report that disclosures using the words "advertising" or "sponsored" increased advertising recognition compared to other conditions, and ad recognition generally led to more negative evaluations.

While suggestive, the lab studies may not capture adequately the actual nature of deliberate consumer response to information in real-world settings, where the use of the information leads to consequential choices. Similarly, reflecting on the survey methodologies employed, Franklyn and Hyman [2013] write, a "limitation is that the surveys asked participants what they had done previously, or would do in response to a specified situation. Asking people to remember or predict their own behavior is quite different than observing their actual behavior. Finally, responses to particular questions may be affected by survey respondents' interpretation of the goals of the survey....Additional work will be required to address these limitations, to the extent they are remediable." Further, past empirical studies have shown that ads affect a very small fraction of the people exposed to them (Lewis and Reiley [2014]). Therefore, with small sample sizes (in hundreds) there is little chance of recording any responses from individuals who may actually be affected by the ads and their formats.

We are aware of only two studies that report revealed consumer behavior in response to changes in advertising labeling or content of similar nature. Edelman and Gilchrist [2012] recruited ($N = 723$) online participants to do their internet search through a web browser window they created, in which the label "Sponsored links" is randomly replaced by the labels "Paid Advertisement" or "Ads." Users assigned to the "Paid Advertisement" label showed about a 25% reduction in ad-clicks relative to those who saw the other labels, and more correctly reported *ex post* that they clicked on fewer advertisements. Their results suggest that the "Paid Advertisement" label may be more salient to searching users. In an article that examines the efficacy of "social advertising" by a non-profit firm, Tucker [2012] mentions that click-through rates on the firm's Facebook posts increased when the words "Please read this ad" were added to the campaign post. This is consistent with the users responding positively when explicitly told the sponsored post is an ad, though, Tucker cautions that "the sample size here is very small, making more definitive pronouncements unwise." Both papers explore only the effects on ad-clicks and do not assess the effects of disclosure on conversion.

3 Empirical Setting

Our study is conducted in collaboration with Zomato, which is one of the largest restaurant-search portals worldwide. Zomato operates in 22 countries and provides a platform for consumers to search and browse through information about thousands of restaurants in many local markets. In 2014, when the data for this study was collected, 30 million unique users used Zomato monthly to search for restaurants. Compared to the overall internet population, Zomato users are more likely to be female; between the age of 25-34; educated beyond college; and less likely to have children. The users in our data are located in large cities in South-Asia and Middle-East.[2]

The Zomato platform provides its users the ability to search for restaurants at their internet website or their mobile app available on Android or Apple iOS smartphones and tablets. On the platform, users can filter down to their specific geographic location and/or conduct text-based search while applying various criteria they prefer to the search including the cuisines they might be looking for. In addition to the cuisine, consumers can choose to specify a search-category (home-delivery / dine-out / night-life) which tells Zomato more about the consumer's intention behind the search.

Our data come from users browsing Zomato's Android app, so we describe a user's search experience on the app in more detail. Searching for a restaurant on the app takes the user to a page that displays search results that satisfy the user's criteria. The left panel in Figure 1 shows an example. The search results are sorted by the search engine's measure of "popularity" of a restaurant, unless the user specifies alternative sorting criteria. Clicking on one of the listings in the search-result takes the user to a restaurant's page which provides more information about the restaurant. This page allows the user to view the detailed menu of the restaurant, its photos and location on a map. It also shows the restaurant's average rating and allows the user to browse through reviews given by other users on the platform.

4 Experiment Design

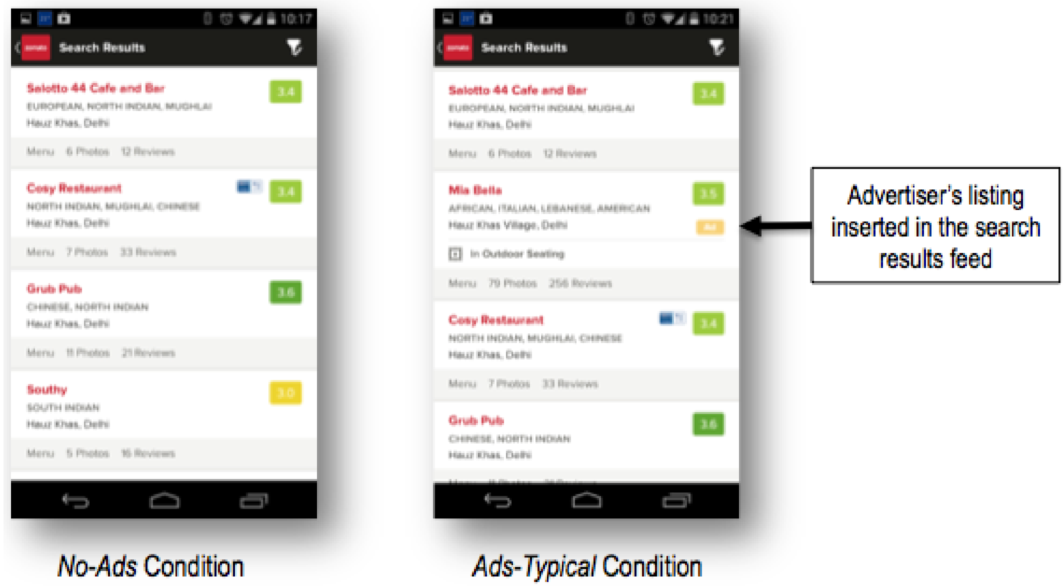
At the time of our study, thousands of restaurants engaged in advertising on Zomato's website, displaying banners for their restaurants. There was however no advertising on the mobile app prior to our experiments. We collaborated with the platform to start experimental mobile advertising, testing various formats of advertising as part of the firm's pre-launch A/B testing. Our experiment was launched in the form of a new update of Zomato's android app hosting on the Google Play app store. Any user who upgraded to this version of the app could potentially be a part of our experiment.

In our experiment, a user, identified by a unique login id, is allocated to one of two experimental conditions. The experimental conditions are as follows:

- *No-Ads* (The control group): A user in this condition does not get exposed to any advertising. The user's experience remains unchanged compared to before the experiment.
- *Ads* (Placing experimental ads): A user in this condition gets the same set of restaurant options in the search-results as a user in the *No-Ads* condition, and in the same sequence. However, unlike the *No-Ads* condition, the experimental-advertiser restaurants' ads are also placed in the search-results. We discuss the selection of the experimental restaurants in detail later in this section.

[2]Since user-level demographics are not collected reliably on the Zomato app, we utilize comparative profiling information from `Alexa.com`, a widely-used provider of internet analytics. Alexa's browsing data come from multiple sources including the users of their browser toolbar. The demographic data are self-reported. We have access to data on demographic comparisons only.

Figure 1: Example of the Search-results Page in the *No-Ads* and the *Ads* Condition.



Notes: The advertised restaurant's listing gets inserted in the search-results feed if the user is in the *Ads* condition. The listings for the other restaurants ("organic" results) remain the same and presented in the same order.

