

TELEVISION AND INTERNET COMMERCIALS AVOIDANCE

by

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DEDICATION

This piece is dedicated to all who made possible my accomplishments, including but not limited to, my parents, Joao Batista and Assunta Teixeira, as well as my reason for moving forward happily, Iva Iovtcheva, and my friends, colleagues and family members: too many to list, given my fortunate life trajectory. Lastly, working with my co-advisor, Michel Wedel, has been a true joy. He has made what is generally regarded as a painful process to be a ‘walk-in-the-park’. Thank you all from the bottom of my heart!

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PREFACE

The late astronomer Carl Sagan once said “Extraordinary claims require extraordinary evidence.” In the following pages, I hope to make some extraordinary and novel claims regarding the consumer behavior towards video advertising. Although the five years in the PhD Program at the Ross School of Business has provided me with much theoretical and empirical evidence for many of my claims, they are by no means ‘extraordinary’. However, more important than the supporting data and findings within this dissertation, in the following pages lays a proposal for developing the methods and approaches that make possible the search for the truth by the interested ones.

TABLE OF CONTENTS

DEDICATION	ii
ACKNOWLEDGMENTS	iii
PREFACE	iv
LIST OF TABLES	vii
LIST OF FIGURES	viii
ABSTRACT	ix
GENERAL INTRODUCTION	xi
CHAPTER	
I. Moment-to-moment Optimal Branding in TV Commercials	1
Introduction	1
Branding and Attention Effects	2
Data	10
Model	15
Results	20
Optimization of Branding Activity	28
Validation Experiment	37
Discussion	41
Appendix 1: Model Specification and Estimation	48

References	53
II. Dynamic Influences of Emotional Reactions on Internet Video Advertisements	58
Introduction	58
Emotion and Attention Effects	61
Data	70
Model	77
Results	94
Discussion	98
Appendix 1: Model Specification and Estimation	101
Appendix 2: Assessing Emotions from Facial Expressions	105
Appendix 3: Convergence of Gibbs Sampler	109
References	110
III. General Discussion	115
Final considerations	115
Future Research Opportunities	117

LIST OF TABLES

TABLE

I.1 Summary of the independent variables	22
I.2 Model comparisons 1	23
I.3 Model comparisons 2	24
I.4 Determinants of commercial avoidance	25
I.5 Brand activity in original and optimized ads	34
I.6 Estimated commercial avoidance for current, optimized and benchmark branding strategies	37
I.7 Comparison between zapping rates of original and altered commercials	40
II.1 Description of the data	75
II.2 Correlations between transformations of functional emotion variables	93
II.3 Emotional influences on commercial avoidance	96

LIST OF FIGURES

FIGURE

I.1 Attention concentration and commercial avoidance	7
I.2 Time-varying parameters of branding activity	27
I.3 Time-varying parameters	32
I.4 Illustration of branding optimization frame-by-frame	35
II.1 Defining latency response based on optimal lag effects	84
II.2 Flow model of response latencies for emotions attention and zapping	85
II.3 Smoothing emotions curves based on functional fitting	88
II.4 Functional smoothing and clustering of Joy and Surprise	91
II.5 Time-varying baseline zapping and dispersion rates	97

ABSTRACT

Chapter 1.

I develop a conceptual framework for understanding the impact that branding activity (the audio-visual representation of brands) and consumers' dispersion of attention have on their moment-to-moment avoidance decisions during television advertising. I formalize this in a Dynamic Probit Model and estimate it with MCMC methods. Data on commercial avoidance through zapping along with eye tracking on 31 commercials for nearly 2000 participants are used to calibrate the model. New, simple metrics of attention dispersion are shown to strongly predict avoidance. Independent of this, central on-screen brand positions, but not brand size, further promote commercial avoidance. Based on the model estimation, I optimize the branding activity under marketing control for ads in the sample to reduce commercial avoidance. This reveals that pulsing the brand presence-- while keeping total brand exposure constant--decreases commercial avoidance significantly. Both numerical simulations and a controlled experiment using original and edited commercials provide evidence of the benefits of brand pulsing to ward off commercial avoidance. Implications for advertising management and theory are addressed.

Chapter 2.

Television commercial avoidance has grown to become one of the top three concerns for both TV advertisers and broadcasters (Danaher 2008, p.82; Donaton 2004). “The bottleneck to consciousness” (Broadbent 1957), attention, grabbing and retaining, is in the forefront of downstream effects for advertising efficacy. Theory and practice agree that most of advertising’s success is attained via evoking emotions in consumers. In this paper, I study the concomitant effect of two positive emotions, joy and surprise, moment-to-moment on both the viewer’s visual attention and on their avoidance decisions (zapping) of Internet commercials. To do so, I propose a novel non-obtrusive means to automatically capture and classify emotions via images from their facial expressions while, at the same time, tracking their eye-movements. Data for 28 commercials across 50 viewers collected at each $\frac{1}{4}$ of a second is used to estimate a simultaneous dynamic Bayesian model via MCMC. I find that Joy reduces zapping momentarily with little persistent effect (if Joy decreases \rightarrow viewers zap), and that this is largely a direct effect, with minimal influence on attention distraction. I also find that Surprise works mainly indirectly by momentarily reducing zapping but at the expense of causing major attentional distraction (mediated by Individual Attention Dispersion). The implication for advertisers is that Joyous ads should improve over time, ending strong. As for using Surprise, the risk in showing the unexpected is to lose the viewer’s engagement with the story line.

GENERAL INTRODUCTION

This dissertation deals with the issue of video advertising avoidance, both television and internet, by consumers as they choose what to attend to (i.e. their focal attention) and when to stop watching (i.e. zapping) commercials. Due to technology accessibility (remote controls; video recorders) and increased advertising clutter, among others, commercial avoidance has skyrocketed in the last decade and has become one of the main concerns of advertisers and media firms. Thus, a better understanding of what drives consumers to avoid watching, zapping, commercials is of utmost importance in order to reap the downstream benefits of advertising effects such as awareness and persuasion.

Certainly there are many paths to understanding and reducing advertising avoidance such as better targeting (i.e. media scheduling) to increase relevance or use of attention-grabbing devices (i.e. famous endorsers, special effects). However, these add huge additional costs to the advertising production and distribution processes. In the following, I study the impact of two very important and virtually cost-free elements that are pervasive to most commercials and have significant effects of consumers' zapping decisions. Essay I deals with the influence of brand images (trademarks, logos, pack shots) on screen and how its presence and saliency ignites avoidance decisions in TV ads.

Essay II deals with positive emotional changes, or lack thereof, and how they affect the decision to continue viewing Internet video ads.

Essay I attempts to solve what I call the ‘brand-name placement problem’: how to weave in the brand (when, where in the screen, how big, how long, how many times) in order to reduce the potential detrimental effects that its presence poses on commercial viewing? In order to answer this question, I measure the most important brand (image) features under advertising control and estimate their marginal effects on zapping. This is done on a frame-by-frame basis while accounting for the dynamic effects of visual attention over time using eye-tracking technology. For that, I propose two novel measures of visual dispersion, Individual and Aggregate Attention Dispersion, and show that both measures are the most important predictors of TV commercial zapping. In the following pages, I show in details the methodological (measurement and modeling) procedures used to arrive at the solution to the ‘brand-name placement problem’. After extensive statistical modeling, simulations and a lab experiments in which I expose participants to different brand placement versions of commercials, I find that Brand Pulsing – on/off-type short and frequent appearances of the brand image – is the optimal strategy in minimizing zapping across various commercial types, viewers and brands.

While Essay I deals with one of the most important features of form in commercials, that of how to expose the brand image, in order to reduce avoidance, Essay II focuses on the impact of content evoking positive emotions on avoidance decisions. More specifically, joy and surprise, as two predominant emotions used in advertising, are measured in an attempt to answer the question: are positive emotions always effective and do they work in the same way to attract and retain viewer attention? To answer this, I

use a similar method to Essay I, namely moment-to-moment analysis with eye-tracking data to measure Individual Attention Dispersion. In addition, I propose to use face-tracking technology to automatically and unobtrusively measure emotions at a high-frequency (4 times per second) as a means to complement attention measures in a dual processes framework. Also, using a Dynamic Hierarchical Bayesian Model, estimated with MCMC Gibbs sampling, I am able to tease out the instantaneous effects of joy and surprise from the persistent effects both on attention dispersion and on zapping likelihood for Internet video commercials. As will be shown in the pages to come, not all positive emotions work in the same fashion to reduce commercial avoidance.

Essays I (Chap. I) and II (Chap. II) can be read separately without prejudice to comprehension.

CHAPTER I

Moment-to-moment Optimal Branding in TV Commercials

Introduction

Effective television advertising contributes to sales and long-term brand equity by building and sustaining brand awareness, associations and attitudes. However, the effectiveness of television advertising may be slipping due to consumers zapping of commercials. Commercial avoidance is facilitated by remote controls and by digital video recorders (DVR) that permit consumers to record and replay TV content without having to see all or parts of commercial breaks. Early reports already indicated that during television commercials, eyes-on-screen, a metric of commercial contact, declined by 47%, with only 7% of the consumers giving ads total attention and 53% reporting divided attention (Krugman et al. 1995). Currently, about 17% of US households are estimated to have DVRs (Steinberg and Hampp 2007) and around 87% skip past ads frequently (Grover and Fine 2006), and these numbers are growing. In addition, the networks have been imposing hefty price increases for ads by raising their per-viewer rates 110% in ten years, despite declines in prime-time audiences of up to 30% (Woolley 2003). Jointly, this leads to inefficiencies in marketing expenditures, increasing costs per viewer, and potential erosions of brand equity. It urges brand and advertising managers to understand

the determinants of commercial avoidance and how to best retain consumers' attention from moment-to-moment during television commercials, in order to optimize brand (the audio-visual representation of it) exposure. This is the focus of the current study.

Specifically, the present research examines the influence that branding in television advertising and consumers' attention have on commercial avoidance. This essay makes three contributions. First, it provides a conceptual framework for understanding the impact that patterns of branding activity have on their avoidance decisions from moment-to-moment during television advertising. It formalizes this in a Dynamic Probit Model, which is estimated with MCMC methods. Data on commercial avoidance along with eye-tracking on 31 commercials for nearly 2000 participants are used to calibrate the model. Second, it proposes new, simple metrics of consumers' attention dispersion based on eye-tracking data and shows that these systematically predict commercial avoidance from moment-to-moment. Third, based on the model estimations, it optimizes branding activity for the sample of ads in question to reduce commercial avoidance. This demonstrates the significant reductions in commercial avoidance that can be attained by changing the pattern of branding activity by using pulsing strategies consisting of repeated brief brand insertions. A controlled lab experiment in which commercials are edited based on the recommendations that follow from the model estimations provides further evidence for the benefits of brand pulsing to ward off commercial avoidance.

Branding and Attention Effects

Branding in Commercials

Branding activity is the way in which brand identity symbols (name, logo, typeface, trademark or pack shot) are present at each moment and across time in the commercial. This activity determines the prominence or conspicuity of the brand in commercials, that is, the extent to which it stands out from other objects and endures in the ad scenes, based on general rules of perception (Palmer 1999). At each moment during the commercial, the brand is more prominent to the extent that it appears larger (versus smaller), more central (versus peripheral) and more separated from its background (versus embedded) visually (Janiszewski 1998, Wedel and Pieters 2000), and simultaneously supported by audio (Bryce and Yalch 1993). Prominence is enduring to the extent that the brand appears more (versus less) frequently and longer (versus shorter) during the commercial.

For consumers, such activity entails important information because the brand helps to comprehend ads and learn from them. Once the brand is identified, consumers can call upon their own personal experiences and memories to establish a context for the ad and its message. For management, branding in commercials is an important decision variable, because of advertising's intended contribution to sales and brand equity. Branding activity is also a source of debate in advertising theory and between marketers and ad agencies, who are trying to balance sales, creativity and other objectives. Some recommend small, unintrusive (Aitchinson 1999) and others large, intrusive branding (Book and Schick 1997). Likewise, there are recommendations to place the brand as early as possible in commercials (Baker et al. 2004, Stewart and Furse 1986), late (Fazio et al. 1992) or early-and-late (Stewart and Koslow 1989).

There is evidence that under conditions of forced exposure--when consumers cannot avoid watching the commercials--early (Baker et al. 2004) and late (Fazio et al. 1992), more frequent and longer branding (Stewart and Furse 1986) can improve comprehension, recall and persuasion. Also, under forced exposure, video-transmitted content is much better learned than the same content in audio, resulting in an 8-to-1 advantage in recall tests after a single exposure (Bryce and Yalch 1993). However, in practice consumers do have increasing control over commercial exposure, which is important. When consumers stop watching commercials before they naturally end, later branding activity in the commercial cannot have the beneficial effects that have been reported for forced exposure conditions. What if one of the main objectives for advertisers investing heavily in commercials, namely to expose the brand, is related to the consumer's decision to continue or stop watching the commercial? I am not aware of research that has examined the influence of the moment-to-moment prominence of brands, such as due to their size and centrality, on commercial avoidance in television commercials. If and how branding activity in commercials impacts consumers' moment-to-moment avoidance decisions remains as yet largely unknown, and the purpose is to shed further light on this issue.

Television commercials are narratives aimed to convey the brand message and at the same time entertain and retain consumers. Because brands convey information, their prominent presence in television commercials is liable to increasing the likelihood of commercial avoidance due to information overload (Woltman Elpers et al. 2003). Moreover, increased levels of branding activity decrease the "soft sell" and increase the "hard sell" character of commercials, and people generally resist the forceful persuasion

that comes with the hard sell (Aaker and Bruzzone 1985, Greyser 1973). Therefore, I predict that higher intensities of branding activity increase the likelihood of avoidance at each moment during the commercial, and establish the contribution that the momentary (size, separation and centrality) and dynamic (frequency and duration) characteristics of branding activity have on this likelihood. Brands carry associations idiosyncratic to each consumer and these certainly should play a role in their avoidance decisions. But, I focus on systematic effects across all consumer-brand dyads and commercial contexts, that may contribute to self-controlled termination of exposure (i.e. zapping) due to very salient branding. In determining these branding effects, it is important to control for factors that may independently affect moment-to-moment commercial avoidance decisions.

Attention Concentration by Commercials

Similar to the visual arts, advertising tries to focus and direct viewers' attention. It aims to point attention to certain parts of the depicted scene, and direct it across scenes in an orchestrated fashion to let the intended narrative unfold. I propose that to the extent that commercials are able to concentrate consumers' attention they are better able to retain them behaviorally as well, thus preventing commercial avoidance. This is consistent with art-theory's (Arnheim 1988) emphasis on "centers of gravity" that concentrate the viewer's eyes on the essentials in paintings, statues or buildings, and with speculations in advertising (Heeter and Greenberg 1985, Perse 1998) that viewers with less focused attention do not actively follow the ad script and may decide to zap away. In the words of Gustafson and Siddarth (2007, p. 587), "...a reasonable hypothesis is that all zaps are associated with looks that have ended, although all completed looks will not end in a zap."

In aesthetic psychology, Berlyne (1971) distinguished two types of visual attention that an individual viewer can express during perception of artful stimuli, termed specific and diversive exploration, and speculated that each would be reflected in distinct patterns of eye fixations (moments that the eye is relatively still and focused on a specific location in space). Specific exploration would lead to concentrated eye fixations on precise locations of the visual scene to seek out detailed information. Diverse exploration would lead to dispersed eye-fixations across larger regions of the scene to search for new stimulation or grasp the gist. Then, to the extent that commercials are successful in focusing and conducting attention, eye-fixations of consumers at each moment across the duration of the commercial will be more concentrated at specific locations. Such a dense pattern of eye-fixations would reflect desirable bottom-up control of consumers' focal attention by characteristics of the commercial. I predict that under such conditions of concentrated attention--with all consumers held together by the commercial--the likelihood of commercial avoidance will be low.

Conversely, dispersed patterns of eye-fixations reflect a lack of bottom-up control due to overriding effects of consumers' goals or tendencies to freely explore the scene. For instance, in an early eye-tracking study with a single participant viewing a painting, Yarbus (1967) observed that specific task instructions led to widely different locations on which the participant focused the eye, and that eye-fixations were most dispersed under a free viewing instruction. Working with print advertising, Pieters and Wedel (2007) found that goals, as specific instances of top-down factors (residing in the consumer), induced distinct spatial attention patterns. Thus, the more that idiosyncratic personal factors dominate attention, the more dispersed the aggregate eye-fixations across commercials

will be. I predict that under such conditions of dominant top-down and limited bottom-up control of attention by the commercial, as expressed in dispersed eye-fixation patterns of consumers, the likelihood of commercial avoidance will be high.

Not only should aggregate patterns of attention dispersion across consumers be predictive of commercial avoidance, but patterns of individual consumers should do so as well. That is, when television commercials successfully concentrate focal attention of most consumers as a group, but fail to do so for a specific consumer--who wanders off from the virtual flock--the likelihood that this consumer avoids the commercial will be high.

FIGURE I.1: Attention concentration and commercial avoidance

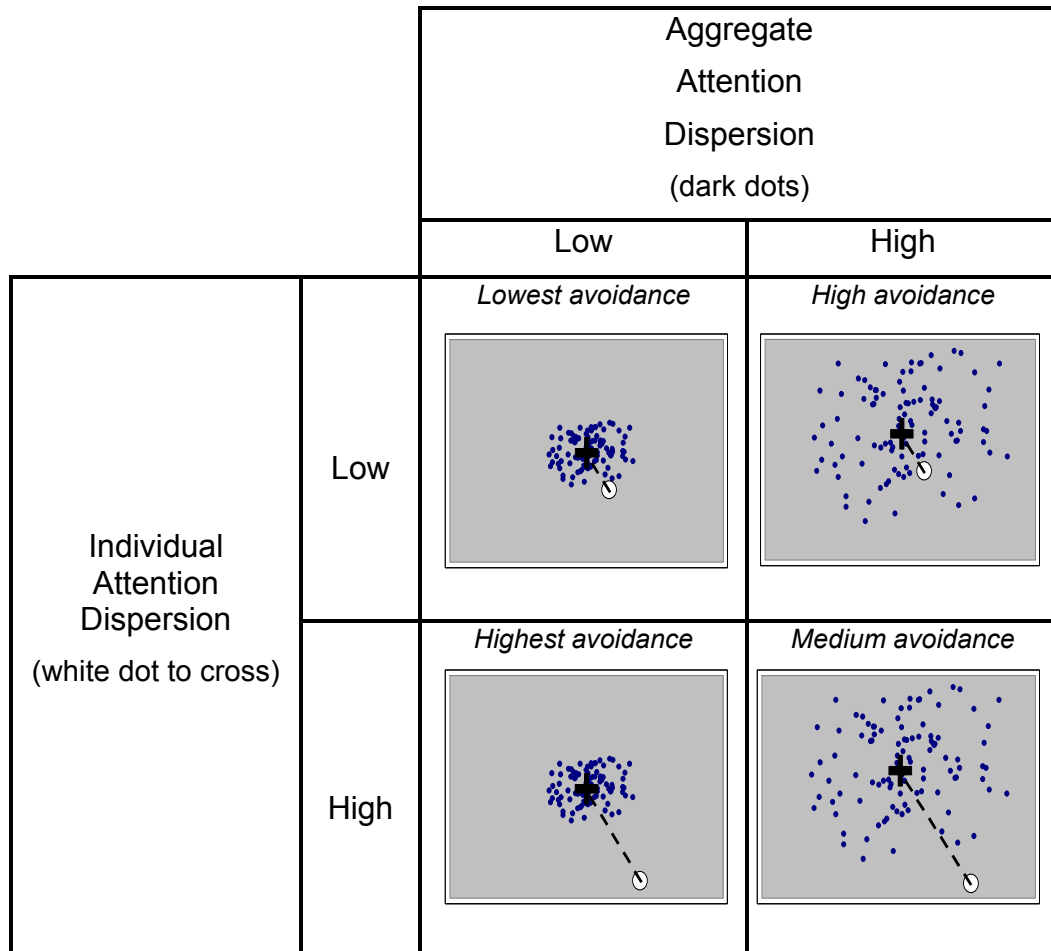


Figure 1 summarizes my predictions about the influence of aggregate and individual dispersion versus concentration of focal attention on commercial avoidance. It indicates that the less concentrated (i.e., more dispersed) the aggregate focal attention of consumers is, the higher the likelihood of commercial avoidance is expected to be. Also, the less concentrated (i.e., more dispersed) the focal attention of an individual consumer relative to the other consumers is, the higher the likelihood of avoidance by this consumer is expected to be. I predict an interaction effect between aggregate and individual attention dispersion, such that avoidance is expected to be highest when a consumer's attention is dispersed from all other consumers who among themselves have a concentrated pattern of focal attention (lower left cell of Figure 1). Then, the commercial is successful in concentrating the attention of most but not the single individual, who wanders off and leaves. These measures of attention dispersion capture the extent to which the creative content of commercials is successful in focusing and retaining consumers.

In establishing the net contribution of branding activity on commercial avoidance, I therefore account for these consumers' attention dispersion patterns. If I were to find that attention dispersion predicts commercial avoidance independent of branding activity, this would be strong evidence for the central function that attention guidance by the creative content of commercials plays in ad effectiveness. To assess the branding and attention effects appropriately, other ad, brand and person characteristics need to be controlled for. I focus on potentially important, objective ad characteristics that may co-vary moment-to-moment with branding, attention and baseline zapping levels.

Controlling for Ad, Brand and Person Effects

Film, television and advertising producers tailor the visual complexity of commercials and other video stimuli to engage viewers and prevent them from channel switching (Lang et al. 2005). The overall visual complexity of commercials at any point in time is jointly determined by the amount of visual material in separate scenes (momentary), and by the pacing of scenes across the commercial (dynamic) (Germeys and d'Ydewalle 2007). Visual complexity refers to all non-representational perceptual material, such as different colors, lines, luminance contrasts, in the commercial with more material increasing the visual complexity (Donderi 2006). Pacing indicates the speed at which different scenes are presented in dynamic stimuli (Lang 2000). Pacing is reflected in discontinuities in the video stream and accomplished by cuts and edits (Bolls et al. 2003, Germeys and d'Ydewalle 2007, Lang 2000), with more cuts and edits increasing the pace.

Visual complexity of images can influence ease of perception, memory, attitudes (Bolls et al. 2003, Germeys and d'Ydewalle 2007, Lang et al. 2005, Pavelchak et al. 1991, d'Ydewalle et al. 1998) and perhaps avoidance decisions. That is, at low levels of visual complexity, commercials may be insufficiently engaging and challenging whereas at high levels they may be too arousing and demanding. Therefore, I expect a Yerkes and Dodson (1908) type of U-shaped relationship between the amount of visual complexity in scenes and the likelihood of commercial avoidance at each moment during the commercial, with the lowest avoidance likelihood at intermediate complexity levels, and the highest levels at the low and high ends of the complexity spectrum (in fact, the original curve is an inverted-U with performance being highest at intermediate levels, which translate into avoidance being lowest at those levels here). Berlyne (1971)

observed a similar pattern in research on the appreciation of paintings varying in levels of visual complexity, which has been replicated for other stationary stimuli as well (Donderi 2006). I extend this by studying avoidance decisions for dynamic visual stimuli.

In addition, in the empirical study, product category, hedonic versus utilitarian, and brand familiarity, low versus high, are controlled for (Pieters and Wedel 2004). Finally, two demographic factors, gender and age, are controlled for, based on findings that males compared to females, and younger compared to older consumers generally zap more (Cronin 1995, Heeter and Greenberg 1985).

In sum, I predict that, while controlling for ad, brand and person characteristics, branding activity in commercials and attention dispersion of consumers jointly influence the moment-to-moment commercial avoidance decisions of consumers. Before specifying the analytic model that allows me to examine specific branding effects in detail, the data on which it is calibrated are described.

Data

Stimuli and Participants

The data for this research were collected by the marketing research company Verify International (Rotterdam, the Netherlands). A sample of 31 regular, newly aired commercials of 25, 30 and 35 seconds were selected. They featured known (Citroen, T-Mobile) and unknown (Radio 538, KWF), national (Albert Hein, Unox) and international (Mastercard, Kodak) brands, from a variety of different product categories (food, durables, public and services, electronics, telecom, clothing), with utilitarian (checking

account) and hedonic (chocolate) purchase motivations. By selecting newly aired commercials, the chances that participants had been exposed to the commercials before are minimized.

Participants were a random sample of 1998 regular television viewers (age 20 to 62, 48% male), consumers of the advertised products, who were paid for participation. Their demographics matched those of the target population. Although all participants watched a long reel of commercials, the data available to me had a maximum of four television commercials per person. On average, each commercial was watched by 111 participants.

Data Collection

Data collection took place at the facilities of the company. Upon entering, participants were led to a non-distracting room and seated in a comfortable chair at approximately 55 cm distance of a 21-inch LCD monitor, with a 1280 x 1024 pixel resolution. The instruction on the screen asked people to watch the commercials, and to stop watching any commercial at any time by zapping. Immediately after zapping a commercial or after it ended without the participant zapping, the next commercial in the sequence appeared. The order of the commercials was randomized across participants to control for serial-position effects. Filler ads were shown between the target ads but no program content was shown, because the study focuses on commercial avoidance, not on channel switching, surfing or grazing (Cronin 1995, Tse and Lee 2001). This experimental setup mimics the common situation of “road-blocking”, in which blocks of commercials are aired at the same time on different channels, so that consumers zapping away from one commercial zap into another one. These avoidance rates are higher than

in similar reports (Krugman et al 1995, Siddarth and Chattopadhyay 1998), but lower than other more recent ones (e.g. Tse and Lee 2001) and reported on current DVR usage patterns (Wilbur 2008).

