The Role and Effectiveness of Advertising Creative Strategy

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Abstract

The core of this thesis comprises three chapters and investigates the nature and the effects of the advertising creative. In the first chapter, I propose a novel framework for evaluating advertising creative, Advertising Creative Strategy (ACS), that is comprehensive, parsimonious, and grounded in the marketing and advertising literature. This framework consists of two elements: The Function of the advertisement, that is what message the advertisement is conveying to consumers (i.e. its content), and the Form of the advertisement, that is the way the message is conveyed to consumers (i.e. its execution). The Function component is based on the notion that advertisements nudge consumers along three dimensions: experience, affect, and cognition (the EAC space). The Form component evaluates the executional complexity of the advertisement and assesses whether its executional elements are structured according to specific creative templates. In the second chapter, I empirically analyze the effect of ACS on consumers response to advertising, i.e. advertising elasticity. Results show that experiential and cognitive cues are the main drivers of advertising elasticity, and that advertisements structured according to creative templates fare better in high involvement product categories. The geometric interpretation of the EAC space also allows for the derivation of contemporaneous and dynamic synthetic measures of interaction among content dimensions. In the third chapter, I assess the way ACS affects the informative or persuasive nature of an advertisement. Results show that cognitive cues drive advertising informativeness, while persuasiveness stems from experiential cues and the structuring of executional elements according to creative templates. This latter result is of particular importance since advertising persuasiveness has been usually identified in the literature by elimination, i.e. by the absence of informative content.

Résumé

Le cœur de cette thèse repose sur trois chapitres qui traitent de la nature et des effets du contenu créatif en publicité. Dans le premier chapitre, je propose un cadre d'analyse novateur pour évaluer le contenu créatif en publicité, dit Stratégie Créative en Publicité (SCP), lequel est compréhensif, parcimonieux et ancré dans la littérature sur la commercialisation et la publicité. Ce cadre est composé de deux éléments : la Fonction de la publicité, qui est le message transmis aux consommateurs (c'est-à-dire le contenu publicitaire), et la Forme de de la publicité, qui est la manière dont le message est transmis aux consommateurs (à savoir l'exécution). La composante Fonction est construite sur l'idée que la publicité encourage les consommateurs de trois manières : par l'expérience, l'affect et le cognitif (l'espace EAC). La composante Forme évalue la complexité d'exécution de la publicité et détermine si les éléments d'exécution sont structurés selon des modèles créatifs précis. Dans le deuxième chapitre, je propose une analyse empirique des effets du SCP sur la réaction des consommateurs à la publicité, soit l'élasticité publicitaire. Les résultats démontrent que les signaux expérientiels et cognitifs sont les principaux vecteurs de l'élasticité publicitaire, et que les publicités structurés selon des modèles créatifs précis fonctionnent mieux pour les produits à forte implication. L'interprétation géométrique de l'espace EAC permet des dérivés de mesures synthétiques d'interaction, tant contemporaines que dynamiques, entre les dimensions du contenu publicitaire. Dans le troisième chapitre, j'examine la manière dont le SCP affecte la nature informative et persuasive de la publicité. Les résultats prouvent que les signaux cognitifs sont à la base du caractère informatif de la publicité, alors que son caractère persuasif émerge des signaux expérientiels et de la structuration des éléments d'exécution selon le modèle

créatif. Ce dernier point est d'un grand intérêt considérant que l'effet persuasif de la publicité est habituellement identifié par élimination, c'est-à-dire en l'absence de contenu informatif.

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Finally, thanks to my parents Cristina and Davide for supporting and encouraging me to pursue a career that took me far away from home. Thank you for believing in me even when all evidence was pointing to the fact that it might have not been a great idea.

Contribution to Original Knowledge

With this thesis, I intend to contribute to the marketing and advertising literature in three ways. In the first chapter, I propose a novel framework for evaluating the advertising creative that is comprehensive (i.e. does not capture only specific elements of the advertising creative), parsimonious (i.e. relies on the evaluation of a limited number of elements, which makes it suitable for large scale scholarly work), and grounded in the marketing and advertising literature. I call this the Advertising Creative Strategy (ACS) framework. The need for such a framework stems from the fact that the evaluation scales available in the literature focus only on some aspects of the advertising creative (e.g Resnik and Stern (1977) on information cues), are too burdensome for large scale applications (e.g. Stewart and Furse (1986) propose a scale composed by more than 200 items), or serve the purpose of a specific study (e.g. Chandy et al. (2001) on the advertising for medical referral services). In the second chapter, I empirically investigate the way the elements of Advertising Creative Strategy affect the demand for products and brands. Extant research in marketing and advertising has investigated the way advertising content affects intermediate measures of advertising effectiveness (e.g. attitude, recall), but to the best of my knowledge I am the first to investigate the way advertising content and execution affect managerially relevant in-market performance measures, i.e. sales. I do so by assessing the way ACS impacts consumer response to advertising: advertising elasticity. Finally, in the third chapter, I investigate the way the composition of a brand's ACS affects advertising informativeness or persuasiveness. To date, advertising persuasiveness has been measured only "by elimination", i.e. via the lack of informative elements. To the best of my knowledge, I am the first to explicitly investigate which elements of the advertising content and execution are the drivers of ad persuasiveness.

Contribution of Authors

This elements of this thesis, i.e. chapters one to three, have been developed with the collaboration and supervision of Professor Demetrios Vakratsas who is an Associate Professor of Marketing at the Desautels Faculty of Management of McGill University and has acted as my doctoral advisor since September 2013.

For Chapter 1, Demetrios Vakratsas developed the general research idea. That is, the evaluation of advertising according to its content and execution. I performed the review and synthesis of the literature and developed the evaluation scale. Demetrios Vakratsas and I discussed the revision of the chapter and the positioning with respect to the literature.

For Chapter 2, Demetrios Vakratsas and I developed the modeling framework. I performed the data management, analysis, and estimation. Demetrios Vakratsas and I discussed the interpretation of the results and the positioning with respect to the literature.

For Chapter 3, I developed the research idea and performed the data management, analysis and estimation. Demetrios Vakratsas and I discussed the interpretation of the results. Demetrios Vakratsas suggested the positioning with respect to the literature.

Introduction

Advertising is about developing content that serves marketers' purposes and its distribution through media. However, most of the empirical research in marketing and advertising has focused on the effects of the latter on sales response, i.e. how media allocation affects sales response (Danaher and Dagger 2013; Kolsarici and Vakratsas 2018; Naik and Peters 2009; Naik and Raman 2003). Much less is known about creative effects. With global advertising expenditures steadily growing over the past decade, reaching approximately $550 billion (GroupM 2018), and small returns on advertising investments reported in the literature (Sethuraman, Tellis, and Briesch 2011), it is imperative to broaden the understanding of the drivers of advertising performance.

While studies have examined the relationship between specific components of advertising content and performance (e.g. Anderson, Ciliberto, and Liaukonyte 2013; Chandy et al. 2001; Sudhir, Roy, and Cherian 2016), extant research has not provided generalizable insights regarding the effectiveness of the advertising creative (Hartnett et al. 2016). This is likely due to the lack of a comprehensive framework for evaluating advertising content and structure which is appropriate for the needs of generalizable empirical applications. Such a framework should be both integrative in terms of synthesizing different advertising theories on the role of advertising creatives, but also parsimonious, so as to facilitate interpretation and organization of relevant findings and application even in large-scale studies.

In this thesis I first address this need by developing an integrative framework, Advertising Creative Strategy (ACS), that is comprehensive, parsimonious, and grounded in the marketing literature. The proposed framework is based on a synthesis of the advertising literature and consists of two components: Function, i.e. what message the advertisement is conveying to consumers (the content of the advertisement), and Form, i.e. how this message is conveyed (the execution of the ad). The Function component adopts a three-dimensional representation of advertising content based on the EAC (Experience, Affect, Cognition) space concept by Vakratsas and Ambler (1999). It is based on the notion that advertising nudges consumers with experiential, affective, and cognitive cues (Bruce, Peters, and Naik 2012). The interpretation of Function according to the EAC paradigm does not only allow for a comprehensive and parsimonious evaluation of the advertising content, but also allows for a geometric interpretation as a three-dimensional Euclidean space which uses the level of experiential, affective, and cognitive cues as coordinates. This also allows for the derivation of important synthetic measures of interaction among dimensions: Focus, synthetically describing the imbalance of the three dimensions in the composition of the ad content, and Variation, describing the evolution of content composition over time. These measures, being a function of all three dimensions, help providing a holistic view of the advertising content. The Form component captures not only the executional complexity of the ad (i.e. the number of technical or artistic devices used) but also whether such elements are structured according to specific templates. In particular, I focus on the creative templates proposed by Goldenberg, Mazursky, and Solomon (1999).

I then investigate the way the components of ACS affect consumer response to advertising, i.e. advertising elasticity, and ultimately sales. Researchers have already explored the effect of advertising content on intermediate (or psychological) measures of advertising performance such as attitude (e.g. Rossiter and Percy 1980) or recall (e.g. Danaher and Mullarkey 2003). However, to the best of my knowledge, I would be the first to assess how advertising content and execution affect advertising elasticity, which represents the response of consumers to advertising in terms of sales, an “in-market” and managerially relevant performance metric. Beyond the contribution to the marketing and advertising literature that such an assessment provides, its importance is well understood by practitioners as well. In fact, a recent Nielsen Catalina study has shown that the advertising creative is responsible for 49% of consumer response (Nielsen 2017). A better understanding of the effects of the advertising creative would hence have both theoretical and practical implications.

Finally, I investigate the effect of ACS components on whether an advertisement affects consumers via information, that is providing economically relevant knowledge about the product and its characteristics, or persuasion, that is enhancing consumers’ perception of product differentiation not based on objective product characteristics. The drivers of advertising informativeness have been addressed by some scholars (e.g. Stern and Resnik 1991). However, contrary to previous research efforts, I identify the drivers of persuasive advertising directly rather than by elimination, i.e. the absence of informative content (e.g. Anderson, Ciliberto, and Liaukonyte 2013). This more precise definition of the drivers of advertising persuasiveness would be also beneficial for practitioners. Knowing which elements of the advertising creative affect information or persuasion, and to what extent, would allow practitioners to better match their advertising strategy and their advertising goals.

Summarizing, the intended contribution of this thesis is three-fold: 1) it proposes a novel evaluation framework of the advertising creative, the ACS framework, which is both comprehensive and parsimonious, hence suitable for large-scale scholarly research and capable of producing managerially relevant findings; 2) it provides an empirical assessment of the effect of ACS decisions on advertising elasticity, with the intent to help managers improve advertising performance through the management of advertising creative which is a much more efficient way compared to media outlays; and 3) it furthers the understanding of how the components of a brand's ACS contribute to the persuasiveness or informativeness of an advertisement.

The rest of this thesis proceeds as follows. In Chapter 1, I introduce the ACS framework providing a review of the relevant literature and describing it in its components. In Chapter 2, I empirically investigate the relationship between ACS and advertising elasticity. I begin by outlining the modeling framework, I introduce the data and the estimation procedure, and report estimation results. I then continue with a discussion of the results and their implications for both practitioners and academics. In Chapter 3, I empirically assess the way ACS elements contribute to the informativeness or persuasiveness of an advertisement. I begin by laying out the theoretical framework and describing the estimation procedure. I then describe the data and report estimation results. I conclude with a discussion of the results and their implications. Ultimately, I will provide an overall summary and discussion of the whole thesis in the Conclusions section.

Chapter 1: Advertising Creative Strategy

1 The Need for an Integrative and Parsimonious Framework

There is little disagreement among academics that the advertising creative contributes critically to marketplace performance (e.g. Anderson, Ciliberto, and Liaukonyte 2013; Chandy et al. 2001; Lodish et al. 1995; Sudhir, Roy, and Cherian 2016). Practitioners also tend to agree. For example, a recent Nielsen Catalina study (NCS) suggests that advertising creative accounts for 49% of sales performance for consumer packaged goods (CPGs) (Nielsen 2017). However, there is less certainty as to which advertising creative elements contribute to marketplace success. Bertrand et al. (2010), for example, note that it is difficult to predict ex ante which advertising elements will be effective. Hartnett et al. (2016), in their replication of the seminal Stewart and Furse (1986) study with sales data, find that it is difficult to draw generalizable conclusions regarding the effectiveness of advertising creative elements. Simply put, how advertisers can "move the needle" with creative remains an open question. A potential reason for this lack of conclusive insights regarding creative effectiveness is that extant research has looked at the advertising creative more as a collection of various, often disparate, elements rather than as a strategic choice for the advertiser. The latter perspective would require a more general framework that reflects the guiding principles of creative design without necessarily being concerned with all tactical aspects of the creative (Frazer 1983). I keep this as guiding principle in the elaboration of the Advertising Creative Strategy (ACS) framework.