Figure 1 shows an example of how the search-results on a mobile device look like in the *No-Ads* and *Ads* conditions. In the *No-Ads* condition, the advertised restaurant's listing ("Mia Bella", in this example) does not appear. In the *Ads* condition the advertiser's listing is inserted in the search-results feed, and appears in the second position in the snapshot. Within the *Ads* condition, we include additional sub-conditions that help understand consumer-response to native advertising. Specifically, we vary two aspects of the advertising format. The first relates to the prominence by which native ads are distinguished from "organic" (non-sponsored) search-results. At one extreme, we create a condition in which there is no distinction between ads and organic content. At the other extreme, ads appear with an added highlight that make them easily distinguishable from non-sponsored content, and, arguably hard-to-miss. In a second manipulation, we experimentally vary within the *Ads* condition, the text used to label the ads. In the baseline condition, we use label an advertisement using the word "Ad", which is commonly used by search platforms such as Google and Yelp. In another condition, we change the label to "Sponsored", to understand users' sensitivity to the manner in which ads are indicated. In total, we implement the following five sub-conditions within the *Ads* condition.

- *Ads-No-Disclosure*: In this condition the advertisers appear in the search results, but there is no label or any other sign differentiating the advertisers' listing from the rest of the search results.
- *Ads-Typical*: In this condition, the advertisers' listings appear in the search results with a label

reading "Ad". This label distinguishes the advertised restaurants from the non-advertised search-results in a format that is typical of paid-search.

- *Ads-Typical-Highlight*: In this condition, the ads appear with the label as in the *Ads-Typical* condition, along with an added highlight along the boundary of the box containing the advertiser's listing. This highlight increases the visibility of the ads significantly, and makes them more distinguishable from the non-advertised restaurants.

- *Ads-Sponsored*: This condition is very similar to *Ads-Typical*, except that users in this condition see a label that reads the word "sponsored" instead of "ad".

- *Ads-Sponsored-Highlight*: This condition is similar to *Ads-Typical-Highlight*, except for the text of the label, which reads "sponsored" instead of "ad".

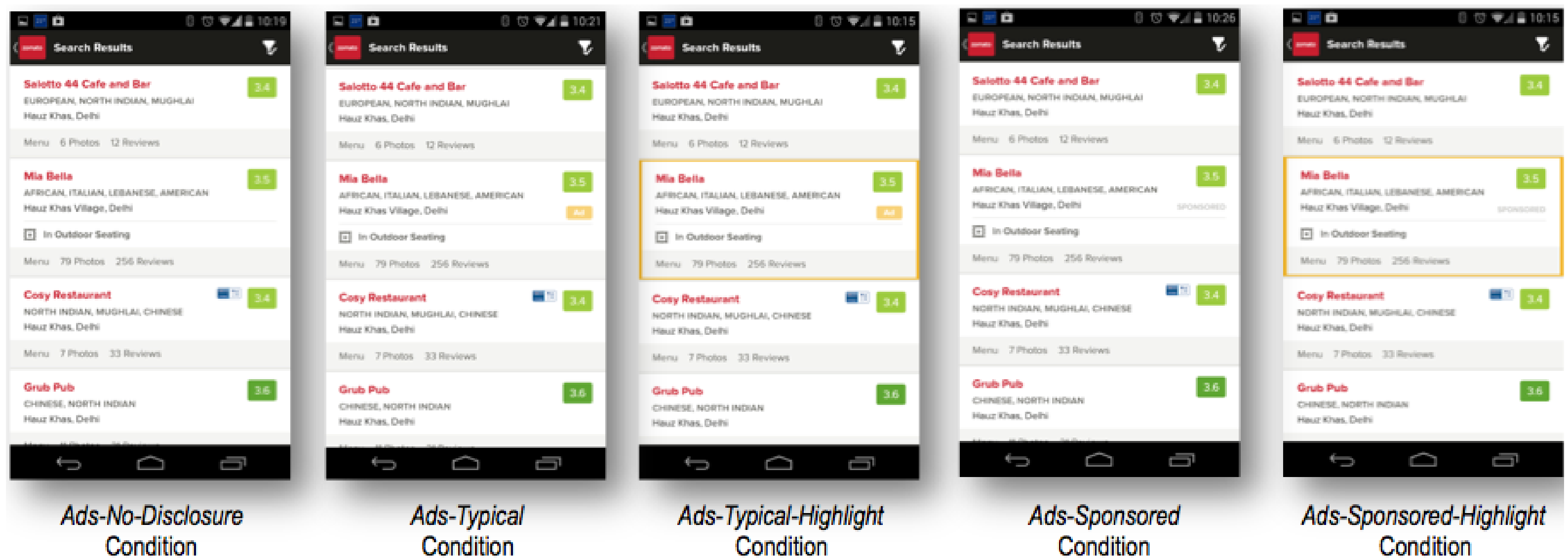
For any search, the sequence of restaurants that appear in the latter four conditions is exactly the same as the *Ads-No-Disclosure* condition. Figure 2 shows a snapshot of how the search-results page looks across the five experimental conditions within the *Ads* condition.

Once a user is allocated to one of the experimental conditions, her allocation remains fixed throughout the time period of the experiment (there is no re-randomization over time). Further, advertising in our experiment occurs only on the page showing the search-results. There is no advertising on restaurant pages hosted on the mobile platform. Also, there is no change in the restaurant pages across the experimental conditions, regardless of whether or not the restaurant advertised.

Experimental Advertisers We pick as advertisers for our experiment those restaurants that intend to advertise to the user on Zomato. Specifically, for any search, our experiment displays the ads for restaurants who *would* have been advertised if the search were conducted on the Zomato website, instead of the mobile app. To understand how this works, recall that the Zomato website had a functioning advertising market during our experimental time frame. Consider a user of Zomato's Android mobile app who conducts a search during our experiment. Once this search reaches the Zomato mobile-ad server, our experiment retrieves ads that would be shown for the same search on Zomato's website, and shows the listing for those restaurants in that users' search results. If the user is in the *No-Ads* condition, or if there is no restaurant that wishes to advertise for the search criteria applied by the user, no ads are displayed.[3]

[3] A page on Zomato's website may be able to display more ads (has more "ad-slots") than the mobile app. In such cases Zomato's proprietary algorithm decides which restaurants are to be advertised on the mobile app. The algorithm's criteria is uniformly applied across the experimental conditions, so differences across conditions do not reflect the effect of these placements.

Figure 2: Example of the Search-results Page in the Five Sub-conditions of the *Ads* Condition.



Notes: The advertised restaurant's listing is placed in the search results at the same position across the five conditions. The other restaurants, called "organic" results are also the same and presented in the same order. The format of advertising varies. In the *Ads-No-Disclosure* condition, ads appear looking exactly as the organic listings. In the other five conditions, there is some distinction between ads and organic listings. In *Ads-Typical-Highlight* and *Ads-Sponsored-Highlight*, the advertised restaurants' listings are highlighted in orange to make them more conspicuous.

Experimental Ads Appear Only on Specific Searches Ads in our experiment appear in search-results *only* when the search criterion is based on (1) location and/or (2) search-category such as "home delivery" and "dine-out" that capture the context of the search. If a consumer includes a cuisine in the search filter (or any other factor apart from location and search-category) she does not see any ads in the search-results, regardless of the user's experimental condition, by design. This is also true if a user sorts the search-results by a criterion different from the platform's default. For example, if a user sorts by restaurant-ratings, no advertising appears on the search-results page, regardless of the user's experimental condition. This step reflects the fact that advertising on Zomato.com is sold based on location and search-category. Thus, experimental ads are effectively being served for only the searches that advertisers contracted on. Incorporating this aspect into the design has two advantages. First, it makes it easier to implement the experiment (because we did not have to go market-by-market to pick advertisers). Second, we ensure that the restaurants that appear as ads are consistent with the user's search query and not unrelated to it. For example, we avoid a situation where a user searches for Chinese restaurants and sees a series of organic restaurants that serve Chinese cuisine, but ads that may not satisfy this criterion.[4] Further, ads served correspond to functioning, in-market restaurants. This enables us to avoid potentially problematic Hawthorne effects due to experimentation.

