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Serial Position Effects on Native Advertising Effectiveness: Differential Results Across Publisher and Advertiser Metrics

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Abstract

The advertising industry has recently witnessed proliferation in native ads, which are inserted into a web stream (e.g., a list of news articles or social media posts) and look like the surrounding nonsponsored contents. This study is among the first to examine native ads and unveil how their effectiveness changes across serial positions by analyzing a large-scale data set with 120 ads. For each ad, the authors use separate "natural experiment" studies to compare the ad's performance as its serial position varies. Subsequently, they conduct a meta-analysis to generalize the results across all studies. The results reveal vastly asymmetric effects of native ad serial position on publishers' metrics (click-based) versus advertisers' metrics (conversion-based). As serial position lowers (i.e., from rank 1 to a lower rank), there are only modest changes in publishers' metrics, but drastic reductions in advertisers'. This pattern is unique to native ads and has not been indicated by prior research on ad serial position. Moreover, the authors show the moderating effects of audience gender and age. The findings provide new and timely implications for researchers and marketers.

Keywords

contingency effects, meta-analysis, native advertising, serial position

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Because of the extremely low click-through rate (CTR, the rate of click per impression) of traditional online display ads (.05% on average according to DoubleClick's Display Benchmarks Tool 2017), publishers (i.e., websites) cannot charge advertisers high fees for such ads and thus are often forced to sell more ad slots to ensure revenue. Doing so leads to clogged web pages with an excessive number of banners and pop-ups, decelerating page loading and damaging viewer experience. Consumers often filter or avoid such ads or view them skeptically (Chatterjee, Hoffman, and Novak 2003), and ad blocking surged by 30% globally in 2016, with a total of 615 million devices using this software (PageFair 2017). As a result, advertisers began seeking alternatives for interruptive display ads, and native ads seemed an ideal candidate.

Native advertising, also referred to as sponsored content or streaming advertising, is an increasingly popular form of disguised online display advertising wherein ad experience matches the format/function of user experience on the platform on which it is displayed. It "camouflages the marketing messages so that they look and sound like editorial (organic) content" (Mansfield 2015). From 2017 to 2018, spending on native advertising was projected to increase by 31% to a total of $32.9 billion, which makes up 58% of all display ad spending (eMarketer 2018). In comparison, in 2010, 63% of all display ad spending was on interruptive banner ads (eMarketer 2012). There has been limited research on native advertising, despite its recent proliferation.

Sponsored listings (native ads) are inserted into a stream of listings such as articles (e.g., sponsored articles inserted in Yahoo! News), social media postings (e.g., sponsored posts on Facebook) and online video titles (e.g., sponsored titles on YouTube). Given the positions available for sponsored items on a website, where an ad would appear is determined by its serial/rank position (we use "serial position" and "rank position" synonymously), which can in turn influence ad performance. How quickly does a native ad's performance change as its serial position lowers (i.e., from rank 1 to a lower rank)? How does the rate of change vary for different performance

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metrics and viewer groups? This study addresses these questions.

Following the online ad literature (e.g., Ghose and Yang 2009; Xu, Duan, and Whinston 2014), we focus on CTRs and conversion rates (CVRs, the rate of conversion per click) as key performance metrics. The stream of listings (including both organic and sponsored listings) is loaded bit by bit as viewers scroll down the web page. An impression is counted when the listing is loaded into the web page and displayed to the viewer. After an impression occurs, the viewer might (or might not) notice it and even click on it. Under the prevalent "pay per click" scheme in the online advertising industry, advertisers do not pay a fee for an ad impression unless the ad is clicked. Thus, for a publisher, CTR is a key metric that determines how much revenue it can generate by displaying ads on the web page. Meanwhile, an advertiser is primarily concerned with CVR or how many conversions occur after clicks, because its business success depends on the number of conversions (e.g., purchases). The CTR and CVR correspond to different stages in the online sales funnel. The classical sales funnel is a multistage process through which a consumer moves toward a purchase (i.e., from attention to evaluation and attitude formation to decision and action; Kotler and Armstrong 2011; Wiesel, Pauwels, and Arts 2011). In the online advertising context, the sales funnel is a web viewer's journey from ad impression to click to conversion.[1] Thus, CTR is the transition rate at the upper funnel (i.e., from impression to click), while CVR is the transition rate at the lower funnel (i.e., from click to conversion). In addition to CTR and CVR, we conduct supplemental analyses on additional performance metrics to make potential financial implications.

Marketers and researchers have long been concerned that the serial position in ad placement can influence ad effectiveness (e.g., Swaminathan and Kent 2013; see Table W1.1 of Web Appendix W1). According to the literature, the serial position effect is different across various types of ads, and there are inconsistent findings within each ad type/media platform. Moreover, previous studies mostly examine undisguised and interruptive ads, and thus their findings may not apply to native ads, which viewers may not recognize as an ad until after clicking on it. As we theorize subsequently, this disguised nature predicts a distinct role of serial position for native ads compared with conventional ads—that is, it may have a modest impact on ad click but a radical impact on postclick conversion. Furthermore, prior research has provided limited insight regarding the contingent effects of ad serial position across consumer groups.

This study is among the first to examine native ad performance across serial positions. Its main contributions are threefold. First, we theorize and empirically investigate a relatively new type of advertising, native advertising, which is of immense managerial and economic importance but rarely studied by marketing researchers. Second, based on large-scale field data, we find that as serial position lowers, the performance of a native ad drops only moderately for publishers (in terms of CTR and revenue per impression) but acutely for advertisers (in terms of CVR and conversion per ad dollar spent). Such vastly asymmetric effects of serial position on publishers' versus advertisers' metrics are unique to native ads and have not been documented or implied by prior research. Managerial insights derived from these findings may encourage potential revolution in the native ad industry (e.g., our findings show that native ad advertisers overpay for lower rank positions and are thus at a disadvantage). Third, we unveil important contingency factors that moderate the serial position effect, including audience gender and age. By taking a contingency perspective, this study not only adds to the literature by providing a more thorough understanding of the serial position effect (i.e., the effect is not homogeneous across audience groups) but also enables practitioners to better optimize native ad performance under various conditions.

Relevant Literature

Literature on Ad Serial Position

Prior research has studied the effect of serial position for interruptive ads on conventional media and certain online ads. However, this literature has provided mixed findings (summarized in Table W1.1 of Web Appendix W1).

Research on the serial position of TV ads has mostly examined viewer memory (e.g., brand recall) as the outcome using lab experiments. Some studies (e.g., Jeong, Tran, and Zhao 2012; Pieters and Bijmolt 1997) find support for a primacy effect on memory (i.e., viewers tend to better remember the ads in the first position of a sequence), while others (e.g., Tse and Lee 2001) document recency effect (the tendency to better remember the last ad in a sequence). Regarding print ads, research based on Starch scores has provided ambiguous results (e.g., Finn 1988). Using an eye-tracking lab study with 88 consumers reading two magazines, Wedel and Pieters (2000) show stronger recency effect than primacy effect on memory. In contrast with the findings in conventional offline media contexts, Li and Lo (2015) show that online video ads (in-stream ad clips inserted in a YouTube video) in the middle positions lead to higher recall than those in the first or last position, based on experiments with 240 college students.

There is also a growing literature on keyword-based sponsored search ads on online search engines. Like most research on online ads, this literature focuses on CTRs and CVRs instead of memory as outcome variables. The impact of ad serial position is inconclusive from this literature. For example, some studies show that CTR and CVR constantly decrease as rank position lowers (Rutz, Bucklin, and Sonnier 2012), some find nonlinear effect of rank position (Agarwal, Hosanagar, and Smith 2011), and others report no significant change in CVR

[1] The online sales funnel is consistent with the central idea of the classical sales funnel: after exposure to an ad, a viewer may or may not pay attention to or click on it; after clicking, the viewer may or may not perceive the ad positively and convert.

across rank positions (Narayanan and Kalyanam 2015). Note that a potential consumer will not see search ads unless (s)he has intentionally searched for a related keyword. Therefore, consumers exposed to them are likely to have already developed interest or purchase intent to some extent (Choi 2016). Because of such preexisting interest, viewers of search ads are more likely to look through lower-ranked ads to find the best match to their interest. Thus, there are still substantial chances for conversions to occur with search ads at lower rank positions (e.g., Ghose and Yang 2009). Similar motivations to scan through lower rank positions are unlikely to exist for other types of ads (including native ads), whose exposures are more random and coincidental.