I base the construction of the ACS framework on studies considering the objective elements constituting the advertising creative. That is the elements constituting the advertising copy (i.e. objective frameworks), as opposed to frameworks focusing on the way consumers perceive the advertisement, that is frameworks identifying the drivers of advertising creativity perceptions (i.e. subjective frameworks) (Baack, Wilson, and Till 2008; Smith et al. 2007). Also, I focus only on those studies that analyze the direct and indirect effect of advertising content on in-market measures of response to advertising (e.g. elasticities). I consider studies investigating the effect of advertising creative on other performance metrics such as, say, intermediate perceptual measures typical of the consumer behavior literature (e.g. attitude, preference, liking) only to the extent to which they are directly relevant to the study of in-market measures.

The literature on the evaluation of advertising content can be divided into two major categories: studies deriving generalized evaluation frameworks, and studies employing customized frameworks evaluating specific characteristics of the advertisement. I begin with a discussion of the former.

1.1 Generalized Frameworks

In response to a controversy between advertising practitioners and critics as to whether advertising provides consumers with useful information, Resnik and Stern (1977) developed a 14-item scale to identify the extent of the informative content of television commercials. They subsequently analyzed 378 randomly selected television commercials broadcasted by the three major US national networks and found that only approximately half of them (49.2%) contained at least one informational cue. This approach to the measurement of informational content of advertising has been used in more than 60 studies across a wide array of media, countries, product categories, and fields of research. The meta-analytic work of Abernethy and Franke (1996) provides a detailed account of the studies employing this evaluation approach highlighting the systematic sources of variation across research scenarios.

Another seminal contribution to this stream of research is the work by Stewart and Furse (1984) in which they presented the preliminary results of their study of more than 1000 television commercials across several brands, product categories, and firms. Their stated goal was to determine what executional devices influence the effectiveness of television commercials. To do so, they reviewed previous research, obtained inputs from advertisers and agencies, and compiled a set of approximately 200 items covering an array of executional factors, formats, and devices. They then evaluated the effect of such factors on three measures of advertising effectiveness: recall, comprehension, and persuasion. Among the factors that positively impacted these measures of advertising effectiveness, the presence of a brand-differentiating message and a strong product focus were the strongest and most relevant. These results were then expanded upon in a book (Stewart and Furse 1986), and in a subsequent replication study (Stewart and Koslow 1989). Hartnett et al. (2016) recently performed a further replication study based on a cross section of 312 television advertisements from several product categories across different countries. Differently from the original study, which examined the effect of advertising content on perceptual measures of effectiveness, the authors investigated the link between content and in-market, short-term sales effectiveness. The measure of short-term sales was provided by their industry partner as an index comparing purchases made by exposed and unexposed households over a four-week period. The results of the original study and subsequent replication studies are not in agreement as to which elements are the most effective, which points to the challenges of empirically generalizing about which elements of the advertising creative work. A challenge that I am addressing in this thesis. Recently, Schweidel, Bradlow, and Williams (2006) employed this framework for a different purpose. They evaluated 50 randomly selected advertisements according to Stewart and Furse's codebook and studied whether variations in consumers judgements of similarity/dissimilarity among advertisements was driven by features of advertisement content. After controlling for familiarity and viewers' attitudinal responses towards the advertisement and the advertised brand, the authors found that a significant portion of the variation in similarity (dissimilarity) ratings could be explained by the presence (absence) of common content elements.

A more recent generalized framework was proposed by Goldenberg, Mazursky, and Solomon (1999) who posited that successful advertisements share a number of identifiable, verifiable, and generalizable execution patterns known as templates. The authors analyzed 200 print ads randomly drawn from a pool of award-winning advertisements and derived by inference a taxonomy based on six major creativity templates: pictorial analogy, extreme situation, consequences, competition, interactive experiment, and dimensionality alteration. Templates should not be confused with creative ideas, but rather should be considered as framing devices within which creative ideas are developed (i.e. ways to organize ideas). The authors argue that templates are less transient than the ideas developed within them, so they can better withstand the changes in social norms and trends that advertising reflects. Empirically, they observe that advertisements based on creativity templates are judged as more creative, and lead to superior brand attitude and better recall. To the best of my knowledge, this framework has not yet been applied in an empirical setting in the literature, probably due to its relatively recent development. The empirical application of this framework represents therefore a further contribution of this thesis to the marketing and advertising literature.

1.2 Customized Frameworks

Unlike the studies mentioned above, several studies in the marketing and advertising literature have examined specific components of the advertising creative developing specific and customized frameworks. Following, I will provide a review of such studies.

Within this category, one stream of research has focused on the effect of appeals. Chandy et al. (2001) analyzed consumer responses to 39 advertisement creatives for a toll-free referral service for medical providers across 23 urban markets in the U.S. The markets varied considerably in age, from 8 months old to more than 10 years. The authors developed a framework to evaluate whether an advertisement contains emotional or rational appeals (i.e. number of emotional/factual benefits mentioned in the ad). They also analyzed whether the ad was framed positively (highlighted benefits) or negatively (highlighted the reduction of risks), and whether the message came from an expert source. They found new markets to be sensitive to rational appeals, expert sources, and negatively framed messages, while positively framed messages and emotional appeals are more effective in mature markets. In a similar fashion, MacInnis, Rao, and Weiss (2002) tested the effect of affective, rational, and heuristic appeals on whether an increase in advertising weight (i.e. an ad has been shown more frequently or to a larger audience) produces significant increases in sales. In a series of two studies, the authors analyzed 47 commercials of frequently purchased brands in mature categories and found that affective appeals create greater weight-induced sales.

Furthermore, they found that advertisements that evoke positive feelings tend to exhibit greater weight-induced sales. They also argued that these results are consistent with the elaboration likelihood framework (Petty and Cacioppo 1986) since consumer ability to process information is high, but motivation to do so is low in mature product categories of frequently purchased goods. More recently, Bertrand et al. (2010) analyzed data from a direct mail field experiment of a "cash loan" lender in South Africa. Content treatments for advertising messages were grouped along two thematic lines: whether an ad is more likely to trigger intuitive (peripheral route or system I) or reasoned (central route or system II) responses (Kahneman 2003). Results showed a significant effect of advertising content on loan demand, and that advertising persuades consumers by appealing to intuition (peripheral route) rather than reason (central route). Furthermore, the authors showed that content effects are also economically significant when compared to pricing effects. A further example of randomized field experiment aimed at understanding the effect of content appeals on response to advertising is provided by Sudhir, Roy, and Cherian (2016). The authors tested sympathy bias theories randomizing advertising content in mailings to 185,000 prospective new and old donors of an Indian charitable organization. They found that monthly framing of the amount asked has a strong effect on donors' response both in terms of donation rates and donation amount compared to daily framing. They also found evidence of the "identified victim" effect. That is, advertisements showing an individually identified victim are more than twice more effective that advertisements featuring an unidentified group of victims. This effect is even larger when the identified victim belongs to an in-group (i.e. a group representing the majority of the population). Ultimately, the authors showed that advertisements featuring victims whose social status or well-being has changed dramatically (e.g. from well-off to destitute) are more likely to elicit sympathy and hence donations.

Some studies have considered content elements related to branding activities. Most notably, Teixeira, Wedel, and Pieters (2010) analyzed 31 television commercials for national and international products to understand the impact of branding activities and consumers' concentrated attention on commercial avoidance. That is, a consumer's decision to zap a commercial. As measures of advertising branding content, the authors identified seven characteristics: presence, size, position, separation, mode per frame, cardinality, and duration across frames. Results showed that branding content of television commercials has a significant effect on decisions to continue or stop watching the commercial. In particular, the presence of the brand, as well as its more central and well separated presence increase the likelihood of zapping. Also, the likelihood of zapping is increased by the longer a brand is present on screen and the later it appears in the commercial. However, the contemporaneous presence of video and audio branding activity marginally decreases the likelihood of commercial avoidance.

The effect of comparative versus self-promotion claims in advertising is a topic that has recently attracted the interest of the marketing and economics literature. In a series of related studies, Liaukonyte (2006), Anderson, Ciliberto, and Liaukonyte (2013), and Anderson et al. (2016) examined the demand-side and supply-side effects of comparative and self-promoting messages on demand for over-the-counter (OTC) analgesics, Liaukonyte (2006) formulated a model in which advertising incrementally affects the perceived quality of a product, which in turn affects product choice. The author distinguished among the contribution to perceived quality of comparative advertising, noncomparative advertising, as well as the perceived quality damage from other products' comparative advertising against the focal product. The authors analyzed more than 5500 commercials broadcasted between 2000 and 2005 and determined whether each ad is comparative or not. Empirical results showed that for brands heavily investing in advertising against the market leader, comparative advertising is more effective than noncomparative advertising. Brands that do not invest heavily in comparative advertising, as well as the market leader, benefit equally from comparative and noncomparative advertising. However, targeted comparative advertising causes significant damage to rival brands. Anderson, Ciliberto, and Liaukonyte (2013) adopted a similar framework to measure the level of information content in 4503 TV advertisements in the over-the-counter analgesics industry between 2001 and 2005 in order to empirically investigate the role of comparative advertising in the trade-off between information and persuasion. Their results show that brands with stronger comparative advantage as well as higher levels of quality tend to include more information cues. Also, comparative advertisements tend to be more informational than advertisements focusing on self-promotion. Finally, larger market share and stronger competition from generic alternatives are associated with fewer informational cues. Finally, Anderson et al. (2016) derived brands' equilibrium incentives to adopt comparative advertising campaigns. The authors found that comparative advertising has the double effect of boosting a brand's and damaging a rival's perceived quality. Overall, the authors found that self-promotion ads have twice the marginal effect of comparative ads, and the net benefit a brand gets from pulling down a competitor is smaller than the damage suffered from the competitor. In other words, comparative advertising is more damaging to rivals than beneficial for the advertiser. Furthermore, a counterfactual study on banning direct comparative advertising showed that such a ban would decrease advertising expenditures and increase profits for all players in the market.

Liaukonyte, Teixeira, and Wilbur (2015) explored the impact of television advertising on online shopping behavior. They analyzed more than 1,200 advertisements for 20 brands in five product categories and coded the content of each ad along four dimensions: action focus - measuring whether an advertisement contains direct-response elements, information focus - assessing whether an ad persuades by informing consumers, emotion focus - indicating whether an advertisement uses emotionally rich content, and imagery focus - to assess whether an advertisement intends to stimulate visual imagery processing. Empirical results showed that television advertising and its content do influence online shopping behavior. Action-focused advertising directly boosts online traffic and purchase, information- and emotion-focused advertisements are negatively associated with internet traffic, but increase purchase having an overall positive net effect on sales. Imagery-focus does not seem to have significant results on online activity.

Ultimately, some studies have investigated the effect of advertising content not based on scales developed by the authors, but on themes identified by the advertiser, industry partner, or policy maker. Bass et al. (2007) and Bruce (2008) studied the dynamic effects of five advertising themes indicated by the data provider. In particular, Bass et al. (2007) developed a Dynamic Linear Model of advertising effectiveness in order to study the direct effects, the interaction, and the wear-out of five advertising themes for a residential telephone service company over a period of 114 weeks between 1995 and 1997. The company classified advertising into five themes: call stimulation, product offer, price offer, reconnect, and reassurance advertisements. The authors found that different themes have significantly different copy wear-out parameters, while all themes showed repetition wear-in effects. Also, they showed that rational advertising (product and price offer ads) wears out faster than emotional advertising. Ultimately, results indicated a negative interaction effect among different creative themes. Bruce (2008) extends the work of Bass et al. (2007) examining the pooling effect of advertising themes, that is the interdependence of themes employed during an advertising campaign. The author found that pooling and varying advertising themes help reduce the wear-out of individual themes. Furthermore, the author found asymmetrical pooling effects between rational and emotional advertisements. That is, for any pair of emotional and rational ad theme, the effect of the rational ad on the emotional one is stronger than the effect of the emotional ad on the rational one. This implies that rational ads reinforce the effect of emotional ads more than emotional ads reinforce the effect of rational ads. In a different domain, Kolsarici and Vakratsas (2010) examined the effect of direct-to-consumer advertising (DTCA) for a new pharmaceutical in a market in which the regulator requires the content of advertising to be of two mutually exclusive types: category-related messages and brand-related messages. The former should communicate information about the disease without promoting any brand. The latter can promote the brand without any reference to therapeutic information. The authors found both category- and brand-related advertising to be effective. However, category-related advertising was more effective during the early stages of the product category. Brand-related advertising, conversely, was more effective once the product category is established and competitors have entered the market. The studies discussed in this section are summarized in Table 1.