Advertising in Our setting is Relevant It is important to note that on account of (a) the personalization implied by search, and, (b) the features of our experiment design, ads in our experiment are very relevant to the users' context. Unlike TV advertising, or advertorials and other forms of native advertising, users who are exposed to ads for restaurants are those who are also searching for restaurants. Further, ads are targeted, both by location and/or by intent. Such targeting ensures that advertised options are aligned with the goals of the searching user. Taken together, these aspects imply that ads in our setting are less likely to be annoying than other contexts. This perspective is useful to keep in mind to interpret the results that follow.

5 Empirical Analysis

5.1 Setup of the Analysis

We now describe the analysis strategy and the process by which we construct our main analysis dataset. Recall that not all searches are eligible for advertising by experiment design. Also, some searches may not be advertised to because no restaurant contracted with Zomato to advertise in response to the search's criteria. The implication of these two features is that not every user who uses the Zomato Android mobile app during our experimental time period is eligible for experimental advertising. In order to obtain a

[4] This would be specifically problematic in the *Ads-No-Disclosure* condition.

sample of users who would be affected by experimental ads, we start by focusing on users who engaged in at least one search that is eligible for advertising.

Once we obtain users in this manner, we then restrict attention to the effect of the first ad exposure to a user on her behavior in her first session after downloading the app update.[5] The rationale behind this step is as follows. If the experimental treatment works – that is, the users in different experimental conditions respond to the ads differently – their search/browsing behavior after the first ad exposure also differs. This difference in search behavior can lead to differences in the exposure to subsequent ads. In other words, all experimental ads after the first one are endogenously exposed. As an extreme example, if ads work in one condition (A) and not in the other one (B), users in condition A who prefer the advertiser may stop browsing after the first ad exposure. Then, users in A who are exposed to the second ad will comprise a selected sub-population. Hence, the individuals across conditions A and B who are exposed to the second ad are not comparable. Put differently, our experiment design provides equivalent comparison sets for the first ad-exposure, but not necessarily for the subsequent ones.

To construct a dataset that reflects this, we take the following steps. For every individual user in every condition, we pick the first search that is eligible for an ad exposure. Each such search may have one or multiple first-advertisers associated with it. The latter occurs if Zomato randomized multiple advertisers for a position. We collect the user's behavior with respect to all advertisers relevant to the search, and stack across all such users in all conditions.[6] In the final dataset so constructed, each observation is a user $\times$ an advertiser. We have 265,975 such users in our data. In total, there are 622 advertisers whose ads are displayed. Table 1 below shows the distribution of the number of users across each experimental condition.

In tests of balance, we verify that users in all conditions have the same probability of having a search that would be eligible for an ad exposure (we fail to reject the null hypothesis that users in all conditions have the same probability of conducting a search to which our experiment serves ads, $p = 0.19$). Further, we verify that the characteristics of the first search with ad-exposure, such as its date and the advertiser associated with it, is the same in expectation across the six experimental conditions.[7]

[5] A session comprises a sequence of actions on the mobile app. A session is said to have ended when there is continuous inactivity for three hours or more. Our goal in constructing sessions in this manner is to collect together a series of actions on the app that map to a distinct purchase occasion.

[6] Suppose on the day when a search occurred, Zomato advertised two restaurants, r_1 and r_2 on the same advertising position. In this case, we study the effect of the user's experimental condition on her behavior with respect to both r_1 and r_2. Finally, note that for the purpose of estimating the precision of our estimates, we cluster the standard errors by individuals, in order to keep the effective number of observations the same as the number of users.

[7] Sahni and Nair (2016) present a series of tests showing that the users in various conditions are similar along these lines and other observable characteristics.

Table 1: Distribution of Users Across the Six Experimental Conditions.

	Condition	Description	Number of Users
1	*No-Ads*	Ads do not appear in the search results	44,233
2	*Ads-No-Disclosure*	Ads appear but are indistinguishable from organic search results	44,637
3	*Ads-Typical*	Ads appear in a typical format: the ad-label reads "Ad"	44,333
4	*Ads-Sponsored*	Ads appear in a different format: the ad-label reads "Sponsored"	44,482
5	*Ads-Typical-Highlight*	Ads appear in the typical format, with an additional highlight around the advertised listing to make the ad prominent	44,454
6	*Ads-Sponsored-Highlight*	Ads appear in the alternative format, with an additional highlight around the advertised listing to make the ad prominent	43,836
	Total		265,975

5.2 Empirical Findings

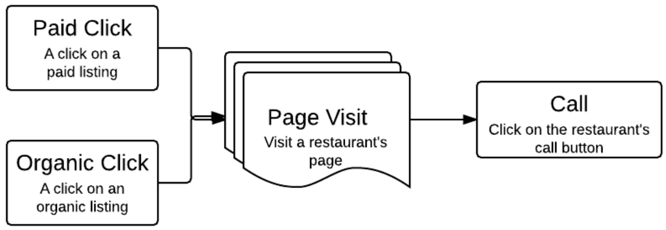
We start by presenting average statistics across the six experimental conditions to describe stylized features of user behavior across conditions. Subsequently, we present our hypothesis tests and analysis related to native advertising.

5.2.1 Means Across Experimental Conditions

The two main outcome variables we focus on are, (1) whether the user visits the advertiser's page during her session (we refer to this as a "page-visit"), and, (2) whether the user calls the restaurant during her session by clicking on the call button on the Zomato app (we refer to this as a "call"). Both (1) and (2) are important to the search platform and the advertising restaurants. A page-visit represents a user considering the advertiser for purchase. A call represents a bottomline measure (conversion metric), that can occur only after the user visits the advertiser's page. In addition to these measures, we also investigate the channel through which the page-visit occurs so as to understand better the user's response to native ads. In particular, we investigate whether the user reaches an advertiser's page by clicking on the advertiser's experimental ad, or through her own search effort (i.e., by scrolling down the in-feed listings and clicking on an organic listing). Figure (3) shows a schematic of the user actions and dependent variables we analyze.

Table 2 presents the means for these measures. Column (1) shows the probability of the user clicking on an advertiser's ad during the session. Since no ads are shown in the *No-Ads* condition, the probability of an ad-click in that condition is zero. Across the other five conditions, the average probability of a user

Figure 3: Sequence of User Actions on the App



Notes: The figure shows the set of actions a user takes we report on in our analysis. In a condition with advertising, a user can click on either a paid or an organic listing for a restaurant. Clicking on either listing takes the user to the restaurant's page. The user can choose to call the restaurant by clicking on the "call" button on the restaurant page.

clicking on the experimental ad is 0.50%. We also see that the probability of clicking on an ad does not vary significantly across the conditions that show experimental ads. Column (2) now shows the chance of a consumer visiting the advertiser's page during her session. Since a user can visit the advertiser's page through organic listings, the visit probability in the *No-Ads* condition is non-zero and equals 0.83%. For the other conditions, this probability is close to 1.1%. The *No-Ads* condition stands out: the variation amongst the five conditions that show the experimental ad is small relative to their difference from the *No-Ads* condition.

