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Trade-Offs in Online Advertising: Advertising Effectiveness and Annoyance Dynamics Across the Purchase Funnel

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Abstract. Digital advertisers often harness technology-enabled advertising-scheduling strategies, such as ad repetition at the individual consumer level, in order to improve advertising effectiveness. However, such strategies might elicit annoyance in consumers as indicated by anecdotal evidence, such as the popularity of ad-blocking technologies. Our study captures this trade-off between effective and annoying display advertising. We propose a hidden Markov model that allows us to investigate both the enduring impact of display advertising on consumers' purchase decisions and the potential of persistent display advertising to stimulate annoyance in consumers. Additionally, we study the structural dynamics of these advertising effects by allowing them to be contingent on the latent state of the funnel path in which each consumer resides. Our findings demonstrate that a tension exists between generating interest and triggering annoyance in consumers; whereas display advertising has an enduring impact on transitioning consumers further down the purchase funnel, persistent display advertising exposures beyond a frequency threshold can have an adverse effect by increasing the chances that consumers will be annoyed. Investigating the dynamics of these annoyance effects, we reveal that consumers who reside in different stages of the purchase funnel exhibit considerably different tolerance for annoyance stimulation. Our findings also reveal that the format of display advertisements and the level of diversification of ad creatives as well as consumer demographics moderate consumers' thresholds for annoyance elicitation. For instance, advertisers can reduce annoyance elicitation as a result of frequent display advertising exposures when they use static rather than animated display ads as well as when they diversify the display ad creatives shown to consumers. Our paper contributes to the literature on digital advertising and consumer annoyance and has significant managerial implications for the online advertising ecosystem.

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Keywords: consumer annoyance • dynamic models • hidden Markov models • digital advertising • ad repetition • purchase funnel

1. Introduction

Online display advertising started as a limited experiment in the 1990s and, since then, it has grown into an industry worth $112.64 billion (eMarketer 2018). To put the size of the display advertising market into perspective, in 2016, digital display ad spending eclipsed search ad spending in the United States for the first time in the history of advertising and accounted for the largest share of digital ad spending. One driving force behind this remarkable growth of display advertising and its establishment as the dominant online advertising channel is the digital transformation of the display ad industry. Admittedly, technology has revolutionized the way that firms deliver advertising messages and connect with customers online (Todri and Adamopoulos 2014, Adamopoulos et al. 2018b). For instance, thanks to various technological innovations, advertisers are able to track consumers' digital footprints (Ghose and Todri 2016) and purchase advertising inventory on a per-impression basis. As a result, firms can effectively harness technology-enabled ad-scheduling strategies and exert great control over the frequency of display advertising exposures at the consumer level.

Advertisers' refined ability to control the frequency of display advertising exposures has important implications for the online advertising ecosystem. On the one hand, the ability to control the media scheduling and engage in increased ad repetition at the individual consumer level has the potential to *improve the effectiveness of display advertising* because it can more effectively influence consumers' learning (Cacioppo and Petty 1979, Naik et al. 1998) and positively affect key communication dimensions, such as recall, attitude, and purchase intention (Sawyer 1981, Campbell and Keller 2003). Also, as websites become cluttered with content, advertisers increase the frequency of individual-level display advertising exposures to draw consumers' attention (Hong et al. 2004). On the other hand, however, digital advertisers' technology-enabled ability to engage in increased ad repetition at the consumer level can lead to excessive display advertising exposures, which might *trigger annoyance in consumers and possibly undermine advertisers' goals* (Aaker and Bruzzone 1985). Specifically, persistent display advertising exposures might elicit annoyance in consumers, because advertising intervenes with the users' main goal, such as navigating the internet or completing a task online (Goldstein et al. 2014, Jenkins et al. 2016).

As a result of the perceived goal impediment, consumers cope with the negative effects of annoyance by actively minimizing the duration of their actual exposure to the advertisements (Woltman Elpers et al. 2003, Goldstein et al. 2014, Wilbur 2016) to eliminate this source of nuisance. For instance, annoyed consumers could scroll to another part of the web page to avoid being directly exposed to display ads that elicit annoyance or, alternatively, could click away from web pages that contain the annoying ads. Fundamentally, these actions of annoyed consumers reduce the time that they are exposed to the display advertisements (that is, in-view time exposure of a display ad). In this paper, we utilize such key consumer behaviors to better understand consumers' annoyance elicitation, allowing the consumer behavior theory to inform and guide the structure of the empirical model.

The substantial issue of consumer annoyance has started gaining traction in the digital advertising ecosystem because of the growing body of anecdotal evidence that digital advertising can be a source of annoyance for consumers. In particular, the remarkable popularity of ad-blocking software[1] (for example, over 500 million downloads worldwide of Adblock Plus as of January 2016 (Williams 2016)) indicates that consumers increasingly seek to avoid exposure to online advertisements. In fact, consumers often cite annoying advertisements as the main reason that they adopt such software (eMarketer 2016). This mainstream adoption of ad-blocking software has detrimental effects both for advertisers, because ad blockers eliminate a channel of communication with the consumers, as well as for publishers, because ad blockers disrupt their main business revenue model (Scott 2016). Hence, it is important for advertisers and publishers to understand consumers' annoyance elicitation in digital advertising and accordingly adapt their marketing and publishing strategies.

Toward this direction, we examine the trade-off between effective and annoying display advertising. We propose a hidden Markov model (HMM) that allows us to simultaneously investigate both the enduring impact of display advertising on consumers' purchase decisions and the potential of display advertising to stimulate annoyance in consumers. Our paper makes a significant contribution to the literature on advertising effectiveness and consumer annoyance in technology-mediated environments. First, this paper conducts an empirical analysis to understand *whether and when technology-enabled frequent display advertising exposures can elicit consumers' annoyance*. Hence, the paper contributes to the nascent but important literature on consumers' annoyance elicitation. To the best of our knowledge, this is the first paper to examine whether display advertising scheduling (for example, the frequency of firm-initiated advertising exposures) can trigger consumers' annoyance. Second, this paper further contributes to the literature on consumer annoyance, because it also examines *the structural dynamics of the effective and annoying display advertising effects* by allowing the corresponding effects to be contingent on the latent state of the purchase funnel in which consumers reside. Hence, this paper not only allows consumers to have heterogeneous responses to advertising with regards to purchase propensity but also captures heterogeneous responses in consumers' annoyance elicitation. This is an important contribution because drawing on existing theories, it is not clear, for instance, whether a consumer who has moved further down the purchase funnel will be more or less easily annoyed with frequent display advertising exposures. On the one hand, one can postulate that consumers who reside in the later stages of the purchase funnel might be less easily annoyed because they might have developed more favorable attitudes. However, on the other hand, consumers who reside in the early stages of the purchase funnel are less informed and thus they might be less easily annoyed because display advertising exposures can convey valuable information to them. Therefore, this question requires empirical investigation and our paper is the first to study these structural dynamics of consumer annoyance. Third, the paper also contributes to the literature by examining whether the format of display ads and the level of diversification of ad creatives as well as consumer demographics *moderate the impact of frequent display advertising* exposures on annoyance elicitation.

Our findings demonstrate that a tension exists between generating interest and triggering annoyance in consumers via display advertising. Although display advertising has an enduring impact on transitioning consumers further down the purchase funnel and increasing the likelihood of a purchase, display advertising exposures beyond a frequency threshold substantially increase the probability that consumers will be annoyed. Investigating the dynamics of these annoyance effects, we reveal that consumers who reside in different stages of the funnel path exhibit considerably different thresholds for annoyance stimulation. In particular, we find that consumers who reside in the early stage of the purchase funnel can be annoyed by as few as three display advertising exposures during the same time period, whereas consumers who reside in a later stage of the purchase funnel would need at least seven display advertising exposures during the same time period to reach a substantial probability of annoyance effects. Moreover, diving into the moderating effect of the type of display advertisements, we find that when consumers are exposed to a higher percentage of animated display ads, they exhibit lower thresholds for annoyance elicitation across the funnel path. Additionally, examining the moderating effect of the level of display ad creative diversification, we find that when consumers are exposed to a diversified set of display ad creatives, they exhibit higher thresholds for annoyance elicitation. Besides, our findings reveal that consumer demographics also moderate the impact of the frequency of display advertisements on annoyance elicitation. Specifically, we find that consumers with higher income and education levels as well as younger and female consumers are more easily annoyed by frequent display advertising exposures. Our paper contributes to the literature on digital advertising and consumer annoyance and has significant managerial implications for advertisers and the online advertising ecosystem.

2. Literature Review

In this section, we discuss the related literature and how this study builds on and extends various streams of research. First, this work is related to the stream of literature examining the effectiveness of advertising and the impact of ad repetition on enhancing the effectiveness of advertising. The literature on advertising effectiveness postulates that the main reason that advertising is effective is that it conveys relevant information to consumers in a direct or indirect way (Nelson 1970, 1974). Specifically, consumers are often not informed about the existence of products or their respective attributes because of the imperfect and asymmetrical information structure of the markets (Stiglitz 1989). Therefore, firms seek to eliminate this type of ignorance by investing in advertising aimed at influencing consumers' learning (Stigler 1961, Bagwell 2007, Animesh et al. 2010, Feng and Xie 2012). Studying factors that can enhance ad effectiveness, prior literature has demonstrated that ad repetition can improve consumers' learning (Cacioppo and Petty 1979, Heflin and Haygood 1985, Naik et al. 1998) and affect various communication dimensions, such as recall, positive attitude, and purchase intention (Sawyer 1981, Campbell and Keller 2003, Anand and Shachar 2009, Ghose and Yang 2009). This renders the increased frequency of advertising exposures an effective digital media scheduling strategy for firms. Also, it has also been shown that frequent ad exposures can further enhance the effectiveness of digital marketing campaigns because of the increased information overload that consumers experience (Hong et al. 2004). In this study, we examine the *trade-off* between effective and annoying display advertising when consumers are exposed to frequent display advertising exposures.

More specifically, our paper contributes to the growing body of literature related to consumer annoyance and irritation in advertising. Focusing on traditional means of advertising, prior studies have shown that irritation can occur as a function of the creative execution of television commercials (Aaker and Bruzzone 1985). In particular, content that overdramatizes a situation and, in general, exaggerates can stimulate annoyance in consumers (Bauer and Greyser 1968, Aaker and Bruzzone 1985). Similarly, consumers can get annoyed when they are exposed to advertisements that are too noisy or strident (Pokrywczynski and Crowley 1993). Moving beyond the traditional means of advertising, annoyance has received scant attention in the context of online media. In this stream of literature, focusing again on the *presentation* of advertising content, a few studies confirm the above finding that advertisements that excessively stimulate consumers' senses can lead to more negative consumer attitudes (Yun Yoo and Kim 2005, Goldstein et al. 2014). An important question, however, which currently remains unanswered, is the extent to which *advertising scheduling* strategies, beyond the advertisement content itself, can stimulate annoyance in consumers. Hence, this paper fills this gap in the advertising and annoyance literature and addresses this question by evaluating whether technology-enabled digital media scheduling strategies can stimulate annoyance in consumers. Additionally, we also examine whether ad characteristics and the level of diversification of ad creatives as well as consumer demographics moderate the impact of frequent display advertising exposures on annoyance elicitation.

Another stream of literature that is related to our paper is that of structural dynamics of marketing activities. Marketing activities have been shown to work in a series of discrete stages, which are often regarded as latent, and capturing dynamics across these stages is important because consumers' behavior may vary as they progress in the decision process (Netzer et al. 2008, Abhishek et al. 2012). These discrete-stage models, also known as "purchase funnel" or "funnel path" models, typically capture the effect of advertising in raising consumers' awareness and then generating interest (Barry 1987, Tellis 2003, Abhishek et al. 2012). This stream of literature discusses the importance of capturing the non-immediate effects of display advertisements and dynamic interactions during the funnel path. For instance, Xu et al. (2014) find that display advertisement clicks not only have a direct effect on purchase conversion but that they also dynamically affect intermediate observed consumer behaviors. Similar to Xu et al. (2014), our model also captures the dynamics of consumers' online behaviors and allows display advertising exposures to have a non-immediate but enduring impact on consumer behavior by transitioning consumers further down the funnel path. Apart from studying annoyance elicitation, our work also extends the seminal work of Xu et al. (2014) because the proposed model does not require consumers to click on the display advertisements in order for the advertisements to have an enduring impact. Allowing for such dynamic effects is important since display advertisements can affect consumers' behavior even when consumers do not directly click on them (Dalessandro et al. 2015). Also, our study not only captures the structural dynamics of advertising effectiveness but also examines the dynamics of the annoyance effects. Therefore, beyond examining whether frequent display advertising can stimulate annoyance in consumers, in addition to the aforementioned contributions, our paper also contributes to the literature on annoyance in advertising by investigating whether these annoyance elicitation effects are contingent on the latent state of the purchase funnel in which consumers reside.

3. Empirical Setting

3.1. Data Set Description

The data set utilized for this study was collected in collaboration with a major U.S. online media analytics platform.[2] The media analytics company handles the entire online campaign of an online retailer who sells credence and experience goods, such as dietary supplements and wellness products. Our observation window is from May to October 2014. During that period, the company ran paid search as well as display advertising campaigns across various websites, whereas it did not engage in other online or offline advertising activities apart from those that we observe in the data set.