Table 1: Evaluation Frameworks

Study	Content Evaluation
Generalized Frameworks	
Resnik and Stern (1977)	14-item scale to evaluate the informative content on TV advertising
Stewart and Furse (1984)	~200-item codebook to evaluate TV advertising executional elements
Goldenberg, Mazursky, and Solomon (1999)	6 creativity templates of successful ads
Customized Frameworks	
Chandy et al. (2001)	Emotional/rational appeals, positive/negative framing, use of expert source
MacInnis, Rao, and Weiss (2002)	Affective/rational/heuristic appeals, positive/negative feelings
Bass et al. (2007) Bruce (2008)	Pre-classified themes, emotional/rational appeals
Bertrand et al. (2010)	Intuitive thinking/reasoned thinking
Teixeira, Wedel, and Pieters (2010)	Branding content characteristics
Kolsarici and Vakratsas (2010)	Generic/brand-related advertising
Liaukonyte, Teixeira, and Wilbur (2015)	Action-focus, emotion-focus, information-focus, imagery-focus
Liaukonyte (2006) Anderson, Ciliberto, and Liaukonyte (2013) Anderson et al. (2016)	Comparative/self-promoting advertising
Sudhir, Roy, and Cherian (2016)	Time framing, identified/unidentified victim, in-group/out-group

2 The Components of Advertising Creative Strategy

The literature review of the previous section broadly suggests that advertising creative strategy consists of two focal components: content and execution. Content can be considered as the *function* of the advertisement or *what* is the message communicated to the audience (Resnik and Stern 1977), whereas execution can be considered as its *form* or *how* the message is communicated (e.g. Stewart and Furse 1986). However, extant research typically focuses only on select elements of the creative strategy. For example, studies on content focus mainly on cognitive (informational) or affective (emotional) elements (Bass et al. 2007; Bruce 2008; Chandy et al. 2001; MacInnis, Rao, and Weiss 2002) and tend to ignore experiential elements whereas evidence suggests that the latter may be a critical dimension of advertising content. For example, Bruce, Peters, and Naik (2012), provide empirical evidence for the existence of experiential intermediate advertising effects. This is consistent with the view of Vakratsas and Ambler (1999) that advertisements not only serve as vehicles of factual information or affective appeals, but also deliver experiential elements, such as suggesting new purchase or consumption patterns, or reinforcing existing ones. They further argue that failing to account for the experiential dimension of advertising content could lead to the overestimation of the role of the other dimensions. In addition, studies to date tend not to integrate different perspectives on the advertising creative. For example, the creative templates proposed by Goldenberg, Mazursky, and Solomon (1999) have not been integrated in scales concerning executional elements of the creative strategy. A potential reason is the length of the scales involved that require extensive content analysis. Hence, a representation of a brand's advertising creative should not only be guided by comprehensiveness, through the inclusion of all relevant perspectives, but also by parsimony.

In sum, the evaluation framework of the advertising creative should provide the following insights: 1) a comprehensive representation of the advertising creative that considers both content and executional components by integrating different relevant perspectives, and 2) such a representation should be parsimonious to facilitate analysis of sales effectiveness and replication. To address these issues, I propose the Advertising Creative Strategy framework and further elaborate upon below. Consistent with this synthesis, the proposed ACS framework consists of two components: Function, identifying what message the advertisement is conveying to consumers (i.e. its content) and Form, describing how the message is conveyed (i.e. its execution).

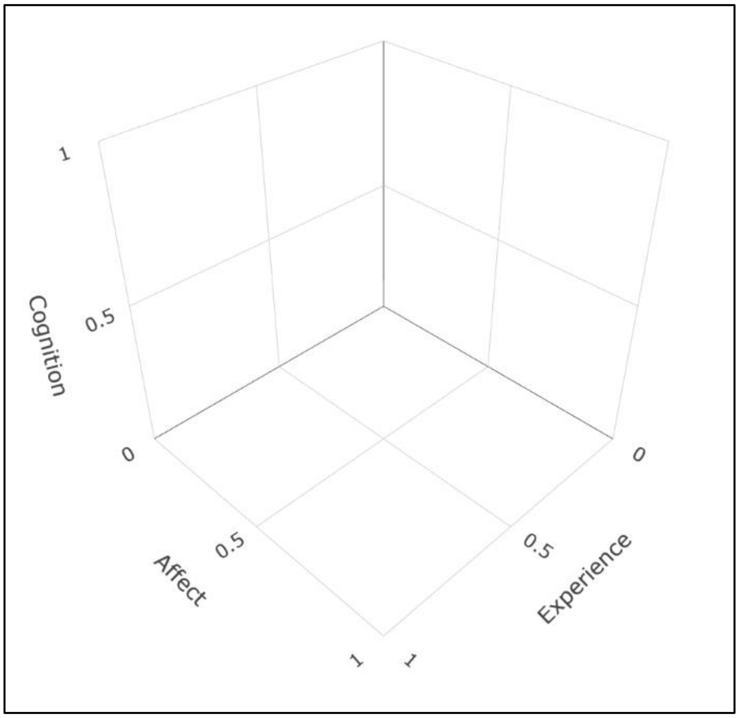
It is worth noting that the ACS framework is not medium-specific but can be used to evaluate advertisements across different media. That is, researchers and advertisers can adopt it to evaluate both video and static advertisements (i.e. ads based on still images such as print or banner ads), which makes it suitable for the analysis of advertisements on both traditional and digital media. Advertisements on traditional and digital media usually share their creative copy. For example, a brand would use the same video ad on TV and YouTube. The main difference between advertising on traditional and digital media is the interactive nature of the latter which refers to the ability for consumers to have an active role with respect to the advertisement through sharing, liking, commenting, or skipping an ad (Acar and Puntoni 2016; Belanche, Flavián, and Pérez-Rueda 2019). These features, although important in driving the effectiveness of digital advertising, would affect performance directly rather than through the creative design of the advertisement. Therefore, it is not necessary to incorporate them into the ACS framework.

I will begin with a discussion of the Function component.

2.1 Function

The review of the relevant literature indicates that messages are frequently not unidimensional, i.e. they do not focus on a specific type of content (e.g. cognitive or affective) but rather use some combination (Chandy et al. 2001). Furthermore, as previously discussed, experiential elements can also critically shape the content of the message. I therefore adopt a three-dimensional representation of advertising content consistent with the "EAC space" of Vakratsas and Ambler (1999). This representation depicts content as a three-dimensional Euclidean space so that advertisements can be placed in it using the level of experiential, affective, and cognitive cues as coordinates. A representation of the EAC space is depicted in Figure 1. There are two main advantages to this approach: first, it is non-hierarchical and therefore holistic, since evidence on a specific hierarchy of effects is limited (Vakratsas and Ambler 1999); second, it uses a Euclidian space representation which allows for the derivation of important metrics such as Focus (emphasis on a specific content dimension) or temporal Variation (variation in the emphasis across time). These metrics are not only relevant for their ability to capture complex interactions among content dimensions parsimoniously, but also represent measures of content divergence, a fundamental driver of creativity perceptions for consumers (Smith et al. 2007). Focus, in fact, captures the extent to which content dimensions diverge from each other, and Variation captures the extent of temporal divergence. I therefore propose that the first component of this framework, Function, relies on the three-dimensional EAC space and develop a scale accordingly. A table with the codebook reporting the scale elements is available in Appendix A.

Figure 1: The EAC Space



The Function component of the scale consists of three parts corresponding to E, A, and C. Experience (E) is the content dimension that has not been explicitly accounted in previous frameworks and scales for advertising creative. Based on the idea that advertising can illuminate usage experience (Deighton 1984; Mehta, Chen, and Narasimhan 2008) I define content directly related to product usage as experiential. I also include the possibility of new usage since Wansink and Ray (1996) propose that brands should encourage consumers to use products in new contexts or promote secondary usage. Furthermore, following Vakratsas and Ambler (1999), I also evaluate if an advertisement aims at reinforcing a current habit. This results in items E1-E3 of the scale. With respect to Affect (A), similarly to Liaukonyte, Teixeira, and Wilbur (2015), I assess whether an advertisement is explicitly designed to generate feelings in the audience (e.g. joy, nostalgia) with item A1, as well as evaluate whether the advertisement mentions emotional benefits gained from purchasing/consuming the product. Chandy et al. (2001) define emotional benefits as the advertising cues that make consumer felt understood in terms of their worries associated the purchase/consumption (item A2). Finally, I base the Cognition component of the framework mostly on the seminal work of Resnik and Stern (1977). However, since the original 14-element evaluation scale developed by the authors is too lengthy, I summarize its elements based on the four P's of marketing: product, price, promotion, and place (C1-C4). Product refers to information about product attributes as well as whether the product presents novel features. Price refers to whether the ad features information about the price of the product or price promotions. Promotion refers to information about promotional activities other than price promotions, and place refers to whether the ad provides information on where to find/purchase the product. Due to its relevance in the marketing literature and the fact that it does not fall neatly in any of the four P's, I also assess whether the ad features reference to the quality of the product (Tellis and Fornell 1988; Tellis and Johnson 2007) either in terms of research certification (e.g. independent research), or in terms of display of the product performance (item C5).

2.2 Form

I evaluate Form based on two concentric components: Execution, which can be thought of as Form's inner component containing various executional elements, and Template, the outer component acting as the structure according to which the executional elements are organized. In their seminal work, Stewart and Furse (1986) analyze TV commercials according to several executional elements, that is the technical or artistic means by which advertisers convey the message of the advertisement to consumers. As pointed out in the literature review, their original scale includes more than 200 different executional elements, which is labor-intensive for large-scale applications. Furthermore, there is no consensus in the literature as to which specific element is effective at driving consumer response to advertising (Hartnett et al. 2016; Stewart and Koslow 1989). Therefore, I base the evaluation of Execution on a summary of the elements that have been consistently shown to be relevant in past research. Namely, I focus on the following four categories: endorsement, format, use of visual devices, and use of mnemonic devices.

With respect to endorsement, I evaluate whether an advertisement features endorsement from a celebrity (Choi, Lee, and Kim 2005; Erdogan 1999), an expert (Tellis, Chandy, and Thaivanich 2000), or regular consumers (Stewart and Furse 1986). This results in item F1 of the codebook in Appendix A. I evaluate whether an advertisement adopts humor (Eisend 2009), drama (Deighton, Romer, and McQueen 1989), animation or story-telling (Stern 1994) as format with item F2. Among the visual elements advertisers use to enhance the execution of an advertisement (Messaris 1997), I identify the use of extreme beauty and extreme ugliness (Bower and Landreth 2001), be it related to the characters in the advertisement or the scenery, and the use of graphical aids (e.g. charts) as the most common (Stewart and Koslow 1989), and capture their use through item F3. Finally, recall is one of the most widely used customer mind-set metrics upon which advertising agencies judge the success of their campaigns (Till and Baack 2005). It is therefore important to account for the presence of elements created to aid brand or product recall: mnemonic devices. Based on Stewart and Furse (1986) and Stewart and Koslow (1989) I identify four main ones: a memorable character associated with a product or a brand (e.g. the Duracell bunny), a memorable catchphrase (e.g. Budweiser's "What's Up"), a memorable sound or audio bite (e.g. Intel Inside), and the disproportionate use of the brand name or image (Teixeira, Wedel, and Pieters 2010), which results in item F4 of the codebook.

Goldenberg, Mazursky, and Solomon (1999) show that when executional elements are structured according to specific templates, they can increase the perception that an advertisement is of higher quality, more creative, and hence capable of producing better attitudes and recall. They identify six templates: Analogy, Extreme Situations, Consequences, Competition, Interactive Experiment, and Dimensionality Alteration. I capture whether an ad follows one of these templates with item F5. The use of the template framework is also desirable because it allows me to further consolidate into the ACS framework other relevant elements discussed in the literature. For example, Mullainathan, Schwartzstein, and Shleifer (2008) propose that individuals think coarsely. That is, they tend to group situations into pre-existing homogeneous categories, and use such categories to perform inference and make decisions. Operationally, the advertiser's effort to nudge consumers' tendency to think heuristically can be captured by the analogy template. Also, previous research has shown that the way an advertisement is framed (positive or negative framing) affects the way consumers react to the advertisement (Chandy et al. 2001; Chang 2008). I capture this through the consequence template.