We now assess how well clicks on advertised listings capture incremental user response to advertising. A click on an advertised listing leads to a page-visit, but this page-visit need not be incremental – the user may have visited the advertising restaurant's page via a click on the restaurant's organic listing even in the absence of the ad. To assess this, we subtract from the probability of a page-visit (reported in column 2), the chance of a page-visit in the *No-Ads* condition, and report this difference in column (3). Column (3) thus represents an estimate of the incremental probability of visitation to a restaurant's page from advertising. If all clicks on ads were leading to incremental page-visits, we would expect the ad-click probabilities reported in column (1) to match the incremental visitation probabilities reported in column (3). On the other hand, if users who click on the ad would have reached the advertiser's page even in the absence of the ad, we expect the numbers in column (3) to be lower than the numbers in column (1). The table shows the latter is the case: the probabilities in column (3) are consistently lower than the corresponding ones in column (1). This difference suggests that many users who click on the ad would have reached the advertiser's page anyway. Column (4) calculates this difference, and shows that about 30% of the users who click on the ads would have reached the advertiser's page using organic listings. These statistics suggest that ad-clicks may not be a good measure to judge the incremental effect of advertising.

Finally, column (5) of Table 2 shows the chance of a user calling the advertised restaurant during her session. The numbers in this column are significantly lower than those in column (2), suggesting that a large proportion of users who visit an advertiser's page end up not calling it. Further, it shows that the calling probability is lower in the *No-Ads* and *Ads-No-Disclosure* conditions relative to the others with disclosure.

5.2.2 Does Native Advertising Work?

We now report on whether advertising affects user outcomes. The premise to the debate on native advertising is that advertising in this format works, and benefits advertisers by driving more traffic and as well as more conversion of traffic to sales. Therefore, we view this analysis as a key prerequisite to the motivation for the subsequent analysis. To implement this test, we regress an indicator of the outcome variables – page-visit and call – on a variable indicating that the user belongs to one of the five conditions in which native ads are served.[8]

Table 3 shows the regression estimates. Looking at column (1), we see that the indicator for the *Ads* condition is positive and statistically significant, showing that native ads drive more traffic to the advertisers' page. At the current estimate, the likelihood of a user visiting the advertiser's page increases by 41% on average (0.34%/0.83%) when it serves an ad of this format on the platform. Column (2) shows the same regression with calls as the dependent variable. We see that the coefficient corresponding to the indicator of the *Ads* condition remains positive and statistically significant, implying that the increase in traffic through incremental page-visits also lead to increases in calls for the advertisers. At the current estimate, reallocating a user to the *Ads* condition increases the chance of a call to an advertiser by about 68% (0.0204%/0.0300%). Taken together, these estimates show that the advertising in our context benefits the advertiser, and has a significant causal effect on the outcome variables we consider.

5.2.3 Do Consumers Fail to Notice "Typical" Native Ads?

We now test whether there is evidence of consumer deception from native formatting of the paid-search ads. As noted previously, deception may occur is a consumer fails to *notice* that the product is advertised, perhaps because she does not see the ad-label, or if she *misinterprets* the ad-label, perhaps because she does not understand that the label used by the platform signifies an ad. Our first cut tests the first mechanism. We investigate whether consumer behavior under typical native advertising is closer to (1) a scenario where ads are clearly and prominently disclosed with an additional highlight, or (2) a scenario in which ads are present, but completely blended with the non-advertised content and indistinguishable from it. To do this, we compare consumer behavior in the *Ads-typical* condition with the *Ads-no-disclosure* and

[8] Articulating the considerations that make a paid-search listing to be classified as "native", the IAB's "Native Advertising Playbook" [IAB, 2013] notes, "While the content and format of organic search engine results varies depending on the search engine and the platform through which the service is being accessed (desktop, mobile, tablet, etc.), there is one definitive principle that defines an ad as native: native ads in search must present their content in a format and layout that is readily available to organic search engine results."

Table 2: Comparisons of Averages Across Experimental Conditions.

No.	Experiment condition	Chance of a click on the Ad	Chance of visiting the advertiser's page			Chance of calling the advertiser
		(1)	(2)	(3)	(4)	(5)
		Average	Average	Difference in chance of visiting the advertiser's page relative to the *No-Ads* condition	[Col(1) − Col(3)] ÷ Col(1)	Average
1	*No-Ads*	–	0.83%	–	–	0.030%
2	*Ads-No-Disclosure*	0.47%	1.10%	0.27%	42.6%	0.031%
3	*Ads-Typical*	0.51%	1.15%	0.32%	37.3%	0.068%
4	*Ads-Sponsored*	0.47%	1.17%	0.34%	27.7%	0.052%
5	*Ads-Typical-Highlight*	0.52%	1.14%	0.31%	40.4%	0.047%
6	*Ads-Sponsored-Highlight*	0.57%	1.26%	0.42%	26.3%	0.058%
	p-value for H_0: Means are the same across the six conditions	< 0.01	< 0.01			< 0.01

Notes: The table reports on raw comparisons of averages across the six experimental conditions. Column 1 shows the probability of clicking on an ad. Note that since no ads are shown in the *No-Ads* condition, the probability of an ad-click is zero in that condition. Column (2) shows the chance of a user visiting the advertiser's page during the session. Since a user can visit the advertiser's page through organic listings, the visit probability in the *No-Ads* condition is non-zero. Column (3) subtracts from column (2), the chance of a visit in the *No-Ads* condition, to show the change in the likelihood of a visit to the advertiser's page relative to the condition in which there are no ads. Numbers in column (3) will be lower than the numbers in column (1) if users who clicked on the ad would have reached the advertiser's page even in the absence of the ad. The table shows this is the case. Column (4) shows that about 30% of the users who click on the ads would have reached the advertiser's page using organic listings. These statistics suggest that ad-clicks may not be a good measure to judge the incremental effect of advertising.

Table 3: Effect of Native Advertising.

	(1) Page-visit			(2) Call		
	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value
Ads (any of the five conditions)	**0.0034**	**0.00038**	<0.01	**0.000204**	**0.000074**	<0.01
Intercept	**0.0083**	**0.00034**	<0.01	**0.00030**	**0.000064**	<0.01
Number of clusters	177,105			177,105		

Notes: The table reports on results from a regression of Page-visits and Calls on a 0/1 indicator of the user being in any one of the five experimental conditions that serve native ads. The standard errors are clustered by user. The estimates in bold are statistically significant at the 5% significance level. The regression is conducted on the data pooling all six experimental conditions. Therefore, the intercept represents the average outcome in the *No-Ads* condition, and the coefficients represent the average change in consumer behavior if the user is allocated to a condition with ads.

the *Ads-highlighted* conditions. The *Ads-highlighted* condition pools the *Ads-typical-highlight* and *Ads-sponsored-highlight* conditions. We pool the data in these two conditions in order to increase the power of our test and do not discriminate between formats with different text in the label. We implement the test in a linear regression framework, in which we regress the page-visit and call outcome variables on an indicator of whether the user is in the *Ads-no-disclosure* condition, or the *Ads-highlighted* condition. The baseline is the *Ads-typical* condition. So, the coefficients on the *Ads-no-disclosure* and *Ads-highlighted* dummies represent the change in the outcome variable from the *Ads-typical* condition.