Infrared corneal-reflection eye-tracking methodology was used to record the focal positions of the viewer's right eye, in an X and Y coordinate system (Duchowski 2003). The method is non-obtrusive to the participant, allowing for head movements within normal boundaries (about 30 x 30 x 30 cm) while facing the television screen. Spatial precision of data collection was 0.5 degrees of visual angle at a sampling rate of 20 ms (50 Hz). To match them to the frequency of standard video frame presentation, the data were combined into 40 ms frames, which results in an average of 750 consecutive frames (moments) for every 30 second commercial.

Measures

Commercial avoidance. The dependent variable constitutes of every recorded avoidance decision, when a participant chooses to stop watching a particular commercial by pushing the button (1 = avoid, 0 = else). The dependent variable is a binary cross-sectional (consumers) repeated measures (ads) time-series, because I have decisions to zap or not for 31 distinct television commercials, each of a maximum of 750 ad frames, for a total of 1998 consumers. That is, I have unbalanced panel data, truncated at each zapping incidence.

Branding activity. Branding activity (name, logo, typeface, trademark or pack shot) was recorded semi-automatically by means of specialized video manipulation/editing software for each frame of a commercial. I identified the brand's (a) presence, (b) size, (c) position, (d) separation, and (e) mode per frame as stationary

characteristics, and its (f) cardinality and (g) duration across frames as dynamic characteristics, as defined next.

“Presence” indicates whether the brand is on screen (1) or not (0) during a particular frame. “Size” is the proportion of the screen, in square pixels, occupied by the smallest rectangle enveloping the brand at each frame, and is zero when the brand is absent (Pieters and Wedel 2004). “Position” indicates whether the brand takes a central (1) or peripheral (0) position on the screen. For this, an imaginary rectangle with the same 4:5 aspect ratio as the 21 inch LCD monitor was defined such that the length of the longest dimension is equal to the viewing angle of the parafoveal field of the eye: 5° from a central axis, to the left and to the right (Duchowski 2003, Rayner 1998). The brand is central if the rectangle boundary to define brand size intersects with the parafoveal rectangle (above) in the center of the LCD screen, and it is peripheral otherwise.

“Separation” indicates whether the brand is well-separated from its background (1) or not, for instance because it is competing with other scene objects or occluded by them (Janiszewski 1998). “Mode” indicates whether the brand was additionally present (1) in audio mode or not (0) in a particular frame. “Cardinality” captures how many times a brand appears non-consecutively in video mode during a specific commercial up to that point, from the first (1) to last (n) brand appearance. Finally, “Duration” indicates how long in seconds a brand with the same cardinality was present consecutively in video mode up to that point.

Control Variables. The level of “Visual complexity” in consecutive frames of the commercial was assessed by the file size in kilobytes of the GIF-compressed image, as in recent, similar applications (Calvo and Lang 2004, Sprott et al. 2002). Compression

algorithms, such as for the GIF, JPG, PDF formats, have been developed in computer vision research to enable different hardware and software to use the same data. To the extent that the visual images contain little visual detail, color, contrast, and contain many redundancies, the algorithms cause larger compressions (Sprott et al. 2002). This makes file size a suitable general measure of the visual complexity of images. In support, research has found the file size of images such as charts, web images and photos to correlate highly and significantly (0.82) with human judgments of visual complexity (Calvo and Lang 2004, Donderi 2006). “Pacing” was measured by the presence of cuts and edits (1) versus not (0) in each frame of the commercials using video editing software. Cuts are due to changing camera positions between scenes, and edits due to changing camera positions within scenes, and both increase complexity, because viewers need to integrate the visual information across discontinuities¹. Cuts and edits have larger complexity effects than more subtle production choices such as zooms and camera moves (Lang et al. 2000).

Information about the gender (1 = male, 0 = female) and age (years) was available from company records. Brand familiarity (familiar = 1, unfamiliar = 0) and product category (utilitarian = 1, hedonic = 0) were coded by two independent judges (initial agreement 96% for brand and 78% for product, with disagreements resolved by discussion).

Data Aggregation

Data processing and analysis is challenging with 750 frames for each of 31 commercials for which eye-movement data are available for a total of 1998 consumers.

¹ Brand appearances (i.e. changes in cardinality) do not necessarily reflect a discontinuity or pace change. They will if the brand appears simultaneously with a change of a scene, but this need not be the case.

To strike a balance between keeping the analysis task manageable and retaining sufficient detail, I averaged the eye movement data to intervals of approximately 240 ms (4.17 Hz) for the 30 seconds ads. In this interval, an eye-fixation and zapping decision can be made (Calvo and Lang 2004, Rayner 1998). The aggregation in 240 ms intervals makes it possible for participants to see the brand and react by zapping within the same interval². For example Mihaylova et al (1999), find (key-press) reaction times in response to visual stimuli ranging from 116-234 ms, depending on the participant and stimulus. The interval is also shorter than the typical interval between pacing events (Germeys and d’Ydewalle 2007) and non-consecutive brands. The aggregation led to a total of 125 frames. To equate 25 and 35 second ads with 30 second ads, I use similar procedures by lowering sampling rates to 5 and 3.57 Hz, respectively, with the differences being perceptually undistinguishable. Frame lengths are chosen to be uniform across all commercials; not doing so would make it difficult to link the frame images to exact fixation points of the eye-tracking data.

Model

I assume that an individual’s decision to continue watching a specific commercial at time point t or to avoid it is based on the (negative) utility derived up to that time point from the commercial:

$$U_{ict}^{\text{avoid}} = D_{ict}^{\text{avoid}} + \varepsilon_{ict}^{\text{avoid}}, \text{ with } \varepsilon_{ict}^{\text{avoid}} \sim N(0,1) \quad (1)$$

where i is individual, c is commercial and t is time-frame of the ad. The variance of the

² I test this in the empirical application.

error term is fixed to 1 for identification since utility is defined up to a scale factor. Thus the probability that individual i avoids commercial c at time-frame t , given parameters Θ_t , is:

$$P(y_{ict} = 1 | \Theta_t) = \Phi(D_{ict})$$

$$\text{where: } y_t = \begin{cases} 1 \rightarrow \text{avoid at frame } t \\ 0 \rightarrow \text{watch at frame } t \end{cases} \quad (2)$$

Five terms make up the deterministic component of the utility (D_{ict}):

$$D_{ict}^{avoid} = \mu_i + \alpha_c + B_{ct} + \left(\gamma^1 \overline{AAD}_{ct} + \gamma^2 IAD_{ict} + \gamma^3 \overline{AAD}_{ct} \times IAD_{ict} \right) + TVC_{ct}. \quad (3)$$

The time-constant intercepts μ_i and α_c are estimated for each individual and commercial, respectively, and are a linear function of individual-specific demographics (age and gender), and brand familiarity and product category (utilitarian or hedonic), respectively. This specification is parsimonious given the large number of individuals and commercials and is similar to Gustafson and Siddarth (2007). Details are in appendix 1.

The branding effects B_{ct} are commercial and time-specific (to simplify notation, I suppress subscripts c in equation 4) and are specified as:

$$B_t = \theta_t^1 \text{Presence}_t + \theta_t^2 \text{Cardinality}_t + \theta_t^3 \text{Duration}_t + \theta_t^4 \text{Size}_t + \theta_t^5 \text{Mode}_t + \theta_t^6 \text{Position}_t + \theta_t^7 \text{Separation}_t,$$

$$\text{with } \tilde{\theta}_t = \Xi + G\tilde{\theta}_{t-1} + \omega_t, \text{ and } \tilde{\theta}_t = (\theta_t^1, \theta_t^2, \theta_t^3, \theta_t^4) \quad (4)$$

Because branding activity may build up irritation over the exposure to the commercial if it becomes too intrusive (presence, separation and size of brand) and enduring (cardinality and duration) (Aaker and Bruzzone 1985, Greyser 1973), the parameters capturing the effects of these branding variables are specified to be time dependent, $\tilde{\theta}_t$. I specify only the branding effects to vary over time to keep the model

parsimonious, and because I find no theory predicting that the effects of the other variables should be time-varying. Factors that affect the dynamics of attention to TV commercials “have generally been ignored by previous research on advertising, even though recent research has established that consumers’ real-time response to a commercial vary significantly over the time of its airing” (Gustafson and Siddarth 2007). I believe brands to be one of such factors. Consequently, time-varying parameters of brand presence allow the effect of a 1-second of brand exposure in the beginning of an ad to be different from when the viewer has potentially seen more of the brands towards the end of the ad.

The fourth term (in parenthesis) in equation 3 reflects the attention dispersion of consumers in each time-frame. This is not a direct factor affecting the consumer’s utility function but, being a process measure, can be regarded as a proxy for the disutility of distracting features. I have the eye fixation (f_{ict}) for individual i and commercial c at time frame t , in x - y pixel coordinates. Extending ideas of Germeys and d’Ydewalle (2007), I propose the variance of f_{ict} as a measure of aggregate attention dispersion (AAD_{ct}) across consumers i for each commercial c at time-frame t . Attention concentration is at a maximum when all eye fixations are on exactly the same screen pixel ($AAD = 0$), and decreases when eye-fixations become more spatially dispersed. In addition, I propose the squared Euclidian distance between an individual’s eye-fixation and the centroid of eye-fixations for all other consumers as a measure of individual attention dispersion (IAD_{ict}) for each consumer i , commercial c and time-frame t . In this definition I implicitly assume that the centroid is on average (across all ad frames) indicative of the desired location of focus of attention. IAD_{ict} ranges from 0 to 2686976 ($1280^2 + 1024^2$). Thus, I have:

$$\begin{aligned} \text{Individual Attention Dispersion : } IAD_{ict} &= \left(f_{ict} - \frac{1}{N} \sum_{i=1}^N f_{ict} \right) \left(f_{ict} - \frac{1}{N} \sum_{i=1}^N f_{ict} \right), \\ \text{Aggregate Attention Dispersion : } AAD_{ct} &= \frac{1}{N} \sum_{i=1}^N IAD_{ict} \end{aligned} \quad (5)$$

The parameters γ^1 , γ^2 and γ^3 (eq. 3) capture the effects of these attention dispersion measures and their interaction. The final term TVC_{ct} in equation (3) captures the effect of the total visual complexity of commercial c at time-frame t . The visual complexity effects are specified in equation (6). For every time-frame, I define visual complexity to be the sum of the consecutive image complexities ($IC_{ct} + IC_{ct-1}$) in the event of an edit or cut ($Pacing_{ct} = 1$) or the image complexity of the current frame otherwise ($Pacing_{ct} = 0$). This is in line with the viewer's perception effort when integrating images that are completely changing or not. The quadratic term of visual complexity allows for a U-shaped effect on avoidance likelihood. Finally, $PaceType$ is a dummy variable indicating a cut (=1) or edit (=0).

$$\begin{aligned} TVC_{ct} &= \beta^0 PaceType + \beta^1 (VC_{ct}) + \beta^2 (VC_{ct})^2, \text{ with} \\ VC_{ct} &= IC_{ct} + Pacing_{ct} \cdot IC_{ct-1} \end{aligned} \quad (6)$$

To summarize, the model describes commercial avoidance as a utility-based decision that is made on a moment-to-moment basis. It specifies specific branding parameters to be time-varying to allow for the evolution of their effects. It accounts for observable individual and commercial heterogeneity partially by the eye-tracking data and by covariates, and for other unobserved sources of heterogeneity, by assuming normal distributions of all parameters.

Estimation Procedure and Inferences

Dynamic Linear Models have been used in advertisement contexts with similar dynamics (Bass et al. 2007; Naik et al. 1998). Here, I develop a Dynamic Probit Model (Gamerman 1998; West and Harrison 1997), by rewriting equations (1) through (6) in a State Space formulation as in equation (7).

$$\begin{aligned} f(Y_t) &= F_t \Theta_t + \varepsilon_t, \\ \Theta_t &= G \Theta_{t-1} + \omega_t \end{aligned} \quad (7)$$

Y is the commercial avoidance indicator variable; f is the probit link function;

$\Theta_t = \{\mu_i, \alpha_c, \tilde{\theta}_t, \theta^5, \theta^6, \theta^7, \beta^0, \beta^1, \beta^2, \gamma^1, \gamma^2, \gamma^3\}$ is the vector of parameters previously defined; F_t is the vector of covariates, blocked by time-varying and invariant ones; G is the evolution matrix of the time-varying parameters; ε, ω are independently distributed with contemporaneously independent time-varying error terms. I specify the evolution matrix, $G = I$, so that Θ_t follows a random walk, which strikes a balance between sequential independence and time-invariance (Martin and Quinn 2002).

I use a MCMC Gibbs sampling in blocks given the HB structure of the model (Billio et al. 2007, Gamerman 1998), using the Forward Filtering Backward Sampling algorithm (Carter and Kohn 1994, Frühwirth-Schnatter 1994). In essence, the estimation is done by drawing the latent values for utilities for all i, c and t , by drawing from a truncated Normal distribution and then proceeding with sampling the remainder of the parameters using the draws of the latent utilities. The MCMC chains are run for 60,000 iterations on 1998 viewers, 31 commercials, and a maximum of 125 time-frames, totaling 293k observations. The posterior distributions of the parameters of 1750 draws were extracted, thinning 1 in 5 draws, after a burn-in period of 51,250. Starting values were obtained from the maximum likelihood parameter estimates from an ordinary Probit model.

Details of the estimation are provided in Appendix 1. Analysis of synthetic data with the MCMC algorithm shows good recovery of all true parameter values (Appendix 2). Convergence of Gibbs sampler was checked through visual inspection of likelihood and diagnostic plots for key model parameters.

Results

Sample Statistics and Model Comparisons

Table 1 provides sample statistics for the 17 independent variables. All independent variables were standardized before analysis to facilitate comparison of parameter estimates³. The condition number of the X-matrix was 3.02. With the exception of the Visual Complexity (VC and VC² were orthogonalized via Gram-Schmidt), all other independent variables have VIF < 10, which indicates that collinearity is not a significant problem (Kutner et al. 2004). Contrary to an assumed high collinearity between IAD and AAD, given that they are functionally tied together, their correlation is only 0.12 in the dataset. This correlation is expected to increase if the number of individual is reduced. For 2000 individuals, it is not a problem.

To examine the contribution of sets of explanatory variables, I first compared the full model to four nested models, using the log-marginal density, LMD. I estimated the LMD using Chib's (1995) method, which requires running several additional reduced chains after the original MCMC chain, but is more appropriate than using the harmonic mean estimator. The results are in Table 2.

³ For each covariate the mean was subtracted and it was divided by their standard deviation. The interaction and squared terms were first computed and then standardized to facilitate comparison of effect sizes.

Model 1 is the benchmark containing only the demographics and brand familiarity and product category type. Model 2 includes the visual complexity measures in addition to the variables in Model 1, and it outperforms this as shown by the higher LMD. Model 3 includes the attention dispersion variables in addition to the variables in Model 2, and it outperforms the latter. In Model 4 the branding activity variables are added to Model 2, and it outperforms that model. Model 5 includes all variables, but no unobserved heterogeneity and no dynamic effects. Its LMD is worse than that of all other models, except for model 1. Model 6 includes all variables, as well as unobserved commercial and individual heterogeneity, but no dynamic effects. It performs better than Models 1 and 5, but worse than all other models. Finally, the full Model 7 clearly performed best amongst all models in terms of the LMD. It predicts commercial avoidance with an average absolute error of only 6.5% across the 31 commercials.

The model comparisons reveal that all sets of variables as well as heterogeneity and dynamics contribute significantly to predicting commercial avoidance, and that branding effects contribute significantly to predicting commercial avoidance even when all other effects are accounted for (Model 7 versus Model 3). Likewise, the attention dispersion measures contribute significantly to predicting commercial avoidance, even when all other effects are accounted for (Model 7 versus Model 4). Finally, even when all explanatory variables are included, including dynamic effects contributes significantly to predicting commercial avoidance (Model 7 versus Model 6)⁴.

⁴ To assess whether there is a significant delay in zapping reaction, I also tested different models with lagged effects of dynamic brand features on zapping. Fit as measured by Log Marginal Density is highest for a contemporaneous Dynamic Probit Model (LMD: -9533) as opposed to models with lags (e.g. Lag 1: -9597 or Lag 2: -9572; I deleted the first 2 observations for each commercial, needed to initialize the lags, to make the LMDs comparable).

TABLE I.1: Summary of the independent variables

Variable	Variation across units	Mean	Std. Dev.	Minimum	Maximum
<u>Branding activity:</u>					
Presence (present = 1)	ad, time	22%	41.2%	0	1
Size (% of screen)	ad, time	2.9%	8.8%	0.1%	61.5%
Position (central = 1)	ad, time	13.9%	34.5%	0	1
Separation (separated = 1)	ad, time	89.1%	31.2%	0	1
Mode (audio = 1)	ad, time	3.2%	17.5%	0	1
Cardinality (1, 2,...)	ad, time	0.79	1.33	0	6
Duration (seconds)	ad, time	1.89	3.62	0	30
<u>Attention Dispersion:</u>					
Aggregate Dispersion (pixels ²)	ad, time	104212	486780	2434	7311820
Individual Dispersion (pixels ²)	ad, time, indiv.	147	289	0	27478
Aggregate × Indiv. Dispersion	ad, time, indiv.	32256972	1.2E+09	0	1.0E+11
<u>Control variables:</u>					
Age (years)	individual	38.3	10.9	20	62
Gender (male = 1)	individual	48.3%	50.0%	0	1
Brand familiarity (familiar = 1)	ad	89.8%	30.3%	0	1
Product category (utilitarian = 1)	ad	60.0%	49.0%	0	1
Pacing type* (cut = 1)	ad, time	44.4%	49.7%	0	1
Visual complexity (Kbytes)	ad, time	180	69	2	662
Visual complexity ²	ad, time	37156	32628	4	438244

*Conditional on a camera shot change.

TABLE I.2: Model comparisons 1

Model	Model Components Included						LML
	Demographics, product-brand	Visual Complexity	Attention Dispersion	Branding Activity	Heterogeneity	Dynamics	
1	Yes	No	No	No	Yes	No	-11231
2	Yes	Yes	No	No	Yes	No	-10021
3	Yes	Yes	Yes	No	Yes	No	-9966
4	Yes	Yes	No	Yes	Yes	Yes	-9690
5	Yes	Yes	Yes	Yes	No	No	-10909
6	Yes	Yes	Yes	Yes	Yes	No	-10237
7	Yes	Yes	Yes	Yes	Yes	Yes	-9639

Determinants of Commercial Avoidance

Table 4 provides the mean, standard error and main percentiles of the posterior distributions from the MCMC draws for the full Model 7. As benchmarks, the estimates of models 6 (the static HB probit) and 5 (the static probit) are also provided in table 3. I will not discuss the parameter estimates of these models here, but it suffices to note that the estimated effects of several of the branding activity variables are different from the full Model 7 (the implications of some of the differences will be pointed out below).

In support of my hypotheses, branding activity had significant effects on the moment-to-moment decision to continue or stop watching the commercial. Specifically, the presence of a brand, independent of the other branding variables, significantly increased the probability to stop watching the commercial (posterior mean estimate = 0.335). Also, when the brand appeared more central and well-separated from the rest of the scene, and later and longer in the commercial (for some periods) the probability to stop watching the commercial increased as well. The size of the brand did not have an

independent effect once the other branding and all other effects were accounted for. Yet, when brands were simultaneously present in audio mode, as opposed to just video or no brand, probabilities to avoid the commercial decreased marginally.

TABLE I.3: Model comparisons 2

Parameter	Dynamic HB Probit (7)		Static HB Probit (6)		Static Probit (5)	
	Mean	SE	Mean	SE	Mean	SE
LMD	-9639		-10237		-10909	
Intercept ¹	-2.602**	0.082	-2.577**	0.022	-2.548**	0.010
Presence ¹	0.092**	0.045	0.096**	0.011	0.091**	0.011
Cardinality ¹	-0.013 ⁺	0.041	0.024**	0.012	-0.003	0.010
Duration ¹	0.040 ⁺	0.039	0.024**	0.013	0.015	0.009
Size ¹	-0.030	0.051	0.005	0.012	-0.007	0.010
Mode (plus audio=1)	-0.011*	0.009	-0.012	0.090	-0.010	0.008
Position (central=1)	0.033**	0.011	0.023**	0.010	0.020*	0.009
Competing (nested=1)	-0.014*	0.010	-0.014*	0.010	-0.023**	0.008
Pace type (cut=1)	0.000	0.010	-0.019	0.009	-0.016*	0.009
Scene Complexity	-0.008	0.011	-0.012	0.011	0.000	0.009
Scene Complexity ²	0.088**	0.033	0.068**	0.031	0.018	0.026
Indv. Dispersion	0.199**	0.011	0.203**	0.011	0.202**	0.014
Aggreg. Dispersion	0.055**	0.021	0.071**	0.018	0.109**	0.024
Indiv.*Aggreg Disper.	-1.249**	0.108	-1.414**	0.096	-1.910**	0.298
Age	-0.003	0.012	-0.002	0.011	-0.003	0.008
Gender (male=1)	0.020**	0.011	0.018**	0.011	0.017**	0.008
Brand familiarity (f=1)	0.001	0.030	-0.010	0.028	-0.017*	0.009
Product category (u=1)	0.037	0.030	0.042*	0.029	0.067**	0.010

Note: ** indicates 95% posterior confidence interval doesn't contain zero; * indicates 90% confidence interval doesn't contain zero; ⁺ indicates 90% posterior confidence interval doesn't contain zero for some time periods. ¹ indicates parameter estimates were averaged in time in model 7 to compare with models 5,6;

In support of my predictions, consumers' attention dispersion strongly predicted the probability to stop viewing the commercials, over and above the effects of all other variables. Specifically, at each moment, a commercial's failure to concentrate all consumers' attention simultaneously increased consumers' probability to stop viewing the commercial. Also, consumers who fail to look where all other consumers concentrate their attention have a higher probability to stop viewing the commercial. The probability

TABLE I.4: Determinants of commercial avoidance

Parameter	Mean	SE	Percentiles of the Posterior Distribution				
			5%	10%	50%	90%	95%
Intercept (t = 0)	-3.641**	0.219	-4.004	-3.925	-3.622	-3.376	-3.301
<u>Branding activity:</u>							
Presence (t = 0)	0.335**	0.099	0.174	0.212	0.332	0.465	0.507
Size (t = 0)	-0.001	0.115	-0.200	-0.147	0.001	0.143	0.189
Position (central = 1)	0.033**	0.009	0.016	0.019	0.033	0.046	0.050
Separation (separated = 1)	0.014*	0.011	-0.005	0.000	0.014	0.026	0.029
Mode (audio = 1)	-0.011*	0.010	-0.027	-0.023	-0.011	-0.000	0.003
Cardinality (t = 0)	0.014 ⁺	0.097	-0.144	-0.109	0.011	0.139	0.186
Duration (t = 0)	0.085 ⁺	0.096	-0.070	-0.035	0.082	0.207	0.249
<u>Attention Dispersion</u>							
Aggregate Dispersion	0.055**	0.021	0.013	0.027	0.057	0.078	0.085
Individual Dispersion	0.199**	0.011	0.181	0.185	0.200	0.214	0.218
Aggregate × Indiv. Disp.	-1.249**	0.108	-1.377	-1.355	-1.284	-1.054	-1.038
<u>Control variables:</u>							
Age	-0.003	0.012	-0.023	-0.019	-0.004	0.013	0.017
Gender (male = 1)	0.020**	0.011	0.001	0.005	0.021	0.035	0.039
Brand familiarity (f = 1)	0.001	0.030	-0.047	-0.035	0.000	0.039	0.053
Product category (u = 1)	0.037	0.030	-0.012	-0.001	0.037	0.075	0.087
Pacing type (cut = 1)	0.000	0.010	-0.018	-0.014	0.000	0.014	0.017
Visual complexity	-0.008	0.011	-0.027	-0.023	-0.008	0.005	0.009
Visual complexity ²	0.088**	0.033	0.033	0.046	0.089	0.128	0.140

Note: ** indicates 95% posterior confidence interval doesn't contain zero; * indicates 90% confidence interval doesn't contain zero; ⁺ indicates 90% posterior confidence interval doesn't contain zero for some time periods.

to stop viewing was lowest when consumers on the aggregate, and each of them individually, concentrated their attention on the same locations in the commercial. This reveals the importance that the attention concentration power of commercials has frame-for-frame in retaining consumers. As predicted for the interaction of IAD and AAD, in particular when IAD is high and AAD is low commercial avoidance is most likely to occur for a particular consumer, as depicted in Figure 1.