The data set contains advertising exposures and user actions, such as direct visits to the advertiser's website and organic search engine clicks. Specifically, the data set contains information that corresponds to display advertising impressions, search clicks (paid and organic), consumers' direct visits to the advertiser's website, and consumer purchases; it is possible to distinguish between brand- and nonbrand-related search queries based on the campaign that was triggered to serve the search advertisement because the corresponding campaigns have refined targeting criteria that prevent a nonbrand search advertising campaign from serving an advertisement to a brand-related search query. With regards to the display advertisements, the retailer used the standardized form of display ads, also known as "banner advertisements." These display advertisements are not specific to product offerings because they do not feature individual products, but, given that the advertiser offers credence and experience goods, the ads feature elements of the expected benefits of such goods; this practice is in accordance with the extant literature on advertising credence and experience goods (Nelson 1974).[3] Regarding the format of the display advertisements, the company utilized various display ad creatives that entailed both animated and static display ads. That is, the display advertisements consisted of either a static image (static display ad) or a multimedia object of animated images (animated display ad); the animated images are a series of static images abutting one another to create an illusion of motion. We should also note that none of the utilized display advertisements used any audio or video. Additionally, none of the utilized display ads "floated" over the web page. Lastly, if a customer makes a purchase, we also observe the corresponding "conversion" on the data set. Using a random sample of real-world consumers, we connect the touchpoints (that is, consumer-firm interactions) that correspond to the same anonymous unique consumer identifier in order to construct the consumer funnel paths.[4]

A unique characteristic of this data set is the access to granular information regarding the viewability of display advertising impressions: we know when an impression was visible on a consumer's screen area and, hence, whether it was deemed viewable.[5] Tracking information regarding the viewability of impressions reveals that a remarkably high percentage of the display advertising impressions is never rendered viewable; similar insights have also been reported from various ad media analytics platforms (Ghose and Todri 2016). In order to accurately estimate the impact of display advertising in generating interest and stimulating annoyance, we filter out all of the non-viewable impressions for the estimation of the model because consumers cannot possibly be affected by ads that they have never seen. Thus, we are able to alleviate biases that could have emerged owing to this measurement error in the frequency of display advertisements to which consumers are exposed. Finally, we also have information on the duration of the exposure to the display advertisements. Table 1 provides the descriptive statistics of the variables at the consumer-day level.

Table 1. Descriptive Statistics of Main Variables

Variable	Mean	Standard deviation	Number of customers
Viewable display ads	0.1185	1.2077	5,000
Brand search clicks	0.0012	0.0524	5,000
Nonbrand search clicks	0.0004	0.0212	5,000
Organic search clicks	0.0013	0.0517	5,000
Direct visits	0.0042	0.0516	5,000
Online purchase	0.0007	0.0267	5,000
In-view exposure of display ads	0.2821	1.6134	5,000

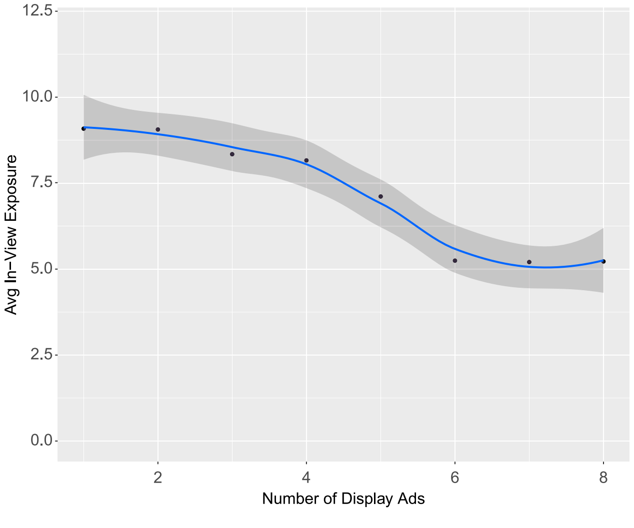
3.2. Model-Free Evidence

In this section, we provide evidence for consumers' annoyance elicitation owing to display advertising scheduling before resorting to a model that places more structure on the data.

Using model-free evidence, we would first like to understand whether technology-enabled frequent display advertising exposures can trigger consumers' annoyance. Hence, before resorting to a model (see Section 4.3), we first examine how consumers' average in-view exposure to display advertisements varies as a function of the number of display advertisements to which a consumer is exposed. As shown in Figure 1, we find that consumers who are exposed to an increasing number of display advertisements seek to minimize their exposure to the ads as indicated by the average in-view time. Considering that consumers seek to actively minimize the duration of their actual exposure to the display advertisements of the brand when they have been annoyed (Woltman Elpers et al. 2003, Goldstein et al. 2014, Wilbur 2016), Figure 1 provides model-free evidence that the frequency of the display advertisements can indeed elicit consumers' annoyance.

Also, our longitudinal data set allows us to capture within-subject changes in the consumers' decisions to entirely avoid the display advertising exposures of the brand as a result of being frequently exposed in the past to display advertising. Hence, before resorting to a model, we also examine whether the percentage of non-viewable display ads (see Section 3.1) increases or decreases as a function of the frequency of display advertisements to which consumers were exposed in the previous time periods. As Figure 2(a) shows, we find that the percentage of the non-viewable display ads exhibits a positive trend (that is, increases) as the number of display advertisements in the previous time periods increases for a consumer. Thus, Figure 2(a) provides additional model-free evidence that the frequency of the display advertisements can indeed elicit consumers' annoyance as suggested by the subsequent increase in the proportion of the non-viewable display ads.

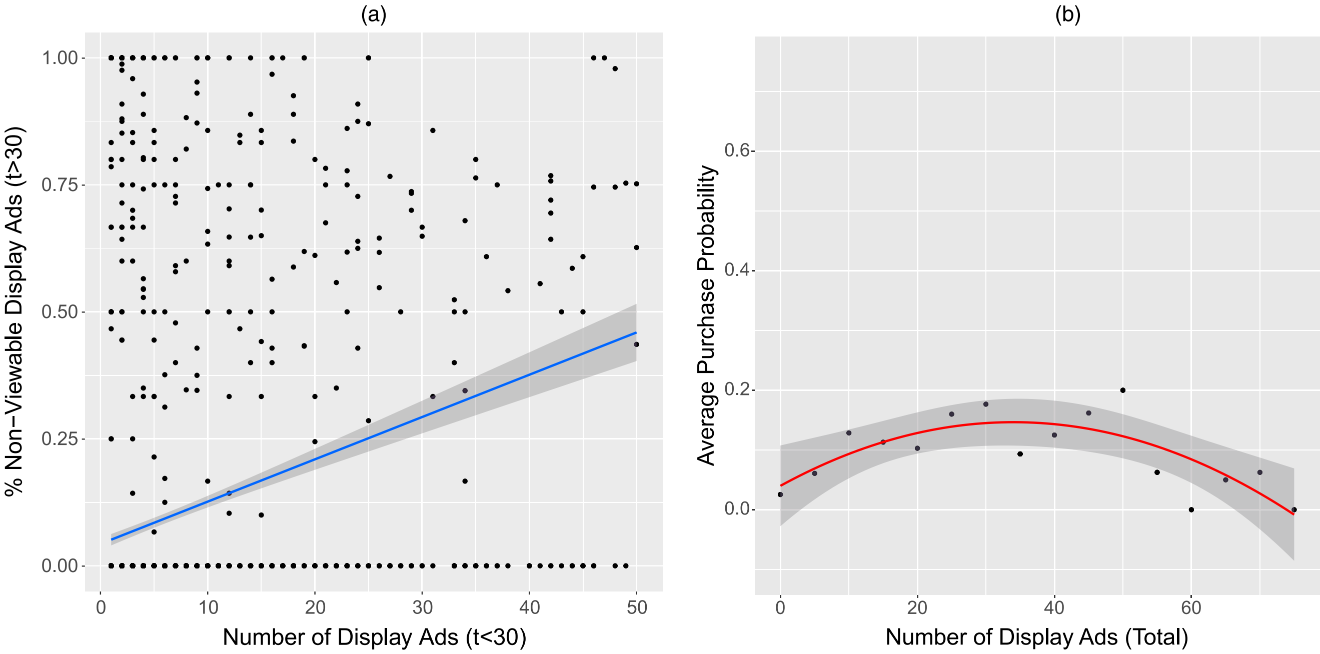
Figure 1. (Color online) Average In-View Exposure of Display Ads as a Function of the Number of Display Advertisements



Furthermore, as a result of consumers' annoyance elicitation, one would expect that excessive exposure to display advertisements could potentially decrease consumers' propensity to make a purchase and eventually undermine advertisers' goals. Hence, without resorting to a model again, we also examine how consumers' average purchase probability varies as a function of the total number of display advertisements to which a consumer is exposed. As shown in Figure 2(b), we find that the consumers' average purchase probability exhibits an inverted U pattern as a function of display advertisements. Hence, Figure 2(b) provides model-free evidence that exposing consumers to an increasing number of display advertisements does not always increase—and can even decrease—their propensity to make a purchase owing to annoyance elicitation. Although it has been shown that display advertising exposures might not always increase consumers' propensity to make a purchase, to the best of our knowledge, this is the first paper to investigate and empirically demonstrate that excessive exposure to display ads can trigger *annoyance* in consumers, unveiling the mechanism of such a negative effect (see Sections 4 and 5).

Overall, the model-free evidence suggests that consumers' annoyance might be triggered by frequent exposures to display advertisements as indicated by the corresponding changes in the in-view ad exposure

Figure 2. (Color online) (a) Percentage of Non-viewable Display Ads as a Function of the Number of Display Advertisements and (b) Average Purchase Probability as a Function of the Total Number of Display Advertisements



times, the percentage of non-viewable ads, and the propensity to make a purchase. In the following section, we resort to the HMM in order to more accurately capture consumers' annoyance elicitation, investigate whether annoyance can be triggered by frequent display advertising exposures, and examine the structural dynamics of the annoyance effects along the various stages of the purchase funnel.

4. Modeling Consumer Behavior Dynamics

4.1. Hidden Markov Model

In order to study the dynamics and the trade-off between effective and annoying digital display advertising, we propose an HMM. An HMM is a type of stochastic signal model in which the system being modeled is assumed to be a Markov process with unobserved hidden states (Rabiner 1989). In particular, an HMM is a doubly stochastic process with an underlying stochastic process that is not directly observable but can be observed through another set of stochastic processes that produce the sequence of observed signals (Rabiner and Juang 1986). Each latent state has a probability distribution over the possible output signals; therefore, the sequence of the signals provides information about the sequence of the states. HMMs have been already used to study temporal pattern recognition problems, such as speech recognition, and they remain the dominant machine learning technique for speech applications. More recently, HMMs have been also used to study various aspects of user behavior involving longitudinal individual-level data (Netzer et al. 2008; Singh et al. 2011, 2014; Abhishek et al. 2012; Sahoo et al. 2012; Kokkodis 2018, 2019). HMMs can also be considered a generalization of mixture models, which are already popular in the fields of marketing and information systems.

HMMs are a powerful modeling technique, the use of which provides significant advantages for our research question and empirical setting. First, an HMM allows us to *capture the latent nature of the states* of a purchase funnel and the consumers' transitions across these states by utilizing the signals that consumers emit in different stages of the purchase funnel. Second, the proposed technique allows us to draw on the *consumer behavior and advertising response theory in order to inform the structure* of the HMM while estimating the effect of time-varying variables, such as advertisements, on assisting consumers' transition further down the purchase funnel. In this way, for instance, the HMM also allows us to capture the non-immediate impact of display advertising on increasing consumers' propensity to make a purchase. Third, the proposed technique enables us to study the *structural dynamics of the effective and annoying advertising effects*—even within a purchase funnel—by allowing the magnitude of these effects to be contingent on the latent state in which consumers reside.