The estimates are presented in Table 4. Looking at the regression with page-visit as the dependent variable (column 1), we see that that the coefficients on the indicators are statistically indistinguishable from zero. This suggests that the estimated likelihood of a user visiting the advertiser's page in the baseline condition – in which with native advertising presented in the typical format – is statistically indistinguishable from the same measure in the other two formats. Therefore, the chance of a user visiting the advertiser's page is similar, irrespective of whether the ad is marked in the typical way, is further highlighted, or is completely blended in the non-advertised content.

Looking at the estimates in column (2), we see that the likelihood of an individual calling the advertiser does vary with the format of advertising. The coefficient with respect to the indicator of *Ads-no-disclosure* is statistically significant and negative. This suggests that the likelihood of the individual calling a restaurant is lower when the ads are completely blended among the non-advertised search results compared to the condition in which ads are labeled in the typical format.[9] On the other hand, we see the coefficient corresponding to the indicator of *Ads-typical-highlight* is negative but statistically indistinguishable from zero. This suggests that the probability of the user calling the advertiser does not change when an additional highlight is placed on the ad.

Overall, the above analysis compares user behavior under the typical advertising format with two extreme formats, one in which the ads are made more salient, and arguably hard to miss, and the second in which the ads are completely blended in the content, and indistinguishable from the non-advertised content. It shows that the user behavior in the typical advertising regime is closer to the former. We conclude that the typical manner in which ads are displayed is sufficient for the consumers to see and respond to ads.

5.2.4 Do Consumers Misinterpret "Typical" Native Ads?

We next examine the data for any change in user behavior when the text in the label indicating advertising is changed from the common format reading "Ad" to "Sponsored", in the way shown in Figure 2. The motivation for this test is to check for any confusion this atypical label may have created in consumers'

[9] This finding is important and has implications for how we think about advertising effects. A companion paper, Sahni and Nair [2016] investigates this question in detail.

Table 4: Assessing the *Ads-Typical* Disclosure Condition.

	(1) Page-visit			(2) Call		
	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value
Ads-no-disclosure	-0.00057	0.00048	0.23	**-0.000287**	**0.000091**	<0.01
Ads-highlighted	0.00036	0.00040	0.38	-0.000091	0.000087	0.30
Intercept	**0.0116**	**0.00028**	<0.01	**0.0005987**	**0.0000638**	<0.01
Number of clusters	221,742			221,742		

Notes: The table reports on results from a regression of Page-visits and Calls on indicators of *Ads-no-disclosure* and *Ads-highlighted* conditions. The *Ads-highlighted* condition pools the *Ads-typical-highlight* and *Ads-sponsored-highlight* conditions. The standard errors are clustered by user. The estimates in bold are statistically significant at the 5% significance level. The regression is conducted on all the data pooled excluding the *No-Ads* condition. Therefore, the intercept represents the average outcome in *Ads-typical* condition, and the coefficients represent the difference between the condition indicated and the *Ads-typical* condition.

minds, which may then materially affect their behavior.[10] We perform this analysis by grouping our data into two categories: the first in which the label used reads "Ad" (combining users in condition *Ads-typical* and *Ads-typical-highlight*) and the second in which the label reads "Sponsored" (combining users in condition *Ads-sponsored* and *Ads-sponsored-highlight*). The rationale behind combining the conditions with and without the additional highlight is to increase the power in the test by increasing the number of observations. To conduct the test, we regress the two outcome variables on the indicator of the label using the word "sponsored".

Table 5 shows the estimates from the regressions. As before, column (1) shows the results with page-visit as the dependent variable and column (2) the results with calls as the dependent variable. Column (1) shows that the coefficient corresponding to the indicator of the "sponsored" label is positive but statistically indistinguishable from zero. Therefore, the likelihood of a page-visit does not change when the text in the label changes from "Ad" to "Sponsored". Column (2) shows a similar pattern for calls as the dependent measure. It shows that the coefficient for the variable indicating the text "sponsored" in the ad label is negative but statistically indistinguishable from zero. This analysis shows that the effect of the native ads is not sensitive to the two types of text used in the label to signify them. We conclude that consumers do not get confused when the manner in which ads are disclosed changes to some extent, especially within the set of standard labels used to indicate advertising in the paid-search industry.

5.2.5 Are Consumers "Tricked" into Conversion by Native Advertising?

One of the criticisms faced by native advertising is that by blending ads into non-advertised content, it makes unsuspecting individuals *click* on the ads and eventually purchase the advertised products. This viewpoint embeds some features of consumer naïveté, that consumers do not meaningfully and deliberately make subsequent choices once they click on advertising messages, either because they are inertial or because they face high search costs. In this section, we analyze the data further to examine *how* the ads work in our empirical context, focusing specifically on the role of ad-clicks to assess this viewpoint empirically.

To start, we compare the likelihood of a user clicking on the native ad when (1) the advertiser's listing is placed in the same format as the organic listings and completely blended with the non-advertised search-results, which is the *Ads-no-disclosure* condition, with (2) the same ads placed in a format that allows consumers to recognize ads, which comprise the remaining four sub-conditions in the *Ads* condition. A comparison of the numbers across Column (1) and Column (2) of the first row in Table 6 shows that more users click on the ad when the ad is distinguishable from non-advertised search-results (0.52% vs. 0.47%).

[10] For instance, Edelman and Gilchrist [2012] say: "The word "sponsored" creates considerable ambiguity. For one, "sponsored" uses the passive voice—leaving unstated the subject of the sentence, i.e. who exactly did the sponsoring. If a user searches for "Priceline" at Google and sees a link to Expedia, who is the "sponsor" of that link? Sophisticated users are likely to understand that "sponsored" means "advertisement." But the disclosure does not specifically inform anyone who does not already know."

Table 5: Assessing the Effects of Disclosure Label Content.

	(1) Page-visit			(2) Call		
	Coefficient	Standard error	*p*-value	Coefficient	Standard error	*p*-value
Ads-sponsored or Ads-sponsored-highlight	0.00066	0.00040	0.10	-0.000010	0.000087	0.90
Intercept	**0.0115**	**0.00028**	<0.01	**0.000559**	**0.0000617**	<0.01
Number of clusters	177,105			177,105		

Notes: The table reports on results from a regression of Page-visits and Calls on indicators of the user being in the *Ads-sponsored* or the *Ads-sponsored-highlight* conditions. The standard errors are clustered by user. The estimates in bold are statistically significant at the 5% significance level. The regression is conducted on the data pooling the four conditions *Ads-typical*, *Ads-typical-highlight*, *Ads-sponsored* and *Ads-sponsored-highlight*. Therefore, the intercept represents the average outcome in the *Ads-typical* or *Ads-typical-highlight* condition, and the coefficients represent the change in behavior when the text "Ad" is replaced by "Sponsored" as shown in Figure (2).

However, this difference is not statistically significant at the conventional level. Recall that, in Section 5.2.3, we also reported that ads increase the bottomline outcome (calls) when they are distinguishable from the organic results. Therefore, our findings from the current analysis show that the effect of our experimental native ads is not likely to be driven through clicks on the ads.