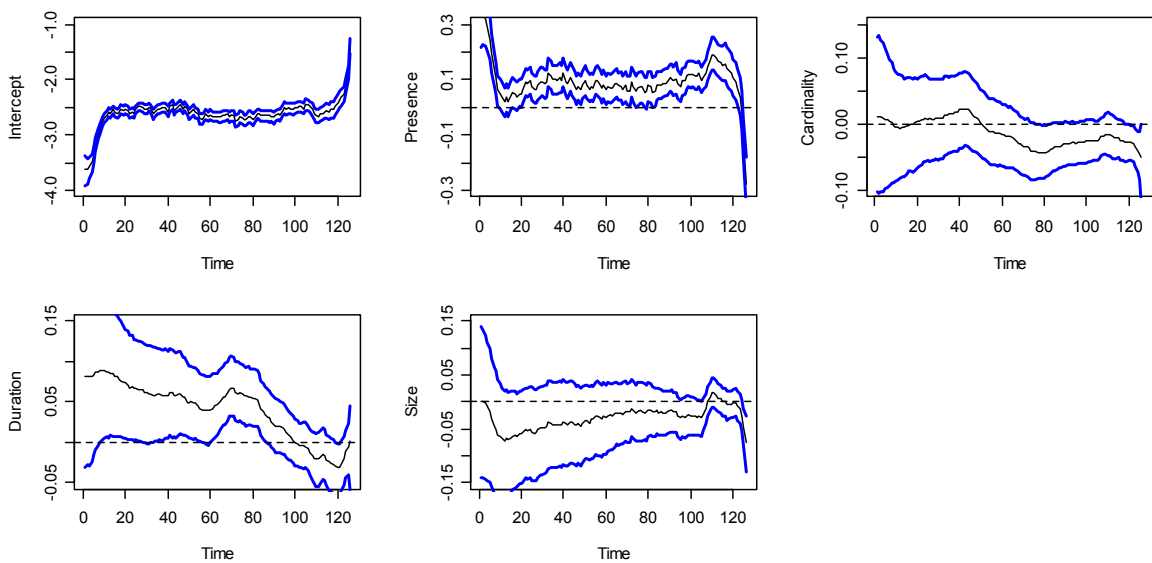
The predicted U-shaped effect of visual complexity on avoidance emerged as well, as reflected in the significant effect of complexity-squared and the non-significant linear term. This is the first evidence for an “optimum level” of visual complexity for commercials at which avoidance is minimal, while both lower and higher levels of visual complexity increase avoidance probabilities. Finally, as expected, males are significantly more likely to avoid commercials than females are. None of the other control variables was significant.

Parameter Evolution

Figure 2 plots the stochastic paths (and 90% confidence intervals) of the posterior parameter values of the intercept and dynamic effects of the brand’s presence, cardinality, duration and size, which are time-varying. Baseline avoidance levels (intercept, top left in Figure 2) are fairly constant throughout the commercials, with less avoidance in the beginning, a stable and long period in the middle, and an increase towards the end. This in itself is a reassuring result because it indicates that there is no point in time, apart from start and finish, when viewers systematically tend to stop viewing more, and which is not accounted for by other covariates in the model. Brand presence drives the avoidance probability up throughout the commercial, except in the last few time-frames, where

brands are generally expected to appear, and consumers expect the commercial to naturally end soon. Apart from the start and end, the effect of brand presence slightly increases over time at instances 10 to 40 and 80 to 110. No strong significant effects emerged for brand cardinality. Higher cardinality of brand presence decreased avoidance towards the second half (marginally significant). Just the opposite effect emerged for duration: prolonged brand presence increased avoidance in the middle (significant) with the effect dying out towards the end.

FIGURE I.2: Time-varying parameters of branding activity: posterior median and 90% Confidence bands



Since variables were standardized, I can compare their relative importance directly. This shows that the order of importance from highest to lowest is (1) attention dispersion metrics, with a combined posterior (absolute) mean effect of 1.50, (2) branding variables, with a total effect of 0.49, (3) visual complexity measures with 0.10, (4) product-brand control variables (brand familiarity and product category) with 0.04 and, (5) demographic control variables (age and gender) with 0.02.

Optimization of Branding Activity

Marketing managers try to maximize the prominence of their brands in commercials, for instance, by exposing them early, long, in the middle of the screen, separated from the rest of the commercial, but at the same time try to maximize the likelihood of retaining consumers, which is a difficult trade-off. As discussed, high levels of zapping are detrimental to the entire TV advertising industry. The networks lose ratings, the advertiser loses viewers to another channel, the subsequent commercials lose potential viewership and the medium fails to engage consumers in the brand communication of firms. Therefore managers aim to maximize the opportunity-to-see the brand, across viewers and time, for a minimum pre-defined level of branding activity. I will next do this optimally, based on the model. I assume that brand owner and ad agency have established the minimum branding level in the commercial, as a precondition. It is then the ad agency's responsibility to maximize opportunities to see the brand and simultaneously minimize the likelihood of avoiding the commercial from moment-to-moment. This decision will be respected in the optimization (within a $\pm 5\%$ tolerance). Formally, I define the brand activity level of commercial c (BAL_c) as the sum across time-frames of the size of the brand, conditional on a brand presence. According to this definition, the brand activity level varies from 0, when there would be no brand appearances in the commercial, to 125 (125 frames \times 100%), in which case the image would always be completely covered with the brand. In practice, observed brand activity levels are much smaller and do not show too much variability across ads, with an average of 4.65 frames or equivalent to 1,116 ms of BAL (not to be confused with the total duration of the brand on screen, which will always be greater than BAL).

The goal of improving patterns of branding can be translated into minimizing the avoidance likelihood for a commercial c , subject to a certain minimum brand activity level, BAL_c . Formally, the maximization criterion Opportunity-To-See (OTS) for a particular commercial c , evaluated over all I participants for the duration T , and coding avoidance as one (1) and non-avoidance as zero (0), I have:

$$OTS_c = \int_{\Theta} \frac{1}{N_i N_t} \sum_{i=1}^{I_c} \sum_{t=1}^{T_c} P(\hat{Y}_{ict} = 0 | \Theta) P(\Theta | \text{data}) d\Theta \quad \forall c = 1, \dots, C \quad (8)$$

Both uncertainties in the decision space as well as in the parameter space are taken into account in the optimization routine (Rossi and Allenby 2003). This objective function is integrated over the posterior distribution of Θ , which is approximated by averaging across the R draws of the MCMC chain:

$$OTS_c = \frac{1}{R} \sum_{r=1}^R \frac{1}{N_i N_t} \sum_{i=1}^{I_c} \sum_{t=1}^{T_c} P(\hat{Y}_{ict} = 0 | \Theta^{(r)}) \quad \forall c = 1, \dots, C \quad (9)$$

I focus on branding decisions that can be made both before and after the actual production of the commercial and even while running the campaign, to allow marketing managers and agencies optimal flexibility. Some post-production changes in branding cannot be easily made without making large aesthetic compromises. For example, whether the brand is embedded within the scene or not, cannot be easily manipulated post-production, and the same goes for the position of the brand. But for some brand feature in certain ads, this is possible (see Validation Experiment). Therefore, I optimize brand presence and size, as instantaneous, and cardinality and duration, as dynamic branding features, with all other variables remaining unchanged from their current values.

To ensure a realistic solution for the optimum branding patterns, constraints are placed on the variables to be in the range of the observed values in the data (see Table 1).

Size and presence of brand are the two decision arguments, since presence at $t = 1, \dots, T$ determines cardinality_t and duration_t. Brand presence is a dichotomous variable, assuming values one or zero for presence or absence, respectively, and size is taken to vary from 0.5% to 75%, subject to the constraint that total brand activity stays the same ($\pm 5\%$ tolerance). The probability of commercial avoidance is a monotonic increasing function of utilities in the model with convex constraints, so that I solve the following set of C decision problems, one for each commercial, in the utility space and map back to the probability space. Equation 10 describes the optimization problem:

$$\begin{aligned} \min_{\substack{\text{size}_t \\ \text{presence}_t}} \sum_{r=1}^R \sum_{i=1}^{I_c} \sum_{t=1}^T D_{\text{cit}}^{\text{zap}} / \Theta^{(r)} \quad \forall c = 1, \dots, C \\ \text{with } \text{presence}_t \in \{0,1\} \\ \text{with } \text{size}_t \in [0.5\%, 75\%] \\ \text{with } \text{BAL} = \text{BAL}_c \pm 5\% \end{aligned} \quad (10)$$

It is noteworthy that the above objective function is linear in presence_t and size_t (see equations 3 and 4) but has non-linear constraints (by definition of BAL, p. 28), and thus may not yield corner solutions. The solution to this optimization problem is a 2 (presence and size) x 125 (total number of time-frames) matrix for each of 31 commercials.

I perform the optimization using a combination of a gradient method and a genetic algorithm (Sekhon and Mebane Jr. 1998). This combines the benefit of a deterministic fast steepest descent, when the gradient of this multidimensional function can be calculated, with the benefit of stochastic search, to avoid local optima solutions. Because of the computational burden I use $R = 10$ in the optimization. While this approach substantially reduces the likelihood that a solution is only a local as opposed to a global optimum, it does not guarantee global optimality because of the high

dimensionality of the problem (250 decision variables), mixed continuous and discrete decision variables and non-linear constraints (BAL_c).

“Ceteris Paribus” Analysis.

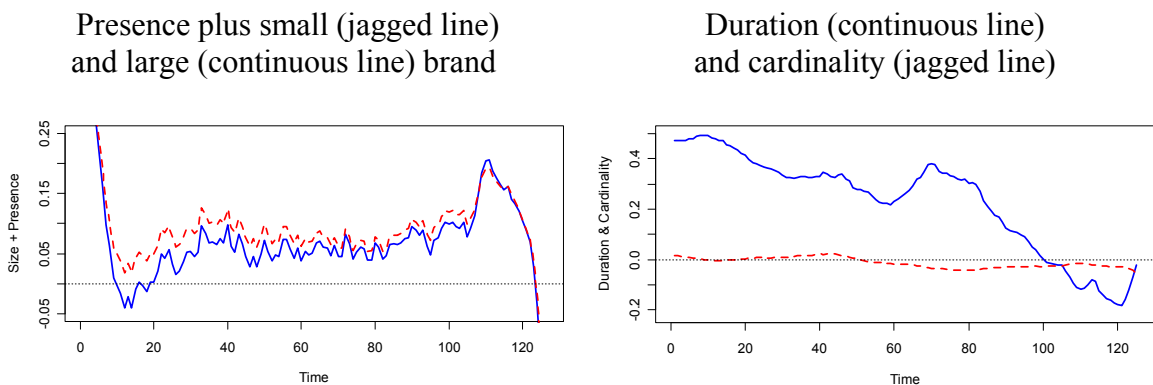
The optimal effect of branding on (minimal) avoidance likelihood depends predominantly on four variables and their estimated time-varying effects: presence, size, cardinality, and duration of the brand. The combination of the effects of these variables will dictate if and when brands increase or decrease avoidance likelihood. In itself, ceteris paribus, a brand presence will increase avoidance. But taking cardinality, duration and size into account, it may in fact decrease avoidance at certain moments, as is the case, for example, for a large brand shown in the beginning. This is illustrated in the left-most graph of Figure 3, where the parameter for “presence” is added to the parameter for “size” for the largest (75%) and for smallest brand size possible (0.5%). Since the Y-axis shows the contribution to avoidance, larger positive values increase and larger negative values decrease avoidance. Notice how the line for the largest brand size is almost always below that for the smallest size, indicating less avoidance. Only towards the end of the ad ($t > 110$) do smaller brands cause less avoidance. Also, note that, for a brief period in the beginning ($10 < t < 20$), large brand appearances systematically decrease avoidance from moment-to-moment.

For dynamic branding effects, one needs to compare the parameter estimates of cardinality and duration. Loosely speaking, for each time period, if the duration parameter is larger than the cardinality parameter, both measured in units of time-frames, then adding a new non-adjacent frame with a brand will decrease avoidance in comparison to adding an adjacent brand. And similarly, if the opposite occurs, then

adding a brand in a subsequent frame is more desirable. These parameters are plotted on the right-most graph of Figure 3 which shows that, for a predefined branding level, non-consecutive brand placements will decrease overall avoidance more than consecutive brand placements from the start of the ad up until the 105th frame. After that, and until almost the end of the commercial, the opposite is true: clumping brands together in time is preferable.

If the proposed model did not have time-varying parameters on cardinality and duration, these differential impacts of consecutive versus non-consecutive branded frame insertions could not be effectively assessed. In particular, the static HB Probit model's parameters in table 3 shows that effects of cardinality and duration are both significant, but equal up to the third decimal place, rendering the zapping effects caused by either spreading out branded frames in time or clumping them together indistinguishable.

FIGURE I.3: Time-varying parameters



Thus, I expect that the optimization results for these commercials should indicate that brands be larger towards the beginning (not in the first second) and at the very end, with size not being critical in the middle portion of the commercial. Also, brand

appearances should be short and frequent in the first 4/5th of the commercial, and be longer and less frequent in the last 1/5th.

Optimization Results

The brand activity level in commercials ranged from 0.38 to as much as 15.25 (mean = 4.65). All 31 commercials were individually optimized, subject to their BAL remaining unchanged. The optimization procedure was carried out in a Linux Grid Server based on processors with 3.0 GHz of speed and 15 GB of memory, taking from 49 to 172 hours of CPU clock time to arrive at the solution depending on the specific commercial. Table 5 presents the results.

On average, avoidance dropped by 7.9% in the optimized compared to the original commercials, with a range from 2.0% to 19.1%. All improved ads were predicted to be avoided less than their original counterparts, and for 12 out of the 31 ads the magnitude of the reduction was larger than the estimation error. The reduction in avoidance is mainly caused by increases in brand cardinality, as predicted in the previous section. Also, apart from the extremes (start and finish of ads), brands that appear later cause more zapping than ones that appear earlier, with larger brands only causing marginally less zapping in the first half of the commercial, as the left graph of figure 3 shows. Total brand duration (the sum of number of frames with a brand appearance) is decreased for those ads with comparatively high original total duration and increased for those with comparatively low total duration, trading it off with size. In other words, if total duration is decreased from the original to the improved version, then size is increased, and visa versa. Thus, managers need to make trade-offs in branding duration and size to strike a balance. The extent to which each of the above issues (increase in

cardinality, earlier brand appearance, total duration, size) is mostly responsible for the optimal solution depends on the specific time-frame, because of the specific way the parameter estimates of these variables vary over time.

TABLE I.5: Brand activity in original and optimized ads

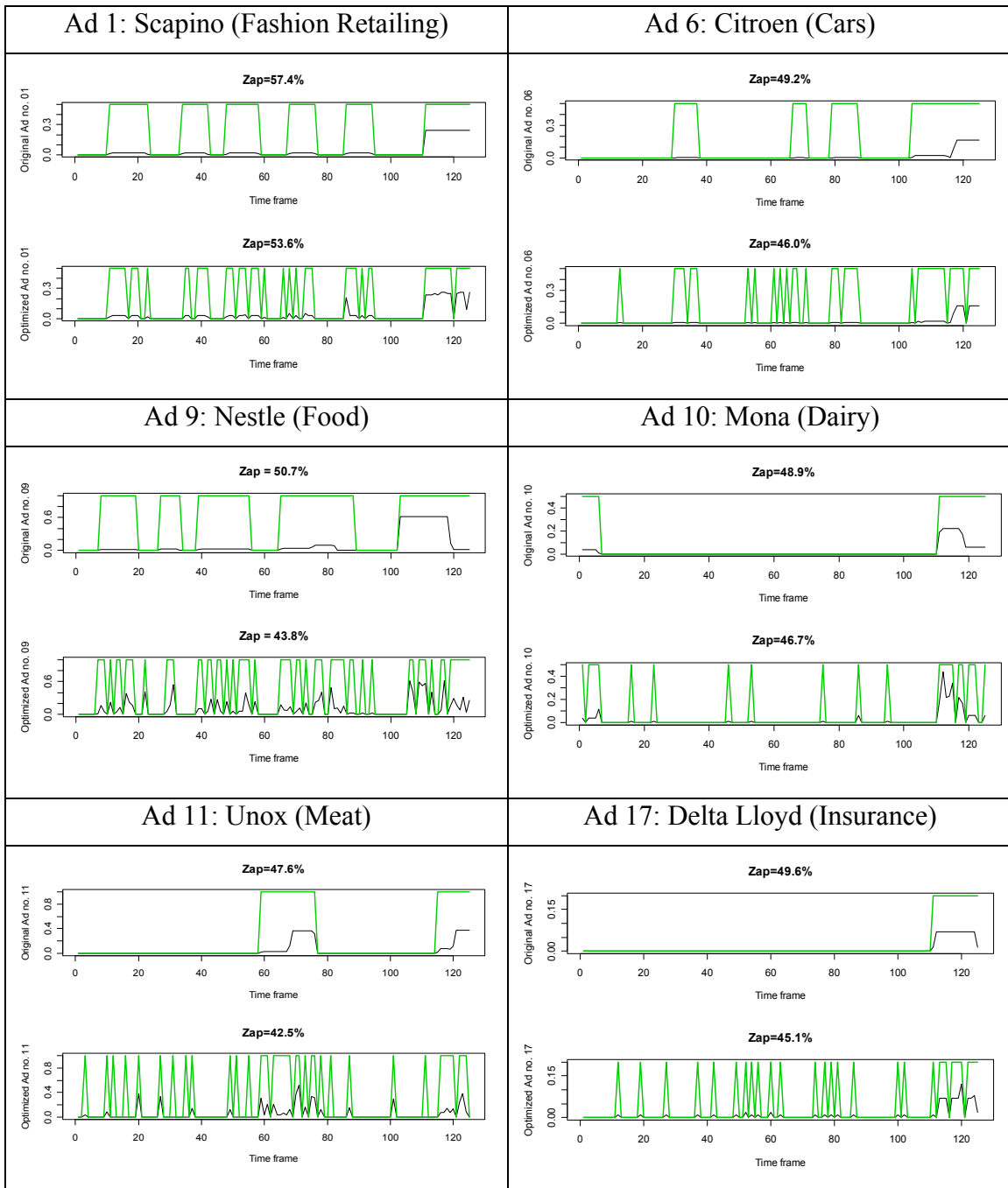
Advertised brand	Original ad					Optimized ad				Reduction in commercial avoidance (%)
	Est. CA (%)	BAL	Card.	Dur.	Mean Size (%)	Est. CA (%)	Card.	Dur.	Mean Size (%)	
1. Scapino	57.4	4.40	6	66	6.7	53.6	18	53	8.7	6.7
2. Schimmelnagels	55.9	2.72	2	44	6.2	53.4	13	45	6.2	4.5
3. Staatsloterij	49.4	2.53	1	34	7.4	46.4	14	41	6.3	6.1
4. Hertog	46.5	6.79	1	25	27.2	40.4	29	41	16.6	13.2*
5. Mona	46.2	1.02	3	29	3.5	43.4	17	34	3.2	6.0
6. Citroen	49.2	1.67	4	44	3.8	46.0	16	43	3.7	6.5*
7. Sportlife	43.5	2.77	2	14	19.8	39.8	20	25	11.5	8.5
8. Post Bank	53.0	2.75	2	24	11.5	50.5	13	32	8.6	4.7
9. Nestle	51.3	12.0	5	83	14.5	41.5	32	48	26.3	19.1*
10. Mona	48.9	2.31	2	21	11.0	46.7	13	23	10.5	4.5*
11. Unox	47.6	5.54	2	29	19.1	42.5	24	39	14.3	10.7*
12. Telefoongids	49.8	0.61	2	21	2.9	48.8	5	20	3.2	2.0*
13. NN-1	57.0	4.15	2	20	20.7	53.4	19	32	13.4	6.4
14. Albert Heijn	53.6	4.92	3	42	11.7	50.1	17	43	12.0	6.5
15. Achmea	53.5	0.73	1	9	8.1	51.2	13	21	3.5	4.3
16. Red Band	53.1	2.98	3	53	5.6	50.3	10	48	6.4	5.3
17. Delta Lloyd	49.6	0.94	1	15	6.3	45.1	22	30	3.3	9.1*
18. Electro World	49.3	10.9	4	43	25.4	44.7	29	48	22.9	9.4
19. Mastercard	47.1	7.02	1	21	33.4	41.4	27	37	19.1	12.1*
20. Unox	56.4	9.16	2	51	18.0	50.8	24	51	18.0	10.0
21. NN-2	53.8	5.28	1	11	48.0	49.4	25	35	15.3	8.1
22. Essent	55.1	2.88	1	38	7.6	53.6	7	39	7.8	2.7
23. SNS Bank	55.0	1.29	1	9	14.4	52.8	16	23	5.6	4.0
24. T-Mobile	46.8	3.29	1	10	32.9	43.8	15	19	17.9	6.3*
25. Radio 538	42.9	1.12	1	8	13.9	39.8	13	18	6.5	7.2
26. KWF	51.5	3.74	1	37	10.1	49.8	11	41	9.6	3.3
27. Kodak	50.6	2.35	2	29	8.1	47.7	14	36	6.9	5.8*
28. Min. of Justice	59.4	0.38	1	11	3.5	57.4	11	21	1.9	3.5*
29. Wadden	41.1	10.5	1	32	32.8	33.8	30	41	26.4	17.7
30. PostBank	55.5	12.1	1	77	15.8	47.5	22	67	18.5	14.4*
31. SMS Land	54.7	15.3	1	125	12.2	46.1	11	115	13.9	15.6

Note: ** indicates 95% posterior confidence interval doesn't contain zero; * indicates 90% confidence interval doesn't contain zero; + indicates 90% posterior confidence interval doesn't contain zero for some time periods.

Figure 4 shows brand presence (thick line) and the size of the brand (thin line) for 6 out of the 31 ads optimized, for the original (upper graph) and the improved ad (lower graph). Notice how, consistent with the predictions in the ceteris paribus analyses, most

of the improved ads have more/shorter brand appearances up to around the 100th frame mark and less/longer ones thereafter.

FIGURE I.4: Illustration of branding optimization frame-by-frame (plots of brand presence and size for six optimized ads. Upper graph is original and lower graph is optimized ad; light thick line is brand presence and dark thin line is size)



The improved solutions have frequent but brief brand appearances. This result is analogous to the finding of pulsing benefits *across exposures* in the advertising effectiveness literature (Feichtinger et al. 1994; Feinberg 2001) but is shown here *within exposures*. It is due to the linearity of the model and the mixed continuous and discrete decision variables, combined with the fact that discrete adjacent brand placements have higher “cost” than non-adjacent ones (Hahn and Hyun 1991).

To validate the findings, I compare in Table 6 the avoidance rates obtained from my procedure (strategy 1) with eight alternative branding strategies, including no branding (strategy 2), current branding practice (strategy 3), and branding strategies that systematically vary part of the commercial in which the brand is placed (first half, second half, all) and its size (largest brand size is 75% and smallest is 0.5%). The avoidance rates of the above strategies are averaged across all 31 ads. Table 6 shows that my optimization solution is better than all these alternative strategies. Note how strategy 2, in which there is even no brand placement, outperforms the other strategies--except the proposed strategy (though not significantly so)--which shows again that brands are avoided by viewers, but that brand pulsing reduces this. Because of the potentially important implications for advertising strategy, the question is pertinent to what extent the main finding of optimal brand-pulsing strategies are not due to idiosyncratic aspects of the data, commercials or model. Therefore, I validate the findings in a subsequent experiment.

TABLE I.6: Estimated commercial avoidance for current, optimized and benchmark branding strategies

Comparison of branding strategies		Mean estimated commercial avoidance (%)	Standard deviation (%)
1	Optimized brand placement (my model)	47.2	5.2
2	No brands present	49.3	4.3
3	1 st half of ad with largest brands	51.0	4.4
4	Current branding practice	51.1	4.5
5	2 nd half of ad with largest brands	51.1	4.2
6	2 nd half of ad with smallest brands	52.5	4.2
7	All ad with largest brands	55.2	4.1
8	1 st half of ad with smallest brands	57.0	4.5
9	All ad with smallest brands	62.6	4.2

Note: Smallest brand = 0.5% of screen size, largest brand = 75% of screen size.

Validation Experiment

I present the results of a lab experiment in which I take six 30 second commercials with varying amounts of total visual branding and alter the number of short non-consecutive brand pulses in order to compare the effects on average zapping rates. Since the objective is to validate the optimality of pulsing, ideally one would reconfigure the patterns of brand pulses to mimic those found in the previous optimization section, i.e. inserting an average of about 17 pulses. However, since not all ads are amenable to post-hoc reengineering of brand placement without compromising their creative execution and cohesiveness, and due to the authors' inability to do so in all cases without the altered version appearing to be tampered with, I proceed to moderately increase (+3 to +5) or decrease (-2 to -4) the number of brand pulses, as seamlessly as possible. Care

was taken to nest the brand while not “hiding” it in the scene and maintaining a constant average brand size.

The stimuli were six⁵ commercials, altered to have either a higher or lower number of brand pulses than the original ones, as well as seven other filler ads that were the same across conditions. The ads were chosen randomly from a pool of ads conveniently available to the researchers and provided by Verify International⁶. For each randomly selected commercial, a subjective evaluation was made in order to decide if modifying the commercial was feasible in the sense of it being technically possible to (1) isolate the brand and replicate it in other time-frames without occluding any images, (2) eliminate some of the frames with the original brand or eliminate the nested brand from the scene and (3) identify every appearance of the brand upon first exposure to the commercial (i.e. no very small or partially obstructed brand images). If the chosen commercial obeyed these conditions, it was used in the experiment, else another ad was chosen from the available pool. For the chosen commercials, the video-editing software Adobe Premiere Pro[™] was used to insert new brand appearances, as uniformly as possible in time to mimic the patterns in figure 4.