In summary, there is continuous debate on the significance and magnitude of ad serial position effect, which appears to vary for different types of ads and different outcome metrics of interest. In addition, although "serial position" shares one basic meaning in both offline and online contexts (i.e., the ordinal position; e.g., first, second, . . .) of an ad in a series of sequentially presented ads (which determines whether an ad would appear earlier or later in the sequence), the way the ads are inserted in the media content could vary. For instance, a series of TV or radio ads often run back to back within an ad pod (i.e., a block of ads clustered right next to one another), a magazine ad appears every few pages, and each online ad (including native ad) is placed at a different slot between the organic contents on a web page or in a video.[2] Such differences further highlight the importance of examining the serial position effect in each context because results from one context may not directly apply to the others. More importantly, compared with the other ad types discussed previously, native ads are more disguised and less interruptive by design (Porter 2016).[3] Viewers are likely to click on a native ad without recognizing that it is in fact an ad (Wojdynski and Evans 2016). Because of this unique nature, the serial position effect for native ads can significantly differ from that for traditional, undisguised ads. Considering the recent proliferation of native ads, our study is meaningful and timely.

Literature on Online Display Ads

Native advertising is a form of online display ad. Thus, we also review the online display ad literature and highlight the uniqueness of our study. Unlike ads in conventional media (e.g., TV, print), online ads allow and encourage users to take immediate actions (e.g., clicks and purchases) on the same device/platform where the ad is displayed. Moreover, for advertisers, instead of pay-per-slot (e.g., time slot on TV or pages/sections on print media), the pay-per-click scheme dominates online ad platforms. Thus, online ad studies focus on CTRs and CVRs as key outcome metrics (e.g., Chatterjee, Hoffman, and Novak 2003; Xu, Duan, and Whinston 2014). Consistent with the literature, we also examine these metrics.

Our study differs from prior research on four major fronts. First, most previous studies examine banner ads (see Table W1.2 of Web Appendix W1), which are interruptive and trigger negative connotations upon impression (Goldfarb and Tucker 2011; Manchanda et al. 2006). In contrast, we focus on native ads, which are designed to counter this nature of banner ads and better blend into the surrounding organic contents (Choi 2016). Only until recently have researchers begun to pay attention to native ads: using lab experiments, Wojdynski and Evans (2016) and Campbell and Evans (2018) examine some drivers (e.g., disclosure format and companion banner ad) of viewers' recognition of and attitude toward native ads, and Sahni and Nair (2016) conduct field experiments in the context of a mobile app for restaurant search to assess the level of consumer deception. Second, although web pages rarely display only one single ad, and viewers are typically exposed to multiple online display ads in a sequence, previous studies (including the three on native ads) have not examined the effect of online display ads' serial positions. Third, because of data restrictions, prior research has typically treated consumer features (e.g., gender, age) as unobservable or has ignored them and thus cannot speak to their moderating impact on ad effectiveness. Fourth, most prior studies use data about one particular advertiser, limiting the generalizability of the results.

Theory

Changes in Native Ad Performance Across Serial Positions

Prior research has suggested two major theoretical mechanisms that explain the impact of online ads' placement positions on their performances: (1) the annoyance effect and (2) the attention effect.[4] Table 1 lists the key differences in these effects between disguised native ads and undisguised ads. Undisguised ads (e.g., banner ads, pop-up ads) are interruptive and thus cause annoyance upon ad impression before click. In contrast, in the case of native ads, viewers can mistake a sponsored listing for an organic listing (e.g., a news article or a regular Facebook post) and thus might not be annoyed until after clicking on the ad (Wojdynski and Evans 2016). Thus, native ads may "postpone" annoyance to later stages of the online sales funnel (from preclick to postclick). As we elaborate next, because of this uniqueness of native ads, the impact of ad serial position may be asymmetric on click-related metrics (e.g., CTR) versus conversion-related metrics (e.g., CVR).

For regular undisguised ads displayed in a sequence, an ad impression tends to trigger greater annoyance as its rank position lowers. This is because viewers become more annoyed

[2] In other words, serial position in our context describes whether an ad is inserted earlier or later (relative to the other ads) in a stream of web content (e.g., listings, articles). For more details, see the "Data and Variables" section.

[3] Search ads are also more interruptive than native ads per industry standard. For instance, similar to other search engines, every search ad on Google "is clearly marked and set apart from the actual search results" (Google 2016).

[4] Other arguments from the literature include primacy/recency effect, perceived quality effect, and fatigue effect, which are less relevant to our context as discussed in the note for Table 1.

Table 1. Theoretical Distinctiveness of Native Ads Versus Undisguised Ads.

A: Undisguised Online Ad (Hypothetical Context for Theoretical Comparison)		B: Disguised Native Ad (Focal Context of the Present Study)	
Changes in CTR (Clicks/Impressions) Across Rank Positions		**Changes in CTR (Clicks/Impressions) Across Rank Positions**	
Annoyance effect	A lower-ranked ad triggers greater annoyance (because, prior to the current ad, the viewer has already been interrupted by other ads and thus becomes less patient with yet another ad) and thus has lower CTR.	Annoyance effect	Native ads look like organic listings and viewers may not recognize them as ads. Thus, annoyance does not significantly increase as ad rank lowers, because the higher ranked ads presented before the focal ad have not caused significant interruption of the viewing experience.
Attention effect	A lower-ranked ad may be less noticeable and attract less attention and thus has lower CTR.	Attention effect	A lower-ranked listing may be less noticeable and attract less attention and thus has lower CTR.
		Conclusion: CTR drops relatively *slowly* as a native ad's rank position lowers because of the *lower* preclick annoyance effect.	
Changes in CVR (Conversions/Clicks) Across Rank Positions		**Changes in CVR (Conversions/Clicks) Across Rank Positions**	
Annoyance effect	A lower-ranked ad can trigger greater annoyance. However, the fact that the viewer has clicked on the ad means that (s)he might be interested in the product advertised. The viewer's interest in the product could mitigate the annoyance effect on CVR.	Annoyance effect	Although viewers are less likely to be annoyed by native ads *before* clicking on them (because of the ads' disguised nature), they may be annoyed *after* realizing that they have been "tricked" (i.e., after clicking on an ad that they thought was an organic listing). Such annoyance swells as ad position lowers (because of increasing chance of repeated exposures and greater time constraint as they browse through the website, both of which amplify annoyance). Thus, native ad CVR can decrease rapidly as its rank position lowers due to the annoyance effect.
		Conclusion: CVR drops relatively *quickly* as the rank position of a native ad lowers because of the *stronger* postclick annoyance effect.	

Notes: Other theoretical mechanisms proposed by prior research on ad serial position include (1) the primacy and recency effect (i.e., viewers tend to better remember the first and the last ads in a sequence), (2) the perceived quality effect (i.e., an ad in a lower position might be associated with lower quality), and (3) the fatigue effect. These theories are relatively less relevant to our context. First, the primacy and recency effect explains the effect of serial position on memory, which is not the focal outcome of our study. Like most studies on online ads, we model clicks and conversions instead of memory. Second, prior research on the perceived quality effect typically considers products that are direct competitors (e.g., Ghose and Yang 2009). For example, in the context of keyword-based search ads, when a consumer searches for the keyword "car insurance," all the ads displayed are from car insurance companies that bid for this keyword. In contrast, native ads inserted into a web stream are "random": products advertised in neighboring native ads are often from different product categories (e.g., car insurance ad in rank 1 followed by video game ad in rank 2). Therefore, product qualities in neighboring native ads cannot be directly compared. Moreover, because native ads are disguised, a viewer is less likely to know whether (s)he has seen other ad(s) before seeing the current lower-ranked ad and, thus, is less likely to develop strong association between ad rank and product quality. Third, the literature generally agrees that visual and psychological fatigue tends to be insignificant within 20 minutes of web browsing (Chi and Lin 1998), and the length of typical viewing sessions on the focal website is shorter than 20 minutes.

after repeatedly seeing interruptive ads (Anand and Sternthal 1990). Increasing preclick annoyance in turn results in decreasing CTR. Moreover, ads in lower positions may be less noticeable and attract less viewer attention (Hoque and Lohse 1999), further reducing the CTR of lower-ranked ads.