4.2. Hidden Markov Model for Consumers' Purchase Funnels

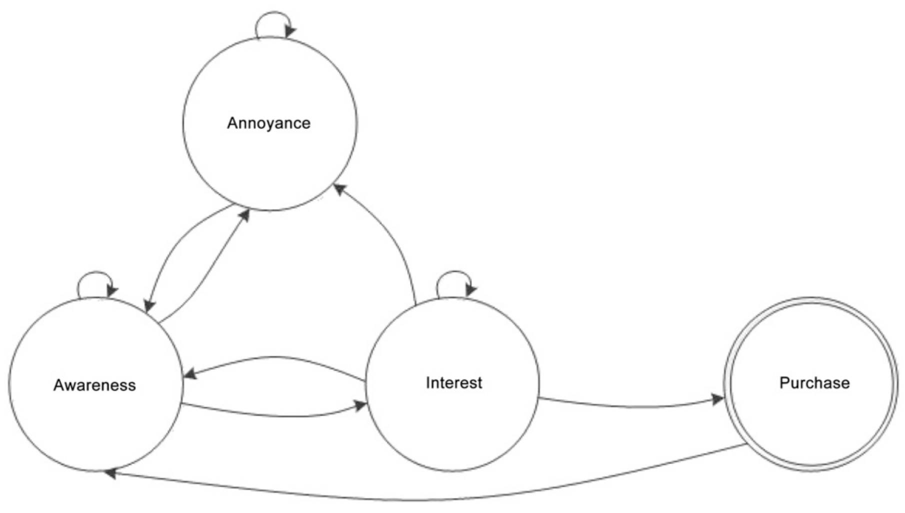
For estimating the proposed HMM that captures consumers' potential annoyance elicitation, we consider the funnel paths of a random set of consumers as discussed in Section 3. For each time period, we observe the advertisements that might affect consumers' transition across the latent states of the purchase funnel as well as the signals that consumers emit in the different stages of the purchase funnel. To capture the annoying effects of advertising, if any, we augment the classic funnel path states (that is, awareness, interest, and purchase) with the additional unobserved state of annoyance. Hence, the proposed HMM consists of three hidden (unobserved) states $s \in$ {Annoyance, Awareness, Interest} and an observed state, the Purchase state.[6]

The proposed model builds on the classical purchase funnel theory that is deeply rooted in the traditional hierarchy of effects models. The hierarchy models generally postulate that advertising is an investment in a process that moves consumers over time through a series of discrete stages, which are often regarded as latent, to the ultimate action of an actual purchase (Barry and Howard 1990). Such a response sequence of buying behavior has been theoretically and empirically verified over the years (Barry 1987). In particular, in the hierarchy of effects model, there has been strong support for the processing sequence in advertising response and especially the notion of sequential hierarchy under which the consumers must first receive information from advertisers raising their awareness, then potentially develop interest as a result of processing relevant information that they actively acquire, and finally possibly take some action, such as purchase the advertiser's product, as a result of the interest (Barry 1987). Hence, in the proposed structure, in the *awareness* state of the funnel path reside consumers who have been targeted by advertisements of the firm and might *passively accept* information; however, they are still not likely to engage in deliberate information search. Consumers in the awareness state are still far away in the funnel path from making a purchase. In the *interest* state reside consumers who *actively search* for information in order to reduce their uncertainty and hence, are likely to engage in deliberate information search activities across channels (that is, direct website visits, organic search clicks, paid search clicks, etc.). For example, consumers who reside in the interest state are more likely to visit the firm's website to collect information about the brand compared with consumers who reside in the awareness state. Additionally, following the extant literature on consumer annoyance, in the annoyance state reside consumers who *actively avoid* the advertisements of the brand. Therefore, consumers who reside in the annoyance state are distinguished from consumers who reside in the awareness or interest state, because annoyed consumers exhibit such fundamentally different behaviors. For instance, when consumers are exposed to display advertisements while they reside in the annoyance state, they seek to actively minimize the duration of their actual exposure to these advertisements (Woltman Elpers et al. 2003, Goldstein et al. 2014, Wilbur 2016), whereas consumers in the awareness state will passively accept such information. Finally, the state of *purchase* is an observed state in which customers express the ultimate interest in the product by completing an online purchase, if any.

Consumers can probabilistically transition among the aforementioned states of the funnel path. In particular, as depicted in Figure 3, consumers who reside in the awareness state might progress further down the purchase funnel and reach the interest state; similarly, consumers who reside in the interest state might probabilistically reach the purchase state. It is important to note that these transitions are also in accordance with the traditional hierarchy framework, which posits that audiences of advertising respond to the messages of such marketing communications in an ordered and sequential way (Barry and Howard 1990). In particular, our structure follows the extant literature, which postulates that a favorable response at one stage of the purchase funnel is a necessary condition for a favorable response at the next stage (Preston and Thorson 1983) and, thus, each stage is temporally before the next. Then, if consumers reach the purchase state, they enter a new funnel path and transition to the awareness state, because the focal products can be purchased repeatedly.[7] Also, we allow backward transitions along the funnel path (for example, consumers' transition from the interest state to the awareness state) in order to capture a possible loss of consumers' interest. These backward probabilistic transitions are also in alignment with the extant literature which suggests that consumers may go back and forth between states of the funnel path (Vakratsas and Ambler 1999, Abhishek et al. 2012). Lastly, as shown in Figure 3, consumers can also transition to the annoyance state from anywhere across the latent stages of the purchase funnel if persistent display advertising exposures trigger their annoyance. If consumers reach the annoyance state, they can probabilistically transition back to the awareness state at any time.[8]

In the HMM, the transition of consumers across the latent states (that is, annoyance, awareness, and interest) is characterized by a Markov process. The transitions are probabilistically determined and can be affected by advertising exposures that consumers encounter in their funnel path. At the initiation of the funnel path, consumers reside in the awareness state. Finally, every latent-state transition is characterized by its own "stickiness," capturing the varying levels of difficulty pertaining to consumers' transitions from

Figure 3. Graphical Representation of Probabilistic Transitions of Consumers Across the HMM States



Notes. A single round circle indicates a latent state, whereas a double round circle indicates an observed state of the purchase funnel. For any given time period, a consumer resides in a latent state of the funnel path (that is, awareness, interest, or annoyance). The transition of consumers across the latent states is probabilistically determined, and the time-varying advertising exposures can affect these transitions. If a consumer makes an online purchase, she transitions into the purchase state, and then, a new funnel path is initiated, because the focal products can be purchased repeatedly.

the state in which they reside to another state. This structure is also substantiated by advertising response theories, because the current literature postulates that the stages in the funnel are not necessarily equidistant from each other (Barry and Howard 1990).

4.3. Hidden Markov Model's Main Components

In this subsection, we first discuss how the aforementioned stochastic process of transitions across the latent states is transformed in the observed outcome sequence of search, advertising response, and buying behaviors (that is, emissions). Then, we elaborate on the main components of the HMM. Consider, for consumer i, a fixed-state sequence $S(i) = S_{i1}S_{i2}S_{i3}\ldots S_{iT}$, where S_{i1} is the initial state for consumer i and $S_{it} \in N = \{1 = \text{Annoyance}, 2 = \text{Awareness}, 3 = \text{Interest}, 4 = \text{Purchase}\}$, and an observed outcome sequence $O(i) = O_{i1}O_{i2}O_{i3}\ldots O_{iT}$ over time periods $t = 1, 2, 3, \ldots, T$. Given the set of latent states and the sequence of observed outcomes, the HMM comprises three elements: (1) the initial-state distribution π, (2) the state transition probability distribution Q, and (3) the observed outcome probability vector A. The probability that we observe the outcome sequence $O(i)$ given the state sequence $S(i)$ and the parameter set $\lambda = \{\pi, Q, A\}$ is

$$P(O(i)|\lambda, S(i)) = \prod_{t=1}^{T} P(O_{it}|\lambda, S_{it}). \tag{1}$$

Then, we can obtain

$$P(O(i)|\lambda, S(i)) = a(O_{i1}|S_{i1})a(O_{i2}|S_{i2})\ldots a(O_{iT}|S_{iT}), \tag{2}$$

where $a(O_{it}|S_{it})$ is the probability of observing outcome O_{it} given that consumer i is in state S_{it} at time period t. Note that $a(O_{it}|S_{it})$ is an element of the outcome probability vector $A(i,t)$. The probability of state sequence $S(i)$ is given by

$$P(S(i)|\lambda) = \pi(i)q(S_{i1}, S_{i2})\ldots q(S_{it}, S_{it+1})\ldots q(S_{iT-1}, S_{iT}), \tag{3}$$

where $\pi(i)$ is the initial probability that consumer i is in state S_{i1} in time period $t = 1$ and $q(S_{it}, S_{it+1})$ is the probability that consumer i is in state S_{it+1} in period $t+1$ given that she was in state S_{it} in period t. Note that $q(S_{it}, S_{it+1})$ is an element of the state transition matrix $Q(i, t \rightarrow t+1)$ for the consumer. The probability that $O(i)$ and $S(i)$ occur simultaneously is then

$$P(O(i), S(i)|\lambda) = P(O(i)|\lambda, S(i))P(S(i)|\lambda). \tag{4}$$

Therefore, the probability of the observed outcome sequence $O(i)$ given the model parameter set λ is the likelihood of observing this sequence, and it is obtained by summing the aforementioned equation over all possible values of state sequence $S(i)$:

$$L(O(i)) = P(O(i)|\lambda) = \sum_{\forall S(i)} P(O(i)|\lambda, S(i))P(S(i)|\lambda). \tag{5}$$

The individual likelihood can also be written in more compact matrix notation as follows (Zucchini et al. 2016):

$$L(O(i)) = \pi(i)\Lambda(i,1)Q(i,1,2)\Lambda(i,2)Q(i,2,3)\ldots Q(i,T-1,T)\Lambda(i,T)\mathbf{1}', \tag{6}$$

where the matrix $\Lambda(i,t) = \text{diag}(a(O_{it}|S_{it}=1), a(O_{it}|S_{it}=2), a(O_{it}|S_{it}=3))$ and $\mathbf{1}$ is a $n \times 1$ vector of ones. The model parameters Q, A, and π to obtain the likelihood of the observed outcome sequence $L(O(i))$ are defined in the following subsections.

4.3.1. State Transition Matrix. In HMMs, the state transition matrix $Q(i,t,t+1)$ is governed by a sequence of first-order Markovian transitions. At each time period t, consumers may probabilistically transition to another state or continue residing in the same state as discussed in Section 4.2. The probability that a consumer i who resides in state j in time period t transitions to state k in time period $t+1$ is denoted as $q_{it}(j,k) = P(S_{it+1} = k|S_{it} = j)$. As previously discussed, the transition further down the funnel path (for example, from the awareness state to the interest state) captures the effectiveness of advertising (that is, the non-immediate but enduring impact of advertising) in increasing consumers' propensity to make an online purchase, whereas the backward transition in the funnel path (for example, from the interest state to the awareness state) captures the loss of interest. At the same time, under the augmented funnel path model, consumers can transition to the annoyance state at any point in time. These probabilistic transitions of customers to the annoyance state capture the annoying effects of frequent display advertising exposures, if any.

Taking into consideration the above, the random walk transition matrix for states $s \in N = \{1 = \text{Annoyance},\ 2 = \text{Awareness},\ 3 = \text{Interest},\ 4 = \text{Purchase}\}$ is defined as follows:

$$Q(i,t,t+1) = \begin{pmatrix} q_{it}(1,1) & q_{it}(1,2) & 0 & 0 \\ q_{it}(2,1) & q_{it}(2,2) & q_{it}(2,3) & 0 \\ q_{it}(3,1) & q_{it}(3,2) & q_{it}(3,3) & q_{it}(3,4) \\ 0 & q_{it}(4,2) & 0 & 0 \end{pmatrix}, \tag{7}$$

where $\sum_{k=1}^{|N|} q_{it}(j,k) = 1$ and $0 \le q_{it}(j,k) \le 1 \ \forall\ j,\ k\ \in N$. To model the transitions of the consumers across the states of the augmented funnel path, we use the multinomial logit model that allows for great flexibility in the transitions. Hence, the transition probability from state j to state k, for $q_{it} \neq 0$, is determined as follows:

$$q_{it}(j,k) = \frac{\exp(PST_{itjk})}{1 + \sum_k \exp(PST_{itjk})}; \quad j,k = \{1,2,3\}, j \neq k. \tag{8}$$

It follows that $q_{it}(j,j) = 1 - \sum_{k,j\neq k} q_{it}(j,k)$. The propensity for transition from state j to state k for consumer i during time period t, PST_{itjk}, is affected by advertising exposures, such as display advertising and search advertising, as well as customer-initiated information-gathering actions that can have an impact toward consumers' propensity to make a purchase, such as direct website visits. The variables that affect the transition probabilities are in accordance with the extant literature on advertising and HMMs (Netzer et al. 2008), and they are grounded on consumer behavior theories. For instance, it has been established that advertising conveys direct or indirect information to consumers (Nelson 1974), and it can have an enduring impact on moving the consumers closer to the purchase state. Hence, the propensity for transition is estimated as follows:

$$\begin{aligned} PST_{itjk} = {} & \beta^A_{jk}\text{Display}_{it} + \beta^B_{jk}\text{BrandSearch}_{it} \\ & + \beta^G_{jk}\text{GenericSearch}_{it} + \beta^D_{jk}\text{DirectVisit}_{it} \\ & + \beta^R_{jk}\text{OrganicSearch}_{it} + \beta^0_{jk}; \\ & j,k = \{2,3\}, j \neq k, \end{aligned} \tag{9}$$

where Display_{it} captures the frequency of display advertising exposures for consumer i in time period t; BrandSearch_{it} captures the frequency of search engine paid clicks for brand-related keywords for consumer i in period t; $\text{GenericSearch}_{it}$ captures the frequency of search engine paid clicks for generic-related keywords (that is, keywords that do not contain the advertiser's brand name) for consumer i in time period t. Hence, the parameter vectors $\beta^A_{jk}, \beta^B_{jk}$, and β^G_{jk} capture the effect of various types of digital advertising (that is, display advertising, branded search clicks, and generic search clicks, respectively) on transitioning customers from state j to state k. Additionally, DirectVisit_{it} captures the frequency of direct website visits to the advertiser's website for individual i at time period t, whereas the corresponding parameter vector β^D_{jk} measures the impact of these direct visits on transitioning customers from state j to state k. In a similar vein, $\text{OrganicSearch}_{it}$ captures the frequency of search engine organic clicks (that is, nonpaid clicks) for consumer i in period t, and the parameter vector β^R_{jk} captures the effect of such actions on consumers' transition from state j to state k. Regarding the consumers' transition to the annoyance state, firm-initiated marketing interactions can stimulate annoyance in consumers. In particular, the probability of transition to the annoyance state is a function of the frequency of display ad exposures at the consumer level during time period t. Hence, the propensity for transition to the annoyance state is captured by $PST_{itj1} = \beta^A_{j1}\text{Display}_{it} + \beta^0_{j1}; j = \{2,3\}$. Finally, consumers who reside in the annoyance state can also probabilistically move back to the awareness state of the funnel path as captured by the corresponding propensity for transition $PST_{it12} = \beta^0_{12}$.[9]

4.3.2. State-Dependent Consumer Behavior. In the HMM, the state-dependent consumer choices O_{it}—also known as emissions—are the advertising response, information-gathering, and purchase behaviors. These state-dependent choices pertain to the probability of the consumer exhibiting these behaviors at time period t, and they are allowed to be contingent on the state in which the consumer resides during that period. We denote the probability of purchase (that is, conversion) as $P(C_{it} = 1|S_{it} = j)$, where S_{it} is the state in which customer i resides at time period t in a Markov process, and C_{it} denotes the decision of the consumer i to make an online conversion at time period t. Similarly, we capture the probability that the consumer will search a specific number of times through different channels and the probability that the consumer will view the display advertisement for v units of time, as described in Table 2. As consumers move further down the funnel path, they are more likely to actively engage in deliberate information search and actively collect information across various information-gathering channels in order to reduce their uncertainty, as discussed in Section 4.4. To summarize, for every consumer, we observe the multivariate outcome of information-gathering, advertising response, and purchase behaviors denoted as $\mathbf{O_{it}} = \{C_{it}, D_{it}, R_{it}, B_{it}, G_{it}, V_{it}\}$ (see Table 2 for the description of consumer actions). Following the extant literature, we allow the observed behaviors to be correlated via the hidden states (Singh et al. 2014, Ascarza et al. 2018). The state-dependent consumer behaviors are modeled as described in the following subsections.