Chapter 2: The Relationship Between Advertising Creative Strategy and Advertising Elasticity

1 Modeling the Effect of Advertising Creative Strategy on Advertising Elasticity

To examine the effects of ACS on advertising elasticity, I employ a state-space formulation. More specifically, I develop a Bayesian Dynamic Linear Model (Harrison and West 1999) that allows me to model advertising elasticity as a function of ACS. State-space models have been widely adopted in the empirical marketing literature to model the dynamic effects of advertising (Naik, Mantrala, and Sawyer 1998), multi-media (Naik and Raman 2003; Zantedeschi, Feit, and Bradlow 2016) and multi-theme advertising response (Bass et al. 2007; Bruce 2008), sequential distribution of new products (Bruce, Foutz, and Kolsarici 2012), advertising in regulated environments (Kolsarici and Vakratsas 2010), financial responses to advertising (Osinga et al. 2011), and the effect of product-harm crises (Liu and Shankar 2015). Using a Bayesian Dynamic Linear Model, my modeling approach accommodates dynamics in the advertising effect. I also control for the effect of competitive actions, other marketing activities, and potential endogeneity concerns via an extensive set of control variables.

Consistent with extant literature, I model a brand's sales as a function of consumers' goodwill towards the brand (Naik, Mantrala, and Sawyer 1998; Nerlove and Arrow 1962) and a set of control variables:

$$\log S_{it} = G_{it} + \alpha_i X_{it} + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma_i^2) \tag{2.1}$$

In the equation above, S_{it} represents the sales of brand i at time t in terms of 1000 Volume Equivalent Units (VEQ). The variable is then log-transformed and centered (i.e. its sample mean is subtracted). G_{it} is the unobservable value of consumers' goodwill towards brand i at time t and represents the latent component (state) of the model. I also include X_{it} as a generic term for controls for potential sources of variability in the level of sales. This term includes seasonal dummies, price, feature and display promotions, and product line length for the focal brand and competitors, as well as competitors advertising spending. All variables are log-transformed and centered. Finally, ϵ_i is a normally distributed error term with zero mean and variance σ_i^2.

I then specify the evolution of goodwill over time as follows:

$$G_{it} = \lambda\, G_{it-1} + \beta_{it} \log Ad_{it}^{*} + \phi cop(Ad_{it}^{*}) + \nu, \quad \nu \sim N(0, \kappa^2) \tag{2.2}$$

In the equation above, $Ad_{it}^{*} = 1 + Ad_{it}$ where Ad_{it} represents advertising spending for brand i at time t. Given the logarithmic formulation of both dependent variable in Equation (2.1) and the advertising variable in Equations (2.2), β_{it} can be directly interpreted as the short-term advertising elasticity for brand i at time t. The autoregressive component of the state equation, λ, represents the amount of goodwill carried over at each time period, and ν is a normally distributed error term with zero mean and variance κ^2. Following Park and Gupta (2012), I control for potential endogeneity bias by including the Gaussian copula term for advertising spending $cop(Ad_{it}^{*})$ and its associated parameter ϕ. The control term is defined as $cop(Ad_{it}^{*}) = \Phi^{-1}(H(Ad_{it}^{*}))$ where $\Phi^{-1}$is the inverse cumulative distribution function of the standard normal distribution, and $H(.)$ is the empirical cumulative distribution function of the variable of interest. The Gaussian copula method corrects for endogeneity bias by jointly modeling the variable of interest and the error term, therefore accounting for their potential correlation. It belongs to the class of "instrument-free" methods (Rossi 2014) and allows for the consistent estimation of parameters when reliable instruments are not available (Wedel and Kannan 2016).

The log-log formulation allows me to directly interpret β_{it} as advertising elasticity, and model it as a function of ACS and other control variables:

$$\beta_{it} = \beta_0 + \sum_{j=1}^{J} \gamma_{ij} ACS_{ijt} + \delta Z_{it} \tag{2.3}$$

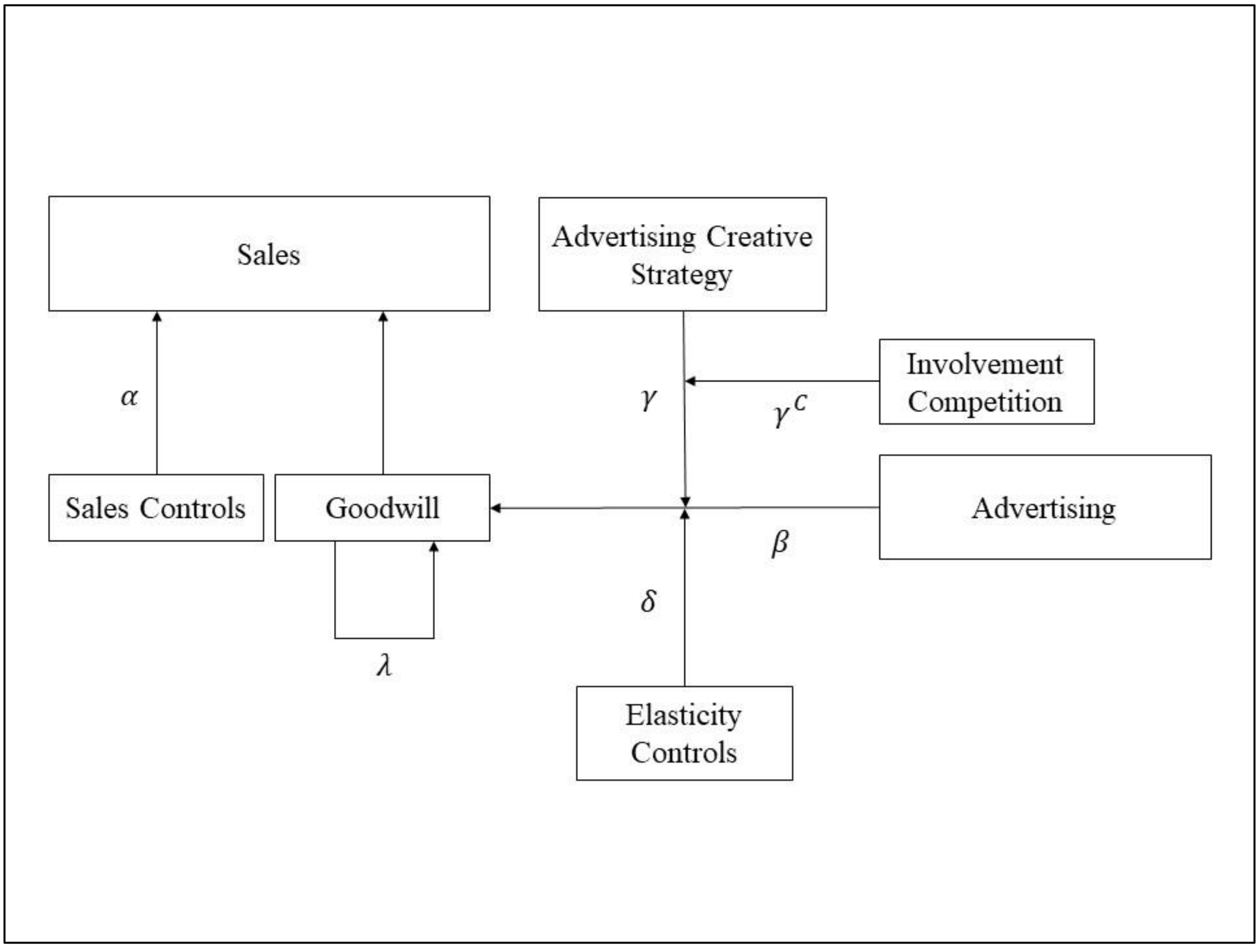
where the term ACS_{ijt} represents the j-th component of brand i's ACS at time t with a corresponding effect γ_{ij}, and Z_{it} represents a set of control variables which includes competitors advertising spending and advertising age, i.e. number of weeks the current advertisement has been on air.

I further account for heterogeneity in the effect of a brand's creative strategy across product categories by modeling it as a function of the level of competition in the product category (Pieters, Warlop, and Wedel 2002) and the level of consumer involvement in the product category (Ehrenberg 1997; Vaughn 1986):

$$\gamma_{ij} = \gamma_j^{C0} + \gamma_j^{C1} Comp_i + \gamma_j^{C2} Inv_i \tag{2.4}$$

I include competition and involvement in the set of control variables in Equation (2.3) as well. Figure 2 graphically summarizes the modeling framework expressed by Equations (2.1) to (2.4).

Figure 2: ACS and Advertising Elasticity - Modeling Framework



2 Empirical Study

2.1 Data

I apply my model to two years of weekly data (104 weeks) from January 2010 to December 2011 for 18 brands across 9 CPG product categories. The availability of information on multiple brands and product categories allows for generalizability of my findings. In addition, managers of CPG brands would be particularly interested in improving advertising performance through the management of advertising creative since advertising elasticities in such categories tend to be low (Sethuraman, Tellis, and Briesch 2011) and advertising creative accounts for 49% of sales performance for consumer packaged goods according to a recent Nielsen Catalina study (Nielsen 2017). The sample includes both food and non-food (e.g. laundry detergents and salty snacks) as well as perishable and non-perishable product categories (e.g. yogurt and frozen meals).

In each category I only consider national brands and select the two brands with the highest market share that advertise on television during the period under study. I obtain data for sales as well as own and competing marketing activities from the IRI Marketing Dataset (Bronnenberg, Kruger, and Mela 2008) and advertising data from the Kantar Media "Stradegy" database. This data includes weekly national advertising spending at the brand and category level, as well as the video files of all television commercials aired nationally during the period of study.

I focus on television commercials since it is the only medium with significant spending for which I have access to all creatives (commercials). This does not represent a limitation since CPG brands rely predominantly on television advertising. Furthermore, many big players are currently reallocating their advertising budget from digital media to television. For example, Procter and Gamble recently reinvested $200 million cut from digital advertising into TV advertising, and Unilever appears to be following a similar route (Adweek 2018). Also, in the dataset, television share of the advertising budget is disproportionately higher than all other media combined for all brands in our analysis, with a minimum of 85%.

I evaluate ACS for each television commercial with trained coders using the following procedure:

1. I download the video files for all commercials aired nationally during the period of interest, which results in a total of 513 video files. Each video file is identified by a unique ID code which, however, is unique to the video file and not to the commercial. That is, the same commercial can be associated with several different IDs. I manually aggregate the data in order to have a unique entry for each commercial for each week in the dataset. I further consolidate commercials into campaigns. That is, I combine commercials that feature the same copy but differ in duration (e.g. 15-, 30-, 45-, and 60-seconds commercials) or with respect to minor aesthetical differences (e.g. the flavor of the product showed in the commercial). I further drop campaigns that air for only one week throughout the observation period as they make temporal effects hard to estimate and usually serve special purposes (e.g. holidays). This process results in a total of 107 campaigns.
2. Two trained research assistants evaluate each campaign based on the ACS framework codebook in Appendix A. Following Liaukonyte, Teixeira, and Wilbur (2015), I instruct coders to watch each commercial at least twice before completing the evaluation. During the coding, coders are allowed to watch the commercial as many times as they need. Also, I instruct coders to work independently and for no more than two hours at a time to avoid

fatigue. At the end of the coding process, discrepancies are resolved through discussion (Neuendorf 2016).

At the end of this process, I am left with a value of Experience (*E*), Affect (*A*), Cognition (*C*), and Execution (*Ex*) for each campaign, and an indicator variable called Template (*Tp*) taking value of one if a given campaign adopts a creative template and zero otherwise.