The experiment used a 2 (original versus altered commercial) by 2 (commercial sequence 1 versus 2) between-subjects design, with 6 commercials as replicates. The commercial sequence factor was included to account for serial position effects. Thus, each participant had the opportunity to see/ zap three (or four) original ads and four (or three) altered ads all interspersed by the seven filler ads. A total of 130 participants

⁵ Originally seven commercials were selected, but one of the commercials used was dropped because the execution was problematic and evaluated by some participants as being tampered with.

⁶ Three of the altered commercials were in the original dataset and three were not.

(undergraduate students, mean age 20 years, 61% male) were randomly assigned to the conditions and first individually watched a 4 minute TV show on the computer to ease them after which a commercial pod with 14 commercials was shown in sequence. They could watch each ad or press the space bar (on which the index finger rested at all times) to skip to the next ad in the sequence. After the last commercial, they answered questions regarding the experiment, engaged in other unrelated tasks, were thanked, debriefed and paid (the equivalent of 8\$ for the complete experimental session, which took about one hour).

The results of the experiment are summarized in table 7. The percentage of commercials zapped across participants ranged from 7% (five participants zapped only one commercial) to 100% (eight participants zapped all commercials), with mean zapping rate of 60% (SD = 25%). This is very similar to the original dataset, with a zapping rate of 55% (SD = 12%) and to zapping rates reported in other studies (Wilbur 2008). Table 7 shows that out of the six commercials, four showed appreciable differences in zapping, ranging from 9 to 25%, between the versions with high and low number of brand pulses. In particular, three commercials altered to have *higher number* of pulses showed major decrease in zapping and one commercial altered to have a *lower number* of original brand pulses showed a major increase in zapping. This is an indication that the findings work both ways, at least in the interval between 1 and 10 brand pulses that I studied: as predicted by the model more pulses decrease zapping and less pulses increase it, holding total BAL constant. For the two commercials that I did not find an effect for, an exact reason is unknown but care should be taken to propose an explanation, since all altered commercials are suboptimal, i.e., they are not professionally executed modifications from

the original, professionally developed TV ads. Also, note that the number of pulses that I could implement is somewhat lower than those suggested by the optimization results.

TABLE I.7: Comparison between zapping rates of original and altered commercials

	Brand	Category	Brand pulses		Zapping rate		% Change
			Original	Altered	Original	Altered	
Increase in brand pulses	Scapino	clothe	5	10	92%	84%	-9%
	Mona	desert	3	6	76%	65%	-14%
	Mastercard	financial	1	5	69%	69%	0%
	Pastrelli	food	5	8	63%	56%	-11%
Decrease in brand pulses	Dommelsch	beer	8	6	60%	75%	25%
	Nike	sports	7	3	66%	66%	0%

Note: Total duration of brand exposure is the same in original and altered commercials.

The zapping rates for versions of the commercials with high pulsing (mean of 67%) were lower than the zapping rates for those with low pulsing (mean of 74%) as shown by a test of proportions at 95% confidence ($p = .02$). Two points are worth noting. First, the average relative reduction in zapping of 9.5% (compared to the 7.9% reduction in the optimization simulation) is attained via increasing the brand cardinality but not the total duration of brand exposure on screen, which remained the same. Secondly, it is important to note that the averaged viewing times for the viewers that did zap are not very different from each other: 17.40 sec. for altered and 17.86 sec. for original commercials. Thus, the brand pulsing strategy within the ad exposures did not erode the viewing time (and possibly the overall quality of the experience) for the viewers that eventually decided to stop watching before the end.

Apart from the evidence from the parameter estimates in the model, and the evidence from the optimization, the results of this experiment provide strong additional

verification that pulsing short brands across time, even if done in a lower than potentially optimal frequency, provide benefits in terms of significantly reducing commercial avoidance levels. Moreover, I conjecture that if brand pulsing is to be simultaneously integrated with ad creation and execution as opposed to post-execution, as was done in this experiment, the additional executional coherence will further contribute to reaping the benefits of this strategy.

Discussion

Branding activity in TV commercials affects the moment-to-moment likelihood that these commercials retain their viewers. Specifically, inserting brands for sustained periods, in particular centrally on the screen, increases the likelihood that consumers stop watching a particular commercial notably. However, the model estimation and optimization procedure suggests that what is “intrusive” is not the total branding activity level per se, but long, sustained brand appearances. Thus, I was able to lower avoidance rates of commercials by merely changing the pattern of brand exposure, while keeping the brand activity level per commercial the same. A pulsing strategy, in which brands are shown more frequently and more briefly instead of infrequently and longer, decreased commercial avoidance rates both in a simulated optimization and in a lab experiment, by about 8 to 10 percent, respectively. For the former, avoidance rates under this optimized branding strategy were even lower than if the brands would not have appeared in the commercials at all. This suggests a parallel between optimal effectiveness of brand pulses within commercials and commercial pulses in a campaign (Feichtinger et al. 1994, Feinberg 2001). Because my objective was to provide a solution to the advertiser’s

problem of how to insert the brand in commercials while retaining viewers' attention, a behavioral foundation for the optimality of pulsing was not provided. Nonetheless, a conjecture is that such brand pulses leave the narrative in the commercial more intact and thereby interfere less with the entertainment goals that consumers generally have when watching television. One common strategy to cope with increased commercial avoidance is to reduce the overall brand activity levels in commercials and place the brand once, completely at the end and long, as reflected in the growing incidence of soft selling, mystery commercials. But my model parameters show that this strategy can only retain attention for one or two seconds of brand exposure at most, and the single exposure only may adversely affect memory and learning in addition (Brown and Craik 2000). The findings show that intrusiveness can be reduced more, without sacrificing brand activity level, using a brand pulsing strategy. The dynamic Probit model, optimization approach and experimental validation on which the present findings are based hold the promise of improving the effectiveness of television advertising through the insights it provides into the moment-to-moment determinants of commercial avoidance. Because of its focus on branding activities that are largely under managerial control, independent of the creative content of commercials, my procedure can be used both before and after final production, and even while the campaigns are in the media. And since adaptations can be made post-production, as was done in the follow-up experiment, improvements are virtually costless. Nonetheless, there may be ads where altering the brand's location, without drastically changing its visual complexity, pacing or other visual elements may be more difficult to do as a consequence of their creative design.

Independent of branding activity and other factors, the ability of commercials to concentrate consumers' visual attention reduced commercial avoidance significantly. Specifically, the smaller the variance in the location of consumers' eye-fixations (aggregate attention dispersion), the lower the likelihood of commercial avoidance was. Also, the closer an individual consumer's eye-fixations were to the center of other consumers' eye-fixations (lower individual attention dispersion), the lower the likelihood of commercial avoidance was. The interactive effect between the two attention dispersion metrics suggests that lower aggregate and individual attention dispersion led to the lowest commercial avoidance likelihoods. As far as I know, these results are the first to show that a commercial's power to concentrate, hold and direct visual attention directly predict consumers' decisions to stay with the commercial or not. The findings support that, indeed, as often speculated upon in advertising, the power to orchestrate attention is crucial to advertising effectiveness. The proposed attention dispersion metrics can be readily derived through eye-tracking of commercials and may prove useful in advertising effectiveness research in general.

Consumers' moment-to-moment decisions to continue or stop watching commercials also depended on the optimal amount of visual complexity in the commercials, independent of all other factors. That is, both under low and high levels of visual complexity, the likelihood to stop watching commercials was higher than under intermediate levels. I believe that this finding is particularly interesting because it was obtained using objective, novel measures of complexity, based on the pacing of commercials and the density of visual information in the GIF-compressed file size of each frame in the commercials. To my knowledge, the present findings are the first to

show that objective measures of visual complexity directly influence consequential consumer decisions. These measures allow marketing managers and advertisers to assess the frame-by-frame visual complexity of their commercials to supplement other quality indicators, and opportunities to fine-tune visual complexity levels to reduce commercial avoidance.

Limitations and Research Opportunities

The issue of how brand pulsing impacts brand attitude measures, purchase intention or many other metrics used to evaluate advertising effectiveness, although important, was not addressed in the current study, as it was outside of the scope. However, to shed some light on this issue, after the validation experiment, I measured on 5-point response scales anchored by ‘Not at all’ and ‘Very strongly’ the extent to which participants felt that: (1) The commercial made me feel good about the brand; (2) The commercial aroused my interest in the brand and (3) The commercial made me evaluate the brand more positively. No significant difference was found between commercials altered to exhibit degrees of brand pulsing and their original counterparts for any of the three measures across the six tested commercials. However, I recognize the need to assess if the optimal brand placement strategy will affect other important ad metrics and future research should attempt to tackle this issue, where the model developed in this paper may be used as a starting point.

Further, given the discrete (frame-by-frame) nature of the data, both a binary choice model and a (discrete time) hazard model could be applied in this context and may provide similar results (Sueyoshi 1995). I choose the frame-by-frame probit model because it ties in directly with the frame-by-frame optimization of the TV commercials,

and because frameworks for dealing with time-varying parameters have been well established for this model (Lachaab et al. 2006). However, a hazard model could be a viable alternative.

One of the limitations of this research design is that viewers watched sequences of commercials back-to-back without programs, and this may have increased the likelihoods of avoidance decisions relative to those obtained under natural viewing conditions at home. Nevertheless, because I employ a frame-by-frame analysis, as opposed to a commercial-by-commercial one, I expect that the zapping instants shown to be systematically affected by brand presence would not be qualitatively different. In addition, in the validation experiment commercials were embedded in a TV show, and the overall zapping rates obtained were very similar. Thus, although there is no reason to expect that the research context may have prompted consumers to become sensitive to qualitatively different factors, only future research can provide definitive answers to this question.

In the present study the impact of programming content of the commercials was not assessed. However, sequential presentation of the commercials is somewhat realistic and reflective of several conditions occurring in practice, in particular those where networks coordinate so called “road-blocks” which are time-synchronized commercial breaks on different channels. In those situations, a consumer who zaps out of a commercial zaps into another one at the other channel. The experimental design is reflective of these situations. It is not unlikely, however, that programs or shows have an impact on attention to commercials (Burns and Anderson 1993). Yet, both zapping rates and the main pulsing finding were replicated in the validation experiment, which did

involve such programming content. A systematic assessment of this effect would need to vary type of program, content, entertainment and information value, among other elements, to understand the influence on ad avoidance. I suggest this as another important avenue for future research.

Another research opportunity concerns improvements of the elementary metrics of visual attention that I could use here. Eye-tracking of dynamic stimuli such as television commercials is challenging because of the doubly-dynamic character of the data. That is, the eyes move across scenes that move themselves or have objects that do so. The resulting large streams of such doubly-dynamic- data are a main reason for the lack of prior eye tracking research of commercials and other dynamic stimuli (Wedel and Pieters 2008). The present findings demonstrated that the aggregate and individual-level attention dispersion measures were strongly predictive of commercial avoidance decisions, even though they are independent of where in the scene consumers' attention was actually located. It seems likely that refining the metrics to include the concentration location (or the advertiser's desired location of focus) will increase their predictive validity, and future research may address this. More generally, in view of their predictive validity for avoidance decisions, future research may examine the factors that influence consumers' attention dispersion in commercials.

Finally, in the optimized commercials, brand size and duration remained in the range of the current values, but the cardinality did not. That is, the average cardinality went from a low 2.0 (original ads) to a mean 17.7 (improved ads). While it wasn't directly a decision variable, this proposed number of non-consecutive brand insertions is far from the maximum cardinality observed in the dataset, 6, but it is not uncommon in

advertising practice. Examples are the recent commercial “The Happiness Factory” for Coca-Cola⁷ with cardinality of 17 (short version), and the 2008 Coca-Cola “Super-bowl commercial”, with a cardinality of 13. Although the average avoidance rates of these commercials is unknown, it exemplifies that the prescribed pulsing strategy is possible and that high levels of brand pulsing are being used by successful firms. Importantly, the validation experiment revealed that the main pulsing result holds up even for more moderate cardinalities.

More than ever, consumers can easily avoid commercials at any point in time. The proposed procedure that relates objective characteristics of commercials and attention-metrics obtained through eye-tracking to consumers’ moment-to-moment avoidance decisions, can be used in advertising testing before and during campaigns and holds the promise to increase television advertising’s effectiveness.

⁷ The happiness factory. <http://www.coca-cola.com/HF/index.jsp>

Appendix I.1

MODEL SPECIFICATION AND ESTIMATION

The deterministic component of the model, D_{ict} , is expressed in a Hierarchical Bayes structure as follows, in what is a summary of equations (3) through (6):

$$\begin{aligned}
 D_{ict} &= \mu_i + \alpha_c + B_{ct} + (\gamma^1 AAD_{ct} + \gamma^2 IAD_{ict} + \gamma^3 AAD_{ct} \times IAD_{ict}) + TVC_{ct} \\
 B_{ct} &= \theta_t \cdot Branding_{ct} \\
 \theta_t &= (\theta_t^1, \theta_t^2, \theta_t^3, \theta_t^4, \theta_t^5, \theta_t^6, \theta_t^7)^T \sim N(\theta^*, \Sigma^*) \\
 TVC_{ct} &= \beta^0 \cdot PaceType + \beta^1 \cdot VisualComplexity_{ct} + \beta^2 \cdot VisualComplexity_{ct}^2 \\
 \beta &= (\beta^0, \beta^1, \beta^2)^T \\
 (\gamma^1 AAD_{ct} + \gamma^2 IAD_{ict} + \gamma^3 AAD_{ct} \times IAD_{ict}) &= \gamma^1 Aggreg.Disp_{-ict} + \gamma^2 Indiv.Disp_{-ct} + \gamma^3 Aggreg.Indiv.Disp_{-ct} \\
 \gamma &= (\gamma^1, \gamma^2, \gamma^3)^T \sim N(\gamma^*, \Gamma^*) \\
 \mu_i &= \Lambda^1 \cdot Age_i + \Lambda^2 \cdot Gender_i + V_\lambda \\
 \Lambda &\sim N(\Lambda_0, \Sigma_\Lambda) \\
 \alpha_c &= K^1 \cdot ProductCategory_c + K^2 \cdot BrandFamiliarity_c + V_\kappa \\
 K &\sim N(K_0, \Sigma_K)
 \end{aligned}$$

Let, time $t = 1, \dots, T$, commercial $c = 1, \dots, C$ and individual $i = 1, \dots, I$. The basic relationship of equations (1) and (2) form the complete Utility Model specification and are expressed as:

$$\begin{aligned}
 Y_{ict} &= \begin{cases} 1: avoid & \text{if } U_{ict} \geq 0 \\ 0: watch & \text{if } U_{ict} < 0 \end{cases} \\
 U_{ict} &= D_{ict} + \varepsilon_{ict},
 \end{aligned}$$

The State Space (Dynamic Probit Model) formulation of the model is (with Ψ_{ic} incorporating $\theta^5, \theta^6, \theta^7, \beta^0, \beta^1, \beta^2, \gamma^1, \gamma^2, \gamma^3$ and Θ_t incorporating $\theta_t^1, \theta_t^2, \theta_t^3, \theta_t^4$ and an intercept θ_t^0):

$$\begin{aligned}
U_{ict} &= \mu_i + \alpha_c + F_{ct} \Theta_t + X_{ict}^3 \Psi + \varepsilon_{ict} \\
\Theta_t &= \Xi + G \Theta_{t-1} + \omega_t \\
\mu_i &\sim N(X_i^2 \Lambda, V_\lambda) \\
\alpha_c &\sim N(X_c^1 K, V_\kappa) \\
\omega_t &\sim N(0, V_\omega) \quad \varepsilon_{ict} \sim N(0, 1)
\end{aligned}$$

Let $G = I_5$ and $\Xi = 0$ and thus, specifying the MCMC inference procedures, I rewrite the equations as:

$$\begin{aligned}
U_{ict} &= D_{ict} + \varepsilon_{ict} \\
U_{ict} &= \underbrace{(X_i^2 \Lambda + \lambda_i)}_{\text{Probit}} + \underbrace{(X_c^1 K + \kappa_c)}_{\text{HB: Variance component model}} + \underbrace{F_{ct} (G^1 \Theta_0 + \sum_0^{t-1} G^j \omega_{t-j})}_{\text{Forward Filter Backward Sample}} + \underbrace{X_{ict}^3 \Psi}_{\text{Bayes Regressionssion}} + \varepsilon_{ict}, \\
\varepsilon_{ict} &\sim N(0, 1) \\
\lambda_i &\sim N(0, V_\lambda) \\
\kappa_c &\sim N(0, V_\kappa) \\
\omega_t &\sim N(0, V_\omega)
\end{aligned}$$

The design matrix, composed of the independent variables X, and dependent variable Y is structured in the following way:

$$X = \{F_{ct} \quad X_c^1 \quad X_i^2 \quad X_{ict}^3\} = \left[\begin{array}{c} 1 \\ Presence_{ct} \\ Cardinality_{ct} \\ Duration_{ct} \\ Size_{ct} \end{array} \right] \left[\begin{array}{c} ProductCategory_c \\ BrandFamiliarity_c \end{array} \right] \left[\begin{array}{c} Age_i \\ Gender_i \end{array} \right] \left[\begin{array}{c} Mode_{ct} \\ Position_{ct} \\ Separation_{ct} \\ PaceType_{ct} \\ VisualComplexity_{ct} \\ VisualComplexity_{ct}^2 \\ Indv.Disper_{ict} \\ Aggreg.Disper_{ct} \\ Indv.*Aggreg.Disper_{ict} \end{array} \right]$$

The prior distribution of parameters are diffuse conjugate distributions:

$$\begin{aligned}
&U_{ict}, \mu_i, \alpha_c \rightarrow \text{specified from model} \\
&\Theta_0 \sim N_5(\mathbf{m}_0 = 0, \mathbf{C}_0 = 10^5 \mathbf{I}) \\
&\Psi \sim N_9(\mathbf{n}_0 = 0, \mathbf{S}_0 = 10^5 \mathbf{I}) \\
&\Lambda \sim N_2(\Lambda_0 = 0, \Sigma_\Lambda = 10^5 \mathbf{I}) \\
&K \sim N_2(K_0 = 0, \Sigma_K = 10^5 \mathbf{I}) \\
&V_\lambda^{-1} \sim G(\rho_\lambda = 2 + 1, (\rho_\lambda R_\lambda)^{-1} = (3 \cdot 0.0001)^{-1}) \\
&V_\kappa^{-1} \sim G(\rho_\kappa = 2 + 1, (\rho_\kappa R_\kappa)^{-1} = (3 \cdot 0.0001)^{-1}) \\
&V_\omega^{-1} \sim W_5(\rho_\omega = 5 + 1, (\rho_\omega R_\omega)^{-1} = (6 \cdot 0.0001 \cdot \mathbf{I}_5)^{-1})
\end{aligned}$$

In order to estimate the unique observation equation via Gibbs sampling, let

$\Phi = \{\Theta_0, \dots, \Theta_T, \Psi, \mu_{i=1}, \dots, \mu_{i=I}, \Lambda, V_\lambda, \alpha_{c=1}, \dots, \alpha_{c=C}, K, V_\kappa, V_\omega\}$ be the full parameter set and

$\Omega_t = \{Y_{i,c,l,t}, X_{i,c,l,t}\}$ the complete data up to time t. The following algorithm describes the

estimation steps along with full conditionals for each ‘sweep’ (iteration) of the Gibbs sampler. All model parameters are estimated simultaneously, by recursively sampling from their conditional posterior distributions, which are given below.

1. Probit (Albert and Chib 1993)

$$\begin{aligned}
&U_{ict} \mid \Omega_T, \Phi \sim \text{Truncated} - N_{\{a,b\}}(D_{ict}, 1) \\
&Y_{ict} = \begin{cases} 0 \rightarrow a = -\infty, b = 0 \\ 1 \rightarrow a = 0, b = +\infty \end{cases}
\end{aligned}$$

2. Forward Filtering-Backward Sampling (Fruhwirth-Schnatter 1994, Lachaab et al. 2006)

Let $U_{ict} - \hat{\mu}_i + \hat{\alpha}_c - X_{ict}^3 \hat{\Psi} = U_{ict}^* = F_{ct} \Theta_t + \varepsilon_{ict}$, $\tilde{U}_t^* = \text{stack}(U_{ict}^*)_{\forall i,c \in t}$,

$\tilde{F}_t = \text{stack}(F_{ct})_{\forall c \in t}$ and $V_{\varepsilon,t} = V_\varepsilon \otimes I_{C,I_t}$.

Forward Filter: Loop forward in time and sample Normal distributions

$$\begin{aligned}
\Theta_t \mid \Omega_{t-1}, \Phi_{-\Theta_t} &\sim N_5(\mathbf{m}_t, C_t), \quad \forall t = 1, \dots, T \\
\gamma_t &= \Xi + G\mathbf{m}_{t-1}, \\
\Gamma_t &= GC_{t-1}G^T + V_\omega \\
C_t^{-1} &= \Gamma_t^{-1} + \tilde{F}_t^T V_{\varepsilon,t}^{-1} \tilde{F}_t \\
\mathbf{m}_t &= C_t(\Gamma_t^{-1} \gamma_t + \tilde{F}_t^T V_{\varepsilon,t}^{-1} \tilde{U}_t^*)
\end{aligned}$$

With dimensions $G = 5 \times 5$, $\Xi = 5 \times 1$, $\Theta = (5 \times 125) \times 1$, $F_t = (C_t \times I_1) \times 5$, $U_t^* = (C_t \times I_1) \times 1$,
 $\gamma_t = 5 \times 1$, $\Gamma_t = 5 \times 5$, $C_t = 5 \times 5$, $\mathbf{m}_t = 5 \times 1$.

Backward Sampler: Loop backwards in time and sample Normal distributions

$$\begin{aligned}
\Theta_T \mid \Omega_T, \Phi_{-\Theta_T} &\sim N_5(\mathbf{m}_T, C_T) \\
\Theta_t \mid \Theta_{t+1}, \Omega_{t-1}, \Phi_{-\Theta_t} &\sim N_5(\mathbf{q}_t, Q_t), \quad \forall t = T-1, \dots, 0 \\
Q_t^{-1} &= C_t^{-1} + G^T V_\omega^{-1} G \\
\mathbf{q}_t &= Q_t[C_t^{-1} \mathbf{m}_t + G^T V_\omega^{-1} (\Theta_{t+1} - \Xi)]
\end{aligned}$$

With dimensions: $Q_t = 5 \times 5$, $\mathbf{q}_t = 5 \times 1$

3. Conjugate sampling (Lachaab et al. 2006)

$$V_\omega^{-1} \mid \Omega_T, \Phi_{-V_\omega} \sim W_5\left(\rho_\omega + T, (\rho_\omega R_\omega + \sum_{t=1}^T (\Theta_t - G\Theta_{t-1})^2)^{-1}\right)$$

4. Bayesian Regression

Let $U_{ict} - \hat{\mu}_i - \hat{\alpha}_c - F_{ct} \hat{\Theta}_t = U_{ict}^{**} = X_{ict}^3 \Psi + \varepsilon_{ict}$, $\tilde{U}^{**} = \text{stack}(U_{ict}^{**})_{\forall i,c,t}$,

$$\tilde{X}^3 = \text{stack}(X_{ct}^3)_{\forall i,c,t}$$

$$\Psi \mid \Omega_T, \Phi_{-\Psi} \sim N_9(\mathbf{M}_\Psi, V_\Psi)$$

$$V_\Psi = (\tilde{X}^3 \tilde{X}^3 + S_0^{-1})^{-1}$$

$$\mathbf{M}_\Psi = V_\Psi (\tilde{X}^3 \tilde{U}^{**} + S_0^{-1} n_0)$$

5. HB: Variance Component Model (Gelfand et al. 1990)

Individual-specific baseline intercepts

Let $U_{ict} - \hat{\alpha}_c - F_{ct} \hat{\Theta}_t - X_{ict}^3 \hat{\Psi} = U_{ict}^{***} = \mu_i + \varepsilon_{ict}$

$$\mu_i | \Omega_T, \Phi_{-\mu_i} \sim N\left(\frac{V_\lambda \sum_{ct} U_{ict}^{***} + \Lambda' X_i^2}{C_i T_i V_\lambda + 1}, \frac{V_\lambda}{C_i T_i V_\lambda + 1}\right), \forall i = 1, \dots, I$$

$$\Lambda | \Omega_T, \Phi_{-\Lambda} \sim N_2\left(\text{Var}_n\left[(X^2)' \cdot \frac{1}{V_\lambda}\right] \mu + \Sigma_\lambda^{-1} \cdot \Lambda_0, \text{Var}_n\right)$$

$$\text{Var}_n = \left((X^2)' X^2 \cdot \frac{1}{V_\lambda} + \Sigma_\lambda^{-1} \right)^{-1}$$

$$X^2 = \text{stack}(X_i^2), \quad \mu = \text{stack}(\mu_i)$$

$$V_\lambda | \Omega_T, \Phi_{-V_\lambda} \sim \text{IG}\left(\rho_\lambda + \frac{1}{2}, R_\lambda + \frac{1}{2}(\mu - X^2 \Lambda)' (\mu - X^2 \Lambda)\right)$$

Commercial-specific baseline intercepts

$$\text{Let } U_{ict} - \hat{\mu}_i - F_{ct} \hat{\Theta}_t - X_{ict}^3 \hat{\Psi} = U_{ict}^{****} = \alpha_c + \varepsilon_{ict}$$

$$\alpha_c | \Omega_T, \Phi_{-\alpha_c} \sim N\left(\frac{V_\kappa \sum_{it} U_{ict}^{****} + K' X_c^1}{I_c T_c V_\kappa + 1}, \frac{V_\kappa}{I_c T_c V_\kappa + 1}\right), \forall c = 1, \dots, C$$

$$K | \Omega_T, \Phi_{-K} \sim N_2\left(\text{Var}_c\left[(X^1)' \cdot \frac{1}{V_\kappa}\right] \alpha + \Sigma_\kappa^{-1} \cdot K_0, \text{Var}_c\right)$$

$$\text{Var}_c = \left((X^1)' X^1 \cdot \frac{1}{V_\kappa} + \Sigma_\kappa^{-1} \right)^{-1}$$

$$X^1 = \text{stack}(X_c^1), \quad \alpha = \text{stack}(\alpha_c)$$

$$V_\kappa | \Omega_T, \Phi_{-V_\kappa} \sim \text{IG}\left(\rho_\kappa + \frac{C}{2}, R_\kappa + \frac{1}{2}(\alpha - X^1 K)' (\alpha - X^1 K)\right)$$

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CHAPTER II

Dynamic Influences of Emotional Reactions on Internet Video Advertisements

Introduction

Television commercial avoidance has grown to become one of the top three concerns for both TV advertisers and broadcasters (Danaher 2008, p. 82; Donaton 2004). This is not an unreasonable concern since it's been found that certain consumer demographics avoid attending to 80% of commercials in which they are exposed in some way or another (Tse and Lee 2001) while 87% of DVR owners actively skip past ads frequently (Grover and Fine 2006). In terms of industry economics, when the majority of TV viewers zap, skip or zip past commercials, the firm's brand being advertised loses the opportunity to communicate. The subsequent brands in the commercial pod lose in the same way. The broadcaster loses viewers to competing TV channels. And the advertising agency gets pressured both by clients (the former) and suppliers (the latter) to resolve the issue, by coming up with commercials that don't trigger these extremely high levels of commercial avoidance behavior.