State-Dependent Purchase Behavior. At any point in time, if considerable interest has been developed, consumers might decide to make an online purchase. We use a binary logit model to model the consumers' decision to make a purchase. Hence, the probability of an online conversion C_{it} is estimated[10] as follows:

$$P(C_{it} = 1|S_{it} = 3) = \frac{\exp(\gamma_3)}{1 + \exp(\gamma_3)}. \tag{10}$$

State-Dependent Consumer Search and Advertising Response Behavior. We model as state-dependent behaviors both the consumers' decision to gather information across various channels—as they progress through the purchase funnel—and the consumers' responsiveness to firm-initiated display advertisements. The following dependent variables that capture the information-seeking behavior of users through different information channels are drawn from Poisson distributions with respective state-specific rate parameter vector $\widetilde{\boldsymbol{\lambda}} = \{\widetilde{\lambda}_{D_j}, \widetilde{\lambda}_{R_j}, \widetilde{\lambda}_{B_j}, \widetilde{\lambda}_{G_j}\}$. Respectively, the variable that captures the average duration of exposure of the consumer to the display advertisements is drawn from an exponential distribution with state-specific parameter $\widetilde{\mu}_j$. Hence,

$$P(D_{it} = d_{it}|S_{it} = j) = \frac{\left(\widetilde{\lambda}_{D_j}\right)^{d_{it}} e^{-\tilde{\lambda}_{D_j}}}{\Gamma(d_{it} + 1)}; \qquad j = \{1, 2, 3\}, \tag{11}$$

$$P(R_{it} = r_{it}|S_{it} = j) = \frac{\left(\widetilde{\lambda}_{R_j}\right)^{r_{it}} e^{-\tilde{\lambda}_{R_j}}}{\Gamma(r_{it} + 1)}; \qquad j = \{1, 2, 3\}, \tag{12}$$

$$P(B_{it} = b_{it}|S_{it} = j) = \frac{\left(\widetilde{\lambda}_{B_j}\right)^{b_{it}} e^{-\tilde{\lambda}_{B_j}}}{\Gamma(b_{it} + 1)}; \qquad j = \{1, 2, 3\}, \tag{13}$$

$$P(G_{it} = g_{it}|S_{it} = j) = \frac{\left(\widetilde{\lambda}_{G_j}\right)^{g_{it}} e^{-\tilde{\lambda}_{G_j}}}{\Gamma(g_{it} + 1)}; \qquad j = \{1, 2, 3\}, \tag{14}$$

$$P(V_{it} = v_{it}|S_{it} = j) = \widetilde{\mu}_j \exp(-\widetilde{\mu}_j v_{it}); \qquad j = \{1, 2, 3\}, \tag{15}$$

where $\Gamma(n) = (n - 1)!$ for $n > 0$.

Table 2. Definition of State-Dependent Consumer Choices

Notation	The description of state-dependent consumer actions
$P(C_{it} = 1\|S_{it} = j)$	The probability that consumer i will make an online purchase at time period t given that she resides in the state j
$P(D_{it} = d_{it}\|S_{it} = j)$	The probability that consumer i will directly visit the advertiser's website d times at time period t given that she resides in state j
$P(R_{it} = r_{it}\|S_{it} = j)$	The probability that consumer i will click on advertiser's organic search results r times at time period t given that she resides in state j
$P(B_{it} = b_{it}\|S_{it} = j)$	The probability that consumer i will click on advertiser's brand-related paid search results b times at time period t given that she resides in state j
$P(G_{it} = g_{it}\|S_{it} = j)$	The probability that consumer i will click on advertiser's generic paid search results g times at time period t given that she resides in state j
$P(V_{it} = v_{it}\|S_{it} = j)$	The probability that consumer i will view the display advertisement on average v amount of time at time period t given that she resides in state j

4.4. State Identification

In this section, we further expand on the identification strategy of our model. We first ensure that the model is fully identifiable with the data set by conducting a simulation. Furthermore, we ensure the identification of the annoyance state and the rest of the latent states of the funnel path by drawing on consumer behavior theories as previously discussed. That is, the relevant consumer behavior theories inform and guide the identifiability constraints in order to ensure the identification of the latent states of the funnel path.

More specifically, to ensure that the model is fully identifiable with empirical data, we first conduct the following simulation. We simulated a data set of display advertising exposures and consumers' search as well as purchase activities, and then, we estimated the proposed model with the simulated data set. Based on the results, we are able to recover the true parameters. This relieves a potential concern about the empirical identification of the model.

Furthermore, to ensure identification of the states, the consumer action probabilities are nondecreasing for the latent states, similar to other papers that have used HMMs to study consumers' behavior (Netzer et al. 2008, Abhishek et al. 2012). More importantly, as discussed below, such identifiability constraints are also substantiated by consumer behavior theories. The following paragraphs illustrate the exact identifiability constraints and discuss in detail the set of consumer behavior theories that inform and guide these constraints in our empirical setting.

As far as consumers' active search behavior is concerned, as consumers move through the discrete stages of the funnel path, they are more likely to actively engage in a deliberate information search process along the purchase funnel in order to reduce their utility uncertainty associated with the purchase under consideration (Howard and Sheth 1969, Bettman et al. 1998, Tam and Ho 2006, Browne et al. 2007). As such, when users move further down the funnel path, they more actively search for information and conduct research engaging in information-seeking activities across channels and reducing any uncertainty. Thus, although consumers in the awareness state might passively accept information about the brand, consumers who have moved further down the funnel path in the interest state are likely to actively search for information. At the same time, consumers in the annoyance state actively avoid the advertisements of the brand and, therefore, exhibit the lowest probability of engaging in information acquisition activities, because annoyance triggered by persistent advertisements negatively affects consumers' brand evaluation, persuasion, and ultimately interest in the brand (Fennis and Bakker 2001, Morimoto and Chang 2006). Hence, the above restriction $\widetilde{\lambda}_1 \leq \widetilde{\lambda}_2 \leq \widetilde{\lambda}_3$ is implemented as follows:

$$\widetilde{\lambda}_j = \widetilde{\lambda}_1 + \sum_{j'=2}^{j} \exp(l_{j'}); \quad j = \{2,3\},\ l_{j'} \in \mathbb{R}. \tag{16}$$

Additionally, as far as the state of annoyance is concerned, persistent advertising exposures can trigger annoyance in consumers, because advertising intervenes with the users' main goal of completing a task online or simply navigating the internet (Morimoto and Chang 2006, Goldstein et al. 2014, Jenkins et al. 2016). As a result of the perceived goal impediment, consumers who have been frequently exposed to persistent advertising exposures cope with the negative effects of annoyance by actively avoiding advertisements. For instance, when annoyed consumers are exposed to display advertisements, they minimize the duration of their actual exposure to them (Woltman Elpers et al. 2003, Goldstein et al. 2014, Wilbur 2016). In the context of digital advertising, annoyed consumers would either move to another part of the web page to avoid being directly exposed to display ads that elicit annoyance or click away from web pages that contain the annoying ads. Annoyed consumers exhibit similar behaviors also in the context of traditional television advertising. For example, they often leave the room or switch television channels to actively and physically avoid annoying advertising (Abernethy 1991). Fundamentally, these reactions of annoyed consumers result in reducing the time that consumers are exposed to the display advertisements (that is, reducing the in-view time exposure for a viewable display impression). Therefore, the identifying restriction pertaining to the average duration μ_j of the user's exposure to display advertisements is as follows:

$$\mu_j = \mu_1 + \sum_{j'=2}^{j} \exp(m_{j'}); \quad j = \{2,3\},\ m_{j'} \in \mathbb{R}, \tag{17}$$

where $\mu_j = \frac{1}{\tilde{\mu}_j}$. Hence, $\mu_1 \leq \mu_2 \leq \mu_3$. We should note that, despite the nondecreasing nature of the aforementioned restrictions, we ultimately rely on the data to uncover whether the corresponding coefficients are strictly larger and what the magnitude of such a potential difference is. Nonetheless, we have also conducted various robustness checks that relax the aforementioned restrictions to further examine and validate the robustness of our findings, as discussed in Section 6.

4.5. Estimation Procedure and Model Selection Criteria

We use maximum likelihood estimation (MLE) to estimate the parameters of the HMM: we use the joint likelihood function to estimate the transition matrix parameters and the state-dependent consumer action parameters described in Sections 4.3.1 and 4.3.2, respectively. In particular, we use the sequential BFGS Newton–Raphson algorithm (LeSage 2005) to maximize the likelihood given in Equation (6). We estimate the proposed HMM with the consumers initially residing in the awareness state for parsimony of model parameters. Nonetheless, we verify the stability of the results by also conducting the analysis with different initial-state distributions as discussed in Section 6. Similarly, we also examine the robustness of the results to various randomly selected parameter starting values.

An important issue that one needs to consider when estimating an HMM is the choice of the number of states in order to accurately capture the underlying consumer behavior dynamics. Greene and Hensher (2003) suggest using the Bayesian information criterion (BIC) when comparing models with different numbers of states. Thus, following their recommendation and the best practices in methodologically similar papers (Singh et al. 2011), in order to choose the optimal number of latent states in the proposed HMM, we use the BIC and AIC measures, which are defined by Zucchini et al. (2016) as follows:

$$BIC = -2\log L + p\log I, \tag{18}$$

$$AIC = -2\log L + 2p, \tag{19}$$

where $\log L$ is the log likelihood of the fitted model, p denotes the number of parameters of the model, and I is the number of users. We estimate the various models that are characterized by a different number of states and we obtain the log-likelihood values reported in Table 3. Comparing the corresponding BIC values, we find that the four-state model (that is, three latent states) outperforms all of the other model specifications and, thus, we proceed with the proposed HMM with four states; the Akaike information criterion (AIC) scores provide consistent results. Thus, we find that the optimal number of latent states that provides the best fit to the data is in accordance with the model presented in Section 4.2.

5. Empirical Results

In this section, we discuss the empirical results of this study based on the proposed HMM. In particular, in Sections 5.1 and 5.2, we report and discuss the estimated coefficients of the transition matrix variables and state-dependent action parameters of the proposed HMM, respectively. Furthermore, in Section 5.3, we examine and discuss how the type of display advertisements and the level of diversification of ad creatives as well as consumer demographics moderate the impact of frequent display ad exposures on annoyance elicitation.

Table 3. Comparison of HMMs with Varying Numbers of States

Model	Number of states	Log-likelihood	BIC	AIC
HMM	Three (two latent)	−339,284.13	678,620.04	678,596.26
HMM	**Four (three latent)**	**−329,919.43**	**659,960.93**	**659,904.87**
HMM	Five (four latent)	−341,524.01	683,240.37	683,152.02

Note. The model highlighted in bold provides the best fit to the data.

Overall, the results reveal that there exists an interesting tension between generating interest and triggering annoyance in consumers. This tension exists because although display advertising has an enduring impact on increasing the likelihood of a purchase by transitioning consumers further down the purchase funnel, display advertising exposures beyond a frequency threshold can also substantially increase the probability that consumers will be annoyed. Additionally, the estimated coefficients also illustrate the structural dynamics of effective and annoying advertising by unveiling how the corresponding effects are contingent on the latent state of the funnel path in which consumers reside. Investigating such dynamics, we find that consumers who reside in different stages of the purchase funnel exhibit considerably different thresholds for annoyance stimulation. This is also important because drawing on existing theories it is not clear whether a consumer who has moved further down the funnel path will be more or less easily annoyed with frequent display advertising exposures. For instance, on the one hand, one could postulate that consumers who reside in the later stages of the funnel path might be less easily annoyed because they might have developed more favorable attitudes but, on the other hand, consumers who reside in the early stages of the funnel path are less informed and, thus, they might be less easily annoyed because display advertising exposures can convey valuable information to them. Interestingly, the structural dynamics of annoyance effects reveal that consumers who reside in the later stages of the funnel path exhibit higher tolerance for annoyance stimulation. We further elaborate on this unexpected finding in the following paragraphs. Also, with regard to the moderating effects analyses, our findings reveal that the type of display ads and the level of diversification of ad creatives as well as consumer demographics moderate the effect of the frequency of the display advertisements toward eliciting consumers' annoyance.