In contrast, for disguised native ads, preclick annoyance may not significantly increase as ad rank lowers. Native ads look similar to the organic listings surrounding them, and viewers may not recognize them as ads (Sahni and Nair 2016). Thus, viewers may not realize whether or how many higher-ranked ads have been presented before a lower-ranked ad. Therefore, a lower-positioned native ad may not be associated with considerably higher annoyance than the top-positioned one. Meanwhile, as viewers scroll down, they are unlikely to experience greater attention reduction on a web page with native ads than on a web page with traditional ads. For these reasons, we propose that, unlike regular display ads, as a native ad's rank position lowers, its CTR only drops at a moderate pace.

Although viewers are less likely to be annoyed by native ads before clicking on them, they tend to be annoyed after realizing that they have been "tricked" (i.e., after clicking on an ad which they initially thought was an organic listing) (Campbell and Evans 2018; Wojdynski and Evans 2016). A viewer may not encounter lower ranked listings unless they scroll down and spend a longer time on the website. Given the limited time available for each website visit, a viewer typically has greater time constraint and exhibits increased impatience as (s)he scrolls down. Thus, a lower-positioned ad may be perceived as a greater disruption or waste of time, causing greater postclick annoyance than a top-positioned one. Moreover, when the

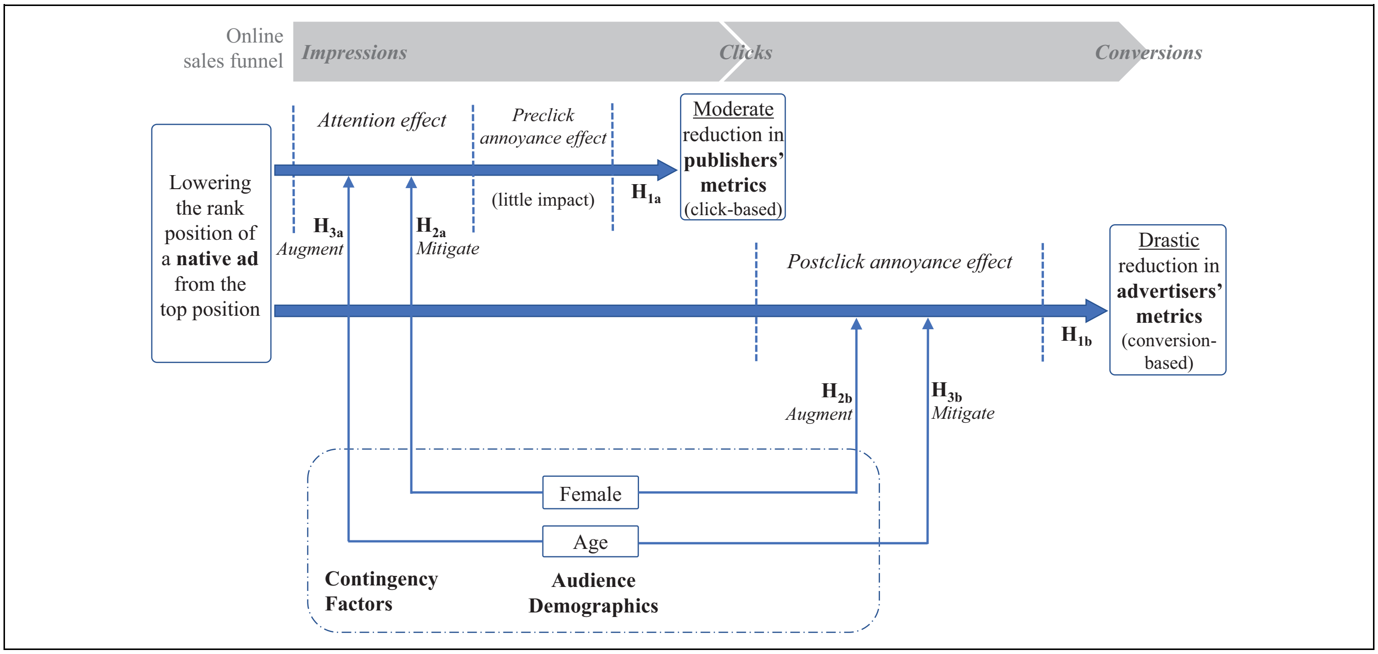

Figure 1. Conceptual framework.

topmost ad is clicked, the viewer has typically just started the viewing session and has not clicked on any other ads; in comparison, by the time a lower-ranked ad is displayed, the viewer might have already clicked on an ad and will thus be highly annoyed if (s)he is tricked by yet another ad. This greater annoyance negatively affects the likelihood of conversions after clicks. Therefore, we expect the CVR of a native ad to decrease rapidly as its rank lowers as a result of the increasing postclick annoyance effect.

In contrast, the effect of postclick annoyance on CVR may not be so severe for regular online display ads. Because of their undisguised nature, web users actively attempt to avoid clicking on them (Chatterjee, Hoffman, and Novak 2003; Goldfarb and Tucker 2011). When viewers do click on such ads, it is often because they are interested in the products advertised, and thus they are less likely to be annoyed after clicking.

Therefore, we expect differential effects of serial position on native ad's CTR versus CVR:

> **H_1**: As a native ad's serial position lowers from rank 1 to rank 2 (or 3), (**a**) CTR drops at a moderate speed while (**b**) CVR drops at a high speed.

Contingency Effects

Although prior researchers have realized the importance of examining serial position effect from a contingency perspective, the moderators they identified are mostly specific to the type of ad under study and do not apply to native ads.[5] The classic persuasion theory (e.g., Petty and Cacioppo 1986) indicates that the nature of the recipient (i.e., the ad viewer) is a key factor that moderates advertising effectiveness. Thus, we examine the moderating roles of two main demographic factors that constantly interest marketers and researchers, namely, gender and age (e.g., Baldiga 2014; Hong et al. 1994; Wolin 2003). These moderators fit in the conceptual framework because they can mitigate or amplify the two main theoretical mechanisms (i.e., attention effect and the annoyance effect) and thus can moderate how native ad performance varies across rank positions (summarized in Figure 1).

Moderating effect of gender. Biological differences (e.g., brain lateralization, chromosomes, hormones) across genders result in cognitive and behavioral differences (Hong et al. 1994), one of which pertains to visual attention. The literature suggests that women's visual attention spreads over a wider range, whereas men's is more focused. For example, Van Aswegen (2015) indicates that women are more discovery-oriented than men when browsing a website. Consistently, using eye tracking, Shen and Itti (2012) find that women and men orient their visual attention differently during listening tasks (e.g., women's saccades are often "distracted" toward background scene elements), Heisz, Pottruff, and Shore (2013) show that women scan more and extract a wider array of visual information than men, and Hwang and Lee (2018) find that women attend visually to more areas than men in the context of online shopping. According to mental health researchers, "women are just biologically wired to pay attention to different things than men are" and thus have widespread attention (Lewis 2016). Thus, we expect that women are more likely to notice and click on lower-positioned listings than men. Therefore, as a native

[5] As Table W1.1 shows, studies on TV ads focused on such moderators as ad duration, commercial break length, and channel switching, whereas those on keyword-based search ads focused on keyword features (e.g., specificity).

ad's position becomes lower, its rate of decrease in CTR can be slower among women than men.