In order to aid comparison among brands, I first standardize *E*, *A*, *C*, and *Ex* (i.e. subtract their mean and divide by their standard deviation, i.e. a z-score transformation) and then transform them into a scale between 0 and 1 by means of the cumulative distribution function of the standard normal distribution. More formally, let x_{kj} represent the value of the *j*-th variable of ACS for the *k*-th campaign as recorded during the coding process, I obtain the transformed value $\tilde{x}_{kj}$ as follows:

$$\tilde{x}_{kj} = \Phi\left(\frac{x_{kj} - \mu_j}{\sigma_j}\right), \quad j \in [E, A, C, Ex] \tag{2.5}$$

where $\Phi(.)$ is the cumulative distribution function of the standard normal distribution and $\mu_j = \frac{\sum_{k=1}^{107} x_{kj}}{107}$ and $\sigma_j = \sqrt{\frac{\sum_{k=1}^{107}(x_{kj}-\mu_j)^2}{107-1}}$. This provides me with a standardized value of Experience, Affect, Cognition, and Execution between 0 and 1, and a dummy variable for Template. Following the ACS conceptualization of the Form component, i.e. that templates represent a particular way to structure the executional elements of a campaign, I include Template in the ACS term of Equation (2.3) only as an interaction with Execution which I term Templated Execution (TEx).

In most cases brands air only one campaign during each period. To account for the rare occasions of multiple campaigns aired in one week, I define each component of the overall ACS of brand i at time t as the average value across all campaigns aired in that week, weighted by the campaign spending in that week. That is, the j-th component of brand i's ACS at time t, is calculated as

$$\tilde{x}_{ijt} = \frac{\sum_{k=1}^{n_i} w_{ikt}\tilde{x}_{ijkt}}{\sum_{k=1}^{n_i} w_{kt}}, \quad j \in [E, A, C, Ex, TEx] \tag{2.6}$$

where w_{ikt} is brand i's spending on campaign k at time t.

The Euclidean space representation of ACS's content (the EAC space), allows me to use more metrics that characterize advertising Function and parsimoniously capture complex interactions among dimensions. More specifically, I construct two brand-specific variables that capture changes in a brand's advertising content composition namely Focus (*Foc*) and Variation (*Var*). Focus indicates the extent to which the elements of the Function component of ACS are represented in an imbalanced manner (i.e. creative strategy focuses only on one or two dimensions rather than featuring all dimensions in similar proportions) and is calculated as the standard deviation of Experience, Affect, and Cognition at each point in time.

$$Foc_{it} = \sqrt{\frac{\sum_{j\in[E,A,C]}\left(\tilde{x}_{ijt} - \bar{\tilde{x}}_{it}\right)^2}{2}} \tag{2.7}$$

where $\bar{\bar{x}}_{it} = \frac{1}{3}\sum_{j\in[E,A,C]}\left(\tilde{x}_{ijt}\right)$.

Similarly, Variation measures the extent to which the Function component of a brand's creative strategy changes over time. I calculate Variation at each point in time as the Euclidean distance between the current and the previous position of a brand's advertising in the EAC space:

$$Var_{it} = \sqrt{\sum_{j\in[E,A,C]} \left(\tilde{x}_{ijt} - \tilde{x}_{ijt-1}\right)^2}. \tag{2.8}$$

These simple operationalizations of Focus and Variation are made possible by the use of the EAC space as framework for evaluating ACS's Function due to its geometric representation. Being a function of Experience, Affect, and Cognition together, these measures allow each dimension not only to affect elasticity directly, but also to also have an indirect effect via the composition of the creative strategy (Focus) and its temporal consistency (Variation). This also represents a way to parsimoniously capture complex interactions among dimensions in a way that also has a meaningful interpretation.

Summarizing, the modeling of ACS is formed by seven elements: Experience (*E*), Affect (*A*), Cognition (*C*), Execution (*Ex*), Templated Execution (*TEx*), Focus (*Foc*), and Variation (*Var*). Therefore, I can rewrite Equation (2.3) as

$$\sum_{j=1}^{J} \gamma_{ij} ACS_{ijt} = \gamma_1 E_{it} + \gamma_2 A_{it} + \gamma_3 C_{it} + \gamma_4 Ex_{it} + \gamma_5 TEx_{it} + \gamma_6 Foc_{it} + \gamma_7 Var_{it}. \quad (2.9)$$

Table 2 reports the summary statistics of the focal variables of this study in their original scale.

Table 2: ACS and Advertising Elasticity - Summary Statistics

Variable	Mean	SD
Sales (1000 VEQ)	227	209
Ad Spending ($1000)	174	321
Experience	0.332	0.330
Affect	0.255	0.312
Cognition	0.345	0.363
Execution	0.290	0.321
Templated Execution	0.059	0.194
Focus	0.134	0.164
Variation	0.142	0.178
Competition	-0.689	0.153
Involvement	3.305	0.286
Ad Age	4.271	6.693
Competitors Ad Spending	5464	5205

Also, Table 3 provides a description of all the variables included in the model.

Table 3: ACS and Advertising Elasticity – Variable Description

Variable	Eq.	Description
S_{it}	(2.1)	Sales of brand i in week t in terms of 1000 VEQ units.
X_{it}	(2.1)	• Season: seasonal dummy variables. • Price: recorded selling price for brand i in week t averaged across UPCs and stores weighted by store All-Commodity Value (ACV). • Feature: indicator for brand i being featured on a store's weekly flier averaged across UPCs and stores weighted by store ACV. • Display: indicator for brand i being on display promotion averaged across UPCs and stores weighted by store ACV. • Line Length: number of unique UPCs of brand i offered in each store in week t averaged across stores weighted by store ACV. • Competitors Price, Feature, Display, and Line Length: all variables calculated as above for each national brand, and then averaged across all competing brands. • Competitors Advertising: advertising spending for all other brands in the category in week t in \$1000.
Ad_{it}	(2.2)	Advertising spending of brand i in week t in \$1000.
Z_{it}	(2.3)	• Competitors Advertising: advertising spending for all other brands in the category in week t in \$1000. • Ad Age: number of weeks an ad campaign has been on air averaged across campaigns. • Involvement: see below. • Competition: see below. • Advertising Copula: Gaussian copula to control for endogeneity (Park and Gupta 2012).
ACS_{it}	(2.3)	• Experience: value of ACS's Experience for brand i in week t. • Affect: value of ACS's Affect for brand i in week t. • Cognition: value of ACS's Cognition for brand i in week t. • Execution: value of ACS's Execution for brand i in week t. • Template x Execution: value of ACS's Execution for brand i in week t when happening within a creative template framework. • Focus: Standard deviation of a brand i ACS *function* elements in week t. • Variation: Euclidean distance of brand i ACS *function* elements between time t and t-1.
Inv_i	(2.4)	Perceived functional risk of the category as in Datta, Ailawadi, and van Heerde (2017).
$Comp_i$	(2.4)	Total market share of top four brands in the category as in Datta, Ailawadi, and van Heerde (2017) (negative).

VEQ = Volume Equivalent Units, ACV = All Commodity Value

2.2 Estimation

Equations (2.1) - (2.4) fully specify my Bayesian Dynamic Linear Model. Equation (2.1) represents the so-called observation equation, linking the latent, unobserved state (goodwill in this case) to observed data. Equations (2.2) – (2.4) represent the components of the state equation, describing the evolution of the latent state. Since Goodwill is latent, and therefore unknown, my modeling framework requires the estimation of two types of parameters: the optimal path of the dynamic state (goodwill), and the static parameters of the model. I estimate both recursively through Gibbs sampling by means of the Forward Filtering Backward Sampling (FFBS) algorithm (Carter and Kohn 1994; Frühwirth-Schnatter 1994) and Conjugate Bayesian (CB) techniques (Allenby and Rossi 1998). This combination has already found application in the marketing literature (e.g. Bass et al. 2007; Bruce, Foutz, and Kolsarici 2012). I provide an overview of the FFBS algorithm in Appendix B.

The Gibbs sampler is composed of three parts: (a) sampling of the optimal path of goodwill for each brand, (b) sampling of each brand's static parameters of the observation equation from their conjugate posterior distribution, and (c) sampling of common static parameters across brands of the state equations from their conjugate posterior distribution. It proceeds as follows. I first fix the initial value of all static parameters in equations (2.1) – (2.4) and obtain a sample of the optimal path of goodwill for each brand by means of the FFBS algorithm. Then, I plug these values in equation (2.1) and sample from the posterior of individual brand level control parameters for each brand imposing standard weakly informative priors. Ultimately, I plug sampled goodwill in equation (2.2) and sample the common static parameters of the state equations from their posterior distribution imposing standard weakly informative priors. I impose the static parameters of the state equations to be equal across brands by stacking the samples of goodwill. I repeat this three-step procedure 30000 times. I discard the first 5000 iterations as burn-in period and then collect one sample each 5 iterations for a total of 5000 posterior samples.

Estimation based on data not deriving from experimental conditions could suffer from bias deriving from endogeneity. Endogeneity arises when the independent variable of a regression model is correlated with the error term. That is, the independent variable is correlated with some unobservable element that has an effect on the dependent variable of interest. This unobserved element, not being explicitly specified in the model, is then absorbed by the error term. The bias in the parameter estimates deriving from the lack of inclusion of relevant independent variables in the model is also known as omitted-variable bias. In most cases, this concern is addressed through the use of Instrumental Variables (IV).

For some marketing applications, valid and reliable instruments are hard to find and this leads to serious concerns about the potential biasedness of the estimated parameters (Rossi 2014). In such cases, researchers must adopt methods that do not rely on instrumental variables to consistently estimate parameters (IV-free methods). Examples of this approach include the Latent Instrumental Variable (LIV) method by Ebbes et al. (2005), the Control Function (CF) approach by Petrin and Train (2010), and the approach proposed by Park and Gupta (2012) based on jointly modeling the potentially endogenous regressors and the error term using Gaussian copulas. Since the validity of this approach is well documented in the literature (Wedel and Kannan 2016), I opt for this method in my modeling framework and control for the potential endogeneity of advertising spending by including the Gaussian copula term in Equation (2.2). The only identifying assumption required by this approach is that the potentially endogenous regressors are not normally distributed. In this case, a Shapiro-Wilk test rejects the assumption of normality.

I prefer standard CB to alternative methodologies, i.e. Maximum Likelihood Estimation (MLE) and Hierarchical Bayes (HB) for two reasons. First, my treatment of endogeneity requires the introduction of an additional control term in Equation (2.2) which affects the correctness of the information matrix and hence the correctness of MLE standard errors. Neither Bayesian nor bootstrap methods would rely on asymptotic properties to derive dispersion measures relative to the parameters of interest, which would make them both suitable candidates. However, typical bootstrap techniques are hard to implement in the presence of time series data due to the potential of disrupting serial correlation. I also reject the idea of using HB since the balanced panel structure of the data and the small size of the data cross-section do not justify the greater complexity,

2.3 Results

I report the estimation results of the model in Table 4. I estimate baseline elasticity (β_0 in Equation (2.3)), that is the elasticity estimate obtained without taking the elements of ACS into account, to be 0.031. This result is slightly lower than the one found in the recent meta-analytic study by Sethuraman, Tellis, and Briesch (2011) who find an overall median elasticity value of 0.05. However, Sethuraman, Tellis, and Briesch (2011) acknowledge that temporal aggregation at the weekly level and the analysis of mature product categories are expected to yield lower elasticities. I also report the value of goodwill carry-over (λ in Equation (2.2)) which I estimate to be 0.681.

Table 4: ACS and Advertising Elasticity – Estimation Results

Variable	Mean	SD	90% HDI Lower	90% HDI Upper
Carry-Over	**0.681**	**0.022**	**0.642**	**0.715**
Baseline Elasticity	**0.031**	**0.009**	**0.016**	**0.045**
Experience	**0.042**	**0.023**	**0.003**	**0.079**
x Competition	-0.142	0.188	-0.451	0.157
x Involvement	-0.008	0.066	-0.120	0.099
Affect	0.000	0.016	-0.026	0.027
x Competition	0.000	0.150	-0.246	0.241
x Involvement	-0.017	0.061	-0.119	0.081
Cognition	**0.038**	**0.021**	**0.003**	**0.071**
x Competition	-0.027	0.115	-0.215	0.165
x Involvement	**0.116**	**0.072**	**0.002**	**0.235**
Execution	-0.006	0.019	-0.037	0.024
x Competition	-0.194	0.126	-0.395	0.018
x Involvement	**0.101**	**0.060**	**0.006**	**0.199**
Templated Execution	-0.003	0.022	-0.040	0.032
x Competition	-0.010	0.147	-0.261	0.226
x Involvement	**0.186**	**0.080**	**0.054**	**0.314**
Focus	-0.034	0.032	-0.087	0.020
x Competition	**0.414**	**0.215**	**0.077**	**0.785**
x Involvement	**-0.276**	**0.113**	**-0.461**	**-0.092**
Variation	**0.038**	**0.016**	**0.012**	**0.065**
x Competition	-0.015	0.125	-0.226	0.187
x Involvement	0.034	0.053	-0.054	0.121
Ad Age	**-0.010**	**0.004**	**-0.017**	**-0.004**
Competitors Ad Spend	**-0.003**	**0.001**	**-0.005**	**-0.001**
Competition	0.016	0.028	-0.030	0.062
Involvement	0.009	0.014	-0.014	0.032
Gaussian Copula	-0.003	0.007	-0.014	0.008

HDI = Highest Density Interval

This indicates that approximately 68% of the contemporaneous effect of advertising gets carried over to the next week, contributing to a higher long-term effect of advertising spending (Leone 1995).