5.1. HMM: Results for State Transition Matrix

Table 4 presents the results of the main HMM. Based on the results, we notice that the parameters that capture the effect of advertising exposures on transitioning the consumers across the various states are

Table 4. HMM Results (State Transitions)

Variables	Coefficients	Standard errors
Transition parameters		
Direct visit (awareness, interest) (β_{23}^{D})	0.7026***	0.0046
Direct visit (interest, awareness) (β_{32}^{D})	−1.2207***	0.0209
Organic search click (awareness, interest) (β_{23}^{O})	0.1388***	0.0144
Organic search click (interest, awareness) (β_{32}^{O})	−0.7945***	0.0059
Brand search click (awareness, interest) (β_{23}^{B})	−0.1010***	0.0101
Brand search click (interest, awareness) (β_{32}^{B})	−1.1698***	0.0130
Nonbrand search click (awareness, interest) (β_{23}^{G})	0.6757***	0.0050
Nonbrand search click (interest, awareness) (β_{32}^{G})	−1.5982***	0.0107
Display ads (awareness, interest) (β_{23}^{A})	1.1481***	0.0637
Display ads (interest, awareness) (β_{32}^{A})	−1.9240***	0.0231
Display ads (awareness, annoyance) (β_{21}^{A})	1.5020***	0.0407
Display ads (interest, annoyance) (β_{31}^{A})	0.7565***	0.0315
Log-likelihood	−329,919.43	
BIC value	659,960.93	
AIC value	659,904.87	

Note. Estimated parameters for transition variables of the HMM with MLE.
***$p < 0.01$ (two-tailed tests for all variables).

statistically significant. This finding first indicates that advertising has a significant impact on transitioning consumers across the funnel path and, hence, increases their propensity to eventually make a purchase. In particular, display advertising exposures increase consumers' propensity to transition from the awareness state to the interest state (that is, forward transition in the funnel path) as revealed by the corresponding state-specific transition coefficient ($\beta_{23}^{A} = 1.1481$). By contrast, display advertising exposures have a statistically significant negative effect on the transition of the consumers from the interest state to the awareness state (that is, backward transition in the funnel path) ($\beta_{32}^{A} = -1.9240$). More importantly, the findings also reveal that the coefficients capturing the effect of display advertising exposures on transitioning the consumers to the annoyance state are positive and statistically significant. Specifically, display advertising exposures can have a significant effect on transitioning consumers to the annoyance state when they reside in the awareness state ($\beta_{21}^{A} = 1.5020$) as well as when they reside in the interest state ($\beta_{31}^{A} = 0.7565$). We further elaborate on this important trade-off between effective and annoying advertising below.

Another important aspect of the proposed HMM is the ability to examine the effect of time-varying variables, such as display advertising exposures, on the transition of the consumers across the latent states. To better understand the estimated transition variable coefficients, we estimate the impact of the frequency of the display advertising exposures on the transition probabilities across the latent states. Figures 4 and 5 depict these transition probabilities for consumers who reside in the awareness state and the interest state, respectively. Evaluating the impact of display advertising on the transition probabilities across the states, we notice that exposing consumers to a display advertisement increases the likelihood that the consumer will move further down the funnel path and exhibit a higher propensity to make an online purchase. For instance, one display advertising exposure increases the likelihood that a consumer who resides in the awareness state will move to the interest state from 33.0% to 52.3%. As the frequency of display advertising increases to two exposures in the same day, the corresponding transition probability further increases to 60.0%. However, as Figure 4 shows, with three display advertising exposures, annoyance effects become significant for consumers who reside in

Figure 4. (Color online) Transition Probabilities as a Function of Display Advertising Exposures in the Same Time Period for Consumers Who Reside in the Awareness State

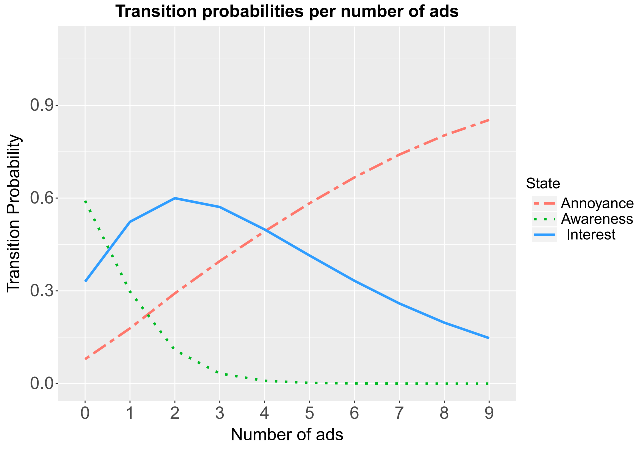
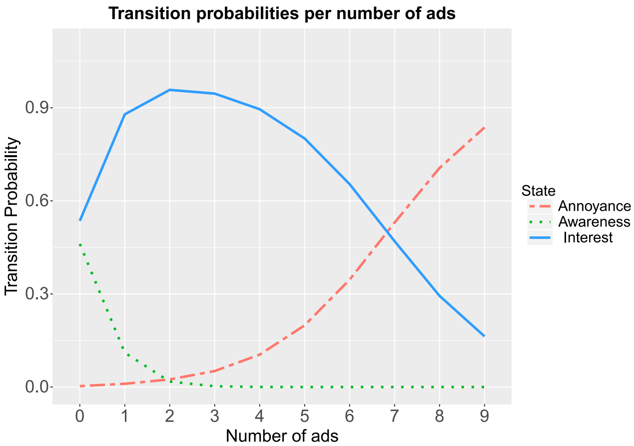


Figure 5. (Color online) Transition Probabilities as a Function of Display Advertising Exposures in the Same Time Period for Consumers Who Reside in the Interest State



the awareness state, because the probability of transitioning to the annoyance state increases to 39.6%. In other words, three display ads in the same time period will lead to a 39.6% chance of annoyance for consumers who passively accept information about the brand. The annoyance effects become even more substantial for consumers who reside in the awareness state when they are exposed to four display advertising exposures in the same period because the probability of transition to the annoyance state greatly increases to 49.3%. We notice that digital advertisers indeed face trade-offs in their decisions regarding the optimal frequency of display advertising exposures at the individual level. On the one hand, display advertising increases the likelihood of transition to the interest state, improving consumers' learning, but on the other hand, display advertising, when it is overutilized beyond a threshold, can also increase the likelihood of transition to the annoyance state.

By contrast, the trade-off in display advertising exposures for consumers who already reside in the interest state are substantially different. As Figure 5 shows, a display advertising exposure increases the probability that a consumer who resides in the interest state will continue residing in the same state. This increase is also important, because the interest state is less "sticky" than the awareness state. We notice, however, that the annoyance effects only become substantial with more than six display advertising exposures in the same time period. In particular, the probability of transition to the annoyance state becomes increasingly significant with more than six advertising exposures across different web pages: six exposures increase the probability to 34.6%, seven exposures increase it to 53.0%, and eight exposures to 70.6%. Overall, this unexpected pattern reveals that consumers in the interest state exhibit higher tolerance for annoyance stimulation compared with consumers who reside in the awareness state.

Furthermore, Figure 6(a) depicts the probability of a consumer residing in a specific state as a function of the number of display advertising exposures. We notice that the overall probability that a consumer resides in the annoyance state becomes larger than the probability that a consumer resides in the awareness or interest state as the frequency of the advertising exposures within the same day increases beyond five display advertisements. Also, when consumers transition to the annoyance state as a result of persistent display advertising exposures, they are likely to stay in the annoyance state, because it is a fairly sticky state.

Also, Figure 6(b) depicts the probability of a consumer making a purchase as a function of the number of display advertising exposures in the same period. As Figure 6(b) illustrates, increasing the frequency of the advertising exposures can increase consumers' likelihood of making a purchase, but exceeding a threshold of display advertising exposures can undermine advertisers' goals.

5.2. HMM: Results for State-Dependent Consumer Behavior

The results presented in Table 5 allow us to gain insights into how consumers behave across the latent states of the purchase funnel. In particular, as shown in Table 5, we see that as consumers move further down the funnel path (forward transitions), they are indeed more likely to engage in information-gathering activities. Consumers who reside in the interest state are more likely to engage in active search behaviors, such as direct visits ($\widetilde{\lambda}_{D_3} = 4.2120$), organic (nonpaid) search clicks ($\widetilde{\lambda}_{R_3} = 1.7854$), brand paid search clicks ($\widetilde{\lambda}_{B_3} = 2.0304$), and generic paid search clicks ($\widetilde{\lambda}_{G_3} = 1.7723$). However, consumers who reside in the awareness state, an earlier stage in the funnel path, hardly engage in such active search behaviors, including organic (nonpaid) search clicks ($\widetilde{\lambda}_{R_2} = 0.7498$), brand paid search clicks ($\widetilde{\lambda}_{B_2} = 0.7113$), direct website visits ($\widetilde{\lambda}_{D_2} = 2.9077$), and nonbrand paid search clicks ($\widetilde{\lambda}_{G_2} = 0.6834$). At the same time, consumers who reside in the annoyance state rarely engage in such information-gathering behaviors, such as direct website visits ($\widetilde{\lambda}_{D_1} = 0.0386$), organic (nonpaid) search clicks ($\widetilde{\lambda}_{R_1} = 0.0365$), brand paid search clicks ($\widetilde{\lambda}_{B_1} = 0.0364$), and nonbrand paid search clicks ($\widetilde{\lambda}_{G_1} = 0.0367$). Another important distinction between the latent states is the tendency of consumers to control their exposure to firm-initiated display advertisements. We notice that consumers who reside in the annoyance state seek to minimize their exposure to display advertisements as captured by the coefficient of in-view exposure ($\mu_1 = 6.4980$) in contrast to the users who reside in the awareness state

Figure 6. (Color online) (a) Probability of a Consumer Residing in a Specific State of the Purchase Funnel as a Function of the Number of Display Advertising Exposures in the Same Time Period and (b) Probability of a Consumer Making a Purchase as a Function of the Number of Display Advertising Exposures

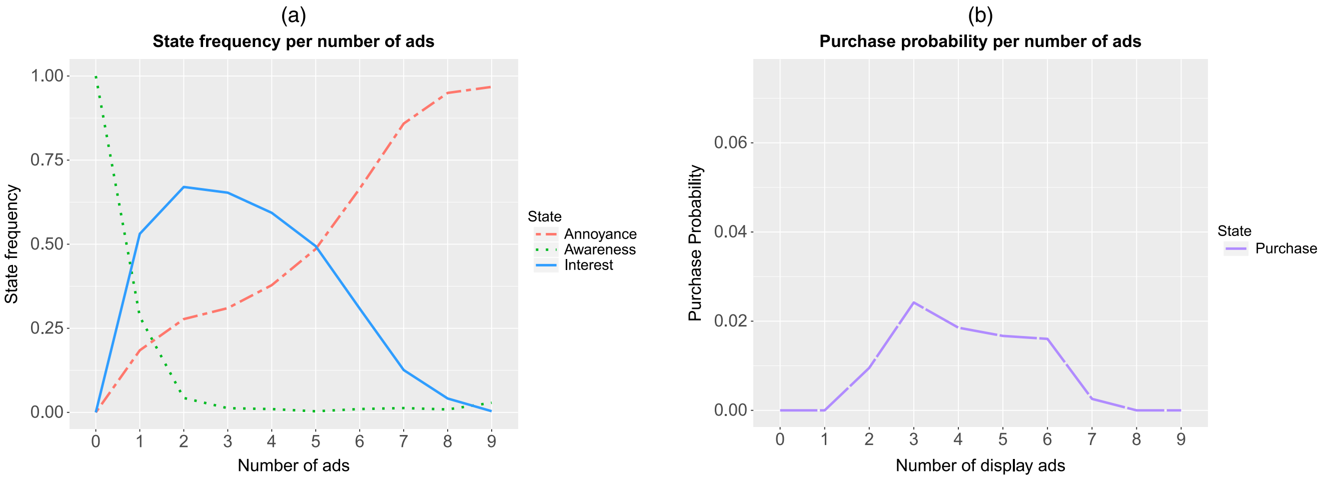


Table 5. HMM Results (Emissions)

Variables	Coefficients	Standard errors
State-dependent choice parameters		
Purchase interest state (γ_3)	−3.8754***	0.0174
Direct website visit annoyance state $(\tilde{\lambda}_{D_1})$	0.0386***	0.0103
Direct website visit awareness state $(\tilde{\lambda}_{D_2})$	2.9077***	0.2140
Direct website visit interest state $(\tilde{\lambda}_{D_3})$	4.2120***	0.0135
Organic search click annoyance state $(\tilde{\lambda}_{R_1})$	0.0365***	0.0103
Organic search click awareness state $(\tilde{\lambda}_{R_2})$	0.7498***	0.0655
Organic search click interest state $(\tilde{\lambda}_{R_3})$	1.7854***	0.0255
Brand search click annoyance state $(\tilde{\lambda}_{B_1})$	0.0364***	0.0093
Brand search click awareness state $(\tilde{\lambda}_{B_2})$	0.7113***	0.0556
Brand search click interest state $(\tilde{\lambda}_{B_3})$	2.0304***	0.0069
Generic search click annoyance state $(\tilde{\lambda}_{G_1})$	0.0367***	0.0105
Generic search click awareness state $(\tilde{\lambda}_{G_2})$	0.6834***	0.0591
Generic search click interest state $(\tilde{\lambda}_{G_3})$	1.7723***	0.0206
In-view exposure annoyance state (μ_1)	6.4980***	0.1510
In-view exposure awareness state (μ_2)	7.1481***	0.0556
In-view exposure interest state (μ_3)	7.9083***	0.0146
Log-likelihood	−329,919.43	
BIC value	659,960.93	
AIC value	659,904.87	

Note. Estimated parameters for emission variables of the HMM with MLE.
***$p < 0.01$ (two-tailed tests for all variables).