However, there can be a faster reduction in CVR among women, whose postclick annoyance may increase more quickly as ad position lowers. After clicking on a disguised ad, viewers may consider the ad deceiving if they find themselves tricked. Compared with men, women consider deception in communication less acceptable and more annoying (Levine, McCornack, and Avery 1992; O'Keefe 1988). Moreover, women are, in general, more sensitive to time constraints in their spare time because of the maternal instinct (e.g., Shaw 1999), and thus their postclick annoyance may increase more quickly as ad position lowers (because the time constraint increases as they scroll down the web page). In addition, when viewers associate an advertiser with an intent to mislead or cheat, the perceived risk of transaction is increased, and women exhibit stronger risk aversion than men (Baldiga 2014). As ad rank lowers and the chance of viewer exposure to preceding ads increases, this negative effect is further amplified because women exhibit stronger reactance to persistent annoyance or repetitive provocation (Mikolic, Parker, and Pruitt 1997). Therefore, we expect the following:

> **H_2**: (**a**) CTR drops faster across ranks for men than for women, whereas (**b**) CVR drops faster across ranks for women than for men.

Moderating effect of age. While both older and younger adults are comparably capable of processing information from accessible sources (Gaeth and Heath 1987), younger viewers have less concentrated and more diffuse attention spread (McCalley 1995) and constantly "jump to the next thing" in the online context (Richtel 2010). Thus, younger viewers may not pay significantly less attention to lower-positioned listings than the topmost listing, thus mitigating the rate of change in CTR as a native ad's serial position lowers. In contrast, older viewers' attention and clicks drop more quickly as ad position lowers.

However, serial reduction in CVR can be slower among older viewers than younger ones. When viewers realize that what they have just clicked on is in fact not an organic listing but a disguised ad, they may perceive the ad as misleading and manipulative. Manipulative ads trigger psychological reactance (Clee and Wicklund 1980), inducing people to "do just the opposite," reducing conversions. As a native ad's serial position lowers, web viewers tend to be more irritated or annoyed after being tricked by it, leading to a further increase in reactance and decrease in CVR. This tendency can be weakened as viewer age increases because psychological reactance to such external stimuli tends to decrease with age (Hong et al. 1994). Prior research has also documented that younger adults report greater exposure to daily stressors (hassles) than older ones (Stawski et al. 2008) and are thus likely to have lower tolerance for and higher annoyance with unwanted distractions, especially under time constraint. Because perceived time constraint increases as viewers scroll down the web page, the postclick annoyance effect can be augmented for younger viewers. Consequently, age is likely to have asymmetric moderating effects for CTR versus CVR:

> **H_3**: (**a**) CTR drops faster across ranks for older than for younger audiences, whereas (**b**) CVR drops faster across ranks for younger than for older audiences.

Data and Variables

We obtained data from a leading global web portal headquartered in the United States. The list of all articles, including both organic and sponsored articles (native ads), is called a "web stream." Sponsored articles are "native" because they are inserted into the web stream and blend in with the surrounding organic articles (for examples, see Figure 2). To better engage users, publishers typically do not display sponsored articles in the first position of the stream. The topmost (rank 1) ad is at the third position of the web stream (i.e., the first and second positions are filled with organic articles); then, there are four positions for organic articles in between every two neighboring ads onward (i.e., the rank 2 ad is inserted at the 8th position of the web stream, rank 3 ad is at the 13th position, and so forth). Our data set includes 120 distinct native ads randomly selected from the portal's database in March 2016, covering approximately 180 million page views. To avoid selection bias caused by targeting, we focus only on nontargeted ads.

We examine two key metrics, CTR and CVR, following the literature (e.g., Ghose and Yang 2009; Xu, Duan, and Whinston 2014). For a publisher, the number of ad impressions it can sell is not infinite, and too many ad slots may jeopardize perceived website quality and, thus, viewer experience. Because publishers attempt to maximize revenue from the limited number of ad slots available and an impression would *not* contribute any revenue until viewers click on it, CTR = clicks/impressions is a vital metric. For an advertiser, who typically aims to enhance conversions to maximize business success, CVR = conversions/clicks is a key metric. To provide further managerial insights, especially potential financial implications, we also discuss three additional outcome metrics in a subsequent section—namely, conversion per impression (CPI), publisher's revenue per impression (RPI), and advertiser's conversion per ad dollar spent (CPD).

The focal contingency factors are viewer age and gender (1 for female and 0 otherwise). In addition to the focal moderators, we include digital access device (desktop, tablet, or mobile), location (country), operating system (OS; Windows, Apple OS, or Android), web page types,[6] and categories of the products advertised as control variables.

[6] The focal portal hosts various types of web pages. We include indicators for leisure (e.g., entertainment) and nonleisure (e.g., finance) web pages, with mixed pages as baseline. This is because, conceptually, leisure and nonleisure web page contents lead to unequal levels of cognitive load (Sweller, Ayres, and Kalyuga 2011), which can influence the perceived annoyance of the ads inserted in the web page (Edwards, Li, and Lee 2002) and, thus, ad effectiveness. As a robustness check, we further classify the leisure/nonleisure web pages into more specific subcategories and use their identifiers as controls instead (Web Appendix W4), and the coefficients of the key variables remain consistent.

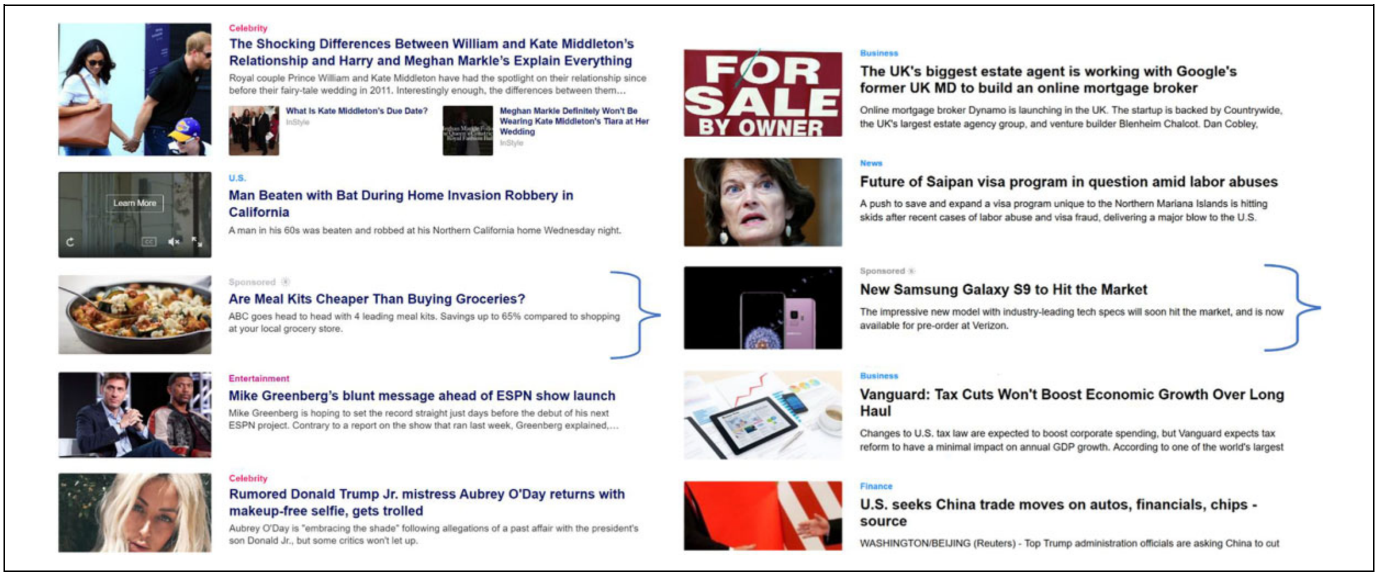

Figure 2. Examples of native ads in web stream.

Notes: In the screenshots, the listings marked with "}" are examples of native ads inserted in a web stream. The ad on the left was for Home Chef, a meal kit and food delivery company, and the ad on the right was for Verizon, promoting a new smartphone.

Uniqueness of the Data

Our data set has several unique features compared with those used by prior empirical research on ad serial position. First, previous studies mostly employ data that is aggregated or averaged by ad and/or by time (Abhishek, Hosanagar, and Fader 2015), such as the average daily ad ranks and performances (e.g., on each day t, this ad's average rank position, total impressions, total clicks, and total conversions). Such data cannot identify the CTR or CVR of each ad at a particular rank. Because of this data restriction, prior studies have treated average daily rank position as a continuous independent variable and further assume a linear relationship between average daily ad rank and average daily CTR or CVR (e.g., Rutz, Bucklin, and Sonnier 2012). Such data also introduces measurement error and aggregation bias (Abhishek, Hosanagar, and Fader 2015). In contrast, our data are disaggregated, and we observe the exact CTR and CVR for each ad each time it was displayed at a specific rank position. Thus, we can directly compare each ad's performance at each rank position and find nonlinear rate of change in ad effectiveness across ranks.