According to a prominent advertising researcher, "Advertisers must have the attention of the consumer before they can achieve any of the other goals." (Tellis 2004, p. 120), referring to other goals such as informing, reminding, persuading and generating loyalty. Other academics (Webb 1979, Celsi and Olson 1988) and practitioners (Du Plessis 2005) follow in placing the roles of attention grabbing and retaining in the

forefront of advertising efficacy. Simply stated, low or no attention leads to little retention (i.e. zapping) and, thus, less than desirable downstream effect on attitudes, memory and behavior. When it comes to these downstream effects, advertising theory and practice also agree that most of advertising's success is attained via evoking emotions in consumers (Vakratsas and Ambler 1999; Du Plessis 2005). But how do emotions effect momentary avoidance decisions?

The field of psychology has predominantly studied negative emotions. Frederickson (2004) claims the reason is that most behavior associated with negative emotions cause pathologies that bring pain and suffering. The advertising field, on the other hand, has mainly been interested in positive emotions, but prioritized focusing on the end effects that they can induce (Edell and Burke 1987; Olney, Holbrook and Batra 1991). Given the inherently dynamic and discreteness nature of commonly used basic emotions in commercials, such as joy and surprise, the goal of this paper is to understand the concomitant effect of positive emotions moment-to-moment on both the viewer's visual (focal) attention and on their conative avoidance decisions.

In order to explain the dynamics involved in consumer's attention patterns and avoidance decisions, I propose a novel non-obtrusive means to automatically capture and classify emotions via images from their facial expressions while, at the same time, tracking their eye-movements. This is done allowing the viewers to freely decide what to watch or not, by letting them zap a commercial at any point in time. This paradigm of self-control of exposure provides many benefits as compared to forced-exposure (i.e. the standard "Watch all ads!" experiment). On a theoretical basis, emotional reactions during self-exposure are more diagnostic in that they "may be substantially stronger in real life

when individuals are less motivated for conscious and elaborate processing of ads and brands.” (Derbaix 1995). On a practical basis, self-exposure engenders more external validity since viewers do control what to attend to on a day-to-day basis.

Also, as a practical matter, using multidimensional measures of emotions helps advertisers understand what works and what doesn’t work. Adding moment-to-moment measures provides additional diagnostic insights into when emotions start or stop working as an attention grabbing and retaining mechanism. Lastly, adding eye movement measures provide the incremental prescriptive insights into the processes of “where” and “what” caused emotions to eventually lead to (or inhibit) commercial zapping.

In this research, I collect data on emotions, visual attention and zapping behavior over time at each $\frac{1}{4}$ of a second across 28 commercials for 50 viewers, resulting in 145k commercials frames of data in which I augment with frame-by-frame brand image features and complexity measures, known to influence zapping, as well as demographics and ad-brand familiarity. I jointly model all these features using a simultaneous Bayesian Frailty model, estimated with MCMC, thus, accounting for observed and unobserved temporal, individual and stimulus-heterogeneity. To the best of my knowledge, this is the first attempt to use both eye and facial expression tracking in advertising research so I also aim to contribute to the field by exploring the statistical and methodological tools needed to separate signal from noise in this type of high-frequency dual processes data.

Apart from the methodological contributions of this paper, I find that while both Joy and Surprise emotions have a direct effect in terms of reducing commercial zapping, as compared to no emotion, Joy has a predominantly direct negative effect on zapping. Surprise has a predominantly indirect effect, mediated by visual attention dispersion.

Since I also show that attention dispersion is positively related to zapping, evoking Surprise in commercials is a “double-edged sword”: it may reduce zapping at the instant it is felt, but it may also cause distraction, which is likely to lead to zapping later on. Also, concerning the dynamic (immediate versus persistent) effects of these emotions, instantaneous changes in feelings of Joy, for the better or for the worse, explain zapping likelihood more than persistent changes do. In other words, consumers adapt online to the feelings of Joy. If you “take it away from them”, they will stop watching, irrespective of the previous levels. This adaptation effect does not happen for surprise: any persistent change in level is much more diagnostic of zapping incidence than the immediate effect.

The rest of this paper is structured as follows. In the next section, I lay down current knowledge and predictions regarding the constructs of emotions, attention and avoidance behavior. Then, in the Data section, I describe the measures used for each construct and explain how the data was collected. The formal statistical model is then proposed, leading to the Results section. Lastly, I talk about the implications of findings for advertising practice and end with general discussions.

Emotion and attention effects

Emotions, like other pervasive but intangible constructs in psychology are subject to great debates when it comes to its definition. Lisa Barrett, a psychologist and researcher on affect, not too long ago wrote “...we don’t agree, as a discipline, on the nature of what we are studying” (Barrett, 1998, p. 6). Her claim is not without basis. Based on a review of more than 25 definitions of emotions, Plutchik (1980, 1982) concluded that there was little consistency and clarity to the definition of the term.

Luckily, emotions are so pervasive to human behavior, and when they appear, they do so surrounded by many noticeable signs such as change in behavior, facial expressions, skin temperature and blood pressure, to name a few, that observation of its presence by measuring its correlates becomes a much easier task than defining its core basis. For example, Putchik (1982) argues that emotions, like memory and perception, are ‘hypothetical constructs’ that can only be inferred by evolution, being evidenced in feelings of attitudes towards the self, physiological changes and orientation towards actions. He bases his claim on the idea of the coupling of emotional sub-systems, physiological (face, focal attention), psychological (feelings, arousal) and response preparation system (action tendencies) as a synchronizer, occurring together and influence each other (Mayne and Ramsey 2001).

It is important to distinguish *emotions* (mental states of readiness which are targeted at a referent and accompanied by physiological processes) from general *affect* (the superset that includes emotions, moods and attitudes), *mood* (a less intense but longer lasting nonintentional affect than an emotion) and *attitudes* (evaluative judgments rather than emotional states). For more details, see Bagozzi et al. (1999).

Emotions in Commercials

Given the objective of understanding the attention concentrating power of emotions, moment-to-moment, as instruments that advertisers use to affect consumers’ desire to keep watching TV commercials, I need to choose at least one of these sub-systems. Hopefully, an adequate choice provides the means to tap into the underlying emotional coordinating system. And when it comes to studying the role of emotions in advertising, the standard practice is to use self-report questionnaires (e.g., Edell and

Burke 1987). Whereas their ease of application is a strength, self-reports are problematic because they may lead to mere measurement effects (e.g. “introspection about one’s emotions often changes them” (Plutchik 1982, p. 530)), invite strategic and socially desirable responding, and may be too crude and late to pick up more faster and more subtle affective responses (Bagozzi et al. 1999; Morwitz and Fitzsimons 2004, Richman et al. 1999). In light of this, I follow a less traditional but promising approach.

From an evolutionary perspective, emotions have two functions: to communicate intentions and to orient action towards survival (Plutchik 1982). Facial expressions are a key component of human emotions (Darwin 1872) and constitute (Ekman 1992) appropriate measures of emotions that (a) can be measured moment-to-moment, (b) are non-intrusive and (c) do not interrupt the consumer’s normal viewing experience. Theories of basic emotions are based on research that show the existence of basic emotional units, which are discrete and universal, motivated by evolutionary theory (Ekman 1992; Plutchik 1980). These universal prototypical patterns have been found for emotions of joy, sadness, surprise, disgust, anger and fear (Ekman, 1994). Izard (1994) proposed in addition to these, interest, contempt, shame and guilt, arguing that complex emotions are combinations of basic ones while Plutchik (1980) added only anticipation and acceptance. Moreover, the facial expressions are known to be good indicators of internal appraisal processes, evaluative judgment and interpretations, which according to the Appraisal Theory: events or stimuli lead to appraisal and emotions are the result of this internal process (for a summary, see Bagozzi et al. 1999 and Han et al. 2007). And, as with emotions, appraisal processes at the sensory-motor level are also hard to be accessible with verbalization-based measures.

Critics of using facial expressions to gauge emotions claim that the mechanisms linking emotions to facial expressions are still largely unknown. Moreover, the powerful role of regulation and expression control through explicit and implicit social norms, among others, and expectations implicate the use of facial expressions to be very challenging, although self-report can suffer from the same issue (Hess, Banse and Kappas 1995). This is worsened by the fact that facial expressions serve as multiple other purposes (i.e. indicating cognition, signaling, and for other bodily functions) (Kaiser and Wehrle 2001). Since expressions are used for signaling, expression management, social goals (Goffman 1959), an attempt to measure emotions via the face has to take into account both the measurement error issue and reduce to the greatest extent possible the social influences as well as control for the individual traits that may explain individual heterogeneity is the use of facial reactions.

With this in mind, Ekman and Friesen (1978) created the Facial Actions Coding System (FACS) method for the reliable and sensitive coding of any facial action in terms of the smallest visible unit of muscular activity, which has proven its usefulness in marketing contexts (Derbaix 1995). Basic emotions were then matched against these facial quanta, based on the idea that each emotion is based on prototypical, innate and universal patterns in the human face. Critics see these basic emotions as modal responses of complex clusters of feelings, of which there are a high number of differentiated emotional states (Scherer, 1984, 1995). But, for the purpose of this research, if there are truly basic emotions or if joy, sadness, surprise, disgust, fear and anger are just typical modal outcomes, I remain agnostic about the issue.

Previous researchers have attempted to use the FACS in manually coding video footage of participants watching TV commercials in an attempt to relate emotional ads to positive attitudes and other measures of ad effectiveness without much success (Derbaix 1995). Derbaix used ten human coders to measure the FACS expressed via the face on reactions to 13 commercials at each 1 sec. interval. He doesn't find significant results for the impact of facial affect on ad and brand attitudes, blaming the choice of commercials and either the coding scheme or the verbally measured dependent variable for that. I follow through with his recommendation that "designing non-verbal measures of a DV should be a priority" by using zapping (i.e. channel switching) as a behavioral measure of advertising avoidance, one which has become even more in vogue given increases in technologically based opportunities for consumers to avoid watching commercials (i.e. DVRs and PVRs). Furthermore, not using forced exposure will reduce the increased attention and unnatural condition of heightened perception of emotional and cognitive cues in commercials.

Individual human coding of FACS is very demanding and unlikely to be used by advertising practitioners to measure emotional reactions in pre and post-test involving many participants and commercials. That is another reason for why I opt to use an automatic statistical classifier of the occurrence of the basic emotions. Using the FACS in statistical computer analysis, Bartlett et al. (1999) showed that algorithms trained on a large dataset are better able to detect the FACS units and classify emotions, as compared to non-experts, while not significantly worse than experts. Automation of emotions classification is thus reliable and provides the fine temporal granularity needed to study the effects of emotions on visual attention and zapping, both of which can occur well

within the 1-sec time window used by Derbaix (Nummenmaa et al. 2009, Mihaylova et al. 1999). With an automatic classifier, I am able to measure emotional reactions at the rate of 4 times per sec. For more details on how the automatic classifier works and pre-test results, please refer to appendix 2.

Emotions expressed in advertising are predominantly positive, and surprise (positive disconfirmation of expectations) and joy (experience of positive outcomes) are most common among these, as the positive emotions experienced by consumers (Frederickson 2004). Since, the vast majority of advertisements explore joy, interest, surprise and disgust (Allen, Machleit and Marine 1988), I initially focused only on joy, surprise and disgust, given that interest is not a basic emotion represented via Ekman's FACS. But infrequency in evoking and unreliability in coding disgust made me abandon it and focus only on joy and surprise. Notably, Derbaix (1995) also reports joy and surprise as the most frequently observed facial expressions of participants watching TV commercials.

Emotions effects on Attention Dispersion and Commercial Avoidance

In Roseman's (1991) Appraisal Theory of emotions, joy and surprise alter in only two appraisal dimensions: motive consistency (joy is positive and surprise is positive or negative) and circumstance caused (joy is certain and surprise is uncertain). Regarding motive consistency, positive emotions are associated with the decision to continue with a plan to attain the goal, whereas negative emotions usually relate to failure to attain a goal and a change of plans (Oatley and Johnson-Laird 1987).

Emotions are also known to influence attention, especially focal visual attention (Lang 1990). Fredrickson (2005) proposed the broad-and-build theory of positive emotions, claiming that positive emotions, including joy and interest, broaden the individual's momentary attention, i.e. sparking urge to explore, and subsequently to build their personal (physical, social and intellectual) resources. Using film clips to induce joy, measured via self-report and facial muscle EMG, she showed that feelings of joy broaden the scope of attention in local-global visual processing tasks (Fredrickson and Branigan 2005). In line with the exploration versus orientation behavioral effect of emotions, Plutchik proposed that joy and anticipation, adjacent (similar in nature) in his 'circumplex' of emotions, also caused a desire for exploration. On the other hand, the diametrically opposite emotion of surprise (dissimilar) would lead to orientation.

In a clustering of more than 200 emotions based on a sorting task from 100 students, Shaver et al. (1987) concluded that these cluster around the similar basic emotions of Ekman with the addition of love. Surprise was, on average, judged to be slightly positive in the evaluation dimension and much higher in the intensity dimension than any other emotion cluster, including joy.

Based on this, on the broad-and-build (B&B) and appraisal tendency (ATF) theories, I predict that Joy and Surprise will reduce contemporaneous zapping (at the onset or shortly lagged) and will disperse people's attention, albeit for different reasons. The highly positive feeling of joy will lead to a desire for visual exploration (B&B). The slightly positive nature of surprise added to the high intensity and unexpected nature of the cause circumstance (ATF) will lead to a moment of halt and subsequent re-orientation of focus of attention (Plutchik's Circumplex). This is perfectly in line with the action

tendencies of moving forward or against objects and images as coping responses of emotions (Frijda 1986). Thus, the relocation of focal attention is a fast way to carry out these action tendencies. The explanation is that moving attention away is effortless, fast and a decision that is not irrevocable. On the other hand, zapping, while not as effortless and fast as gaze redirecting, is a decision that can't (in this study) or is not frequently (in home) undone. In the next section, I explain how attention dispersion (or concentration) is measured.

Regarding the magnitude of these effects, surprise is also different from Joy in the sense that it is an example of immediate emotions, which are “instances of visceral factors that grab people’s attention and motivate them to engage in specific behavior, also playing a critical role in intertemporal choices” (Loewenstein 2000). Thus, I also expect that, to the extent that surprise is higher in intensity as evaluated by Shaver and colleagues and visceral, surprise should have a stronger effect on focal attention dispersion than joy.

Role of dynamics of emotional effects. On another note, emotions that are discrete may have an immediate effect as well as a delayed and persistent one. I pose that the above motive consistency plan is not one that occurs instantaneously. At first occurrence, emotions should have a faster “attention grabbing” effect, but the persistent effect on volition may not be in the same causal direction. For example, upon encountering a hazardous snake or insect, we direct attention and then tend to choose to avoid movement in that direction. This may or may not occur for surprise depending on if it is or isn't motive-consistent. On the other hand, for joy, the sequential reactions should be predominantly motive consistent given the entertaining nature of many advertisements.

So, focal attention and non-zapping should go directionally hand-in-hand under the influence of joy. In line with the opposite temporal impact of certain emotions, previous research has shown that "...sad expressions do not produce avoidance behavior (e.g. changing the channel)...", by claiming that automatic vigilance suggests that negative information is more attention grabbing (Small and Verrochi 2009). Generally stating, "sometimes emotions spur one onto action; at others times emotions inhibit or constrain action" (Bagozzi et al. 1999).

Given the lack of specific moment-to-moment theories differentiating Joy from Surprise, I use an amalgam of the ones previously discussed, including Pluchik's evolutionary argument for the exploration and orientation role of basic emotions, Fredrickson's sequential Broad-and-Build theory and the distinguishing dimensions of the Appraisal Tendency Framework. My hypothesis is that Joy, as an emotion that spurs one onto action, will have the same direction of effect for the instantaneous change (i.e. derivative) as for the persistent (i.e. level) effect, while Surprise will have the opposite, one of impairment then reorientation to action.

Controlling for Ad, Brand and Person Effects

To control for the well-know effect that brand images (logos, trademarks, pack shots) can have on causing zapping decisions as well as, possibly, on visual attention, I control for features of the brand image, apart from presence, such as position, separation in the scene, cardinality and duration (see Chapter 1). Visual complexity, as the non-representational perceptual material, such as different colors, lines, luminance contrasts, in the commercial (Donderi 2006) is also accounted for and known to have a U-shaped

relationship to zapping likelihood (see Chapter 1). Also, brand familiarity is known to moderate the relation between attitudes of ad on brand attitude (Derbaix 1995). So, I measure brand as well as ad familiarity and conjecture directionally similar effect on attention dispersion and avoidance behavior: viewers concentrate and are less likely to zap familiar brands but disperse and are more likely to zap familiar ads. The length of the commercial should be related to dispersion and zapping with longer commercials causing more dispersion and zapping. Finally, two demographic factors, gender and age, are controlled for, based on findings that males compared to females, and younger compared to older consumers generally zap more (Heeter and Greenberg 1985).

In sum, I predict that, while controlling for ad, brand and person characteristics, emotions of Joy and Surprise in commercials affect the moment-to-moment commercial avoidance decisions of consumers directly, via reducing zapping, and indirectly by causing an increase in attention dispersion of the viewer, with a posterior decrease of dispersion for Surprise due to reorientation. Furthermore, attention dispersion should also affect zapping in itself (Chapter 1). For lack of theoretical guidance, the net effect of these two routes to avoidance behavior will not be speculated any further. It will be empirically verified. Before specifying the statistical model that allows me to examine the above predictions in detail, the data on which it is calibrated are described.

Data

In an experiment, spatial attention and overt emotional facial reactions to emotional versus neutral commercials, as well as zapping incidence were simultaneously measured. Apart from exposure of all respondents to a randomized set of

emotional/neutral commercials, no manipulation was conducted. Previous research has concluded that facial emotional expressions show only strong reactions at clearly definite moments during exposure (Derbaix 1995) since emotions in ads are largely vicarious. Therefore, I selected 14 extreme (very joyful and/or surprising) commercials, after a pre-test confirming their ability to evoke the intended emotions at certain instances. Since the stimuli were not randomly chosen, this analysis aims to discover the potential of commercials to have moment-to-moment emotional effects, not the average effect in the market place of TV ads.

Stimuli and Participants

The participants recruited for the experiment were 58⁸ students and staff of a major northeastern American university, ranging in age from 18 to 49 (mean=22) with 53% male adults. They received \$10 for participation. The stimuli were 28 TV commercials embedded in web pages, half of them chosen to evoke either feelings of overt joy (e.g. smile and laughter) or of surprise (e.g. mouth open and elevation of eyebrows). Most were successful in a pretest (see details in appendix 2). They spanned many product categories such as beverages, CPGs, telecom, cleaning supplies and financial services for know (Budweiser, Nivea, Dell, etc.) and largely unknown brands (Lincoln Insurance, Mercator, Rockstar Drinks, etc). The other half was made up of non-emotional (neutral) mainly informative TV ads for the same product categories as the emotional counterparts. In order to counterbalance the non-random choice of emotional

⁸ 8 of these had equipment problems during the data collecting and were discarded, resulting in an effective sample size of 50 participants.

stimuli (which could reduce zapping incidence⁹), and to avoid overburdening the participants in an unnatural way with sequences of strong and alternating emotions (joy and surprise), I interspersed each emotional commercial with a neutral counterpart to act as an “emotional buffer”.

Data Collection

Participants were greeted, given consent forms to sign and told that they would be led to a room in which they were seated in front of an eye-tracker with camera and shown a short 4 minute sitcom followed by a series of 28 TV commercials. After calibrating their eyes to the equipment, they were shown instructions on the screen stating that, for each commercial, they could either watch it until the end, zap to the next one by pressing the space bar or click on the link provided in the bottom of the page with a mouse to go to the brand advertiser’s web page. If they clicked on the link, they were sent to a 1-page mock-up site for that brand so as to provide a benefit for the interested participant but at the same time not presenting too much information so as to make the participants not stay too long at the brand’s site. The link at the end of this webpage sent them to the next commercial in the sequence. All participants were asked to keep one hand over the space bar and the other over the mouse at all times. The goal of showing commercials as web pages with links to-from mock websites is to reduce demand effects from artificial facial expressions by distracting them into ‘using eye-trackers to understand how people surf web pages with video ads’.

⁹ This resulted in an average zapping rate of 48% (s.d. 21%), slightly lower and with higher standard deviation than zapping rates reported in previous research , 55%, s.d. 12% (Chapter 1).

The reel of 28 commercials were sequenced such that for each emotional commercial shown, there was a randomly assigned neutral one that followed and care was taken to not match up ads with the same product category. After the participants saw the complete reel and had the opportunity to zap undesired commercials, they were conducted to a computer terminal in another room to answer questions about each of the commercials that they were presented (familiarity, feelings, attitudes), as well as questions about their demographics and some demand check questions. The entire experiment lasted around 45 minutes.

In order to measure the focus of attention for each participant, eye-tracking equipment was used. A Tobii 1750 eye-tracker unobtrusively (no head or chin gear) measured eye movements using infrared cameras embedded in the rim of a TFT monitor at the rate of 50 Hz with spatial resolution of less than 0.5 degrees of visual angle. The participants had complete freedom of head movement within a virtual 30 cm³ box. Facial expression footage from each participant was collected by means of a MiniDV camera coupled to the eye-tracker and aimed at the participant's face. The continuous video images served as input to the emotion detection software which works by fitting a virtual facemask to the image of the face. The fitting adjusts face form (eyes, eyebrows, nose, face and mouth delimiters) so as to capture 64 deviations in the line segments that relate to the Facial Actions Coding System (FACS) of Ekman. These measures are processed virtually online at the rate of 4 Hz using a Bayesian Neural Network Classifier calibrated on the images of the Cohn-Kanade database, a well-known benchmark. The output is the probability that the viewer is exhibiting one of Ekman's six basic emotions (joy, sadness, fear, surprise, disgust or anger) or a neutral state. For this purpose, I use

only the measures associated with Joy and Surprise. For more details on the accuracy or a pre-test of the algorithm, please see the appendix 2.

Measures

In table 1, I provide summary statistics of the variables collected, the definitions and details of which are described in the sequence.

Commercial avoidance. The dependent variable is every avoidance decision, when a participant chooses to stop watching a particular commercial by pushing the space bar (1 = avoid, 0 = else). Since a zapping can only occur once for a participant-ad combination, zapping at each time-frame is always conditional on a non-zap at the previous time-frame. In the dataset collected, the dependent variable structure is one of a binary cross-sectional (participants) unbalanced repeated measures (commercials) time-series.

Emotions. The output of the emotions detection algorithm is a classification accuracy measure ranging from 0 to 1 for each time-frame for Joy and for Surprise, where the highest the measure, the highest is the likelihood that the viewer is feeling the respective emotion at that 250 ms instant.