($\mu_2 = 7.1481$) or interest state ($\mu_3 = 7.9083$). Overall, these estimates indicate the likelihood of the user to engage in information-gathering actions and their responsiveness to the advertising exposures increases as consumers move further down the funnel path.

5.3. Moderating Effects: Extending the HMM

In this subsection, we discuss how the type of display advertisements and the level of diversification of display ad creatives as well as consumer demographics, such as income, age, gender, and educational level, moderate the impact of frequent display ad exposures on annoyance elicitation.

5.3.1. Moderating Effect: Animated Display Ads. With regard to the heterogeneity of the display advertisements, the advertiser used both animated and static display ads. Below, we discuss the results of an expanded

HMM that incorporates information regarding the type of advertisements to which consumers were exposed in order to investigate, for instance, whether animated ads moderate the effect of frequent advertisement exposures on annoyance elicitation contingent on the state of the purchase funnel in which consumers reside.

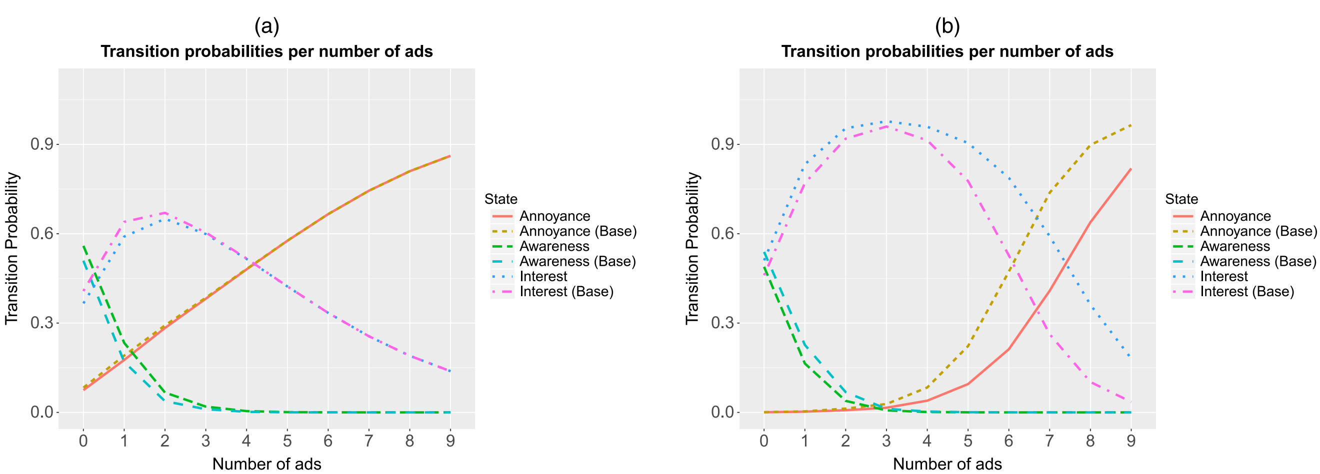
Although animation is a prominent feature in display advertising, from a theoretical point of view, the role of animated ads on advertising effectiveness remains unclear because the literature has generated contradictory findings. On the one hand, animated ads have been found to generate positive attitudes toward the ad. The theoretical framework of motion effect theory can explain such desirable effects of animated ads; motion effect theory postulates that consumers pay attention to visually silent stimuli (Detenber and Reeves 1996) and, hence, when they are exposed to animated ads, they focus their attention on the source of the motion and process the information (Sundar and Kim 2005). In such cases, animation can indeed enhance the effectiveness of banner advertisements. On the other hand, animated ads have been found not to enhance ad recall or improve other performance metrics (Bayles 2002). This could be explained by the limited capacity theory, which postulates that consumers have limited cognitive resources (Lang 2000) and, hence, when greater resources are invested toward processing the advertisements, there are insufficient resources for storing the message (Sundar and Kalyanaraman 2004). Also, animated display ads can elicit annoyance because of the increased cognitive cost that consumers face (Goldstein et al. 2014). Our paper adds to this stream of literature by examining whether animated ads accentuate or attenuate the impact of frequent advertisement exposures on annoyance elicitation.

Tables A.1 and A.2 in the online appendix present the results of the extended HMM model that examines the moderating effect of animated display ads on the frequency of those ads. Figure 7 (Figure 8) visualizes how the annoyance probabilities change as the percentage of the animated display ads shown to consumers decreases (increases) for consumers who reside in the awareness and interest states. Overall, we find that animated ads have a positive moderating effect on both forward transitions of consumers in the funnel path and annoyance elicitation. Suppose, for instance, that a consumer is targeted with four display ads in the same day. If 50% of these ads are animated ads, the transition probability of moving to the annoyance state for a consumer in the awareness state is 48.2%, whereas the transition probability of moving to the annoyance state for a consumer in the interest state is 8.4%. However, when 25% of the ads are animated ads, the probability of annoyance elicitation decreases to 48.0% for consumers in the awareness state and to 3.9% for consumers in the interest state. On the contrary, when 75% of the ads are animated ads, the probability of annoyance elicitation increases to 16.9% for consumers who reside in the interest state and has a negligible effect for consumers who reside in the awareness state. Overall, our findings reveal that animated display advertisements increase the probability of annoyance elicitation in consumers; this moderating effect is more prominent for consumers who reside in the interest state.

5.3.2. Moderating Effect: Diversification of Ad Creatives.

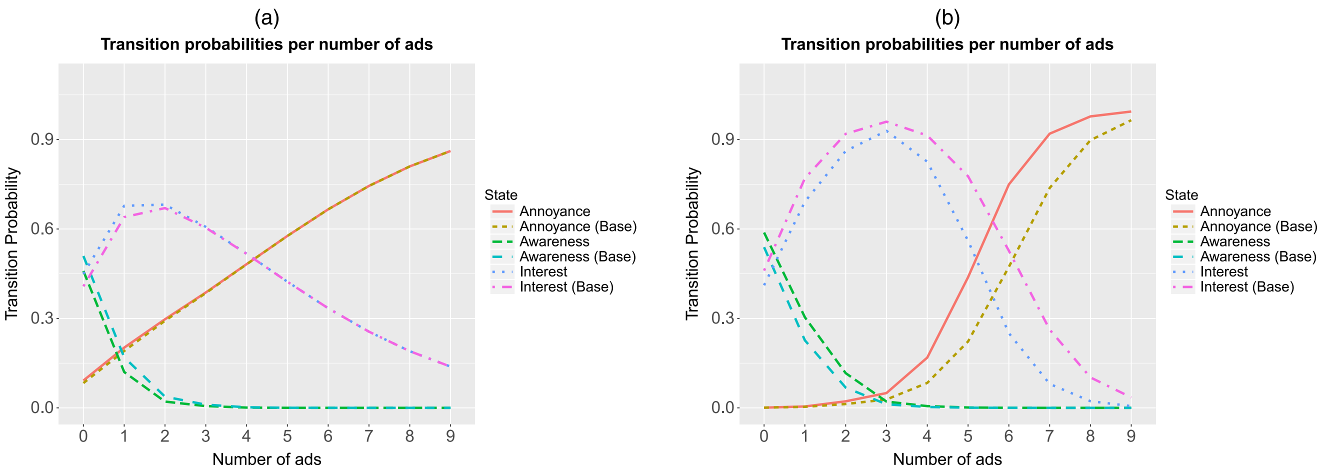
With regard to the heterogeneity of the display advertisements, the retailer also used various display ad creatives. Below, we discuss the results of an expanded HMM model that incorporates information

Figure 7. (Color online) Moderating Effect of Animated Display Ads: Transition Probabilities as a Function of Display Advertising Exposures for Consumers Who Reside in the (a) Awareness and (b) Interest States



Note. These figures visualize the shifts in the annoyance probabilities when animated ads decrease to 25% from 50%.

Figure 8. (Color online) Moderating Effect of Animated Display Ads: Transition Probabilities as a Function of Display Advertising Exposures for Consumers Who Reside in the (a) Awareness and (b) Interest States



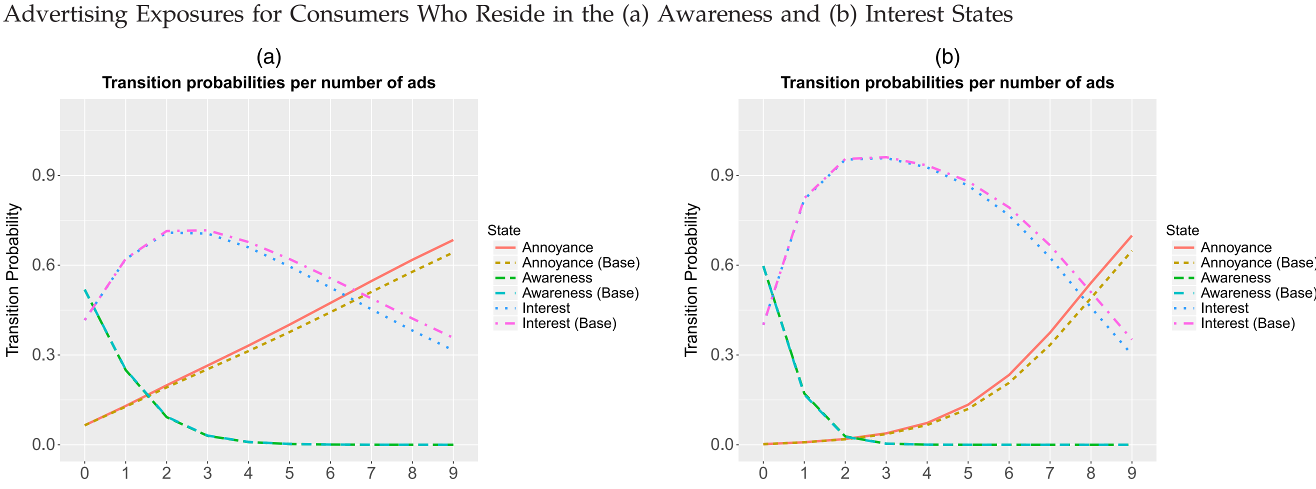
Note. These figures visualize the shifts in the annoyance probabilities when animated ads increase to 50% from 75%.

regarding the level of diversification of ad creatives shown to consumers in order to investigate, for instance, whether a diversification strategy with regard to the advertising creative content according to the consumers' history of advertising exposures moderates the effect of frequent display advertisement exposures on annoyance elicitation.

The effect of varying the display advertising creative content across the advertising exposures has been largely overlooked in the extant literature. An exception is the study of Braun and Moe (2013), which found that using an ad creative diversification strategy can increase website visits and conversions. Our paper further extends their work by examining whether such a display ad creative diversification strategy accentuates or attenuates the impact of the advertisement exposures across the different stages of the purchase funnel. Also, extending our main contributions, our work also adds to the stream of work on consumer annoyance by examining whether and how a display ad creative diversification strategy moderates the effect of frequent advertisement exposures on consumer annoyance elicitation.

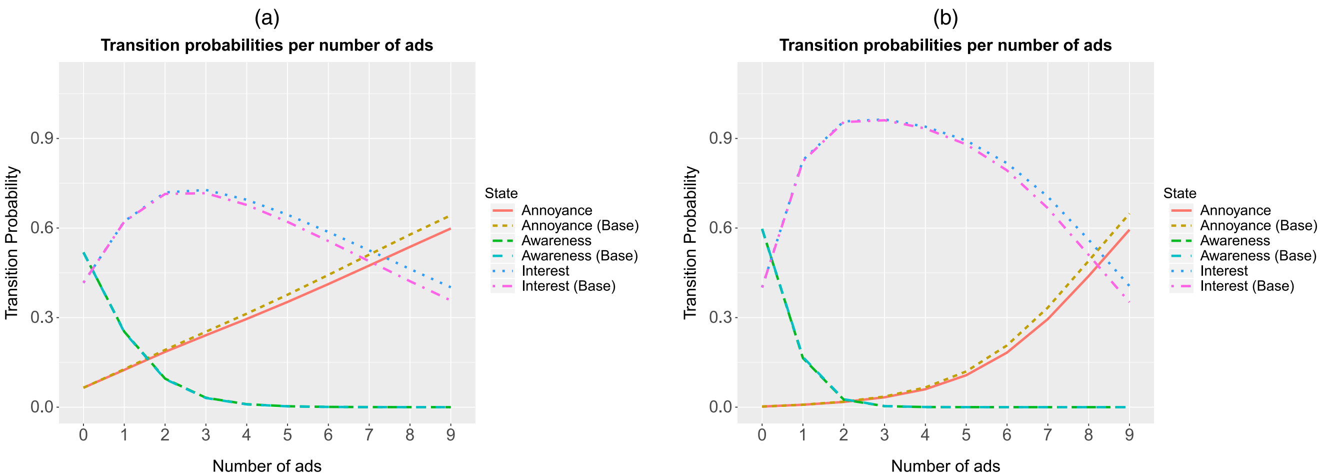
Tables A.3 and A.4 in the online appendix present the results of the extended HMM model that examines the moderating effect of the ad creative diversification strategy on the frequency of ad exposures as captured by the relative number of distinct advertising creatives compared with the total number of advertising exposures.[11] Figure 9 (Figure 10) visualizes how the annoyance probabilities change as the relative number of display ad creatives shown to consumers decreases (increases) for consumers who reside in the awareness and interest states. Overall, we find that diversifying the display ad creatives shown to consumers decreases the chances of annoyance elicitation.