With respect to the Function component of ACS, Experience has only a significant main effect (0.042), which indicates that the direct effect of Experience on elasticity is equal across product categories. Conversely, for Cognition I find both the main effect (0.038) and the interaction with Involvement (0.116) to be significant, indicating that the higher the involvement with the product category the greater the effectiveness of an increase in cognitive cues.

In terms of the Form component of ACS, I find both Execution and the interaction between Execution and Creative Template (Templated Execution) to be significant only with respect to the level of category involvement (0.101 and 0.186 respectively). This implies that campaigns that are more complex execution-wise (i.e. include more executional elements) are more effective in product categories with higher levels of involvement. This relationship is further strengthened in the case in which a campaign is structured according to a creative template.

I also find significant effects of Focus and Variation, which is indication that holistic metrics of advertising strategy integrating all three dimensions of content in the EAC space play a significant role in shaping advertising elasticity. To my knowledge, this the first study to report this type of finding. In particular, I find Focus to be positively associated with a category's level of competition (0.414) and negatively associated with a category's level of involvement (-0.276). This implies that well-balanced ads, which include experiential, affective, and cognitive cues of equal proportions, perform better in high involvement product categories. Conversely, in categories that exhibit a high level of competition, ads focusing only on some of the *Function* dimensions tend to perform better. Overall, Variation exhibits a positive effect (0.038). That is, changing the composition of advertising creative strategy has a consistent positive effect on advertising elasticity across all product categories. This result implies that consumers are positively responsive to variations in the overall composition of a brand's advertising content and is consistent with the concept of divergence in creativity (Smith et al. 2007).

With respect to elasticity controls, I find a negative significant value for Ad Age (-0.010) indicating that advertising effectiveness decreases with the number of weeks an advertisement has been on air. That is, newer ads tend to perform better than ads that have been aired for a longer period. This is consistent with the repetition wear-out effect that has been reported in the advertising literature (Naik, Mantrala, and Sawyer 1998). Furthermore, I find a small but significant negative effect of Competitors Ad Spending (-0.003) which indicates that the level of competitive advertising decreases a brand's own advertising elasticity, consistent with the interference effect reported in the literature by Danaher, Bonfrer, and Dhar (2008). Finally, I find the coefficient associated with the Gaussian copula for advertising spending to be not significant. This implies that there is no significant correlation between advertising spending and the error term, hence minimizing the risk of biased results due to endogeneity. This is not entirely surprising since I use relatively high-frequency (weekly) time-series data and adopt an extensive set of control variables (Rossi 2014).

Further concerns about potential endogeneity bias could regard the estimation of advertising content effects on advertising performance as well as the effect of Variation. The first refers to advertisers potentially deciding to change advertising content based on observing current advertising performance or, more generally, potentially choosing content based on the results or expectations deriving from some optimization procedure. With regards to the former, advertisers usually set spending budgets and creative directions over long periods of time, e.g. once a year, and cannot easily, if at all, make changes as they go (Shapiro 2018). With respect to the latter, research has shown that marketers suggest only general creative directions rather than specific guidelines to advertising agencies, which then generate the actual creative content of advertising campaigns (Koslow, Sasser, and Riordan 2006). Furthermore, marketers and the creative staff of advertising agencies are likely driven by different performance evaluation criteria. For example, advertising awards are widely perceived as indicators of advertising performance for advertising agencies, while they are not of much interest to marketers (Helgesen 1994). This greatly mitigates the concern of endogeneity in the selection of advertising content.

A similar argument could be made for the concern regarding endogeneity in the estimation of Variation. That is, given the generality of marketers' creative directions discussed above, it is unlikely for the changes in advertising content leading to a certain level of Variation to be the result of systematic expectations about performance. Managers of higher performing brands, however, could have access to higher advertising budgets which could be then used to create more ad copies. As Koslow, Sasser, and Riordan (2006) note though, marketers tend to be more concerned with different decisions than creative ones. Therefore, it is more likely for potential budget differences to be allocated to more easily quantifiable, and therefore justifiable, metrics such as media spending or scheduling.

I test the proposed formulation against a specification including elasticity and category controls (Model 1), a specification including ACS only (Model 2), a specification including ACS and elasticity controls (Model 3) and a specification including ACS and category controls (Model 4). I compare models using WAIC, the Watanabe-Akaike Information Criterion (Watanabe 2010) which is the fully Bayesian approach to model selection based on information criteria (Gelman et al. 2013). Results in show that my proposed specification outperforms competing ones having the lowest value of WAIC.

Table 5: ACS and Advertising Elasticity - Model Comparison

	Model 1	Model 2	Model 3	Model 4	Proposed Model
ACS		X	X	X	X
Controls	X		X		X
Category	X			X	X
WAIC	48005.89	49219.45	47696.45	47063.43	46008.70
Rank	4	5	3	2	1

I also report the predicted elasticities for each brand based on their respective average levels of ACS components in Table 6.

Elasticities range from 0.004 to 0.052 which is consistent with the literature for this type of product categories and data interval (Sethuraman, Tellis, and Briesch 2011). Although not central to this investigation, I also report the estimates of the brand-level sales controls of the observation equation, i.e. Equation (2.1), in Table 7. All results exhibit good face-validity. Compared with advertising elasticities, price and promotions are more effective (Ataman, Van Heerde, and Mela 2010), with Display promotions exhibiting overall the highest elasticity.

Table 6: ACS and Advertising Elasticity - Predicted Brand Elasticities

Category	Brand	Elasticity
Coffee	Folgers	0.013
	Maxwell House	0.014
Cold Cereals	Honey Nut Cheerios	0.052
	Honey Bunches of Oats	0.047
Facial Tissues	Kleenex	0.027
	Puffs	0.052
Frozen Dinners	Stouffers	0.021
	Marie Callenders	0.038
Laundry Detergents	Tide	0.014
	Gain	0.010
Paper Towels	Bounty	0.004
	Scott	0.010
Salty Snacks	Doritos	0.017
	Lays	0.014
Soup	Campbells	0.052
	Progresso	0.052
Yogurt	Yoplait Light	0.017
	Dannon Light N Fit	0.021

Table 7: ACS and Advertising Elasticity - Sales Controls Estimates

		Own Brand								**Competitors**									
		Price		**Feature**		**Display**		**Line Length**		**Price**		**Feature**		**Display**		**Line Length**		**Advertising**	
Category	**Brand**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Coffee	Folgers	(ns)		1.12	0.35	4.03	1.18	(ns)		-0.54	0.34	(ns)		(ns)		(ns)		(ns)	
	Maxwell House	-0.92	0.43	2.56	0.53	7.00	1.47	0.33	0.18	(ns)		1.16	0.58	(ns)		(ns)		(ns)	
Cold Cereals	Honey Nut Cheerios	(ns)		(ns)		4.02	0.66	0.19	0.06	(ns)		(ns)		(ns)		(ns)		0.05	0.03
	Honey Bunches of Oats	-2.77	0.29	(ns)		1.71	0.45	-0.38	0.06	(ns)		(ns)		(ns)		(ns)		0.05	0.02
Facial Tissues	Kleenex	-1.47	0.28	1.61	0.27	7.87	1.30	(ns)		(ns)		(ns)		(ns)		-0.78	0.42	0.01	0.01
	Puffs	(ns)		2.14	0.51	2.85	1.75	0.19	0.11	0.88	0.44	(ns)		2.17	0.75	-0.72	0.33	0.01	0.01
Frozen Dinners	Stouffers	-1.27	0.32	0.43	0.21	2.82	0.82	1.20	0.26	-1.41	0.58	(ns)		-1.63	0.69	(ns)		(ns)	
	Marie Callenders	2.84	0.48	(ns)		3.23	0.81	(ns)		-2.22	0.70	(ns)		(ns)		0.13	0.70	(ns)	
Laundry Detergents	Tide	-1.99	0.50	1.22	0.23	2.41	0.93	-0.62	0.17	(ns)		0.98	0.43	(ns)		1.31	0.37	(ns)	
	Gain	-1.70	0.34	0.45	0.25	3.25	0.82	(ns)		(ns)		(ns)		-1.04	0.65	(ns)		(ns)	
Paper Towels	Bounty	-1.93	0.98	3.09	0.64	2.90	1.39	(ns)		(ns)		(ns)		(ns)		(ns)		(ns)	
	Scott	(ns)		3.07	1.02	6.62	1.53	(ns)		(ns)		(ns)		(ns)		(ns)		-0.14	0.07
Salty Snacks	Doritos	-1.96	0.42	0.62	0.25	1.84	0.55	-0.30	0.12	(ns)		(ns)		(ns)		3.33	1.05	(ns)	
	Lays	(ns)		0.61	0.32	4.70	1.15	-0.31	0.20	-5.56	1.72	(ns)		(ns)		4.56	1.75	(ns)	
Soups	Campbells	(ns)		1.13	0.31	7.62	1.91	1.47	0.31	-0.74	0.45	0.90	0.37	1.59	0.71	2.01	0.67	0.02	0.01
	Progresso	-2.36	0.59	0.844	0.352	8.98	1.61	1.89	0.06	(ns)		1.05	0.56	2.17	0.86	(ns)		(ns)	
Yogurt	Yoplait Light	(ns)		0.38	0.12	5.11	1.01	0.33	0.18	-2.13	0.41	0.34	0.15	1.45	0.87	(ns)		0.05	0.01
	Dannon Light N Fit	-1.21	0.43	(ns)		5.09	1.10	0.72	0.23	-1.77	0.41	(ns)		(ns)		1.32	0.47	0.07	,018

(ns) indicates that the 90% Highest Density Interval includes 0

3 Discussion and Implications

When discussing results with respect to ACS's Function, it is necessary to consider the complex effect of each of the EAC dimensions on advertising elasticity. Each of the dimensions, in fact, affects elasticity directly as well as indirectly via both a contemporaneous and a dynamic interaction with all other dimensions. These interactions are captured by Focus and Variation respectively. Failing to account for these indirect routes would lead to an incorrect assessment of the way EAC dimensions affect advertising elasticity. In fact, Experience and Cognition appear as the only relevant dimensions shaping advertising elasticity. However, the lack of a significant estimate of Affect does not indicate that changes in affective cues do not impact advertising elasticity, only that they do not impact it directly but indirectly through the contemporaneous and dynamic interaction with the other dimensions captured by Focus and Variation.

At first, the lack of a direct effect of affective elements might appear at odds with previous findings which have suggested a positive effect (e.g. Bertrand et al. 2010; Chandy et al. 2001; Liaukonyte, Teixeira, and Wilbur 2015; MacInnis, Rao, and Weiss 2002). However, previous studies do not account for experiential elements. Such an omission could have possibly led to biased results as Vakratsas and Ambler (1999, page 35, Generalization 1) suggest: "*Experience, Affect, and Cognition are the three key advertising effects, and the omission of anyone can lead to overestimation of the effect of the others.*" In fact, MacInnis, Rao, and Weiss (2002), who find significant effects of affective elements, also acknowledge that ads are bundles of elements and

"... it is entirely possible that ads that contained affective cues also contained other cues" (page 403).

The dominance of experiential and cognitive cues finds strong theoretical support in the consumer behavior literature. Deighton (1984) describes the function of advertising as two-fold. On one hand, advertising prepares consumers to the usage experience, so that when it occurs, they evaluate it more positively (experiential cues). On the other hand, advertising informs consumers of a brand's best attributes, resolving ambiguities in purchase decisions and influencing what is retained in memory after usage (cognitive cues). These effects are known as predictive and diagnostic framing respectively. Framing effects have been demonstrated both in experimental conditions (e.g. Deighton 1984; Hoch and Ha 1986; Smith 1993) and in empirical studies (Deighton, Henderson, and Neslin 1994; Tellis 1988).