Attention dispersion. Following results in Chapter 1, I calculate both Individual (IAD) and Aggregate Attention Dispersion (AAD) using the X and Y-coordinate focal eye positions detected from the eye-tracker. As a function of the binary focal position f_{ict} , for individual i , commercial c and time-frame t , IAD and AAD (for N such individuals) are defined as¹⁰:

¹⁰ For a large number of individuals, collinearity between IAD and AAD should not be significantly high, despite the fact that they are functionally tied together by definition. The same is true for the sample variance, which can be interpreted as a mean of squared deviations.

TABLE II.1: Description of the data

Variable	Variation units	Mean	Std. Dev.	Minimum	Maximum
Zapping	across 28 ads	48%	21%	10%	86%
Zapping	across 50 ind.	48%	21%	11%	93%
<u>Emotion:</u>					
Joy Level	ad, time, ind.	15.4%	32.0%	0.0%	100.0%
Joy Difference	ad, time, ind.	0.0%	2.0%	-14.6%	14.6%
Joy Absolute Difference	ad, time, ind.	0.0%	1.8%	0.0%	14.6%
Surprise Level	ad, time, ind.	4.4%	19.1%	0.0%	100.0%
Surprise Difference	ad, time, ind.	0.0%	1.4%	-14.5%	14.1%
<u>Attention dispersion:</u>					
Individual dispersion (pixels ²)	ad, time, ind.	59	42	0	302
Aggregate dispersion (pixels ²)	ad, time, ind.	6837	3276	696	24860
Aggregate × Indiv. dispersion	ad, time, ind.	4.6×10^5	5.0×10^5	0	5.3×10^6
<u>Control variables:</u>					
Visual complexity ² (Kbytes ²)	ad, time	2.0×10^4	2.9×10^4	3.6×10^1	3.7×10^5
Presence (present = 1)	ad, time	23.6%	42.5%	0	1
Duration (seconds)	ad, time	4.6	9.5	0	87
Cardinality (1,2,...)	ad, time	1.2	3.4	0	39
Age (years)	ind.	22	4.7	18	50
Gender (male = 1)	ind.	53.4%	0.50	0	1
Ad length (seconds)	ad	43	18.5	15	100(60)*
Ad familiarity (familiar = 1)	ad, ind.	7.6%	0.26	0	1
Brand familiarity (familiar = 1)	ad, ind.	59.0%	0.49	0	1

Note: Only one commercial in the dataset was longer than 60 sec so I used its data up to this amount so as to reduce the computational burden in estimating time-varying parameter. The eliminated portion corresponds to 0.9% of the original data.

$$\begin{aligned}
\text{IAD}_{\text{ict}} &= \left(\mathbf{f}_{\text{ict}} - \frac{1}{N} \sum_{i=1}^N \mathbf{f}_{\text{ict}} \right)' \left(\mathbf{f}_{\text{ict}} - \frac{1}{N} \sum_{i=1}^N \mathbf{f}_{\text{ict}} \right) \\
\text{AAD}_{\text{ct}} &= \frac{1}{N} \sum_{i=1}^N \text{IAD}_{\text{ict}}
\end{aligned} \tag{1}$$

Control Variables. Also following Chapter 1, visual complexity in each frame of the commercial was assessed by the file size in kilobytes of the GIF-compressed image. Branding measures were obtained semi-automatically by means of Adobe Premiere Pro, specialized video editing software, for each frame of a commercial. Only the measures estimated to be (marginally) significant in Chapter 1 were recorded. These were Presence, Position, Separation, Mode, Cardinality and Duration. Ad length was obtained directly from the stimuli.

Lastly, the participants' age and gender, as well as their previous familiarity with the commercial and with the brand, were obtained via a questionnaire at the end of the experiment.

Data Aggregation

Eye-tracking data was collected at the rate of 50 Hz, facial emotions were measured at 4 Hz and commercial frame measures (brand images and complexity) were measured at the standard 25 Hz. To equate the data frequency while avoiding missing data or interpolation issues, I aggregate eye movements and stimulus frame data to 4 Hz, or a time-frame window of 250 ms. This value is within an average fixation duration for dynamic stimuli (Rayner 1998) as well as serves as a lower bound for visually-based response latencies (Mihaylova et al 1999).

Model

As in Chapter 1, I assume that an individual i 's decision to continue watching a specific commercial c at time-frame t , or to zap it, is based on the (negative) utility derived during t . Thus, the probability that individual i decides to avoid commercial c at time-frame t , given parameters Θ_t , is:

$$P(y_{ict} = 1 | \Theta_t) = \Phi(D_{ict})$$

where: $y_t = \begin{cases} 1 \rightarrow \text{zap} \\ 0 \rightarrow \text{watch} \end{cases}$ (2)

Regarding the deterministic component of zapping a commercial, D_{ict} , I assume additive separability of strictly individual, commercial and time-specific baseline avoidance rates. Previous literature has shown that viewer's tolerance or zapping behavior is demographic specific (Heeter and Greenberg 1998), varies according to content (see Chapter 1) and is dynamic within an ad, for example, with non-monotonic varying instantaneous zapping rates throughout its duration (Gustafson and Siddarth 2007). Additive separable individual and trial (each commercial) random effects are known in the duration biostatistics literature as Frailty Models and are widely used due to their parsimony in the number of parameters to be estimated. In the data in this essay, this translates into a reduction of the ict -specific fixed and random effects parameters from $ICT = 50 \times 28 \times 240 = 336.000$ to $I+C+T = 318$.

Given the binary nature of the dependent variable, I assume that the unobserved random utilities for the avoidance decisions are normally distributed. Sueyoshi (1995) shows that duration models can be reinterpreted as discrete binary dependent variables, with Logit and Probit being special cases. The choice for the latter is due to the data

structure and the straightforwardness of using time-varying coefficients (Lachaab et al. 2006). Adding to the assumptions, the exogenous aggregate influence of individual and stimuli specific regressors, I can write the previous equation as:

$$\text{Probit}(\text{Zap}_{ict}) = \mu_i^{(1)} + \alpha_c^{(1)} + \theta_t^{(1)} + X_{ict}^{(1)}\Psi^{(1)} + \varepsilon_{ict}^{(1)} \quad (3)$$

where, the RHS of the equation is composed of the individual, commercial and temporal baseline zapping rates, followed by the aggregate effects and the unobserved component of utility, linearly associated to the dependent variable by the Probit link function. $X^{(1)}$ is made up of the emotion, Attention Dispersion, visual complexity and branding covariates. Due to collinearity between the measures of the latter, I incorporate only brand Presence, Duration and Cardinality, leaving out Position, Separation and Mode.

In line with parsimony, I shrink random effects to aggregate means via Hierarchical Bayes. μ_i and α_c are estimated for each individual and commercial, respectively, and are a linear function of demographics (age and gender) and individual-commercial characteristics (ad length, ad and brand familiarity). Additionally, I allow the time-specific zapping baseline to evolve stochastically in a random walk fashion with drift (as in Chapter 1). Details are in appendix 1.

To measure the extent to which the emotions of Joy and Surprise affect moment-to-moment commercial avoidance decisions, above and beyond the direct effect in equation 2, I estimate the mediating role of attention dispersion via a model similar to the one used for zapping¹¹. The motivation for this is that, focal attention dispersion, aside from zapping, is yet another way in which consumers behave in order to avoid watching

¹¹ Although equally conceivable, this was not done in essay 1, given that IAD was used as a control variable and not much additional insight would have come from modelling this relationship.

commercials. While zapping is a conscious and active decision, one which has the consequence of irreversibility, IAD is a measure that taps into the deviation of focal behavior “from the herd”. While the consumer avoids consciously or not looking at particular objects, she can always go back to the herd. Individual Attention Dispersion here is seen as a mechanism used to orient to or avoid objects on the screen for short periods of time, while zapping is the ultimate means to avoid all objects for all time. So, apart from emotional influences speculated in the theory section, it is conceivable that the other covariates be related to and influence both IAD and zapping in the same way.

In line with this premise, as in the case for zapping a commercial, there should also be demographic, commercial and temporal specific baseline distractions as well as the marginal contribution of other covariates. Images such as brands, and their features, can also be contributors to idiosyncratic dispersion, as can be highly complex (or very simple) visual stimuli. Given this, and the fact that IAD is a quadratic Euclidian distance measure (positive and skewed), I model it with a log-linear model and in similar Frailty form (additive separability of random effects):

$$\text{Log (IAD}_{\text{ict}}) = \mu_i^{(2)} + \alpha_c^{(2)} + \theta_t^{(2)} + X_{\text{ict}}^{(2)}\Psi^{(2)} + \varepsilon_{\text{ict}}^{(2)} \quad (4)$$

, where similarly to the zapping model, the RHS incorporates demographics, individual-commercial and $X^{(2)}$ captures the rest of the covariates discussed above.

If gaze-based attention dispersion and zapping behaviors are truly means used by viewers for avoidance of objects, scenes or whole ads, then the effect of the regressors used in both models will capture influences that are not independent from each other. Thus, the error terms should be correlated. So, in order to incorporate the covariation in

zapping decisions and IAD, where both are influenced by the same subset of covariates (less IAD and AAD), as well as the predicted latter influence on the former, I need to simultaneously estimate this dependent structure. I do so by estimating jointly the effect of emotions, attention and covariates on zapping and the effect of emotions and covariates on attention. Stacking the error terms into $\boldsymbol{\varepsilon}_{ict}$, the simultaneous model is:

$$\begin{pmatrix} \text{Probit}(\text{Zap}_{ict}) \\ \log(\text{IAD}_{ict}) \end{pmatrix} = \begin{pmatrix} \mu_i^{(1)} + \alpha_c^{(1)} + \theta_t^{(1)} + X_{ict}^{(1)}\Psi^{(1)} + \psi_{11}^{(3)}\text{IAD}_{ict} + \psi_{21}^{(3)}(\text{IAD} * \text{AAD}_{ict}) \\ \mu_i^{(2)} + \alpha_c^{(2)} + \theta_t^{(2)} + X_{ict}^{(2)}\Psi^{(2)} \end{pmatrix} + \boldsymbol{\varepsilon}_{ict} \quad (5)$$

To summarize, equations 5 describes a bivariate Dynamic Simultaneous (Probit + Log Linear) Frailty Model. The Probit describes zapping as a utility-based decision that is made on a moment-to-moment basis and is a direct and indirect function of emotions, as well as focal attention measures and other covariates that capture individual, commercial and temporal heterogeneity. The Log-Linear model estimates Individual Attention Dispersion as a function of emotions and covariates, also capturing the three important sources of idiosyncratic baseline heterogeneity. Jointly estimated, these two models should help understand the processes and relative importance with which Joyful and Surprising scenes impact the consumer's decision to continue watching a commercial or not. And in the latter case, how can the moment-to-moment individual behavior of focal attention help explain the process by which Joy or Surprise has a possibly detrimental effect on continued interest in watching commercials?

Estimation Procedure and Inferences

Given that the behavioral responses of visual attention, facial emotions and volitional zapping do not occur simultaneously (i.e. having different reaction times), in

this section, I propose to estimate mean latencies from emotions to IAD and to Zapping. I also discuss the issue of the direction of causality between emotions and the attention dispersion measures, IAD and AAD. Before doing so, it is important to highlight the theoretical implausibility that AAD, as an aggregate measure of attention dispersion across viewers, directly influence an individual's emotion, let it be Surprise or Joy. The simple reason being that viewers watch commercials individually and should not be affected by other viewers' behaviors that are unobservable to them. But it is very well possible that Individual Attention deviations may affect this viewer's emotions. So, I am able to conjecture three scenarios: IAD mediates emotions, emotions mediate IAD or both reinforce each other. In all these cases, as hypothesized before, IAD, Surprise and Joy directly cause Zapping.

Therefore, a parsimonious model of both emotional effect and spatial attention effects should contemplate only direct effects of AAD as well as direct and indirect effects of Surprise, Joy and IAD. The question now is what is the direction of causality between IAD and emotions? In an attempt to answer the question in this context, I make the assumptions that causality is met with two sufficient conditions. First, the two constructs have to be strongly correlated with each other, controlling for other known factors. Secondly, a construct is causal to its effect if it has temporal precedence over the other. Obviously this need not be the case in general. Nonetheless, short and fast paced commercials, differently from long movies, have the property that viewers are not forward-looking in that they can't (or won't) consistently and systematically predict "future" feelings based on current images. There is little motivation to do so, since the "future" will arrive in a matter of seconds and the cognitive effort is not worth the pay-

off: watching something better with these saved seconds. Thus, emotions result only due to current and past stimuli, I do not assume commercials evoke anticipatory emotions as studies by Bagozzi, Baumgartner and Pieters (1998). Now, even with the properties of correlation and temporal precedence, it may be that a third construct may be influencing both attention dispersion and emotions, albeit at different latencies, and thus inducing an apparent relationship that mimics causality. It is clear that in this context, the stimulus image and sounds act that way. Unfortunately, there's no systematic means for figuring out which features, dimensions or components of the image that separately cause, for each viewer, emotions, focal attention and commercial avoidance. So, despite the stimuli being undeniably the sole cause of all consumer behavior, inability to accurately categorize and measure the stimulus in general, and image in specific, forces one to use these process variables. I assume no other element, aside from commercial stimulus, plays a predominant role in simultaneously causing changes in focal attention (IAD), overt emotions or zapping behavior across viewers and commercials.

So whether emotions may be driving IAD changes or vice-versa (or both), lets assume that at time $t = T1$ the commercial stimulus (visual+audio) is shown to the viewer and has an effect on IAD (and on AAD). If that stimulus is to also cause an emotional reaction, current literature is unanimous in claiming that it will be exhibited much after the eyes react, given that the facial expressions are much slower (Hansen and Hansen 1994), causing a reaction at time $t = T1 + t'$. The direct effect on the decision to zap the commercial should be even slower but is unknown. Now, allowing for the possibility of these effect on Surprise/Joy and IAD to propagate (i.e. cause influences) to each other, it

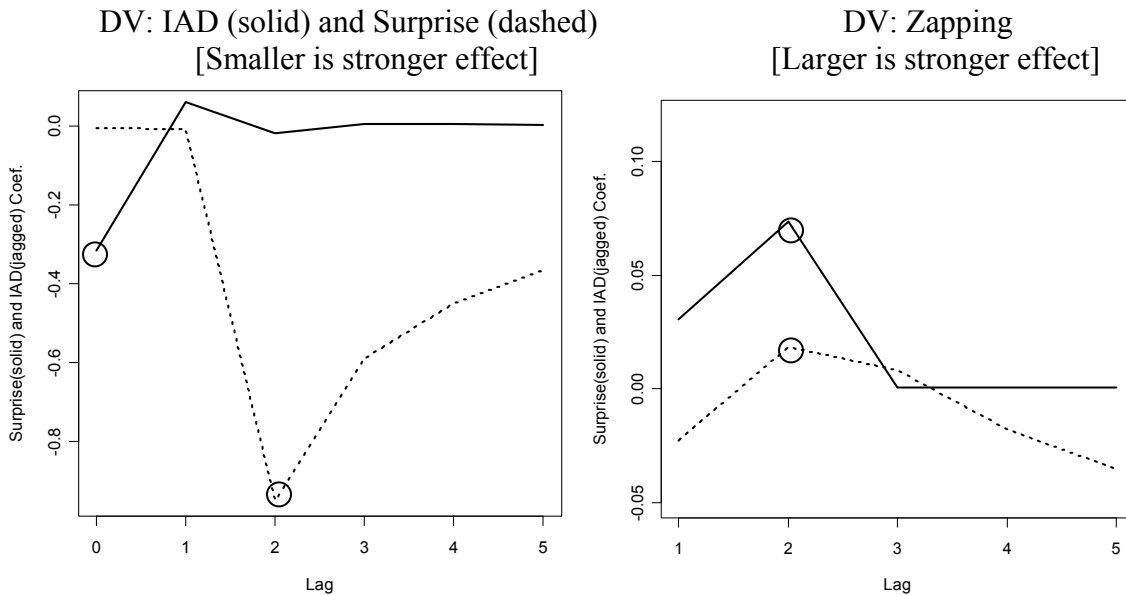
becomes an empirical question to measure the appropriate latency at which this can be picked up by statistical correlation.

To find the appropriate latency, I regress each variable¹², Surprise/Joy or IAD, on the other, controlling for other conjectured commercial, individual and brand-specific effects, for various lags, from 0 (effect occurs within 250 ms) to lag 5 (within 1500 ms). The lag with the highest regression parameter, and thus fit, should be the one which best explains the influence of the regressor on the regressand. This indicates the appropriate average peak latency response among the alternatives. Obviously, latency may be viewer, stimulus and time specific, nonetheless, I simplify to an aggregate best lag analysis. The graph in Figure 1 (left) shows the parameter effects of Surprise on IAD (solid line) and of IAD on Surprise (dashed line) for simultaneous and lag 1 to 5 models. All values are significant at 5%. Notice that the best fitted model indicates that Surprise is related to changes in IAD within 250 ms (lag 0) while IAD is more strongly related to changes in Surprise after a lag of 2 frames (500 to 750 ms). Given this longer latency of IAD on Surprise, it is plausible that the stimulus caused changes in IAD and this propagated to create an emotional feedback effect from Surprise to IAD, and back to Surprise. On the other hand, controlling for the direct stimulus effect on Surprise, it would seem very unlikely that the mere deviation of a viewers eyes from the rest of the viewers (higher IAD) could systematically “induce” the appearance of an emotion strong enough to evoke a facial expression. Both findings, directionality and latency, are in line with the findings of Nummenmaa, Hyona and Calvo (2009) who find evidence suggesting that emotionally salient content cause eyes to orient (1st saccade) both reflexive and voluntary starting at

¹² All latency analyses presented in this section are valid for both emotions but only shown for Surprise, given that Joy was qualitatively equivalent.

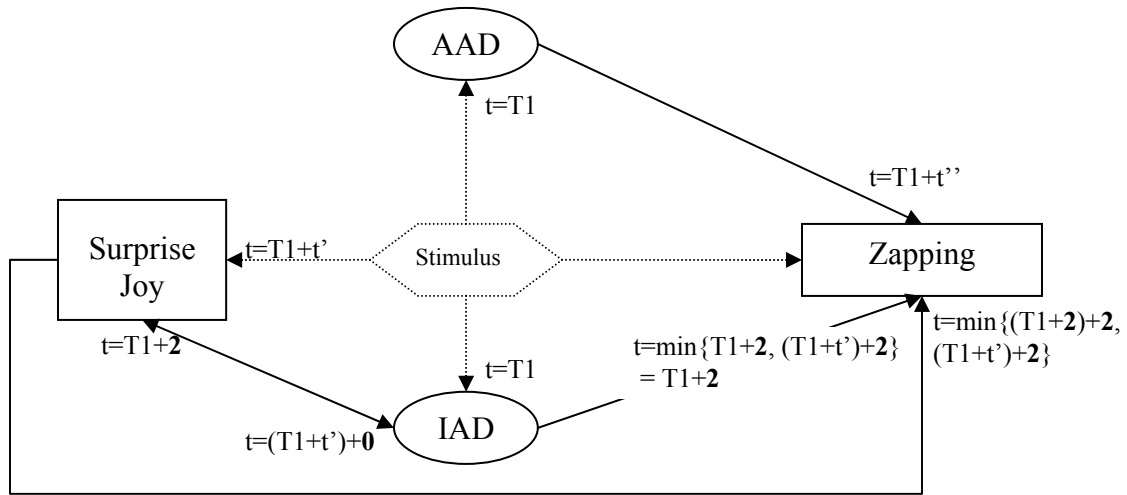
160 ms and peaking at 320 ms of complex scene perception. Given the lack of any evidence for a fast enough causal effect, I abandon the conjecture of a direct effect of IAD on Surprise or Joy and only propose to model the reverse.

FIGURE II.1: Defining latency response based on optimal lag effects



Similarly, it becomes important to understand the latency of zapping response from changes in emotions and IAD. So, I proceed, this time with a binary (Probit) regressions of zapping on emotions, IAD, AAD and all other individual, commercial and brand specific covariates, altering the lag variables independently for Surprise/Joy and IAD. It is clear that these emotional-based effects can't cause physical reactions simultaneously so I only test for values of lag corresponding to 250 to 1500 ms. Figure 1 (right graph) shows that the predicted positive effects of both Surprise and IAD on zapping occur more strongly with a lag of 2 frames for each. Thus, the final model should contemplate direct effects of these constructs with latency from 500 to 750 ms, as the appropriate mean peak response.

FIGURE II.2: Flow model of response latencies for emotions attention and zapping



Note: Numbers in bold are the result of lag regression estimates in the previous figure; t' is the latency from visual to facial response; t' is latency from visual to physical response. For a certain individual, IAD influences AAD only when the number N of viewers is small. In this case, $N=50$ makes the relation practically negligible.

To summarize the findings above, figure 2 depicts a flow model of latency effects (i.e. time measured only in flows) from the stimulus onset to the main processes constructs for the time at which the causal construct causes an effect. One-sided arrows depict unidirectional causality and double-sided arrows depict *potential* bidirectional causality, which is not evidenced based on the lag results. Notice that, based on the discussion and empirical findings above, the start of the direct stimulus effect on Surprise/Joy is assumed to be at $t=T1+t'$ while the indirect effect of stimulus on Surprise/Joy is estimated to be at $t=T1+2$. For IAD, the direct effect is assumed to be at $T1$ while the indirect effect, via emotions, is at $T1+t'$. Each route, direct and indirect, combines to cause an effect on zapping. The routes necessarily passing through IAD start causing a predicted effect on zapping at the minimum between the direct route plus the direct latency route of IAD, $T1+2$, and the indirect route plus the latency from Surprise to IAD and the latency to Zapping, which is $T1+t'+2$. Thus, the minimum effect of zapping

after the stimulus is received and “processed” through both attention and emotional routes is 2 time-frames after visual attention is mobilized. As for the routes passing necessarily via Surprise/Joy, the minimum response latency is $T1+2$ frames if the route comes from IAD or $T1+t'+2$ if the route is direct from Surprise. Obviously, the minimum will depend upon if the difference between the direct effect of the stimulus on surprise and its direct effect on IAD is shorter than 2 time-frames or not.

In summary, the estimated attentional, emotional and physical response latencies estimated from the data provides the following guidelines for determining corresponding lag effects in the final model:

1. Model the effect of IAD (and AAD) on Zapping with a lag of 2 frames (500 to 750 ms)
2. Model the effect of Surprise and Joy on IAD with no lag (0 to 250 ms)
3. Do not model the effect of IAD on Surprise/Joy given lack of theoretical or empirical evidence.
4. Model the direct effect of Surprise and Joy on Zapping with a lag 2.

Clustering and Functional smoothing

One of the main purposes of this paper is to evaluate the moment-to-moment effects of Joy and Surprise, both in terms of visual attention concentration and of affecting zapping likelihood. The use of facial expression to measure online emotions, while novel and unobtrusive, is not without its own drawbacks. One problem that I have to deal with is measurement error. Another problem is that the output of the software is not an emotion intensity measure, but a probabilistic estimate of the emotional state.

While clean facial expression such as an intense smile or laughter increase the probability output by the software, it need not be the case that higher classification certainty is correlated with emotional intensity, even though Hess, Banse and Kappas (1995) compared facial EMG measures with Izard’s Differential Emotion Scale to find that that intensity in the expression was indeed strongly associated with intensity of the emotional state. Therefore, I need to evaluate the raw output of the software (i.e. classification probabilities of emotions) over the duration of different commercials and compare across participants to understand the most typical emotional profiles or patterns as a means to define measures that are related to attention and zapping, both instantaneous and persistent.