Figure 9. (Color online) Moderating Effect of Ad Creative Diversification: Transition Probabilities as a Function of Display Advertising Exposures for Consumers Who Reside in the (a) Awareness and (b) Interest States



Note. These figures visualize the shifts in the annoyance probabilities when the ad creative diversification ratio decreases from 50% to 25%.

Figure 10. (Color online) Moderating Effect of Ad Creative Diversification: Transition Probabilities as a Function of Display Advertising Exposures for Consumers Who Reside in the (a) Awareness and (b) Interest States



Note. These figures visualize the shifts in the annoyance probabilities when the ad creative diversification ratio increases from 50% to 75%.

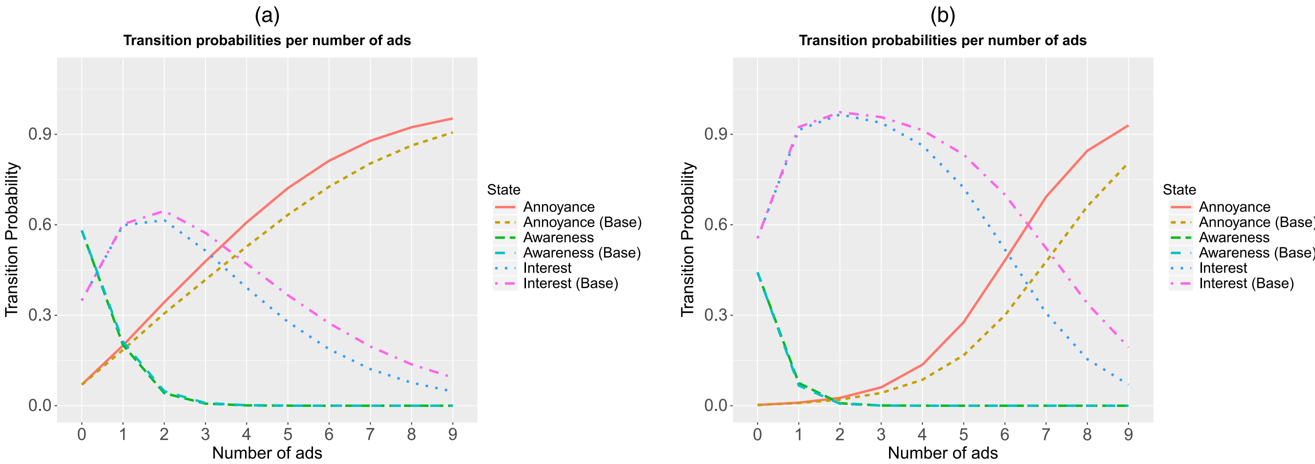
Suppose, for instance, that a consumer is targeted with three display ads. If all of these advertising exposures entailed different display advertising creatives, the transition probability of moving to the annoyance state for a consumer in the awareness state is 25.5%, whereas the transition probability of moving to the annoyance state for a consumer in the interest state is 3.2%. However, when consumers were exposed to the same single display ad creative over these three display ad exposures, the probability of annoyance elicitation increases to 27.7% for consumers in the awareness state and 4.0% for consumers in the interest state. The corresponding effect is more pronounced with more frequent advertising exposures; for instance, with seven advertising exposures, the probability of annoyance elicitation increases from 46.7% to 51.7% for consumers in the awareness state and from 29.3% to 39.7% for consumers in the interest state. Hence, our findings reveal that diversifying the display ad creatives shown to consumers can decrease the chances of annoyance elicitation and this moderating effect is more prominent for consumers who reside in the interest state.

5.3.3. Moderating Effect: Consumer Demographics. In order to further enrich the model beyond behavioral characteristics, we extract consumer demographics at the zip code level using the census data to supplement our own data set.[12] We extend the HMM to examine whether demographic variables, such as income, age, gender, and educational level, moderate the effect of frequent advertisement exposures on annoyance elicitation. In particular, to capture any heterogeneous effects of these demographic variables and taking into consideration the parsimony of the model, we allow the coefficients of the corresponding variables to vary for forward (for example, awareness to interest) and backward transitions (for example, interest to awareness) in the purchase funnel.

Tables A.7 and A.8 in the online appendix present the results of the aforementioned extended HMM. This extended model yields several interesting findings. First, it is important to note that the main findings of the paper remain consistent in this extended version of the model as well. Second, allowing demographics to moderate the effect of the frequency of the display advertising exposures, we find that demographic variables have a statistically significant moderating effect on the impact of the frequency of the display advertisements toward eliciting consumers' annoyance.

In order to better understand the moderating effects of the demographic variables, we have visualized the shifts in the transition probabilities as the corresponding demographics change. In particular, as far as the income is concerned, as shown in Figure 11, we see that for individuals with higher income levels, the probability of transitions to the annoyance state increases regardless of whether they reside in the awareness state or the interest state. For example, an increase of $10,000 in the level of median income increases the probability of transition from the awareness to the annoyance state from 41.8% to 47.9% when consumers are exposed to three display advertisements in the same time period; similarly, the probability of transition from the interest to the annoyance state increases from 4.2% to 6.1% when consumers are exposed to three display advertisements in the same time period. Thus, income has a positive moderating effect on the frequency of the display advertisements toward transitioning the consumers in the annoyance state. This finding has significant implications for the advertising scheduling

Figure 11. (Color online) Moderating Effect of Income: Transition Probabilities as a Function of Display Advertising Exposures for Consumers Who Reside in the (a) Awareness and (b) Interest States



Note. These figures visualize the shifts in the annoyance probabilities when the median income increases by $10,000.

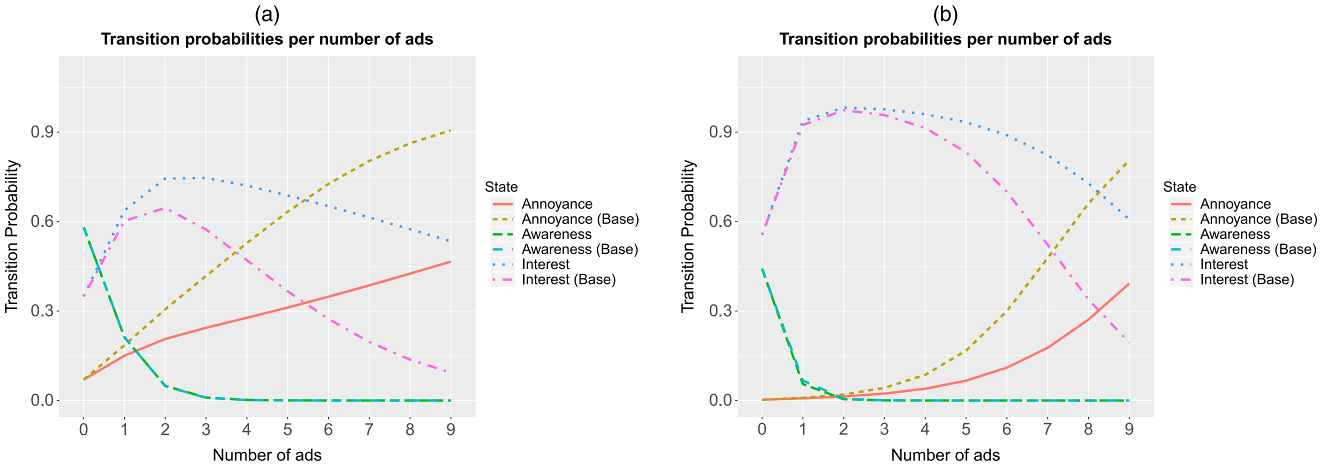
decisions of marketers because individuals with higher income levels are often regarded as a highly desirable target group across industries.

Additionally, as far as age is considered, as shown in Figure 12, we see that as median age increases, the probability of transition to the annoyance state decreases for consumers who reside in either the awareness or interest state. For example, an increase of about five years in the median age decreases the probability of transition from the awareness to the annoyance state from 41.8% to 24.4% when consumers are exposed to three display advertisements in the same time period. Similarly, it decreases the probability of transition from the interest to the annoyance state from 4.2% to 2.3% when consumers are exposed to three display advertisements. Thus, overall, age has a negative moderating effect on the frequency of the display advertisements toward transitioning the consumers in the annoyance state. This finding also has significant implications for the advertising scheduling strategies of firms. Our findings highlight the need to adapt the advertising schedules of firms when targeting younger consumers because they tend to exhibit lower tolerance levels for annoyance elicitation.

As far as gender is considered, as shown in Figure 13, we find that the probability of transition to the annoyance state is slightly decreased for male consumers when they reside in the awareness state and has a negligible difference—compared with women—when they reside in the interest state. Hence, advertisers should also consider this heterogeneity effect of annoyance elicitation when they devise their advertising schedules.

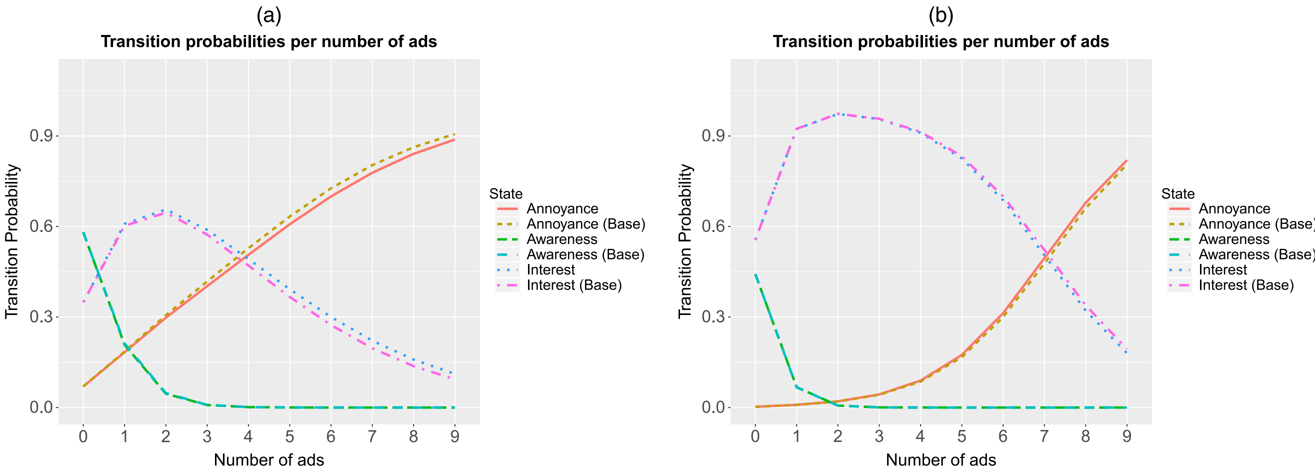
Last but not least, as far as the level of educational attainment is considered, we see that, for individuals

Figure 12. (Color online) Moderating Effect of Age: Transition Probabilities as a Function of Display Advertising Exposures for Consumers Who Reside in the (a) Awareness and (b) Interest States



Note. These figures visualize the shifts in the annoyance probabilities when the median age changes by one standard deviation (about five years).

Figure 13. (Color online) Moderating Effect of Gender: Transition Probabilities as a Function of Display Advertising Exposures for Consumers Who Reside in the (a) Awareness and (b) Interest States



Note. These figures visualize the shifts in the annoyance probabilities when the male ratio increases by one unit.