Results also indicate that EAC content dimensions do not only influence effectiveness directly, but also indirectly through Focus and Variation. The effect of Focus depends on the level of consumer involvement in the product category as well as the level of competition. For example, in product categories with high competition, a focused strategy is the most effective. High competition refers to the fact that market share in the product category is fragmented among several brands rather than being concentrated in the hands of few major players. A higher number of major players implies a greater number of major brands advertising their product which would then lead to greater advertising clutter. In this scenario, ads placing a disproportionate emphasis on some dimensions only might have a greater chance to attract consumer attentions by making the message more specific, hence breaking through the advertising clutter (Pieters, Warlop, and Wedel 2002) and mitigating the interreference effect of competitors' advertising reported in the literature (Danaher, Bonfrer, and Dhar 2008) and confirmed in this study. Conversely, a balanced creative strategy is more effective in high involvement categories. That is, those categories for which the level of processing is high since consumers have the motivation to engage in a more careful consideration of the purchase situation (Petty and Cacioppo 1986). In these categories, in fact, consumers are likely to engage in the consideration process in a more comprehensive manner and are likely to respond to ads featuring all cues.

A further finding is that Variation in ACS over time is an important driver of advertising effectiveness. Consistent with the results of Lodish et al. (1995), who show that changes in advertising copy result in larger advertising returns, these findings suggests that consumers are responsive to changes in the overall composition of advertising content. To the extent that such variation results in a perception of novelty about the ad, this is also consistent with the notion of divergence being the main driver of consumers' perceptions of advertising creativity (Smith et al. 2007). Furthermore, coupled with the negative effect of advertising age (i.e. the number of weeks a campaign has been on-air), this result confirms that advertising effectiveness is a dynamic construct subject to both repetition and copy wear-out effects (Bass et al. 2007; Bruce 2008; Naik, Mantrala, and Sawyer 1998).

One reasonable concern in this regard is that the costs associated with frequently changing the content of a brand's ACS (i.e. producing a high level of Variation) would outweigh its benefits. However, current business practices and scholarly research indicate that it is unlikely for an increase in Variation to result in a significant increase of advertising costs. In fact, long established managerial best practices suggest that brand managers would request to be presented with different advertising copies to choose from by advertising agencies, or at least different ideas based on similar advertising copies (Ding and Eliashberg 2002; Gross 1972). Also, a recent report from the Association of National Advertisers shows that the vast majority of advertising agency compensation agreements have a fixed or labor-based fee structure (ANA 2017). Therefore, selecting more rather than fewer advertising copies should not result in significantly higher costs.

With respect to the Form component, results show that creative templates are an effective method of structuring an advertising campaign's executional elements, especially in high involvement categories. The fact that advertising creatives for high involvement categories require more structure can be attributed to a more extensive processing of ads (Petty, Cacioppo, and Schumann 1983). This result is of particular importance since the effectiveness of templates has not been empirically tested in the marketing and advertising literature and has been linked only to creativity perceptions. To the best of my knowledge, this is the first work to empirically assess the impact of templates on advertising effectiveness.

Overall, these results with respect to a brand's ACS show that both Function, including its relative composition and evolution over time, and Form represent two crucial drivers of advertising effectiveness. Therefore, advertisers should consider both content and executional factors in their advertising creative decision-making.

3.1 Simulation Study

To illustrate the influence of the Function dimensions of ACS as well as the role of the holistic measures of Focus and Variation, I report the results of a simulation study in Table 8. I assume that an advertiser can modify the composition of the Function component of ACS by up to three units across Experience, Affect, and Cognition. For example, the advertiser can lower Affect by one unit and increase Experience and Cognition by one unit, increase Experience by three units, or increase Cognition by simply one unit. In other words, the advertiser chooses which dimension(s) to boost (or weaken) to increase elasticity through ACS. As starting EAC coordinates (time t) I use the overall average value of each dimension, $(\bar{E}, \bar{A}, \bar{C}) = (0.332, 0.255, 0.345)$. A variation of one unit equals 0.05 on the 0-1 scale. The goal of the simulation is to find the allocation strategy that produces the highest increase in elasticity moving from t to t + 1 (first period), and subsequently from t + 1 to t + 2 (second period). I perform the simulation for the cases of high and low competition and high and low involvement. For both competition and involvement, I define high and low levels as one standard deviation above and below their respective average.

Table 8: ACS and Advertising Elasticity - Simulation Study

	Experience	**Affect**	**Cognition**	**Increment from t**
High Competition				
t + 1	0	0	3	89%
t + 2	0	0	3	187%
Low Competition				
t + 1	0	3	0	141%
t + 2	2	0	1	368%
High Involvement				
t + 1	0	0	3	16%
t + 2	3	0	0	25%
Low Involvement				
t + 1	3	0	0	37%
t + 2	3	0	0	81%

In the case of high competition, I observe that the best course of action for an advertiser is to increase Cognition by 3 units both in the first and second period. Although Experience is overall the most effective Function dimension and the level of competition in the product category does not moderate the effectiveness of EAC, allocating all available units to Cognition in both periods increases content focus, which produces higher elasticities under conditions of high competition. Furthermore, allocating all three available units in both periods produces the highest possible amount of content variation, which in turn positively affects elasticity.

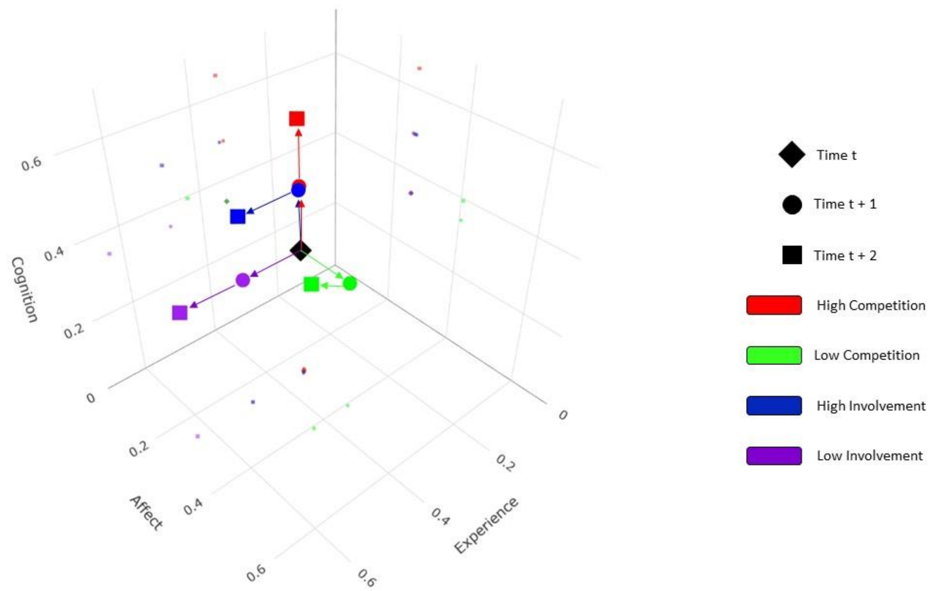
For low competition, I observe that the optimal strategy is to allocate all units to Affect in the first period, and one unit to Experience and two units to Cognition in the second period. This result might seem counterintuitive at first since Affect does not have a significant direct effect. However, it proves the importance of accounting for indirect effects, in this case Focus. Categories with a low level of competition respond better to balanced advertisements (low Focus), and in this case Affect acts as a balancing dimension in the first period. At time *t*, Affect is lower than Experience and Cognition. Therefore, allocating units to either Experience or Cognition would result in unbalanced content, which would have a negative effect on elasticity. This also implies that the positive effect of increasing content balance is stronger than the positive contribution of Cognition and Experience. This is not the case in the second period, however, since content at $t + 1$ is already well balanced. At this stage, the advertiser's best option is to allocate units to both Experience and Cognition. This would, in turn, increase Focus, which is detrimental to elasticity. However, this is counterbalanced by the positive main effect of Experience and Cognition.

For high involvement categories, the best course of action would be to allocate three units to Cognition in the first period since high levels of involvement enhance the effectiveness of cognitive elements. However, allocating all available units to Cognition in the second period would increase focus too much. Therefore, the optimal solution is to allocate all three units to Experience in the second period. Since the effectiveness of Cognition is lower in low involvement categories, the best course of action in such categories is to allocate all available units to Experience in both periods. Similarly, to the high competition case, this is also the choice that maximizes content variation. The last column of Table 8 reports the extent to which the selected optimal allocation benefits advertising elasticity compared to the starting value at time t. Results range from a 25% elasticity increase in the case of high involvement categories to almost a four-fold increase in the case of low competition.

The simulation results can be graphically summarized in Figure 3 which depicts the recommended ACS dynamics. For the cases of high competition and low involvement the recommended strategy does not involve a change in the direction of the positioning in the EAC space. For the former, the strategy should be to move content along the experience dimension whereas for the latter content should move along the cognition dimension. By contrast, a change in the direction of content position is required for the cases of low competition and high involvement.

In sum, these results illustrate the richness of the findings of this study and their relevance to advertising practice. I further elaborate on the latter by offering recommendations to advertising managers.

Figure 3: ACS and Advertising Elasticity - Simulation Study



3.2 *Recommendations for Advertisers*

Based on the empirical results and the illustration of the simulation exercise, I elaborate on five recommendations for advertisers with regards to strategic decisions on the advertising creative. First, findings, illustrated through the simulation, suggest that advertisers should vary the content, or at least its distribution among the three EAC dimensions, rather than maintain the *status quo*. This is consistent with the idea of keeping a creative "fresh" through copy changes (Lodish et al. 1995). Hence:

1) Advertisers should vary the composition of advertising content over time, regardless of the characteristics of the product category.

In terms of category-specific guidelines, I recommend the following:

2.a) In high competition product categories, advertisers should focus their content on cognitive elements;

2.b) In low involvement product categories, advertisers should focus their content on experiential elements;

2.c) In low competition categories, advertisers should balance Experience, Affect, and Cognition;

2.d) In high involvement categories, advertisers should alternate their emphasis between cognitive and experiential elements in order to leverage the trade-off between the positive effect of cognition and the positive effect of a balanced creative strategy. Furthermore, in this case content should be structured according to one of the creative templates.

4 Summary and Conclusions

In this chapter of the thesis, I have investigated the relationship between Advertising Creative Strategy and advertising elasticity via the use of a theory-grounded integrative framework which consists of two components: Function, or *what* message advertising is conveying to consumers (i.e. its content), and Form, or *how* this message is conveyed (i.e. its execution). I have adopted this framework to empirically examine the effect of ACS on advertising elasticity for 18 products across 9 CPG product categories by means of a Bayesian Dynamic Linear Model. Results indicate that Experience and Cognition positively influence advertising elasticity directly, with the effect of Cognition also depending on the level of involvement in the product category. I have also found the level of executional complexity of an advertisement to have a positive effect on advertising elasticity for high involvement product categories, which is enhanced in case its executional elements are structured according to a creative template. Furthermore, I have showed the importance of accounting for the interaction among the dimensions of the Function component of ACS. I have showed that balanced advertisements (low Focus), that is advertisements in which the dimensions of Function are present in similar proportions, perform better in high involvement categories. However, focusing only on some dimensions (high Focus) might help to differentiate advertisements, which results more effective in categories with a high level of competition. I have also found that varying the composition of advertising content over time, i.e. Variation, is positively associated with advertising elasticity regardless of the product category.

These results also confirm previous findings of the advertising literature, which I consider an indicator of the validity of my modeling approach: advertising elasticity is overall low, dynamic and has a sustained long-term effect, the effectiveness of an advertisement wears out with repetition, and competitors advertising interferes with the effectiveness of a brand's own advertising.

This work contributes to the marketing literature in different ways. To the best of my knowledge, I am the first to comprehensively investigate the relationship between advertising creative and advertising elasticity. I accomplish this by using a novel framework (ACS) for evaluating advertising creative that is comprehensive and parsimonious and based on a synthesis of the advertising literature. Also, I believe I am the first to empirically test the creative template framework of Goldenberg, Mazursky, and Solomon (1999).