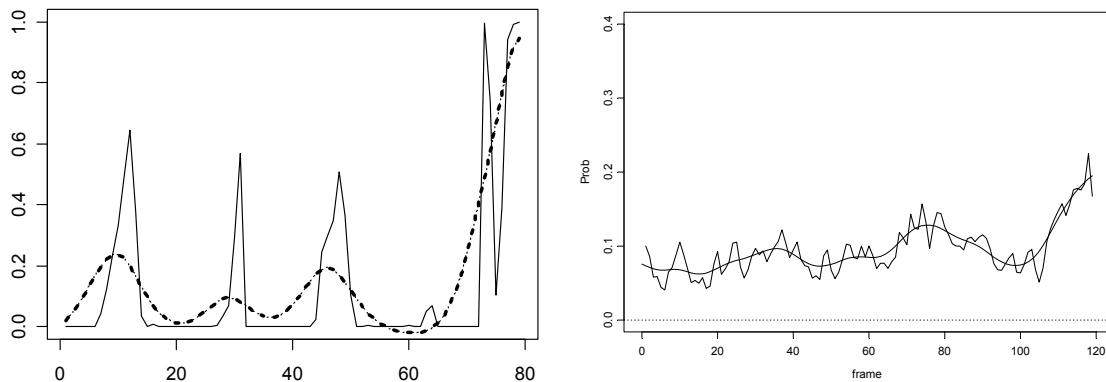
Fully Bayesian approaches to independent variables measured with error is an “...extremely difficult problem in terms of global rates of convergence.” (Berry, Carroll and Ruppert 2002, p. 160). So, to deal with the measurement error issue, I chose to use Functional Data Analysis (FDA) since these tools are appropriate for mapping discrete data into functional spaces to represent their patterns in the temporal domain and facilitate comparison across multiple samples in a dataset (Ramsey and Silverman 1997). The basic idea of FDA is to represent data points $e_i(t_1)$ measured in time $t = t_1, \dots, T$ through a linear combination of $s=1, \dots, S$ basis functions, $g_s(t)$, with $S < T$. In this application, I have emotion $e_{ic}(t)$ for individual i , commercial c and time t , which is expressed as smooth functions of time. So, for $g_s(t)$, I choose the family of B-splines in 3rd degree polynomials and knots equal to the number of time-frames until zapping, for each individual, so that:

$$e_{ic}(t) = \sum_{s=1}^{S_{ic}} g_s(t) \cdot b_{ics}, \quad \forall i=1, \dots, I \quad \forall c=1, \dots, C \quad (6)$$

The weights b_{ics} attached to each time-indexed basis function are estimated by least squares. In order to control the degree of smoothing, a penalty term λ is needed as parameter in the fitting procedure. Since the interest is in smoothing the data enough to have a smooth 2nd derivative function, I choose this parameter to be equal to 10 to the power of the order to be smoothed (Ramsey and Silverman 1997), or $\lambda=100$. As can be seen in the left graph of figure 3, a viewer's raw classification probability for joy is smoothed enough to get rid of the few spikes, but not eliminating the presence or location of these expressions captured by the software. One confirmation of the ability in FDA to reduce the noise-to-signal assumed to be caused by measurement error is given by comparing the average raw versus smoothed emotions. The graph on the right in figure 3 shows that the average of the functional curves for all viewers for a particular commercial aptly captures the dynamic pattern in the data.

FIGURE II.3: Smoothing emotions curves based on functional fitting

Left graph: Raw (continuous) versus smoothed (jagged) Joy emotion for a viewer who zapped. Right graph: Average of raw versus of smoothed Joy for all viewers in one ad.



With the raw emotions mapped into functional space via FDA¹³, I now proceed to resolve the second issue, namely to generate candidate measures that characterize the

¹³ Note that emotions have been converted from discrete $e_t \in \{0,1\}$ to continuous $e(t)$ and are represented as such in computer memory.

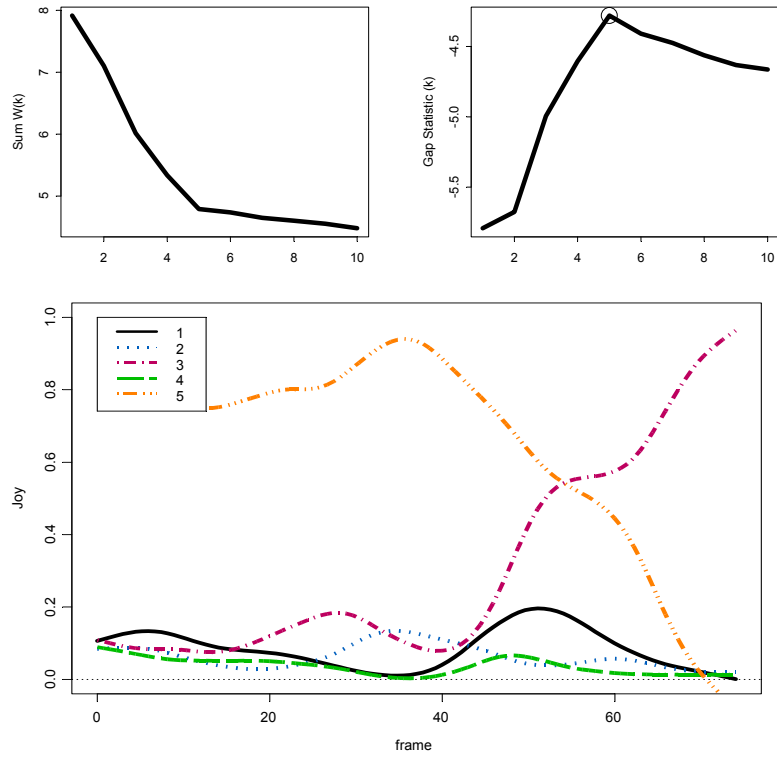
(variations of) temporal patterns of emotional response. The idea is to reduce the dimensionality of the problem from $50 \times 28 = 1400$ viewer-commercial functional curves to few a more manageable groups of typical emotional patterns, and use this to drive the choice of measures to relate to differences in zapping rates, both instantaneously and persistent. The steps to accomplish this are described in the sequence.

I first separate the functional response curves by commercial and cluster them using a hierarchical Ward procedure. This choice is so because the Ward method minimizes the sum of within-cluster variance, which is consistent with the FDA fitting procedure. The distance metric used is defined to be the integral of squared Euclidian distances between the functional curves $e_i(t)$ for each pair of viewers, in the domain represented by the start of the commercial and the earliest zapping time between the two. The idea is to compare emotional responses only during the time in which both viewers actually saw the commercial and could have non-null emotions. Since the domain of integration varies by viewer pairs, I standardize the integral to the domain's length. Also, to avoid that, at a certain period, a high difference between two viewers (emotional spike) have a disproportional effect on the distance measure compared to a null emotion, I apply the double log transform ($\ln\{-\ln\{e\}\}$) to the functional values effectively compressing the values away from zero. If I were to cluster the data solely based on this distance metric of level curves, I could potentially lose diagnostic information regarding derivatives. So, I apply the same distance measure described above to the FDA fitted 1st derivatives of the data. In the clustering algorithm, I use a weighted average (convex combination) of the functional level responses as well as the functional derivatives, with weights inversely

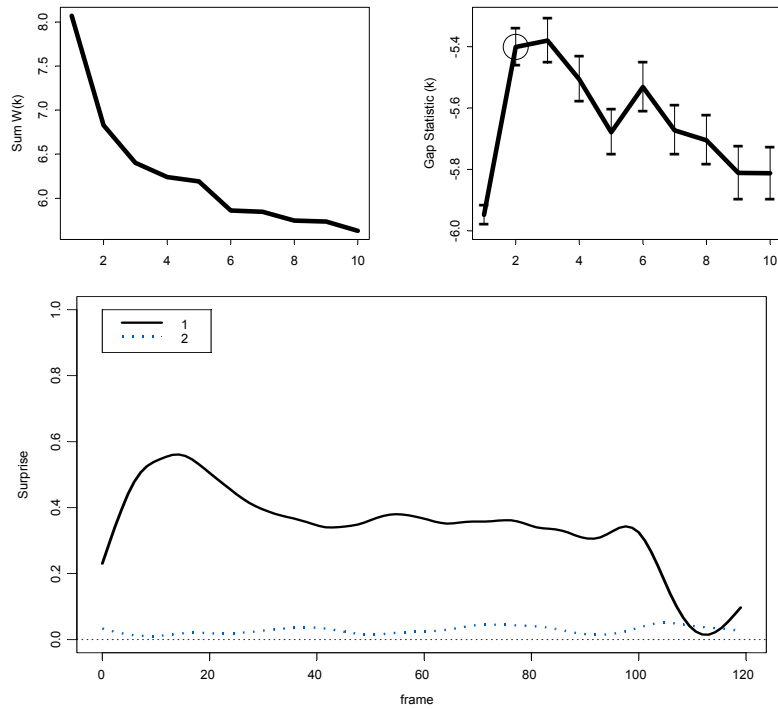
proportional to the range of each distance. This keeps the relative importance of derivatives and levels approximately equal.

The clustering across viewers is done separately by commercial and emotion, and the number of clusters is defined by means of the Gap Statistic (Tibshirani et al. 2001). This method was chosen because (1) it is based on the same measure of fit as the Ward's method (Sum of Squared Distances), (2) it uses a prior-type (reference) distribution, (3) contrary to many other optimal number of clusters methods, it can detect no clustering (or 1 cluster) and (4) the authors show that their method is fairly robust and performs better than many other techniques (see Tibshirani et al. 2001). Essentially, the Gap statistic compares the log of SSD in the data as a function of the number of clusters with the analogous expected measure under a reference distribution and chooses the number of clusters in which the former decays faster than the latter, for the first time, reproaching each other after that. Intuitively, it is a parametric approach to find "kinks" in the curve of log SSD. Agnostically choosing the uniform distribution for the location of the functional level and derivatives values, the Ward+Gap procedure generates between 2 and 5 clusters for the Joy emotional commercials, between 2 and 3 clusters for the Surprise emotional commercials and mostly 1 or 2 clusters for the neutral commercials. Two examples, for emotional commercials clustered using Joy (top) and Surprise (bottom), are presented in the figure 4, where SSD and Gap statistics curves are plotted as a function of number of clusters, followed by the mean emotional response for the optimal number of clusters. The optimal cluster number is circled on the second graph. Noticeable differences in emotional responses (level, derivative, patterns) can be seen in the third graph of each example, which aid in choosing measures that can discriminate amongst them.

FIGURE II.4: Functional smoothing and clustering of Joy (top) and Surprise (bottom)
 Clockwise from top-left: Within-cluster SSD, GAP statistic and Joy curves by cluster



Clockwise from top-left: Within-cluster SSD, GAP statistic and Surprise by cluster



Visual inspection of the average clustered curves for Joy across the 14 emotional commercials revealed four features that could help explain differences in average zapping levels by cluster. Two level-based measures detected were (1) the pure level measure and (2) the accumulated level at each instant, both of which could help explain the delayed effects hypotheses of why some clusters had more/less zapping than others. Further, (3) the pure derivative as well as (4) the absolute derivative were related to zapping differences, depending on the commercial. For some commercials, zapping was lower for clusters possessing increased Joy, as compared to decreasing. However, for other clusters, both increasing and decreasing Joy were associated with lower zapping than similar level and flat emotional response. With respect to clustering of Surprise, I found differences in the patterns of (5) level and (6) accumulated level, as well as (7) derivative, but no absolute derivative causes. One conjecture is that, surprise, being a more short-lived emotion, often is not as persistent as Joy. In other words, decrease in joy may be a negative aspect of an otherwise joyful commercial but decrease in surprise is just a “return to equilibrium”. Interestingly enough, Baumgartner et al. (1997) come up with very similar measures, namely peak and end emotion (captured here by level), speed or magnitude of linear change (derivative) and sum of momentary experiences (accumulated level), when evaluating the moment-to-moment affective reactions on overall judgment of the commercial.

In order to be able to use these seven measures to model its moment-to-moment effects on attention and zapping, it is important that collinearity is not present to a large extent. The correlations of the seven variable are provided in table 2 and show higher than 0.5 correlation between Surprise level and Accumulated Surprise ($\rho=0.59$) and for

Joy and Accumulated Joy ($\rho=0.61$). In light of this, I drop both the accumulated measures and keep only five measures that describe most of the prototypical emotional reactions in common, while disregarding many of the idiosyncratic emotional experiences. Level measures are intended to test the persistent effects, while derivative and absolute derivative should give insights into the instantaneous effects hypothesized.

TABLE II.2: Correlations between transformations of functional emotion variables

	Measures Detected in Curve Clustering					
	Joy Level	Joy Difference	Joy Abs. Difference	Surprise Level	Surprise Difference	Joy Level Accumulated
Joy Level	1.00					
Joy Difference	0.02	1.00				
Joy Absolute Difference	0.41	-0.04	1.00			
Surprise Level	-0.08	-0.02	0.03	1.00		
Surprise Difference	0.01	-0.17	0.02	0.01	1.00	
Joy Level Accumulated	0.61	-0.11	0.27	0.00	0.01	1.00
Surprise Level Accumulated	-0.01	0.01	0.04	0.59	-0.10	0.05

Note: Due to high correlation, Joy and Surprise Accumulated Level measures were eliminated from model.

Estimation of simultaneous model

Given the Frailty and HB structure of the model, MCMC with Gibbs sampling in blocks is used augmented by draws of the latent utility for all i , c and t from the Probit mapping. For estimation of the θ_t , Forward Filtering Backward Sampling algorithm (Frühwirth-Schnatter 1994) is used; for μ_i and α_c , separate conditional Bayesian shrinking

models are used; and for Ψ , a simple linear regression block is carried out. Elements of the Variance-covariance matrix of ε_{ict} were obtained via post-processing.

The MCMC chain is run for 50,000 iterations on a total of 145 k observations. The posterior distributions of the parameters of 2000 draws were extracted, thinning 1 in 10 draws, after a burn-in period of 30,000. Starting values were obtained from the maximum likelihood parameter estimates from independent Probit and Log-Linear models. Details of the estimation are provided in Appendix 1. Convergence of Gibbs sampler was checked through visual inspection of likelihood and diagnostic plots for key model parameters (see Appendix 3), since running multiple chains is computationally infeasible.

Results

Emotional Consequences on Commercial Avoidance

All independent variables were standardized before analysis to facilitate comparison of parameter estimates and collinearity is not a significant problem since any pair of variables with correlation higher than 0.5 resulted in one of them being dropped from the model. Table 3 provides the mean, standard error and main percentiles of the posterior distributions from the MCMC draws for the simultaneous model. In support of my hypotheses, all five emotion-related variables significantly reduce zapping. Similarly to what was found in Chapter 1, IAD increases zapping, while the interaction with AAD reduces it (sig. at 10%). Regarding the parameters relating emotional effects on Individual Attention Dispersion, instantaneous increases in Joy reduce IAD, with no non-symmetric effect (Joy Absolute Difference is n.s.). This goes counter to the hypothesis

based on broad-and-build theory. Viewers do not disperse, they concentrate, in the imminence of feeling joy. For Surprise, instantaneous increases increase IAD, in support of the prediction derived from the Appraisal Tendency Framework. As for the persistent effect (level), increases in Joy and in Surprise reduce IAD. Again, these results are counter to the broad-and-build theory but very much in line with the predicted “halt then reorient” aspect of surprise claimed by Plutchik. The prediction that the level of Surprise would be more impacting on IAD than Joy was indeed confirmed (2.5 times more). To sum up the effects, feelings of overt Joy causes viewers to agglomerate (IAD decreases), at the appearance of the emotion and during its presence, reducing the Individual Attention Dispersion, and ultimately reducing zapping. Overtly felt Surprises act fast to increase IAD and then decrease it leading to a concentrating of the focal attention, while also ultimately reducing zapping.

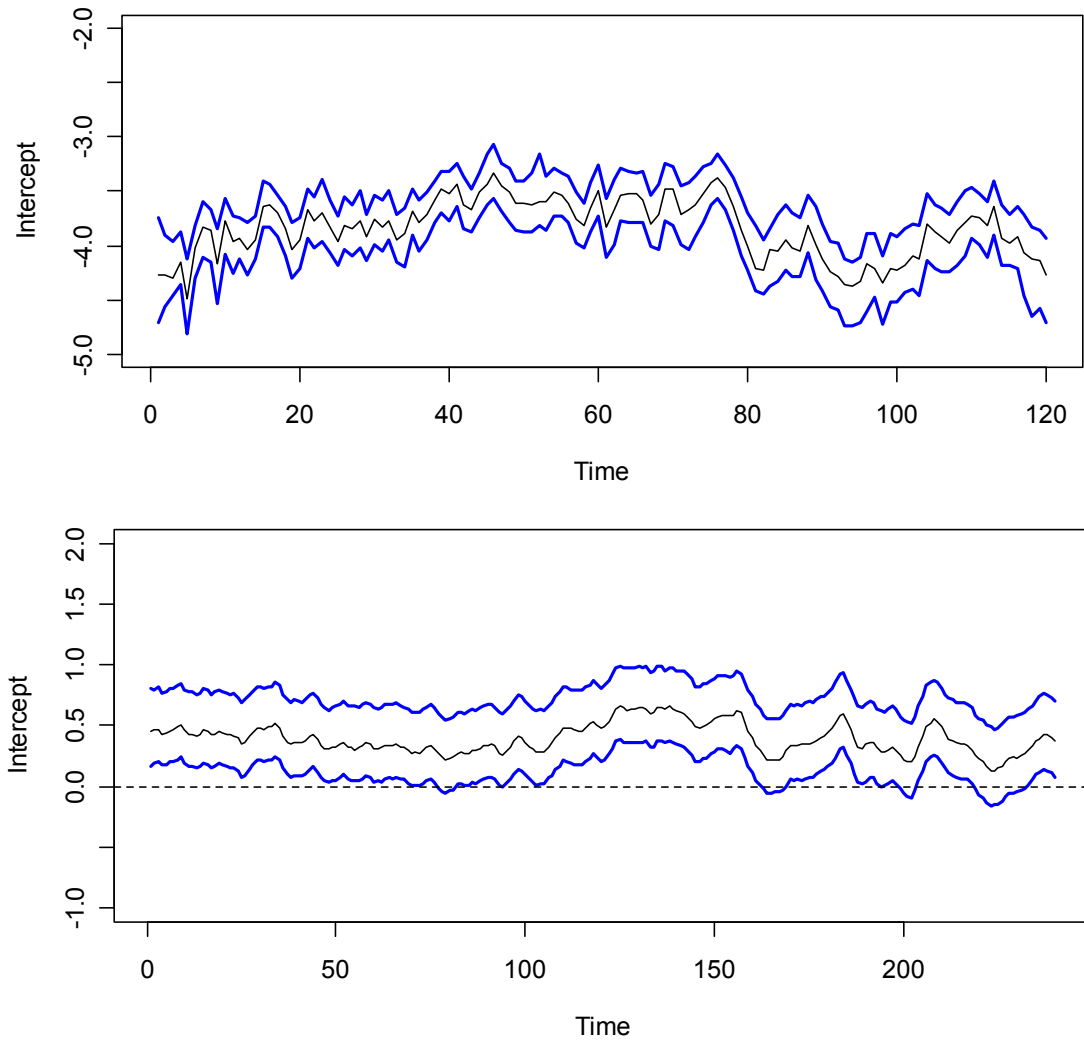
For the other covariates, with the exception of Visual Complexity², all other effects are in the same direction for the zapping and IAD models, indicating that what drives Zapping also tends to drive IAD, as conjectured (i.e. they’re both avoidance mechanisms). Gender, as with Cardinality, is not significant for Zapping but it is for IAD. For Brand familiarity, the opposite occurs, it affects Zapping but not IAD. All other covariates are significant for both. Lastly, figure 5 shows the time-varying baseline Zapping and IAD intercepts, intended to capture inherent dynamics in these time series, not explained by the regressors. Notice that the Zapping baseline evolves in time with no major increase while the IAD baseline is fairly constant. This is a good indication that there is no other systematic effect of other omitted variables that induce Zapping or IAD at specific periods of time that are not accounted for in the model.

TABLE II.3 : Emotional influences on commercial avoidance

Parameter	Dependent Variable: Zapping					Dependent Variable: IAD				
	Mean	SE	Percentiles of the Posterior Distribution			Mean	SE	Percentiles of the Posterior Distribution		
			5%	50%	95%			5%	50%	95%
Intercept (mean)	-2.321**	0.106	-2.495	-2.320	-2.148	0.000	0.002	-0.003	0.000	0.003
<u>Emotion:</u>										
Joy Level	-0.376**	0.027	-0.420	-0.377	-0.326	-0.021**	0.002	-0.024	-0.021	-0.017
Joy Difference	-1.250**	0.046	-1.326	-1.253	-1.161	-0.005**	0.002	-0.008	-0.005	-0.002
Joy Absolute Difference	-0.900**	0.043	-0.971	-0.903	-0.816	0.001	0.002	-0.003	0.001	0.005
Surprise Level	-0.140**	0.021	-0.177	-0.135	-0.111	-0.054**	0.002	-0.058	-0.054	-0.050
Surprise Difference	-0.162**	0.014	-0.188	-0.160	-0.140	0.005**	0.002	0.002	0.005	0.008
<u>Attention dispersion:</u>										
Individual dispersion	0.053**	0.015	0.027	0.054	0.078					
Aggregate dispersion	0.034	0.021	-0.006	0.036	0.066					
Aggreg.*Indiv. dispersion	-0.015*	0.011	-0.034	-0.014	0.002					
<u>Control variables:</u>										
Visual complexity ²	0.031**	0.013	0.012	0.031	0.055	-0.030**	0.002	-0.034	-0.030	-0.027
Presence (p = 1)	0.042**	0.015	0.018	0.042	0.066	0.044**	0.003	0.039	0.044	0.048
Duration	0.077**	0.023	0.031	0.078	0.112	0.047**	0.003	0.042	0.047	0.052
Cardinality	-0.024	0.019	-0.054	-0.025	0.007	-0.024**	0.003	-0.028	-0.024	-0.019
Age	-0.093**	0.054	-0.186	-0.091	-0.013	-0.031**	0.002	-0.034	-0.031	-0.028
Gender (m = 1)	0.018	0.051	-0.058	0.020	0.100	0.026**	0.002	0.022	0.026	0.029
Ad length	-0.097**	0.055	-0.181	-0.100	-0.002	-0.024**	0.002	-0.028	-0.025	-0.021
Ad familiarity (f = 1)	2.980**	0.292	2.476	3.000	3.415	0.021**	0.002	0.018	0.021	0.024
Brand familiarity (f = 1)	-0.097**	0.051	-0.177	-0.100	-0.008	-0.001	0.002	-0.004	-0.001	0.002
Variance of error term	1	0.000				0.599	0.017			
Covariance of error term	0.000	0.004				0.000	0.004			

Note: ** indicates 95% posterior confidence interval doesn't contain zero; * indicates 90% confidence interval doesn't contain zero.

FIGURE II.5: Time-varying baseline zapping (top) and Dispersion (bottom) rates



Note: Individual Attention Dispersion is standardized.

Implications for advertising

In terms of using Joy and Surprise as attention grabbing (reduce IAD) and retaining (diminish zapping) mechanisms, the practical implications of the estimated parameters are threefold. First, the net effect of an increase in a certain emotion is the result of indirect influence of (1) an instantaneous effect on IAD, (2) a persistent effect on IAD and (3) the direct effect on Zapping. A formal mediation analysis (not provided) shows the relative importance of each route. In this regard, 75% of the explained effect

on Zapping is explained by the emotion measures (67% by Joy alone), while Surprise Level is the biggest predictor of IAD variations, with 16%, out of 14 variables. Second, both variables have symmetric effects on Zapping, with Joy formally tested. This means that commercial that evokes Joy in the beginning and then stops doing so at time T is as likely to cause momentary zapping as one that just evoked Joy and then stops at time T. There is little goodwill “bought” with the viewer in accumulating joyous moments from the past. So advertisers should, above all, try to increase Joy consistently as the ad progresses to maximize the benefits of this emotional engagement tool. This finding is consistent with Kahneman’s Peak-and-end Theory (Kahneman 2000) and Loewenstein and Prelec’s Negative-Time Discounting Theory (Loewenstein and Prelec 1993), being an example of both. And third, as a tool to retain viewers, Surprise is a “double edged sword” which can get viewers engaged and reduce zapping on the spot, but the downside is the distraction from the main elements of the storyline. And, given the simultaneous estimation of IAD on Zapping, this distraction has the potential to lead to zapping.

Discussion

Advertising avoidance behaviors, in all its possible forms, has become one of the most serious problems that the whole advertising industry faces today. Without attention to TV commercials, the “bottleneck to the consciousness”(Broadbent 1957), the likelihood of downstream effects such as persuasion and memory influences become highly unlikely. By studying the dynamics involved in emotional reaction to commercial acceptance or avoidance, I pose that zapping versus not-zapping is a natural behavioral response to emotions (approach/continue versus avoid/disrupt ongoing activity). In this

research, I aim to solve a puzzling question: do positive emotions always work in grabbing and retaining attention?

This is the first study, as far as I know, to closely examine moment-to-moment discrete emotions in conjunction. It is the first to disentangle the influence of two important positive emotions (joy-surprise), where prior research has emphasized negative emotions, or simplistically focused on overall valence. It is the first to combine continuous, unobtrusive visual attention measures (eye movements) with continuous, unobtrusive, emotions measures (facial expressions). It combines this in a simultaneous dynamic model which allows diagnostic information about the specific moments in commercials that trigger consumers to zap them, with potentially wide-ranging implications for commercial development, testing and media-planning.

Emotions have direct behavioral implications, and we know very little about the influence of moment-to-moment emotional effects. Here I provide a first step towards the integrated unobtrusive (eye-and-face tracking), precise moment-to-moment measurement of emotions and its immediate effects on video commercial viewers. The findings suggest that feelings of expressed Joy reduce zapping and this is largely a direct effect, with little effect on attention distraction. But as soon as viewers stop feeling this Joy, they tend to zap away. I also find that Surprise works mainly indirectly by momentarily reducing zapping but at the expense of causing major attentional distraction. Therefore, advertisers should be careful when creating TV and internet video commercials which attempt to evoke Joy and/or Surprise. If using Joy, start modest and save the best for last is the best recommendation because you can't count on viewers' goodwill to keep watching if the ad can't keep the level of Joy high. As for Surprise, the risk of showing the unexpected is to

lose the viewer's engagement with the story line. So if you surprise them, you better be able to subsequently concentrate their attention or they'll leave.