Second, native ads are not triggered by a search query, and thus, their appearances are not determined by their relevance to the viewer. Neighboring native ads are often irrelevant to one another and rarely belong to the same product category. This is in sharp contrast with the context of sponsored search ads, in which neighboring ads are typically direct competitors. Moreover, unlike search ads, a native ad in rank m is not inherently more relevant than that in rank n ($m < n$). For these reasons, in our data, the native ads displayed to each viewer on each web page are random in nature.

Third, while viewer characteristics (e.g., demographics) were typically unobservable in prior studies (e.g., Rutz, Bucklin, and Sonnier 2012), we explicitly account for viewer characteristics in the model and examine how they moderate the effectiveness of native ad at each rank position.

Model Specification

Each of the 120 sample ads has its own advertiser and creative content. It is thus unwise to simply aggregate the ranking effect across different ads. Therefore, we conduct separate studies for each ad and then use meta-analysis to conduct an "analysis of analyses" across the separate studies. Specifically, we first conduct a separate study to examine the relative performance of a particular ad in rank r ($r \geq 2$) versus the same ad's own performance in rank 1 (the topmost rank position) under each unique "campaign scenario" (CS). A CS means a particular native ad viewed by a particular type of viewer under a particular circumstance. In other words, each CS is a unique combination of all possible variations in the native ad itself, viewer characteristics, web page type, and other contextual factors (e.g., viewing device and location). Within each CS, the same ad's rank positions are "manipulated"/altered while all other relevant factors are held constant. Thus, each CS can be considered an individual "natural experiment" with ad rank as the focal treatment. Meta-analysis then integrates the results from all individual natural experiments to obtain an overall estimate of the relative effectiveness of native ad at each rank position. As we specify subsequently, the dependent variable in meta-analysis is the ratio of ad effectiveness (e.g., CTR, CVR) on rank r relative to rank 1 under each CS. To test the moderating effects, we further fit a meta-regression model using the contingency factors as explanatory variables.

Meta-analysis has been extensively applied in such areas as medical research and biostatistics to combine results from various scenarios or studies (Altman 1991). The fixed-effect meta-analysis assumes that, for study s (s = 1, 2, . . . , N), one observes the effect size or outcome measure y_i, which often takes the form of log-odds-ratio or log-relative-risk in frequency analysis (Tarone 1981). Assuming $y_s \sim N(\theta_s, v_s)$ in each study s, where v_s is the squared standard error (SE), meta-analysis provides an overall estimation of the outcome measure across all N studies as

$$\theta = \sum_s \theta_s w_s \Big/ \sum_s w_s, \tag{1}$$

where $w_s = 1/v_s$. Thus, meta-analysis estimation is a weighted average of the outcomes from various individual studies, and the weight is proportional to the inverse of the variance. Such "inverse-variance weighting" naturally assigns higher weight to a study with lower variance (i.e., higher confidence in the outcome). However, the fixed-effect model assumes no inter-study variability and is thus prone to various sources of heterogeneity.

In comparison, the random-effect meta-analysis model (Equation 2) has less restrictive assumptions and is more suitable to our context considering the heterogeneity across different ads/scenarios. It assumes that the included studies represent a random sample from a population of studies addressing the focal research question. Here, the true effect/outcome of each study is sampled from a normal distribution (i.e. $\theta_s \sim N(\mu, \sigma_\theta^2)$; Hedges and Olkin 2014).

$$y_s = \mu + u_s + e_s, \ \text{where}\ u_s \sim N(0, \sigma_\theta^2), e_s \sim N(0, v_s). \tag{2}$$

This approach also uses inverse-variance weighting, that is, each study is weighted by $w_s = 1/(v_s + \sigma_\theta^2)$, where v_s is again the squared SE of y_s and σ_θ^2 is replaced by its estimator in practice.

Thus, we apply the random-effect model in Equation 2 to test H_1. Specifically, by estimating μ_r^{CTR} of the following model, we can estimate a meta-analysis weighted average of the relative CTR at each rank r (r $\geq$ 2) compared with rank 1:

$$\log(RR_{i,\,CTR}^{r,S}) = \log\left(\frac{\frac{B_i^{r,S}}{A_i^{r,S}}}{\frac{B_i^{1,S}}{A_i^{1,S}}}\right) = \mu_r^{CTR} + u_{i,\,CTR}^{r,S} + e_{i,CTR}^{r,S}$$
$$\text{where}\ u_{i,\,CTR}^{r,S} \sim N(0, \sigma_{\theta,\,CTR}^{r}{}^2),\ \ e_{i,\,CTR}^{r,S} \sim N(0, v_{i,\,CTR}^{r,S}). \tag{3}$$

$RR_{i,\,CTR}^{r,S}$ is the observed CTR of rank r relative to rank 1 (i.e., the "risk ratio" in meta-analysis research; Tarone 1981) for each native ad i (i = 1, 2, . . . , 120) in each possible scenario S = {g, a, d, p, os, l} defined by a unique combination of viewer gender (g), age (a), device (d), web page type (p), OS (os), and location/country (l); A and B represent impressions and clicks, respectively; the squared SE of $\log(RR_{i,\,CTR}^{r,S})$ is estimated as $v_{i,\,CTR}^{r,S} = \frac{(A_i^{r,S} - B_i^{r,S})}{A_i^{r,S} B_i^{r,S}} + \frac{(A_i^{1,S} - B_i^{1,S})}{A_i^{1,S} B_i^{1,S}}$ following Bewick, Cheek, and Ball (2004). Each experiment (CS) is then weighted by $w_{i,CTR}^{r,S} = 1/(v_{i,CTR}^{r,S} + \sigma_{\theta,\,CTR}^{r}{}^2)$.

When there is a need to test moderating effects, researchers employ the mixed-effect meta-regression model (e.g., Rosario et al. 2016; You, Vadakkepatt, and Joshi 2015). It is a generalized form of the random-effect meta-analysis model that allows inclusion of regressors/moderators. Suppose that each study has a vector of contingency factors $\mathbf{X}_s$; the mixed-effect meta-regression model is specified as

$$y_s = \beta_0 + \mathbf{X}_s^T \boldsymbol{\beta} + u_s + e_s, \ \text{where}\ u_s \sim N(0, \sigma_\theta^2), e_s \sim N(0, v_s). \tag{4}$$

The coefficient vector $\boldsymbol{\beta}$ denotes the impact of the moderators on the studies, and each study is again weighted by $w_s = 1/(v_s + \sigma_\theta^2)$. Notably, while $\mathbf{X}_s^T \boldsymbol{\beta}$ captures observed heterogeneity, u_s captures the unobserved heterogeneity across studies.

Accordingly, we specify the following model to test the effects of the moderators (H_2–H_3):

$$\log(RR_{i,\,CTR}^{r,\,S}) = \log\left(\frac{\frac{B_i^{r,S}}{A_i^{r,S}}}{\frac{B_i^{1,S}}{A_i^{1,S}}}\right) = \beta_{0,r}^{CTR} + X_i^S \boldsymbol{\beta}_r^{CTR} + u_{i,\,CTR}^{r,S} + e_{i,CTR}^{r,S}$$
$$\text{where}\ u_{i,\,CTR}^{r,S} \sim N(0, \sigma_{\theta,\,CTR}^{r}{}^2),\ \ e_{i,\,CTR}^{r,S} \sim N(0, v_{i,\,CTR}^{r,\,S}), \tag{5}$$

where $\mathbf{X}$ is a vector of the focal moderators and control variables as specified in the "Data and Variables" section, and $\boldsymbol{\beta}_r^{CTR}$ represents the impact of the moderators on the log relative CTR of rank r. Similarly, we can specify the models for CVR and additional outcome metrics (details in Web Appendix W2). Web Appendix W3 discusses more about the appropriateness of using meta-analysis models in this study.