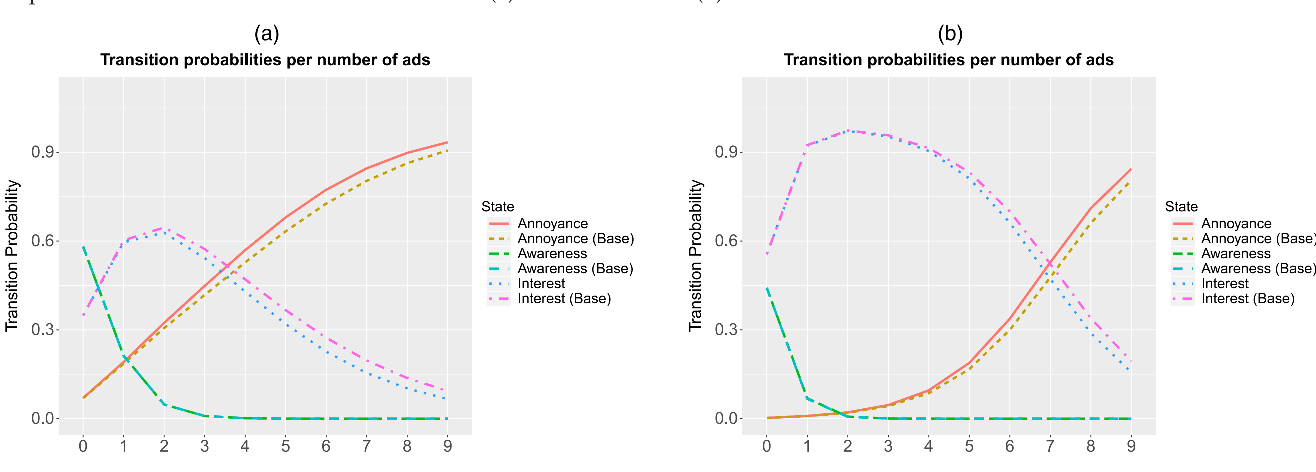
with a higher educational level, the probability of transition to the annoyance state increases regardless of whether consumers reside in the awareness state (Figure 14(a)) or the interest state (Figure 14(b)). For example, a one-unit increase in the educational level increases the probability of transition from the awareness to the annoyance state from 41.8% to 44.8% when consumers are exposed to three display advertisements in the same time period. Similarly, it increases the probability of transition from the interest to the annoyance state from 4.2% to 4.6%. Thus, in general, the educational level has a positive moderating effect on the frequency of the display advertisements toward transitioning the consumers in the annoyance state. This finding too has important implications for the advertising scheduling decisions of firms, and it is especially important for brands that cater to an audience with higher educational levels.

6. Robustness Checks

In this section, we evaluate the sensitivity of our results and the robustness of our findings to a variety of alternative specifications and robustness checks. Overall, the conducted additional analyses suggest that the findings of this study are highly robust.

First, in order to assess the sensitivity of our results to alternative model specifications, we rerun our analyses with various alternative initial-state distributions. In particular, for an HMM with a transition matrix that is a function of time-varying covariates, the initial-state distribution can also be specified as the stationary distribution of the transition matrix

Figure 14. (Color online) Moderating Effect of Education: Transition Probabilities as a Function of Display Advertising Exposures for Consumers Who Reside in the (a) Awareness and (b) Interest States



Note. These figures visualize the shifts in the annoyance probabilities when the minimum education ratio increases by one unit.

calculated by solving the equation $\pi = \pi\widetilde{Q}$ under the constraint that $\sum_{s=1}^{n} \pi_s = 1$, where $\widetilde{Q}$ is the transition matrix with the parameter estimates and all of the covariates are set to the mean value of the corresponding variables across individuals and time periods. We find that the estimated transition probabilities are positive, thus confirming that the transition matrix is aperiodic and irreducible, which in turn ensures the existence and uniqueness of the stationary distribution. The estimated HMM with the initial-state distribution fixed at the aforementioned stationary distribution of the transition matrix yields very similar results as shown in Tables A.9 and A.10 in the online appendix, further corroborating our findings. To further alleviate any remaining concerns regarding the initial distribution assumption, we also proceed with estimating the initial distribution parameters of the HMM directly from the data and the results remain robust under this specification as well. Hence, our findings are highly robust to alternative initial-state distributions.

Second, we also examine alternative specifications for the emission matrix. For example, we aggregate the different types of consumers' information-gathering actions in the emission matrix into a single variable capturing collection of information across all channels. Tables A.11 and A.12 in the online appendix report the results of the aforementioned model specification, whereas Figure A.1 in the online appendix visualizes the corresponding transition probabilities; the findings remain consistent. Additionally, we also conduct various robustness checks to examine the robustness of the findings when we relax the non-decreasing identification restrictions regarding the emission variables discussed in Section 4.4. As shown in Tables A.13 and A.14 (Tables A.15 and A.16) in the online appendix, when we remove the restrictions with regard to the λ parameters (μ parameters), our findings remain robust. Furthermore, to alleviate any concerns regarding the price as a potential confounder, we allow the deviation from the mean product price during each time period to affect consumers' decision to make an online purchase. Tables A.17 and A.18 in the online appendix report the results of the aforementioned HMM; we find that our results remain robust.

Examining additional alternative specifications for the transition matrix, we allow, for instance, the transition from the annoyance state to be affected by firm-initiated marketing interactions (that is, display advertisements). As shown in Figure A.2 and Tables A.19 and A.20 in the online appendix, our findings remain consistent. Similarly, we find that the results are robust to alternative-state transitions across the latent stages of the purchase funnel. We also examine the robustness of the moderating effects by using, for instance, alternative specifications to capture the advertisers' display ad creative diversification strategy. In particular, we examine the moderating effect of the maximum frequency of repeated exposures to the same display advertising creative and we find that our results remain very similar.

Additionally, we check the robustness of our results to alternative period-length specifications beyond the one used in Section 4.3.1 (that is, day). In particular, we estimated the HMM with the alternative units of half a day and two days, and the results are robust. Finally, we also check the sensitivity of the HMM results to alternative specifications, such as explanatory variables in the current and/or previous time period as well as a hierarchical Bayes approach, and the results remain robust.

7. Discussion and Managerial Implications

The main contribution of this study is the investigation of consumer annoyance effects in the context of display advertising. In order to examine our research questions, we build an HMM that captures the trade-off between effective and annoying display advertising by allowing persistent advertising exposures to not only have an enduring impact on consumers' purchase decisions but also, potentially trigger annoyance in consumers. To the best of our knowledge, this is the first paper to investigate whether and when frequent exposures to display advertising can trigger annoyance in consumers, unveiling an important mechanism of the potential negative effect of display advertising. Our findings reveal that an interesting tension indeed exists in display advertising between generating interest and triggering annoyance in consumers, highlighting the impact that advertising scheduling can have on annoyance elicitation. This tension exists because although display advertising has an enduring impact on increasing the likelihood of a purchase by transitioning consumers further down the purchase funnel, display advertising exposures beyond a frequency threshold can also substantially increase the probability that consumers will be annoyed. Another important contribution of this paper is the investigation of the structural dynamics of effective and annoying advertising by allowing the corresponding effects to be contingent on the latent states of the purchase funnel in which consumers reside. Investigating such structural dynamics, we reveal that consumers who reside in different stages of the funnel path exhibit considerably different tolerance thresholds toward annoyance stimulation. For instance, we find that the threshold of annoyance in display advertising exposures is about two times higher for consumers who reside in the interest state compared with those in the awareness state of the funnel path. Additionally, the paper further contributes to the literature by also examining whether the type of display advertisements (for example, animated versus static ads) and the level of diversification of ad content as well as consumer demographics (for example, income, age, gender, and educational level) moderate the impact of frequent display advertising exposures on annoyance elicitation. Our findings reveal that the type of display advertisements and the level of diversification of ad creatives as well as various consumer demographics indeed moderate the impact of frequent ads and affect consumers' threshold for annoyance elicitation; the corresponding effects are both statistically and economically significant.

Apart from contributing to the academic literature, the findings of this paper also have important managerial implications for firms that utilize digital advertising. Our findings reveal the interesting trade-off between effective and annoying display advertising exposures and, thus, they highlight the need for digital advertisers to adapt their online display advertising scheduling and optimize the frequency of individual-level exposures taking into consideration the probability of triggering consumers' annoyance and the detrimental effects of annoyance elicitation. If annoyance elicitation is ignored, advertisers not only bear the cost of displaying the frequent annoying advertising exposures but also, bear the opportunity cost of not transitioning the consumers further down the purchase funnel to eventually reach the purchase state. Also, the aforementioned opportunity cost can further increase if annoyed consumers increasingly adopt ad-blocking technologies and entirely block future advertising exposures as a result of consumer annoyance. Hence, advertisers need to effectively adapt their media scheduling strategies of delivering advertising exposures in order to stimulate interest without triggering annoyance. Additionally, the moderating effect analyses also have important managerial implications for the advertisers. In particular, our analyses reveal that advertisers should seek to use static—rather than animated—display ads as well as diversify the display ad creatives according to the consumers' history of advertising exposures in order to reduce the chances of annoyance elicitation. Similarly, the advertisers should adapt their scheduling strategies, taking into consideration the demographics of consumers and their moderating effect on the frequency of advertising exposures in order to reduce annoyance stimulation. In addition, when deciding their media scheduling strategies, advertisers should also take into consideration the stage of the purchase funnel on which consumers reside because we have illustrated in this paper that consumer annoyance elicitation can vary considerably across these different stages. The ability of the proposed HMM to incorporate additional time-varying covariates in the transition probability matrix allows advertisers to further investigate the impact of other context-specific marketing strategies and firm-initiated actions (Adamopoulos and Todri 2014, 2015) on consumers' annoyance elicitation and purchase funnel progression. Moreover, using the proposed HMM, practitioners can segment the customers into different groups that capture the latent stages of the funnel path and further examine the heterogeneous effect of various other marketing stimuli to devise additional strategies that can leverage such heterogeneous effects. For instance, such segmentation provides an important tool to advertisers to predict consumers' subsequent behaviors and devise effective marketing media scheduling strategies to maximize the probability that the consumers will move forward in the purchase funnel.

Furthermore, our finding that a tension exists in display advertising between stimulating interest and generating annoyance also has significant managerial implications for publishers and the advertising network affiliates. For instance, this finding reveals the need for publishers and advertising networks to facilitate the granular tracking of advertising exposures at the consumer level and provide the appropriate mechanisms that would allow advertisers to enforce a limit on the frequency of advertising exposures at the individual consumer level. Also, given the importance of the revealed structural dynamics in the advertising effectiveness and annoyance elicitation, our findings also indicate that it would be strategically meaningful for the publishers and advertising networks to track subtle signals of consumer browsing behavior at a granular level. Such tracking capabilities would allow advertisers and publishers to make appropriate inferences regarding the trade-off between advertising effectiveness and consumers' annoyance elicitation. If such mechanisms are neglected, annoyance effects can hurt the main business revenue models of publishers and advertising network affiliates because consumers actively avoid ads as a result of annoyance elicitation.

7.1. Limitations and Future Research Directions

Our paper has also limitations that arise primarily from the restrictions of the data set. For instance, in this study, we do not consider the effect of organic word-of-mouth interactions to which some consumers could potentially be exposed. Future research can also examine how the annoyance effects triggered by persistent advertising exposures vary for different product categories and brands as well as for various levels of consumer uncertainty. Also, because of the limitations of the data set, we are not able to investigate the impact of interactions with competing firms and examine the effect of market-specific actions on advertisements, because this information is not available to the advertiser. Following the example of Li et al.

(2017), who develop an attribution model that captures the impact of interactions with competing firms, future research could also further investigate the effect of market-specific actions. Notwithstanding these limitations, we hope that our paper paves the way for more research in the increasingly important and emerging stream of work that examines the impact of technology-enabled marketing strategies (Adamopoulos et al. 2018a) for firms and consumers.

Endnotes

[1] Ad blocking or ad filtering is a type of software that can remove or alter advertising content from a web page.

[2] The individual-level data have been collected via cookies and advanced tracking techniques. Because of the nature of the data-sharing agreement, we are unable to reveal the name of the firm.

[3] All products are associated with one single brand of the company rather than multiple brands, and the products are not new in the market.

[4] In order to ensure randomness, the consumers have been sampled as follows. First, a list of the unique anonymized customer identifications was extracted from the database of the company. This list of customer identifications did not have any duplicates, and shuffling was performed to ensure that the order is random. Second, after assigning a sequential number to each customer identification, we randomly sampled customer identifications without replacement from that list. Third, we extracted all of the touchpoints associated with these customer identifications. This process of random sampling provides an equal probability of sampling a consumer and ensures that no selection bias is introduced to the sample.

[5] Information on viewability is collected through (1) a geometric method that typically involves comparing the position of the four corners of the ad relative to the host web page and then comparing the four corners of the browser's viewport relative to the host web page as well as (2) browser optimization monitoring techniques.

[6] When we estimate the HMM, we confirm (rather than arbitrarily fix) the number of latent states also based on the fit of the model to the data set in order to accurately capture the consumer behavior dynamics (see Section 4.5).

[7] As a robustness check, we have evaluated the sensitivity of the results to alternative initial-state distributions. For instance, the initial-state distribution can also be specified as the stationary distribution of the transition matrix of the HMM. We find that our results are robust to alternative initial state distributions, as discussed in Section 6.

[8] As a robustness check, we have evaluated the sensitivity of the results to alternative specifications regarding the transitions of the consumers from the annoyance state to the rest of the funnel path states as well as among all of the latent states of the funnel. We find that our results are robust to such alternative specifications, as discussed in Section 6.

[9] We have examined alternative specifications for the probabilistic transitions of the consumers from and to the annoyance state, as discussed in Section 6. We find that our results are robust to various alternative specifications.

[10] As a robustness check, we have evaluated alternative specifications for modeling consumers' decision to make a purchase. We find that our results are robust to such alternative specifications, as discussed in Section 6.

[11] As a robustness check, we have evaluated alternative specifications for capturing the diversification strategy of display ad creatives. We find that our results are robust to such alternative specifications, as discussed in Section 6.

[12] We have been able to extract demographics for 87.8% of the customers. Table A.5 in the online appendix provides a description of the demographic variables. Table A.6 in the online appendix provides descriptive statistics for consumers with demographic information; we do not find any statistically significant differences.

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