Research Opportunities

Most of the theory based predictions of emotional influences on zapping were confirmed as well as the predictions regarding the influence of surprise on attentional dispersion. However, counter to the predicted increase of dispersion due to joy, I found that viewers concentrate attention. While further research is needed to precisely pinpoint the reasons for this mismatch between the broad-and-build theory and the results, one speculation comes to mind. Joyous commercials tend to be of two classes, funny and so called "warmth feelings" ads. Both generate laughter and smiles, although humor tends to evoke laughter and warmth ads evoke smiles. A speculation is that the broad-and-build theory was designed to explain emotions derived from warmth feelings and not from humor. Since most of the joyous commercials are humor-based, viewers can be concentrating attention mainly due to the humor elements than exploring as a result of warm feelings of joy. But only future research will settle the issue.

Apart from signaling internal emotional states, facial expressions are also influenced by contextual factors. In this experiment, I did not manipulate social context, i.e. presence or relationship of people in the room with the participants. Understanding the role of social context is crucial. That is, presence of others may (1) strengthen the natural emotion (joy=joy), (2) suppress the natural emotion (sadness=not show, stiff upper lip) or perhaps even (3) convert it (depression experienced but joy expressed). Ekman himself has done much research on lying, deceit and facial emotion coding of when does the face not tell the truth.

Appendix II.1: Model specification and estimation

The basic simultaneous model of Zapping and IAD involves an individual-specific baseline, a commercial-specific baseline, a time-dependent baseline, regressors specific to each DV and IID Normal errors. I allow for correlation between the estimation of both regressions by specifying a full covariance matrix of the error term but restrict the variance of the Probit regression to 1 for identification reasons. The model can be written hierarchically as:

$$\begin{pmatrix} \text{Probit}(\text{Zap}_{\text{ict}}) \\ \log(\text{IAD}_{\text{ict}}) \end{pmatrix} = \begin{pmatrix} \mu_i^{(1)} + \alpha_c^{(1)} + \theta_t^{(1)} + \mathbf{X}_{\text{ict}}^{(1)} \boldsymbol{\Psi}^{(1)} + \psi_{11}^{(3)} \text{IAD}_{\text{ict}} + \psi_{21}^{(3)} (\text{IAD} * \text{AAD}_{\text{ict}}) \\ \mu_i^{(2)} + \alpha_c^{(2)} + \theta_t^{(2)} + \mathbf{X}_{\text{ict}}^{(2)} \boldsymbol{\Psi}^{(2)} \end{pmatrix} + \boldsymbol{\varepsilon}_{\text{ict}},$$

$$\begin{pmatrix} \mu_i^{(1)} \\ \mu_i^{(2)} \end{pmatrix} \sim \begin{pmatrix} \text{N}(\mathbf{X}_i^{(3)} \boldsymbol{A}^{(1)}, \mathbf{V}_\lambda^{(1)}) \\ \text{N}(\mathbf{X}_i^{(3)} \boldsymbol{A}^{(2)}, \mathbf{V}_\lambda^{(2)}) \end{pmatrix}$$

$$\begin{pmatrix} \alpha_c^{(1)} \\ \alpha_c^{(2)} \end{pmatrix} \sim \begin{pmatrix} \text{N}(\mathbf{X}_c^{(4)} \boldsymbol{K}^{(1)}, \mathbf{V}_\kappa^{(1)}) \\ \text{N}(\mathbf{X}_c^{(4)} \boldsymbol{K}^{(2)}, \mathbf{V}_\kappa^{(2)}) \end{pmatrix}$$

$$\begin{pmatrix} \theta_t^{(1)} \\ \theta_t^{(2)} \end{pmatrix} \sim \begin{pmatrix} \text{N}(\theta_{t-1}^{(1)}, \omega_t^{(1)}) \\ \text{N}(\theta_{t-1}^{(2)}, \omega_t^{(2)}) \end{pmatrix}$$

$$\boldsymbol{\varepsilon}_{\text{ict}} \sim \text{N}\left(\mathbf{0}, \begin{bmatrix} 1 & \sigma_{12}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 \end{bmatrix}\right)$$

In the structure above, I assume additive separability of strictly individual, commercial and time-frame baseline zapping rates as well as attention dispersions (via IAD). Additive separable individual and trial (commercials) random effects are known in the biostatistics survival literature as Frailty Models and are widely used due to their parsimony in the number of parameters to be estimated. In line with parsimony, I shrink the random effect parameters to aggregate covariate specific ones via Hierarchical Bayes. Lastly, I incorporate dynamics in zapping baseline rates that evolve stochastically via a Random Walk throughout the course of a commercial. This is in line with Siddarth and

Gustafson (2008) and Chapter 1. To conform to the reciprocity of Zap and IAD as avoidance processes in the model, I also allow attention (IAD) to have a time-varying intercept.

The design matrix, composed of the independent variables X, is structured in the following way:

$$\left\{ X_{ict}^{(1)} \quad X_{ict}^{(2)} \quad X_i^{(3)} \quad X_c^{(4)} \right\} = \left(\begin{array}{c} \left[\begin{array}{c} Joy_{ict} \\ JoyDiff_{ict} \\ JoyAbsDiff_{ict} \\ Surprise_{ict} \\ SurpriseDiff_{ict} \\ AAD_{ict} \\ VisualComplexity_{ct}^2 \\ Presence_{ct} \\ Duration_{ct} \\ Cardinality_{ct} \end{array} \right] \left[\begin{array}{c} Joy_{ict} \\ JoyDiff_{ict} \\ JoyAbsDiff_{ict} \\ Surprise_{ict} \\ SurpriseDiff_{ict} \\ VisualComplexity_{ct}^2 \\ Presence_{ct} \\ Duration_{ct} \\ Cardinality_{ct} \\ Age_i \\ Gender_i \\ AdLength_c \\ AdFamiliarity_{ic} \\ BrandFamiliarity_{ic} \end{array} \right] \left[\begin{array}{c} Age_i \\ Gender_i \end{array} \right] \left[\begin{array}{c} AdLength_c \\ AdFamiliarity_{ic} \\ BrandFamiliarity_{ic} \end{array} \right] \end{array} \right)$$

The only branding variables used were the ones that were significant or marginally significant in Chapter 1 and had correlations less than 0.5 in the data. Thus, Brand Position, Competing and Size were eliminated from the design matrix due to high correlations with Brand Presence.

In order to estimate the above model, let:

$$\begin{aligned} V_{ict}^{(1)} &= \mu_i^{(1)} + \alpha_c^{(1)} + \theta_t^{(1)} + X_{ict}^{(1)}\Psi^{(1)} + \psi_{11}^{(3)}IAD_{ict} + \psi_{21}^{(3)}(IAD * AAD_{ict}) \\ V_{ict}^{(2)} &= \mu_i^{(2)} + \alpha_c^{(2)} + \theta_t^{(2)} + X_{ict}^{(2)}\Psi^{(2)} \end{aligned}$$

Then, I map the binary zapping decisions into the utilities space via:

$$U_{ict}/IAD_{ict}, \dots \sim \text{Truncated} - N_{\{a,b\}} \left(V_{ict}^{(1)} + \sigma_{12}^2 \sigma_{22}^{-1} (IAD_{ict} - V_{ict}^{(2)}), \sigma_{11}^2 - \sigma_{12}^2 \sigma_{22}^{-2} \sigma_{21}^2 \right)$$

Now, let:

$$U_{ict}^* = U_{ict} - \mu_i^{(1)} + \alpha_c^{(1)} \quad \text{and} \quad IAD_{ict}^* = IAD_{ict} - \mu_i^{(1)} + \alpha_c^{(1)}$$

Then, given the latent draw of utilities, I re-write the original model as a bivariate DLM as follows:

$$\mathbf{Y} \Psi^{(3)} = \theta_t + \mathbf{X} \Psi + \varepsilon_{ict}$$

or

$$\begin{bmatrix} U_{ict}^* & IAD_{ict} & IAD^* AAD_{ict} \\ IAD_{ict}^* & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ -\psi_{11}^{(3)} \\ -\psi_{21}^{(3)} \end{bmatrix} = \begin{bmatrix} \theta_t^{(1)} \\ \theta_t^{(2)} \end{bmatrix} + \begin{bmatrix} \mathbf{X}_{ict}^{(1)} & 0 \\ 0 & \mathbf{X}_{ict}^{(2)} \end{bmatrix} \begin{bmatrix} \Psi^{(1)} \\ \Psi^{(2)} \end{bmatrix} + \begin{bmatrix} \varepsilon_{ict}^{(1)} \\ \varepsilon_{ict}^{(2)} \end{bmatrix}$$

In order to estimate the unique observation equation via Gibbs sampling, let

$\Phi = \{\theta_0, \dots, \theta_T, \Psi, \Psi^{(3)}, \mu_{i=1}, \dots, \mu_{i=I}, \Lambda, \mathbf{V}_\lambda, \alpha_{c=1}, \dots, \alpha_{c=C}, \mathbf{K}, \mathbf{V}_\kappa, \mathbf{V}_\omega, \Sigma\}$ be the full

parameter set and $\Omega_t = \{Y_{i,c,l,t}, X_{i,c,l,t}, X_i^{(3)}, X_{i,c}^{(4)}\}$ the complete data up to time t. The

following algorithm describes the estimation steps along with full conditionals for each

‘sweep’ (iteration) of the Gibbs sampler. All model parameters are estimated

simultaneously, by recursively sampling from their conditional posterior distributions,

which are given below.

Gibbs sampling estimation steps:

1. Probit mapping to get utilities U_{ict}
2. Sample the covariance matrix Σ from Inverse-Wishart
3. Forward-Filtering Backwards-Sampling to get $\theta_{1:T}^{(1)}$ and $\theta_{1:T}^{(2)}$
4. Sample $\omega^{(1)}$ and $\omega^{(2)}$ from Gamma Distributions
5. Bayesian Regression to Sample $\Psi^{(1)}$ and $\Psi^{(2)}$
6. Bayesian Regression to Sample $\Psi^{(3)}$
7. Hierarchical Bayes step to sample $\mu^{(1)} \Lambda^{(1)} \mathbf{V}_\lambda^{(1)}$ and $\mu^{(2)} \Lambda^{(2)} \mathbf{V}_\lambda^{(2)}$
8. Hierarchical Bayes step to sample $\alpha^{(1)} \mathbf{K}^{(1)} \mathbf{V}_\kappa^{(1)}$ and $\alpha^{(1)} \mathbf{K}^{(1)} \mathbf{V}_\kappa^{(1)}$

9. Post-process (or Nobile's (2000) method) to recover restricted parameters

given $\sigma_{11} = 1$.

The prior distribution of parameters are diffuse conjugate distributions:

$U_{ict}, \mu_i, \alpha_c \rightarrow$ specified from model

$$\theta_0 \sim N_2(\mathbf{m}_0 = 0, C_0 = 10^2 \mathbf{I})$$

$$\Psi \sim N_{25}(\mathbf{n}_0 = 0, S_0 = 10^{25} \mathbf{I})$$

$$\Psi^{(2)} \sim N_2(\mathbf{n}_0 = 0, S_0 = 10^2 \mathbf{I})$$

$$A \sim N_2(A_0 = 0, \Sigma_A = 10^5 \mathbf{I})$$

$$K \sim N_2(K_0 = 0, \Sigma_K = 10^5 \mathbf{I})$$

$$V_\lambda^{-1} \sim G(\rho_\lambda = 2 + 1, (\rho_\lambda R_\lambda)^{-1} = (3 \cdot 0.0001)^{-1})$$

$$V_\kappa^{-1} \sim G(\rho_\kappa = 2 + 1, (\rho_\kappa R_\kappa)^{-1} = (3 \cdot 0.0001)^{-1})$$

$$V_\omega^{-1} \sim W_5(\rho_\omega = 5 + 1, (\rho_\omega R_\omega)^{-1} = (6 \cdot 0.0001 \cdot \mathbf{I}_5)^{-1})$$

$$\Sigma_\sigma^{-1} \sim W_2(\rho_\sigma = 2 + 1, (\rho_\sigma R_\sigma)^{-1} = (3 \cdot 0.0001 \cdot \mathbf{I}_2)^{-1})$$

Appendix II.2: Assessing moment-to-moment ad emotions from facial expressions

In this section, I provide details about the pre-test and procedures used to (1) evaluate the participants' capability of overtly expressing felt emotions with matching facial expressions as well as (2) the ability of the software to correctly identify these emotions. TV commercials, used as stimuli, may or may not be successful in evoking certain emotions due to reasons such as the short time for viewer to engage emotionally with the storyline, the inherent commercial appeal that causes viewers to reject persuasive appeals or simply due to the inability of the commercial to retain engagement.

In order to assess item 1 above, 21 TV commercials of duration ranging from 15 to 120 sec. from known and unknown brands, of various product categories (fast food, CPG, telecom, services, beverages, etc.) were selectively chosen for the AdForum database. The selection criteria were that the ad agency's description of the spot had to contain objectives relating to causing the viewer to experience one of the six basic emotions that I was interested in capturing: joy, sad, angry, surprise, disgust and fear. A total of 15 ads were chosen, in which two to three had descriptions about each of the six emotions, as well as 6 neutral (mainly informative) ads which were interspersed between the others such that one neutral ad always followed three emotional ads, none of which sequentially evoked the same emotion.

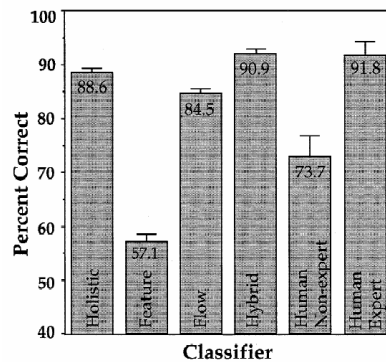
The participants in the pilot were 14 graduate students (about 50% female, age from 25 to 35) that allowed their faces to be filmed during the experiment. There were three conditions: an experimenter was in the same room as the participant, or the participant was alone in the room or the participant was alone and told that a webcam

would capture her reactions to the commercials and be shown to a friend or her choice. Participants entered the test room and were sequentially allocated to one of the three conditions, told that the objective of the experiment was to obtain their opinion regarding the effectiveness of a series of commercial. They were also told that they would watch a short 4 minute sitcom and then 15 minutes of commercials while being filmed for documenting purposes. After watching the show and ads, they were given a questionnaire about their demographics, familiarity of brand and ad as well as a series of 5-point items regarding affect felt for each commercial, aided by an image of the commercial.

To gauge the capability of the chosen commercials to evoke facial expressions typically associated with the six basic emotions, content analysis was done with the video recordings. Ekman's Facial Actions Coding System (FACS) was used to detect the facial reactions prototypical of each emotion. While the participants' response in the questionnaire showed that the highest average emotion felt in all commercials was the same as the advertiser's intention, as described in AdForum, the video images only showed facial signs of evoked emotions for joy (smiles and laughter in many instances and subjects), disgust (few instances for many subjects), surprise (few instances for many subjects) and sadness (rarely for a few subjects).

In order to assess the ability of the emotions classification software, graciously provided by Nico Sebe (of Cohen et al. 2003), to correctly classify the emotion from the video images of facial expressions, the software was used to classify each participant's footage for all 21 commercials and showed that, in comparing with the subjective content analysis, the software consistently matched the classification for the emotions of joy, surprise and disgust. Research intended to compare the ability of human (experts and

non-experts) subjective classification of emotions from facial expressions with those of automatic statistical classifiers based on computer image analysis (Holistic, based on features, on flow and their “hybrid” combination) shows that these automatic classifiers can be as good as when done by human experts, while significantly better than those done by non-experts (Bartlett et al. 1999). See comparison below.



Source: Measuring facial expressions by computer image analysis, Bartlett et al. 1999.

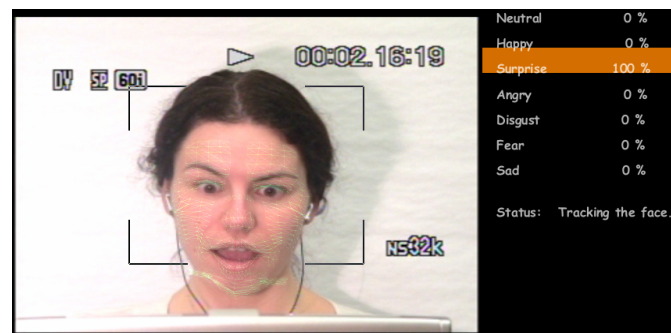
Specifically, tests conducted using Cohen and colleagues’ automatic computer image classifier on a variety of participants (varying age, race, gender, amount of facial hair) was presented in Cohen et al. (2003) and provide evidence that the highest classification accuracy rate was for surprise, followed by joy (happy). Interestingly enough, joy and surprise (sadness to a lesser extent) were also the most frequently observed facial expression by visual inspection and FACS coding in Derbaix’s (1995) facial coding of emotional reactions to TV commercials. See classification accuracy in the table below, where high diagonal values represent correct classification and high off-diagonal values represent error classification.

Person-independent average confusion matrix using the TAN classifier

Emotion	Neutral	Happy	Anger	Disgust	Fear	Sad	Surprise
Neutral	78.59	1.03	3.51	8.18	1.85	5.78	1.03
Happy	0	86.22	4.91	5.65	3.19	0	0
Anger	2.04	4.76	66.46	14.28	5.21	6.09	1.14
Disgust	3.40	1.13	10.90	62.27	10.90	9.09	2.27
Fear	1.19	13.57	7.38	7.61	63.80	3.80	1.90
Sad	5.55	1.58	13.25	11.19	3.96	61.26	3.17
Surprise	0	0	0	0	2.02	4.04	93.93

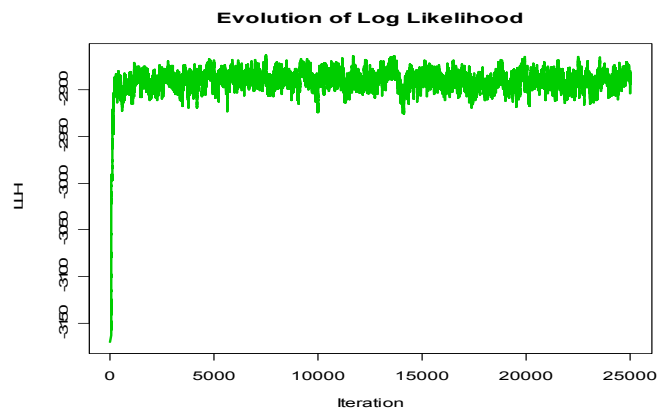
Source: Facial expression recognition from video sequences, Cohen et al. 2003.

Therefore, given that these two emotions are frequently and well detected both from subjective human evaluations and automatic statistical classifications, they were the ones chosen to be explored further as the basis of this research. For illustration purposes, prototypical emotional facial responses are shown below along with software classification output for two participants viewing different commercials that agreed to have their image reproduced.



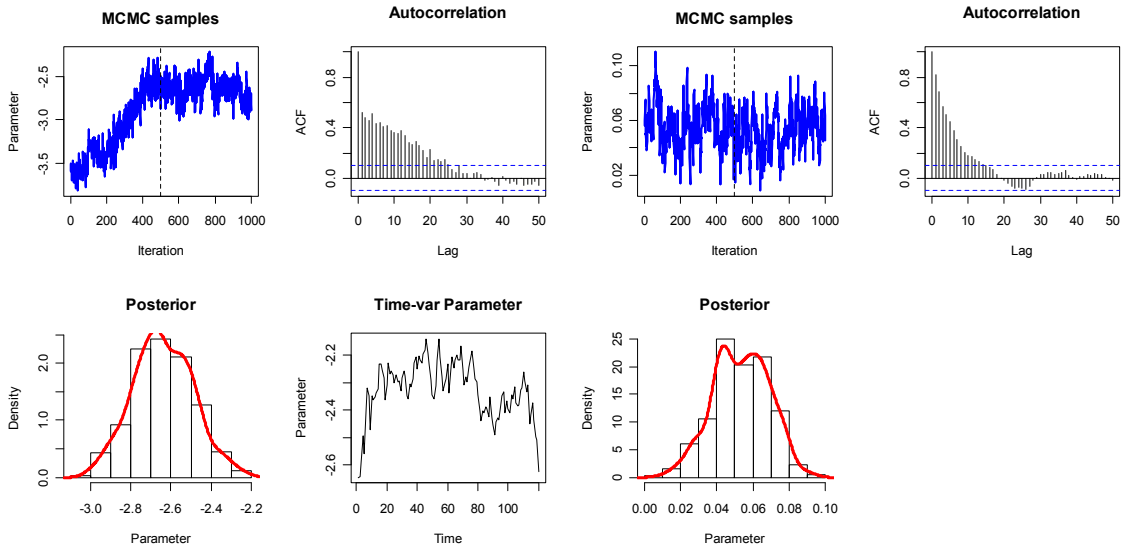
Appendix II.3: Convergence of Gibbs Sampler

I provide the trace plot of model Log Likelihood to visually evaluate convergence (top) as well as parameter diagnostics, trace plot of Gibbs samples, autocorrelation function and posterior distribution with kernel smoothing, for two main parameters of interest (bottom). Convergence, good mixing and unimodality are visibly fair.



Time-varying base-line Zapping parameter

Effect of IAD on Zapping parameter



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CHAPTER III

General Discussion

Final Considerations

Based on Greyser's conjecture of brands acting as cues for hard-sell attempts, and using visual saliency theory, I pose that the sheer appearance of a brand on screen may trigger viewers to zap commercials. If true, this creates a placement problem for advertisers to solve because it is unrealistic to completely eliminate brands from commercials. Given this premise, I develop a methodology to assess the impact of branding on zapping using the commercial frame (240 ms) as the unit of analysis so as to capture the dynamic moment-to-moment effects of each subsequent, and possibly different, brand exposure. Using data collected from a marketing research firm, and controlling for known individual and stimulus heterogeneity, as well as variations of focal attention over the course of the commercial, I find that brand appearances indeed trigger zapping. This effect is systematic and apart from familiarity or likeability of the brand. Moreover, the more salient the brand is on screen (central, separated, enduring, etc.) the stronger is the likelihood of consumers zapping the ad, increasing this detrimental effect. Finally, my original goal of solving the 'brand placement problem' is attained from the statistical model's parameters by showing that the major cause of

brand-triggered zapping lies in exposing the brand on screen for too long, consecutively. The solution is to pulse the brand – short and frequent brand appearances – which is found to be the optimal strategy for minimizing commercial zapping. An example of Brand Pulsing is found in car ads that show the logo on the car (brand) at various fast camera shots and cuts in different scenes (pulsing) while the car is being driven around. Both simulations and a controlled experiment were conducted and show evidence for this novel finding.

An important by-product of Essay I was finding that Individual (IAD) and Aggregate Attention Dispersion (AAD) metrics, which are simple functions calculated from the raw output of any modern eye-tracking equipment, are shown to account for the majority of variation in zapping decisions. That is why both IAD and AAD were used as controls in Essay I and as mediators in Essay II, with significant and new results. I recommend that any future research using moment-to-moment analysis in advertising, especially for dynamic stimuli (e.g. videos), incorporate these promising measures.

As for Essay II, guided by Appraisal Tendency theory, Broad-and-Build and Plutchik's Circumplex (see References, Chap. 2), I propose to measure the instantaneous and persistent impacts of joy and surprise on visual attention and commercial avoidance. The major finding is that these emotions differentially impact attention attraction and commercial retention. Joy affects zapping mainly in a direct and instantaneous manner while surprise has a predominantly indirect (via IAD) and persistent effect. In terms of advertising practice, these findings suggest that joyous commercials should start modest, gradually attempt to cause stronger emotions and finish strong, since there seems to be a strong adaptation effect to joy. As for surprising instances in commercials, they should be

used only if attention can be easily regained afterwards because there is positive reduction in zapping but a negative increase in attention dispersion. These findings were only possible due to the creation of a procedural and statistical methodology to jointly model emotions and attention in dynamic stimuli using high-frequency unobtrusively collected measures. I am not aware of any work in advertising or other field which has attempted to use both eye and face-tracking technology.

Future Research Opportunities

Additional research around the novel attention dispersion metrics, IAD and AAD, may constitute important avenues for future research. In this dissertation, these simple yet relevant measures were successfully used as controls and mediators for understanding the impact of brand images and emotional content on video commercial avoidance. While they have not been tested on static stimuli such as print ads or for studying the role of various images/features on other measures of ad effectiveness such as recall and attitudes, their ease of measurement and strong explanation power in the current context provides two good reasons for their incorporation in many other attention-contingent domains.

Another issue that begs additional research is further understanding the reasons why viewers tend to zap systematically more upon exposure to brands. This viewer behavior is still largely unknown and may very well shed light to the meaning of brands to viewers during TV or Internet consumption. Additionally, the finding that Brand Pulsing reduces this adverse effect of brand exposure is only limited to zapping. Future research needs to assess what are the implications of this brand placement strategy for downstream effects such as awareness, recall and persuasion.

Finally, in measuring the immediate versus persistent effects of joy and surprise on attention and zapping, much of the interactions between these emotions as well as the interaction of each with the appearance of the brand, complexity of scene, pace, etc. were neglected. More practical insights are bound to be found when taking these interactions into consideration as well as drilling down on the difference between mirth (humor ads) and warmth (feel good ads), both of which evoke expression of joy when felt. These and many other important issues to advertising theory and practice can and should be pursued by the interested researcher. The methodology presented in this dissertation is a first step in this direction, one that holds promising results according to the author. ■