Results

Changes in CTR and CVR as Serial Position Lowers

Table 2, Panel A, presents the estimation results from the random-effect meta-analysis model (Equation 2) to describe the overall relative effectiveness of each rank across all CSs. For ease of interpretation, we convert each estimate of μ into a percentage (by taking its exponential) with rank 1 as baseline (100%) and report the results in Table 2, Panel B. Notably, as the rank position of a native ad becomes lower, CVR decreases at a much higher speed than CTR. For example, CVR in rank 2 is only 15.9% of that in rank 1, on average, whereas CTR in rank 2 is 97.0% of that in rank 1. This pattern is consistent with our expectation in H_1 and can be attributed to the unique nature of native ads. Prior research on the serial position of other types of online ads

Table 2. Results on Native Ad CTR and CVR Across Serial Positions.

A: Results of Random-Effect Meta-Analysis Without Moderators (H_{1a} and H_{1b})

	DV: Relative CTR at Rank r				DV: Relative CVR at Rank r			
	$\log(CTR^{rank=2}/CTR^{rank=1})$		$\log(CTR^{rank=3}/CTR^{rank=1})$		$\log(CVR^{rank=2}/CVR^{rank=1})$		$\log(CVR^{rank=3}/CVR^{rank=1})$	
	μ	SE	μ	SE	μ	SE	μ	SE
	−.030**	.003	−.057**	.003	−1.837**	.009	−3.111**	.013

B: Results of Meta-Analysis Converted into Percentages (Rank 1 as Baseline; Rightmost Two Columns Present Estimates from Alternative Methods for Comparison)

Relative CTR	Estimates Based on Random-Effect Meta-Analysis		Estimates Based on Naive Aggregation	Estimates Based on WLS
Rank 1	100.0%		100.0%	100.0%
Rank 2	97.0%		90.5%	95.9%
Rank 3	94.5%		86.0%	91.1%

Relative CVR	Estimates Based on Random-Effect Meta-Analysis		Estimates Based on Naive Aggregation	Estimates Based on WLS
Rank 1	100.0%		100.0%	100.0%
Rank 2	15.9%		21.1%	22.7%
Rank 3	4.5%		10.8%	13.0%

C: Results of Mixed-Effect Meta-Regression with Moderators (H_2 and H_3)

	DV: Relative CTR at Rank r				DV: Relative CVR at Rank r			
	$\log(CTR^{rank=2}/CTR^{rank=1})$		$\log(CTR^{rank=3}/CTR^{rank=1})$		$\log(CVR^{rank=2}/CTR^{rank=1})$		$\log(CVR^{rank=3}/CTR^{rank=1})$	
Variable	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Constant	−.085**	.008	−.148**	.011	−2.231**	.022	−5.566**	.063
Age	−.0010**	.0002	−.0016**	.0002	.017**	.001	.065**	.004
Gender (male as baseline)								
Female	.011*	.005	.013	.007	−.123**	.015	−.157**	.038
Device (desktop as baseline)								
Tablet	−.098	.069	−.282	.177	.829	1.095	Tablet	−.098
Phone	−.051	.032	−.105	.065	.451**	.137	Phone	−.051
Web page content (mixed as baseline)								
Leisure	.011	.009	−.018	.017	.733**	.046	1.943**	.540
Nonleisure	.025	.024	.021	.026	−.868*	.417	−1.218*	.560
OS (Windows as baseline)								
Apple	.058**	.006	.121**	.008	−.444**	.024	.011	.067
Android	.017	.039	.029	.056	−.408	.228	−1.480*	.716
Locations	Included in the model as control variables							
Product categories	Included in the model as control variables							

*Significant at .05.
**Significant at .01.
Notes: Two-tailed tests of significance. Location indicators include Australia, Canada, and the United Kingdom, with the United States as baseline. Product category indicators include retail, health and beauty, travel, financial services, and automobile and digital products, with others as baseline.

has not documented similar effects. Also in Table 2, Panel B, we present the estimates based on naive aggregation and weighted least square (WLS) regression (with logged CTR or CVR as dependent variable, rank indicators as independent variables, and the inverse of squared SE of CTR or CVR as weights) to compare with meta-analysis estimates. Their differences further confirm the importance of using random-effect meta-analysis that accounts for the heterogeneity and differential estimation uncertainties across various scenarios (for further discussion, see Web Appendix W3). That said, the results from all three methods indicate vastly asymmetric effect of native ad serial position on CTR versus CVR (i.e., CVR drops much more rapidly than CTR as serial position lowers).

Contingency Effects

The results of the mixed-effect meta-regression with moderators (Equation 4) are reported in Table 2, Panel C.

With $\log(CTR^{rank\,=\,r}/CTR^{rank\,=\,1})$ as the dependent variable, the positive coefficient of viewer gender (female indicator) is significant for r = 2 but nonsignificant for r = 3. The results provide partial support for H_{2a} and indicate that the speed of reduction in CTR from rank 1 to rank 2 is mitigated among women. With $\log(CVR^{rank\,=\,r}/CVR^{rank\,=\,1})$ as the dependent variable, the negative coefficient of female indicator is significant for both r = 2 and r = 3. The results support H_{2b}, indicating that women's CVR decreases at an even faster rate than men's as rank position lowers.

We find strong support for H_{3a} and H_{3b} because age has negative and significant coefficients in CTR models and positive and significant coefficients in CVR models. Thus, as native ad rank lowers, the speed of reduction in CTR is amplified while that in CVR is mitigated for older audiences.

Drawing on the model coefficients, we plot Figure 3 with both the relative (plotted in bars, with rank 1 as baseline 100%) and absolute values (plotted in lines) of estimated CTR and CVR at each rank under each condition. We would like to point to a discrepancy between the conclusion based on relative values and that based on absolute values in one particular case related to H_{2b}: while the relative values indicate that the CVR change from rank 1 to rank 2 is larger for women (100% − 14.76% = 85.24%) than for men (100% − 16.70% = 83.30%) and support H_{2b}, the absolute values indicate otherwise (.0800 − .0118 = .0682 for women and .0822 − .0137 = .0685 for men). This discrepancy is due to the inherently higher level of overall CVR (and, thus, higher baseline value) for men than for women.[7] Depending on managerial needs, practitioners may decide whether to focus more on relative or absolute changes in this case.[8] Nevertheless, both relative and absolute values plotted in Figure 3 and the meta-regression coefficients lead to consistent conclusions regarding each corresponding hypothesis except for H_{2b}.

Analyses on Additional Outcome Metrics

Table 3 reports the results from supplemental analyses of additional outcome metrics. First, we consider the likelihood of conversion per ad impression (CPI = conversions/impressions = CVR × CTR). Because of the drastic change in CVR but only modest change in CTR across rank positions, the result pattern of CPI largely mirrors that of CVR. Specifically, there is a fast drop in CPI across ranks (as reported in Table 3, Panels A and B), and the moderating effects of gender and age on CPI are similar to those on CVR (as reported in Table 3, Panel C). Second, we analyze two metrics that could potentially generate more direct profitability implications: (1) publisher's revenue generated from each ad impression (RPI = CTR × CPC, where CPC represents cost per click) and (2) number of conversions per ad dollar spent (CPD = CVR/CPC), which is directly proportional to the advertiser's return on investment (ROI). Because the variations across rank positions in CPC are much smaller than those in CTR or CVR, the result patterns of RPI are dominatingly determined by CTR, and CPD results are largely consistent with CVR results. As we report in Table 3, Panel B, there is a faster drop across ranks in CPD than in RPI. We discuss the potential financial implications of these results in the "General Discussion" section.

Robustness Checks

Web Appendix W4 presents several robustness checks. First, we explicitly account for potential sources of endogeneity (e.g., bid, other ads on the same web page) and employ alternative modeling approaches such as the copula method, WLS model, and mixed-effect linear model with random-coefficient specification. Second, we explain why our model and empirical setting allow us to avoid other potential biases pointed by prior research. Third, we rerun the analyses with a subsample of gender-balanced native ads. Fourth, we control for carryover effects by including each ad's prior daily number of impressions and prior average rank position. Fifth, we include the gender × age interaction term as an additional moderator in the model. The results remain consistent with the main analysis.