To better understand the behavior of individuals who click on the ads, we compare the behavior of users who arrive on the advertiser's page after clicking on the ad, with those who arrive on it through their own search by clicking on its organic listing. We start by comparing the propensity to continue search, which we define by an indicator of whether the user visited other restaurant page(s) during the same session subsequent to clicking on an advertised listing. Row (2) of Table 6 shows the likelihood of continued search of a user who arrives on an advertiser's page after clicking on an ad. Row (3) shows the likelihood of continued search for individuals who do not click on the ad. Looking down the columns, we see that the probabilities of continued search are higher in row (2) compared to row (3), whether of not ads are disclosed. On average, about 85% of the individuals who arrive at the advertiser's page after clicking on its ad continue to explore other options (row 2). This number is lower (73% on average) for individuals who arrive on the page after clicking on an organic listing (row 3). The drop in continued search between ad-clickers versus organic-listing-clickers is statistically significant (p-val < 0.01), as noted in row (4) of the table. The differences are not significant across the two groups of users in columns (1) and (2). This suggests that, irrespective of whether ads are distinguishable from the other content, individuals who click on the ad are more likely to continue other options, further reinforcing the notion that ad-clicks do not represent well the effect of advertising on an advertisers' outcomes.[11]

Along similar lines, we next compare the probability of an individual calling a restaurant separately by whether she clicks on the restaurant's ad or not. Row (5) shows the chance of a user calling the advertiser conditional on clicking on its ad. Row (6) shows the corresponding probability for users who arrive at the advertiser's page through their own search. These estimates show that the probability of calling is higher when the user arrive at the page through their own search. This is more evident for the users who see the ads with some form of distinction from the organic listings (column 2). Interestingly, across columns for both rows (5) and (6), we see that the probability of a user calling the advertiser is higher when she sees the ads with disclosure. The difference is particularly large and significant among individuals who did not click on the experimental ads; viewing (and not clicking) the experimental ads that are distinguishable from the organic listings generates an 89% increase in the call probability of individuals who arrive at the advertiser's page (from 2.62% to 4.94%).

[11] The inadequacy of clicks to assess the efficacy of paid-search has been pointed out in other academic research. For instance, Ursu [2015] shows that clicks on search listings are not a good way to assess the effects of search listing position, because bookings on hotels randomized into listing positions on Expedia do not increase systematically with position, even though clicks do. However, Ursu's data allows her to explore these for only organic listings, not paid-ads.

Inference We conclude two things from the above analysis. First, the incremental gains due to advertising is not driven through clicks on ads. Clicks on the ads do not seem the main channel by which the causal effect of advertising works: "Ad-clickers" are more likely to continue searching for better options than "organic" clickers. Rather, ads appear to work through exposure – individuals view the ads, update their impression of the advertiser, and continue to search. Eventually, if they decide to pick the advertised option, consumers reach it through search or organic clicks. Consequently, if a product is advertised, conveying to the consumers that it is advertised is important, as seen in our data. In a companion paper, Sahni and Nair [2016] show that these effects are consistent with a signaling explanation for the role of advertising. A second implication is that users in our data are sophisticated consumers of advertising. Users get exposed to advertising, process the information, search and act on their exposure in a deliberate manner. They are likely not being tricked into purchase by clicking on native ads.

5.2.6 Effects on Consumers

The analysis so far studied consumers' interactions with advertisers, and found that advertisers' outcomes under typical advertising formats are closer to an extreme scenario in which the ads are prominently highlighted, rather than the other extreme wherein ads are not disclosed at all. In this section, we focus on overall outcomes for the consumers (not just with respect to the advertisers) and ask: does the experimental variation systematically change overall choices made by consumers? Answering this question helps us further gauge whether the consumers' actions under typical advertising are closer to the condition with no-disclosure or the condition with an additional highlight.

We conduct the analysis using a regression framework. We identify 10,834 restaurants that received at least one call from any user in our experiment. For each of these restaurants we observe the number of calls received by the restaurant from users in each one of the five conditions in which ads appear (i.e., rows 2-6 in Table 2). We also observe each restaurant's characteristics on Zomato, specifically, the average rating it received, the number of times the restaurant got rated, and an index of the average price of food at the restaurant, all at baseline. To standardize these characteristics within a market, we categorize them into deciles, so each characteristic varies from 1 to 10 (10 being the highest). Indexing restaurants by r and conditions by c, we stack across restaurant-condition combinations and estimate the following regression,

$$\begin{aligned} Calls_{rc} \quad = \quad & \textit{Ads-Highlighted}_{rc} \times (\beta_1 \text{Rating}_r + \beta_2 \text{Number of Ratings}_r + \beta_3 \text{Price Index}_r) + \\ & \textit{Ads-No-Disclosure}_{rc} \times (\gamma_1 \text{Rating}_r + \gamma_2 \text{Number of Ratings}_r + \gamma_3 \text{Price Index}_r) + \\ & \delta_1 \textit{Ads-No-Disclosure}_{rc} + \delta_2 \textit{Ads-Highlighted}_{rc} + \psi_r + \epsilon_{rc} \end{aligned} \tag{1}$$

The *Ads-No-Disclosure* is an indicator of the condition in which ads are presented but not disclosed. As before, *Ads-Highlighted* is an indicator of whether the observation pertains to an experimental condition in

Table 6: Exploring Search, Clicks and the Mechanism Driving Ad-Response.

	(1) Ads placed with no indication (*Ads-no-disclosure* condition)		(2) Ads placed with some indication (five conditions pooled)		H_0: The means in columns (1) and (2) are equal
	Mean	Standard error	Mean	Standard error	p-value
(1) Percentage of users clicking on ads	0.47%	0.03%	0.52%	0.01%	0.07
(2) Prob of continuing to search, conditional on visiting an advertiser's page via an ad-click	85.79%	1.88%	84.75%	0.92%	0.61
(3) Prob of continuing to search, conditional on visiting an advertiser's page for users who did not click on ads	74.92%	1.64%	72.55%	0.83%	0.21
(4) p-value: Testing the null hypothesis that means in rows (2) and (3) are equal	<0.01		<0.01		
(5) Prob that an advertised restaurant is called for users who click on its ad	1.74%	0.70%	2.76%	0.42%	0.21
(6) Prob that an advertised restaurant is called for users who visit its page but do not click on its ad	2.62%	0.71%	4.94%	0.48%	<0.01
(7) p-value: Testing the null hypothesis that means in rows (5) and (6) are equal	0.49		<0.01		
(8) Prob that an advertised restaurant is called for users who do not click on its ad (not specifically for those who visit its page)	0.023%	0.006%	0.041%	0.004%	<0.01

Notes: The table presents averages, standard errors and hypotheses tests to examine differences between users who do or do not click on experimental native ads. Observations in the data are categorized into two groups: (1) individuals in the condition that show experimental ads with no distinction from the rest of the non-advertised content (*Ads-no-disclosure)*, and (2) individuals in any one of the four conditions that show native ads in a format that is distinguishable from the rest of the content (the four conditions included are *Ads-typical, Ads-sponsored, Ads-typical-highlight, Ads-sponsored-highlight*). Column (3) shows the p-values from testing the null hypothesis that the means in columns (1) and (2) are equal.

which ads are highlighted (conditions *Ads-Typical-Highlight* or *Ads-Sponsored-Highlight*). As the base, we include the conditions in which ads are presented without a highlight (*Ads-Typical* and *Ads-Sponsored*). The across-restaurant heterogeneity is controlled for by fixed effects (ψ_r). The parameters βs and γs estimate whether the outcomes for the restaurants change systematically with the degree of highlighting across the experimental conditions.

Table 7 shows the estimates of the model. Standard errors are clustered at the restaurant level. The estimates show that the β coefficients – corresponding to the terms interacting with *Ads-Highlight* – are statistically insignificant. This implies that users' calling behavior does not change systematically between the typical advertising format and the format with an extra highlight, as found in the means comparisons reported previously.

Looking next at the γ coefficients (corresponding to the terms interacting with *Ads-No-Disclosure*), we see these are statistically significant (marginally, joint p-value = 0.07). These imply that users in the condition that presents the ads in the typical format, systematically call different restaurants (in terms of the considered characteristics), compared to the condition in which ads are not disclosed. Specifically, when the ads are not disclosed, calls are shifted to restaurants with lower ratings, and to those that have received ratings more times in the past. Further, the fact that these interactions are statistically significant suggest that statistical power considerations are not driving the main finding that the γ coefficients are statistically insignificant.

Overall, the above analysis reiterates that users' calling behavior under typical advertising is closer to the condition that clearly highlights the ads, as compared to the condition that does not disclose the ads. Although this analysis cannot speak directly to consumer welfare, it shows that the consumer actions do not change materially when the ads are made more prominent, suggesting that the concern for welfare losses from current disclosure standards in paid-search may be minimal.

Summary Taken together, these results imply that native advertising benefits advertisers and the search platform, and typically used formats of disclosure currently used in the paid-search marketplace do not seem to materially deceive consumers.

6 Epilogue

Following the experiment, Zomato launched mobile advertising on its Android App in November 2014.[12] The ads used the "Sponsored" label format with a picture and logo of the advertiser into the search results so as to clearly and prominently make advertising salient to searching users. This decision was driven in part by the fact that no adverse user reaction or drop in calls to restaurants was seen from disclosure as

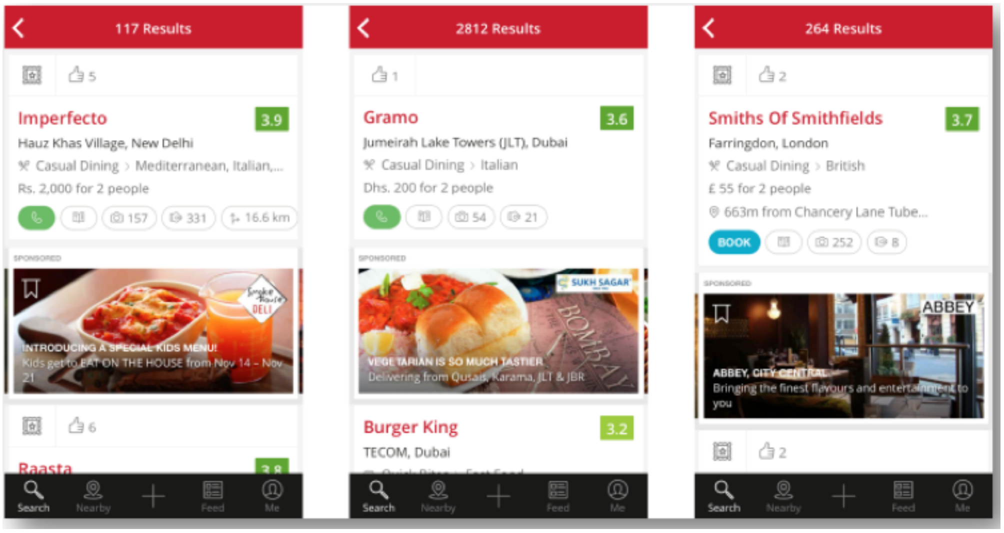
[12] See `http://techcrunch.com/2014/11/28/restaurant-guide-zomato-launches-mobile-ads-and-prepares-to-move-into-payments/` for an announcement.

Table 7: Change in Consumer Calling Patterns with Advertising Disclosure.

	Dependent measure: Number of calls to the restaurant		
	Coefficient	Std. Error	p-value
Ads-Highlighted×Rating	-0.001	0.003	0.79
Ads-Highlighted×Number of Ratings	0.002	0.003	0.59
Ads-Highlighted×Price Index	-0.004	0.003	0.13
Ads-No-Disclosure×Rating	**-0.008**	**0.004**	**0.04**
Ads-No-Disclosure×Number of Ratings	**0.009**	**0.004**	**0.05**
Ads-No-Disclosure×Price Index	0.004	0.003	0.25
Ads-No-Disclosure	-0.034	0.026	0.19
Ads-Highlighted	0.022	0.021	0.30
Intercept	0.403	0.004	$<$0.01
Fixed effect for each restaurant?	Yes		
Number of restaurants	10,843		
Number of observations	10,843×5		

Notes: Estimates from the linear model in (1). Standard errors are clustered at the restaurant level. An observation is a restaurant times an experimental condition. The interaction terms signify a shift in calls to restaurants with the corresponding characteristics. The terms interacting with the *Ads-Highlighted* dummy are statistically insignificant, implying no systematic change in calls caused by making typical disclosure formats more prominent. Two of the three terms interacting *Ads-No-Disclosure* are statistically significant at the conventional level. Together, the three interaction terms involving *Ads-No-Disclosure* are marginally significant (p-value = 0.07). These estimates show some evidence of difference in calling patterns between the conditions with and without disclosure. Specifically, not-disclosing ads in the typical manner leads to decrease in calls for restaurants that are highly rated and rated fewer number of times in the past.

Figure 4: Screenshot of Post-Experiment In-Feed Advertising Introduced into the Mobile App.



Notes: The figure shows a screenshot of the ad disclosure format introduced into the Zomato mobile platform after the experiment. Ads are prominently displayed in the search results page with a picture and logo of the advertising restaurant along with a label noting "sponsored".

part of this experiment. Figure (4) presents a screenshot of the new format implemented.

7 Conclusions

An assessment of whether native advertising deceives consumers and tricks them into materially changing their actions related to paid-search is presented. The assessment utilizes a field experiment implemented on a large restaurant search platform. The novelty of the experiment is in presenting a way to assess the possibility of deception via revealed preference arguments. The experimental design randomizes users into conditions in which the sponsorship of a listing by an advertiser is disclosed prominently or not at all. Deception is said to have occurred if actions under typical standards of disclosure seen in the marketplace look closer to the counterfactual world in which advertisement status is not revealed. An advantage of the set-up is that user actions related to both the advertisement and the product being advertised are tracked precisely, so as to assess the "material" nature of any possible effects from the interventions.

The empirical results do not provide evidence for substantive deception: user actions under typical disclosure look very similar to the prominently displayed condition. Further, users seem to be sophisticated consumers of advertising, making restaurant choices deliberately after substantial search and exploration, and do not seem to be "tricked" by native formatting into purchasing products. Overall, our results inform the recent debate about native advertising, as well as the more long standing one about separation between advertising and content in media. While we caution against extrapolating the finding of no-deception to other types of media, we conjecture that our findings regarding consumer sophistication may be relevant in other media settings.

References

A. Bakshi. Why and how to regulate native advertising in online news publications. *Journal of Media Law and Ethics*, 4(3/4):4–47, 2015.

T. Blake, C. Nosko, and S. Tadelis. Consumer heterogeneity and paid search effectiveness: A large scale field experiment. *Econometrica*, 83(1):155–74, 2015.