Discussion

Recently, online advertising platforms are making an active shift toward native ads. For example, an increasing amount

[7] We focus on the serial position effect and the moderating role of gender; the baseline difference across genders (i.e., the main effect of gender) is beyond the scope of this study. By examining relative values, we can tease out the baseline difference across consumer groups and pinpoint the effect of serial position within each consumer group.

[8] For example, if they are targeting on a particular group of consumers (e.g., women only) and need to understand the relative importance of getting the ad placed at the top (e.g., given that an advertiser's focal audience is women, how much is rank 2 worth compared with rank 1?), they can refer to relative values.

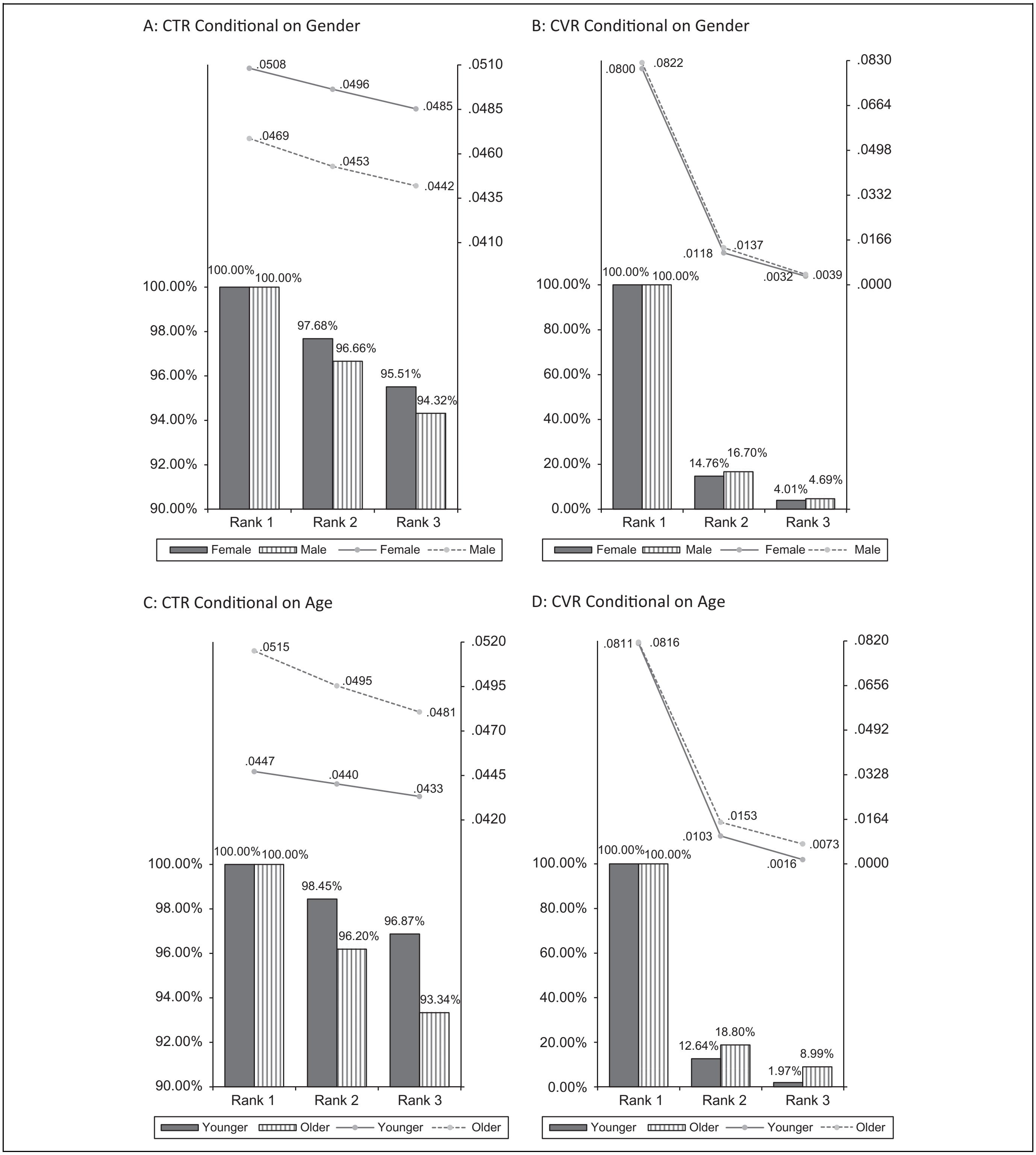

Figure 3. Changes in native ad performance across ranks contingent on each moderator.

Notes: The bars are plotted based on proportional values (with rank 1 as baseline 100%) and correspond to the left axis. The lines are plotted based on absolute values and correspond to the right axis. Age is treated as a continuous variable in the model. In Panels C and D, for demonstration purposes, the younger and older groups are divided at the mean.

of revenue for Facebook comes from sponsored posts and streaming ads inserted in pages (Choi 2016). Our study is among the first to study native ads, unveiling how the key success measures for publishers and advertisers change across rank positions and identifying important contingency factors, based on unique data on 120 native ads.

Table 3. Results on Additional Metrics.

A: Results of Random-Effect Meta-Analysis Without Moderators

DV: Relative RPI at Rank r				DV: Relative CPD at Rank r				DV: Relative CPI at Rank r			
$\log(RPI^{rank=2}/RPI^{rank=1})$		$\log(RPI^{rank=3}/RPI^{rank=1})$		$\log(CPD^{rank=2}/CPD^{rank=1})$		$\log(CPD^{rank=3}/CPD^{rank=1})$		$\log(CPI^{rank=2}/CPI^{rank=1})$		$\log(CPI^{rank=3}/CPI^{rank=1})$	
μ	SE	μ	SE	μ	SE	μ	SE	μ	SE	μ	SE
−.049**	.003	−.087**	.004	−1.818**	.010	−3.081**	.013	−1.900**	.009	−3.233**	.011

B: Meta-Analysis Estimates Converted into Percentages (with Rank 1 as Baseline)

	Relative RPI	Relative CPD	Relative CPI
Rank 1	100.0%	100.0%	100.0%
Rank 2	95.2%	16.2%	15.0%
Rank 3	91.7%	4.6%	3.9%

C: Results of Mixed-Effect Meta-Regression with Moderators

	DV: Relative RPI at Rank r				DV: Relative CPD at Rank r				DV: Relative CPI at Rank r			
	$\log(RPI^{rank=2}/RPI^{rank=1})$		$\log(RPI^{rank=3}/RPI^{rank=1})$		$\log(CPD^{rank=2}/CPD^{rank=1})$		$\log(CPD^{rank=3}/CPD^{rank=1})$		$\log(CPI^{rank=2}/CPI^{rank=1})$		$\log(CPI^{rank=3}/CPI^{rank=1})$	
Variable	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Constant	−.116**	.008	−.192**	.013	−2.203**	.021	−5.526**	.063	−2.430**	.020	−5.764**	.056
Age	−.000**	.000	−.001**	.000	.016**	.001	.064**	.004	.017**	.001	.063**	.003
Female	.011*	.005	.006	.008	−.092**	.014	−.134**	.034	−.069**	.013	−.094**	.034
Tablet	−.136**	.049	−.201	.134	.983	1.044	1.935	1.141	.575	1.085	1.709	1.188
Phone	−.029	.021	−.114**	.040	.443**	.131	1.566**	.365	.420**	.135	1.343**	.382
Leisure page	.027	.019	.018	.020	.712**	.044	1.988**	.489	.724**	.042	1.806**	.447
Nonleisure page	−.000	.024	−.037	.030	−.725	.397	−1.001*	.507	−.692	.413	−.947	.542
Apple OS	.077**	.006	.158**	.009	−.459**	.023	−.072	.061	−.423**	.023	.148*	.063
Android OS	.015	.039	.065	.065	−.380	.218	−1.810**	.648	−.334	.226	−1.053	.683

Notes: In Panel C, all other control variables are included in the model.

Theoretical Contributions

Although the literature on ad serial position has a long tradition, the change in ad performance across serial positions is nonobvious depending on (1) the type of ad and (2) the outcome metrics studied. It is necessary to study the effect of serial position for native ad because (1) it is highly unique (disguised and less interruptive compared to the types of ads previously studied), (2) different parties involved (e.g., publishers, advertisers) are concerned about different outcome metrics, and (3) it is an economically important and fast-growing multi-billion-dollar industry (eMarketer 2017). We develop a theoretical framework that predicts a distinct pattern of serial position effect for native ads (as opposed to disguised ads) and empirically test it with large-scale data from the field. The results demonstrate vastly asymmetric effects of native ad serial position on publishers' metrics (click-based) versus advertisers' metrics (conversion-based). Such result pattern has not been documented or implied by prior research.

It is also imperative to take one step further and understand under what conditions native ads' effectiveness changes more quickly (or slowly) across serial positions. Prior research on the serial position effect has offered limited insight regarding its contingency factors, especially about how it may vary across viewer groups (see Table W1.1 of Web Appendix W1). Most empirical studies on online ads have treated viewer features as unobservable and thus have rarely examined how they may moderate ad effectiveness (see Table W1.2 of Web Appendix W1). In comparison, we take a contingency perspective in theoretical development and empirical testing and demonstrate that (1) the relative speed of cross-rank change in native ad effectiveness is conditional on viewer gender and age and (2) these viewer demographics exhibit asymmetric moderating effects on publishers' metrics versus advertisers' metrics.

Our study is based on large-scale behavioral data from the field. As commented by Sudhir, Roy, and Cherian (2016), while lab experiments and surveys unveil novel psychological processes behind a phenomenon, empirical insights from field data are also valuable because they reveal the relative economic magnitude of the effect, and thus, practitioners can directly apply them to make marketing decisions. Moreover, unlike most empirical studies on online advertising, which analyze one particular online advertiser, we use meta-analysis to conduct "analysis of analyses" of a large number of ads across various product categories to better generalize the results.

Managerial Implications

Our findings on the asymmetric and contingent effects of native ad serial position on CTR versus CVR provide new and timely managerial insights for marketers. Moreover, we provide supplemental analyses of additional metrics (e.g., RPI, CPD) to proffer potential financial implications.

We show that, in the native ad context, advertiser's metrics reduce drastically from the topmost rank to lower ranks. Such radical reduction has not been documented by prior empirical research on online ads' serial positions, which has mostly been conducted in the context of search ads. For example, using search ad data from an online retailer, Ghose and Yang (2009) find that CVR of the lowest rank is still over half of that in rank 1; similarly, based on search ads for a retailer of consumer durables, Narayanan and Kalyanam (2015) report no significant decrease in CVR as rank position decreases (except from rank 5 to 6). In contrast, we find that, for native ads, the CVR in rank 2 and rank 3 is only 15.9% and 4.5%, respectively, of that in rank 1. Furthermore, research based on search ads suggests that prominent rank positions are not necessarily more profitable. For instance, Ghose and Yang (2009) and Agarwal, Hosanagar, and Smith (2011) find higher profits at the middle position than the top position. In contrast, in the context of native ads, advertisers' CPD (proportional to ad profit or ROI) in the topmost rank position is dominantly higher than any lower position (CPD at rank 1 is over 5 times as much as that at rank 2 and over 20 times of that at rank 3; see Table 3, Panel B). In other words, for each dollar spent at rank 2, the advertiser gets less than one-fifth of the conversions it would have gotten for the same dollar spent at rank 1. Therefore, native ad advertisers overpay for lower rank positions.

Currently, in the online advertising industry, ad platforms for both search ads and native ads (including our focal ad portal) share very similar bidding and ad ranking systems (e.g., Edelman, Ostrovsky, and Schwarz 2007), which do not allow advertisers to preselect the rank position for the ad (i.e., an advertiser cannot place a separate bid for each rank position).[9] Under such systems, an ad could incur similar costs per click at two neighboring rank positions. These systems might be fair to search ad advertisers but not to native ad advertisers, because a native ad's value to the advertiser (CVR) decreases disproportionally faster than its cost does as rank position lowers. For advertisers, the ideal bidding system should allow them to place a separate bid for each rank position, and the ideal bid at each rank should be proportional to the expected CVR.

Meanwhile, the publishers (e.g., YouTube, Yahoo!, Facebook) face a dilemma. On the one hand, they want to enhance revenue by selling more ad slots; on the other hand, too many ads destroy user experience. Thus, a publisher may be motivated to eliminate unprofitable ad slots (e.g., it can consider removing lower-position slots if its revenue per ad insertion drops significantly as the position lowers). Recall that an ad impression does not contribute any revenue to the publisher unless it is clicked on, and thus, a publisher's revenue depends on CTR. We find only modest reduction in CTR as native ad position lowers. Moreover, under the bidding system that is currently dominating the industry, publishers' RPI also

[9] Each advertiser submits only one bid for each keyword (in the context of search ads) or for each ad (in the context of native ads). Then, the ad portal's algorithm will rank the ad based on its bid and other factors as explained in Appendix W4. If the ad is clicked on, the focal advertiser pays the adjusted bid of the advertiser that is ranked right below it, capped by the focal advertiser's own bid.

remains relatively stable across rank positions (e.g., RPIs in rank 2 and rank 3 are 95.2% and 91.7% of that in rank 1, respectively). Thus, it may be unwise for publishers to eliminate lower-rank ad positions, which can serve as an important source of ad revenue.

Our results indicate that the cross-rank change in native ad effectiveness varies across viewer groups. The findings point to the importance for marketers to adjust their practices in accordance with the contingency factors such as viewer gender and age. For example, for advertisers to optimize conversion and ROI, it is more imperative to get their ads on the top rank position when the audience includes women and younger customers (compared to men and older customers). On the other hand, publishers may consider increasing the density of native ads in the upper portion of the web page for men and older viewers. These implications are readily applicable because of the increasing feasibility of precision targeting.

Finally, while native ads proliferate in the online ad industry, they may be subject to stricter regulations in the future. Advertisers may face legal consequences when using disguised ads on certain user groups (e.g., children), and are under increasing pressures to use more salient disclosures (Campbell and Grimm 2018). Wojdynski and Evans (2016) suggest that native ad disclosures could influence its level of disguise or the rate of ad recognition (e.g., when using alterative disclosures such as "sponsored content," "advertisement," "brand-voice," and "presented by [sponsor]," the percentage of participants who can recognize a native ad ranges from 2% to 13%). We could expect that, when practitioners have to adopt more salient disclosures and make native ads less disguised/more easily recognizable, the result pattern that we propose in Table 1, Panel B, would become weaker, and the serial position effect of native ads could become more similar to that of conventional disruptive ads (Table 1, Panel A).

Directions for Future Research

In this study, we theorize and empirically demonstrate native ads' serial position effects using large-scale field data. Future researchers could use lab experiments to further explore the uniqueness in consumer psychology/behavior in the context of native ads, which has rarely been studied by prior research. In addition to serial positions, future research could examine other drivers of native ad performance, such as consumer mood states and adjacent articles,[10] or compare the performances of native ads inserted in user-generated content (e.g., social media posts) versus professionally generated content. Native ads inserted in web streams with clear rank orders are prevalent in leading native ad platforms such as Facebook and Yahoo!. However, just like search ads, there can be variation across publishers in terms of how native ads are displayed. For example, some websites may display ads in a cluster of small thumbnails without clear rank orders (in fact, such clustered ads are not strictly "native" or disguised because they are not seamlessly inserted into organic listings and thus are easier for web viewers to identify). Similar to the literature on search ad ranks, we focus only on in-stream native ads with rank orders and leave the other possible formats of native ad displays for future research. Finally, native advertising can be considered one form of disguised marketing. Practitioners might employ alternative ways to disguise the source of promotion, such as sponsored influencer marketing (Joshi 2009). The theory that we propose in this study (e.g., regarding the annoyance effect) might apply to some other forms of disguised marketing, which future research could further explore and empirically test.

[10] The placements of adjacent articles are nonstrategic in our context and can be considered randomized in each CS.

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