M. Carlson. When news sites go native: Redefining the advertising– editorial divide in response to native advertising. *Journalism*, pages 1–17, 2014.

M. Coddington. The wall becomes a curtain: Revisiting journalism's news-business boundary. In M. Carlson and S. C. Lewis, editors, *Boundaries of journalism: Professionalism, practices and participation*, pages 67–82. New York: Routledge, 2015.

B. Edelman and D.S. Gilchrist. Advertising disclosures: Measuring labeling alternatives in internet search engines. *Information Economics and Policy*, (24):75–89, 2012.

M. Engle. Updated search engine letter from ftc. *https://www.ftc.gov/sites/default/files/attachments/press-releases/ftc-consumer-protection-staff-updates-agencys-guidance-search-engine-industryon-need-distinguish/130625searchenginegeneralletter.pdf*, June 2013.

D.J. Franklyn and D.A. Hyman. Trademarks as search engine keywords: Much ado about something? *Harvard Journal of Law and Technology*, 26(2), Spring 2013.

FTC. Ftc consumer protection staff updates agency's guidance to search engine industry on the need to distinguish between advertisements and search results. *www.ftc.gov/news-events/press-releases/2013/06/ftc-consumer-protection-staff-updates-agencys-guidance-search*, June 2013.

FTC. Commission enforcement policy statement on deceptively formatted advertisements. *https://www.ftc.gov/public-statements/2015/12/commission-enforcement-policy-statement-deceptively-formatted*, Dec 2015.

M. Hoetzel. Spending on native advertising is soaring as marketers and digital media publishers realize the benefits. *http://www.businessinsider.com/spending-on-native-ads-will-soar-as-publishers-and-advertisers-take-notice-2014-11*, 2015.

C. Hoofnagle and E. Meleshinsky. Native advertising and endorsement: Schema, source-based misleadingness, and omission of material facts. *Technology Science*, 2015121503, 2015.

IAB. The native advertising playbook: Six native ad categories, six marketplace considerations, and iab recommended disclosure principles. *http://www.iab.com/guidelines/native-advertising/*, December 2013.

IAB. Iab concerned about ftc guidance on native advertising. *http://www.iab.com/news/iab-concerned-about-ftc-guidance-on-native-advertising/*, Dec 2015.

B.J. Jansen, A. Brown, and M Resnick. Factors relating to the decision to click on a sponsored link. *Decision Support Systems*, 44:46–59, 2007.

R. A Lewis and D. H Reiley. Online ads and offline sales: measuring the effect of retail advertising via a controlled experiment on yahoo! *Quantitative Marketing and Economics*, 12(3):235–266, 2014.

M. Mitchell. State of the news media 2015. *http://www.journalism.org/2015/04/29/state-of-the-news-media-2015/*, April 2015.

N. Sahni. Effect of temporal spacing between advertising exposures: Evidence from online field experiments. *Quantitative Marketing and Economics*, 13(3):203–247, 2015.

N. Sahni and H. Nair. Does advertising serve as a signal? evidence from field experiments in mobile search. *working paper, Stanford GSB*, 2016.

M. Sebastian. Wall street journal adopts native ads, tactic its editor has said can lead to faustian pacts. *Advertising Age*, March 2014.

J. Sonderman and M. Tran. Understanding the rise of sponsored content. In *https://www.americanpressinstitute.org/publications/reports/white-papers/understanding-rise-sponsored-content/*. American Press Institute, 2013.

C. Tucker. Social advertising. *working paper, MIT Sloan School of Management*, 2012.

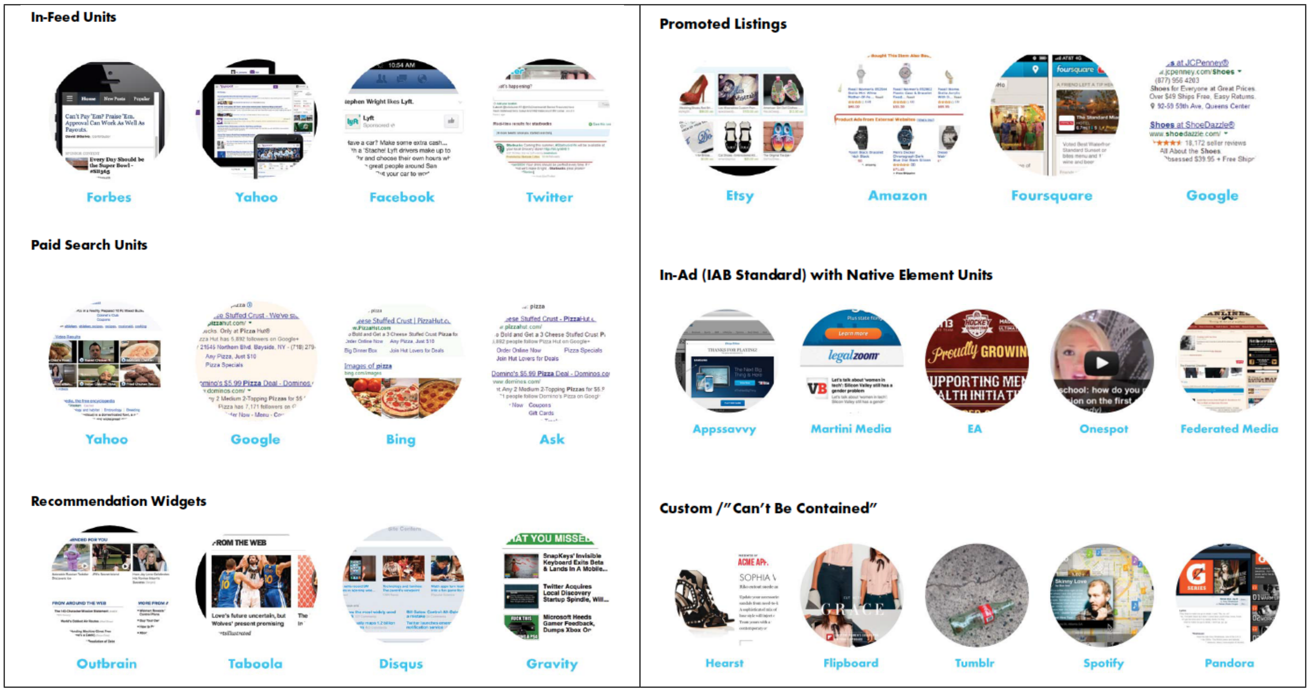
K. Tutaj and E. A. van Reijmersdal. Effects of online advertising format and persuasion knowledge on audience reactions. *Journal of Marketing Communications*, 18(1), 2012.

R. Ursu. The power of rankings: Quantifying the effects of rankings on online consumer search and choice. *working paper, University of Chicago*, 2015.

B. W. Wojdynski and N. J. Evans. Going native: Effects of disclosure position and language on the recognition and evaluation of online native advertising. *Journal of Advertising*, 10.1080/00913367.2015.1115380, 2015.

Appendix: Types of Digital Native Ads

Figure 5: Six Digital Native Ad Categories: Official IAB Definition.



Notes: The Figure shows a schematic with examples of the 6 core classifications of digital native ads by the Interactive Advertising Bureau, the official trade association of the digital advertising industry in the US. This paper pertains to the second category, "Paid Search Units". Source: IAB [2013].