This work is not free of limitations. Most notably, I acknowledge the relative homogeneity of product categories in the sample. Including a more diverse set of brands and product categories (e.g. products at the early stages of the product lifecycle or durables) would certainly benefit the robustness and generalizability of these results. Also, including advertising on media other than television would shed further light on whether the medium by which advertising reaches consumers affects the effectiveness of the different components of ACS. A further limitation of this study is the lack of extensive accounting for the creative decisions of competing brands. The sample of this study only includes two top brands in each category. However, including more brands in each category would allow me to better assess the degree to which the creative strategy of a brand differs from that of the rest of its competitors. That is, the degree of advertising originality which has been shown to be an important driver of advertising effectiveness (Qiu, Vakratsas, and Dall'Olio 2019). Furthermore, my modeling effort does not consider all the possible drivers of advertising performance. For example, I do not attempt to model the optimal scheduling of advertising, which limits the normative implications of the model. Finally, exploring other and more complex functional forms than log-log would complicate the model specification, but could unveil a more nuanced set of results.

Chapter 3: Advertising Creative Strategy and the Drivers of Advertising Informativeness and Persuasiveness

During Super Bowl 53, Anheuser-Busch used one of its advertisements to shame the rivals of one of its major brands of beer, Bud Light, for using corn syrup in their fermentation process. This sparked the prompt response of one of them: Miller Light. On its social media, in fact, the brand punched back revealing that its beer is slightly lower in calories (96 vs. 110) and contains less than half the carbohydrates than Bud Light (3.2g vs. 6.6g). In this case, both brands adopt what economists call *informative* advertising (Galbraith 1998) in which the advertisement conveys economically relevant information to consumers by explicitly informing them of product characteristics. Always during Super Bowl 53, Stella Artois portrayed actors Sarah Jessica Parker and Jeff Bridges impersonating their iconic characters, Carrie Bradshaw of Sex and The City and The Dude of The Big Lebowski, swapping their signature cocktails for a pint or a bottle of the Belgian beer. The title of the commercial was “Change Up the Usual”. In this case, unlike in the case of Bud Light and Miller Light, the advertisement does not provide any explicit information about the product or its characteristics. This type of advertising is usually termed as *persuasive* (Galbraith 1998). Stigler and Becker (1977) and Becker and Murphy (1993) posit that this type of advertising interacts with consumers’ utility function in a way that the consumption of a more advertised product provides in itself more utility to the consumer. This is consistent with the “market power” theory of advertising (Bain 1956; Comanor and Wilson 1967) according to which advertising acts as a persuasion tool by increasing perceived product differentiation, and as such artificially decreasing substitutability among competing alternatives creating brand preference that is not based on product characteristics.

Likely due to its consistency with the consumer utility maximization theory underlying most models in both economics and marketing, empirical research has mostly focused on determining which elements of the advertising creative make an advertisement informative, identifying the constituting elements of persuasive advertising only by elimination, i.e. via the absence of informative content elements (Resnik and Stern 1977). In this study, I adopt the Advertising Creative Strategy (ACS) framework developed earlier in this thesis in order to identify the drivers of advertising informativeness and persuasiveness, assessing which elements of the advertising creative contribute to make an advertisement informative, but most importantly to explicitly identify what makes an advertisement persuasive.

In order to distinguish between informative and persuasive effects of the different components of ACS, I observe their impact on the interaction between advertising spending and price. According to the "advertising as information" hypothesis (Nelson 1974; Nelson 1975), advertising that provides consumers with relevant information about the product makes them more aware about product characteristics as well as available alternatives, lowering search costs and making markets more competitive. This would then increase price sensitivity. Conversely, the "market power" hypothesis posits that advertising artificially increases preference for a certain brand, isolating it from the forces of competition, and hence lowering price sensitivity (Kihlstrom and Riordan 1984). Therefore, I consider ACS components that lead advertising to increase price sensitivity as drivers of advertising informativeness and ACS components that lead advertising to lower price sensitivity as drivers of advertising persuasiveness.

Some authors adopt alternative strategies to empirically identify informative and persuasive effects of advertising. For example, Ackerberg (2001) uses the distinction between inexperienced and experienced consumers (consumers who never bought in a certain product category vs. consumers who previously bought), arguing that informative advertising is more effective for inexperienced consumers while experienced consumers are more affected by persuasive (or "image") advertising. Also, Ackerberg (2003) distinguishes informative from persuasive advertising by observing that informative advertising affects the consumer learning process about a certain brand/product, while persuasive advertising directly affects a consumer preference for a brand. Ching and Ishihara (2012) disentangle the informative and persuasive role of detailing for prescription pharmaceuticals assuming that the informative component is linked to the exogenous characteristics, i.e. chemical composition, of the product while the persuasive component is brand specific.

However, the identification strategy based on the interaction of advertising spending and price is more in line with previous research approaches in the marketing literature. For example, Kanetkar, Weinberg, and Weiss (1992) and Sethuraman and Tellis (2002) both find advertising to have mostly and informative role based on advertising increasing consumer price sensitivity. It also represents a more general approach that is not limited by the use of data on new brands or products to distinguish between inexperienced and experienced consumers, the computational burden of fully structural dynamic learning models, or category specific as in the case pf prescription pharmaceuticals.

A comprehensive examination of the building blocks of advertising informativeness, and most importantly persuasiveness, is important for two consequent reasons. First, from a theoretical perspective, it allows to explicitly account for all the elements of the advertising creative rather than defining persuasive elements only by exclusion. In the definition of persuasive elements by exclusion, the assumption is that all elements of the advertising creative that are not explicitly identified as informative are implicitly considered to be persuasive. This assumption is overly simplistic as some components of the advertising creative might neither contribute towards advertising informativeness nor towards advertising persuasiveness. Even assuming that all advertising creative components contribute to making an advertisement informative or persuasive, a comprehensive examination of these drivers would allow for a more precise evaluation of potentially different effects of the various components. From a practical standpoint, in fact, assessing the different effects of all components of the advertising creative would grant advertisers a more accurate control over the desired advertising output. That is, advertisers would be better able to dose the different creative components to achieve the desired level of informativeness or persuasiveness.

The remainder of this chapter proceeds as follows. First, I will review the relevant literature and link the components of Advertising Creative Strategy to advertising informativeness and persuasiveness. Then, I will introduce the empirical modeling framework, highlight the estimation procedure, and present the results. I will conclude by discussing the empirical results and analyzing their implications for both theory and practice.

1 Theoretical Framework

The analysis of adverting as informative or persuasive based on content elements has mostly focused on the identification of the former. In their seminal paper, Resnik and Stern (1977) develop a method for measuring advertising information content based on 14 distinct "information cues". Their approach has since been used in more than 60 studies across several disciplines analyzing different media (Harmon, Razzouk, and Stern 1983; Stern and Resnik 1991), countries (Hong, Muderrisoglu, and Zinkhan 1987; Madden, Caballero, and Matsukubo 1986), and product categories (Stern, Krugman, and Resnik 1981; Weinberger and Spotts 1989). Abernethy and Franke (1996) provide a comprehensive review of the studies adopting the Resnik and Stern method. The underlying assumption of these studies, however, is that the persuasiveness of an advertisement is inversely proportional to the number of information cues, identifying then persuasive content by elimination. In their analysis of 378 television commercials, Resnik and Stern also noted that the majority of advertising done by retailers (i.e. local advertising) contains informative content, while the majority of national advertisements do not. Based on this finding, many researchers have used the geographical level of advertising, i.e. national vs. local, as proxy for the nature of its content (Ataman, Van Heerde, and Mela 2010; Leszczyc and Rao 1990; Mitra and Lynch Jr 1995).

Some authors have developed their own assessment scales of information content that is industry-specific. Anderson, Ciliberto, and Liaukonyte (2013) argue that the Resnik and Stern method classifies content into categories that are too broad, inevitably omitting some information that consumers might find relevant. For this reason, they develop their own scale accounting for information cues that are specific to their field of inquiry (OTC analgesics). A similar approach is used by Liaukonyte (2006) and Anderson et al. (2016).

Contrary to most studies that focus on identifying only the informative components of advertisements, Bertrand et al. (2010) explicitly categorize potential persuasive content elements in addition to informative ones. They use data from a direct mail field experiment for cash loans to assess whether advertising affects consumer demand triggering intuitive or deliberative responses. They associate persuasive content elements to the former and informative content elements to the latter. However, their categorization of content elements as informative or persuasive is limited by the experimental nature of their study. That is, the number and specificity of treatment conditions.

1.1 The Role of Function

The Function component of ACS is based on the Experience-Affect-Cognition (EAC) space proposed by Vakratsas and Ambler (1999), which implies that each advertisement nudges consumers along a mix of experiential, affective, and cognitive dimensions. Advertisements can be positioned within the EAC space using the magnitude of each dimension as coordinates. Function features items that assess whether an advertisement seeks to generate or reinforce behavior, i.e. the Experience dimension, stimulate an affective or emotional response, the Affect dimension, or contain rational or cognitive appeals, the Cognition dimension.

The link between advertising, experience, and consumer evaluation has long been established in the literature (Hoch and Ha 1986). Many scholars believe that advertising prepares consumers to the usage experience so that when it happens it would be evaluated more positively. This is usually referred to as the predictive framing (Deighton 1984; Deighton, Henderson, and Neslin 1994; Tellis 1988). The experiential nudges captured by the Experience dimension could help preparing consumers to the purchase or usage experience in two ways. As an example, an advertisement showing a product being used could be informative as consumers would directly receive valuable information on product usage. At the same time, this experiential cue could make consumer feel more familiar with the consumption situation, which would represent a persuasive effect. Given that both the informative and persuasive nature of experiential cues could be in theory justified, I choose to treat it as an empirical problem.

The role of affective cues in advertising is to stimulate emotional reactions. Many authors find that advertising focusing on emotional elements triggers intuitive responses as opposed to reasoned ones (Bertrand et al. 2010; Kahneman 2003; Petty and Cacioppo 1986). An advertisement highlighting emotional benefits deriving from purchasing or consuming a product (Chandy et al. 2001), for instance, does not differentiate the brand from its competitors based on explicit product characteristics but affects each consumers' individual perception of differentiation. Therefore, it is reasonable to expect Affect to be a driver of advertising persuasiveness.

The parallel between cognitive nudges and the information content of an advertisement is the most natural. The elements composing the Cognition dimension, in fact, reflect the four P's of marketing (product, price, place, and promotion) as well as brand/product quality which clearly represent the source according to which advertising aims at informing consumers about price and other product characteristics. Furthermore, in clear contraposition with the role of emotional cues, i.e. Affect, research suggests that elements appealing to consumer rationality trigger deliberative and reasoned responses (Bertrand et al. 2010; Kahneman 2003; Petty and Cacioppo 1986). Therefore, I believe it is reasonable to expect a stronger presence of cognitive elements in an advertisement to be associated with a higher degree of informativeness.

1.2 The Role of Form

The Form component of the Advertising Creative Strategy includes Execution and Template as its building blocks. Execution refers to the set of artistic and technical devices advertisers adopt to convey the desired message to consumers and is based on four major groups: endorsement, format, visual devices, and mnemonic devices. These represent a summary of the most relevant executional elements from the seminal work of Stewart and Furse (1984) and subsequent replications (Hartnett et al. 2016; Stewart and Furse 1986; Stewart and Koslow 1989). As for the Experience dimension of the Function component of ACS, it is not clear whether Execution should be expected to drive informativeness or persuasiveness. Execution represents the way the content of the advertisement (its Function) is conveyed to consumers. Therefore, it should be neutral with respect to the goal of the advertisement. As an example, imagine an advertisement for an energy drink featuring a famous athlete endorsing the product. Whether that advertisement is informative or persuasive depends on what the endorser says or does in it. She could discuss some characteristics of the product, which would drive the advertisements informativeness. Alternatively, she could be simply portrayed in action, which would persuade consumers by letting them infer the benefits of the product or increase their subjective utility of consuming a product advertised by that particular athlete.

The Template element of the Form component is based on the taxonomy developed by Goldenberg, Mazursky, and Solomon (1999) and captures specific structures according to which an advertisement executional elements are organized. These have been found to increase consumers' judgement of creativity. While Execution may not have a role in determining the nature of an advertisement, creative templates aggregate executional elements in a way that is suggestive to consumers. For example, a Sport Utility Vehicle portrayed in water together with a group of hippos as if it were part of the pack (analogy template) indicates how suitable that vehicle is for off-road adventures. This does not provide consumers directly with explicit information about product characteristics but is intended to persuade consumers by letting them infer the implicit quality of the product. Consistent with the structure of the ACS framework, Template acts as a framing device for advertising executional elements, therefore it shows its effect only through the interaction with Execution: Templated Execution. Therefore, I believe it reasonable to expect Templated Execution to contribute towards advertising persuasiveness.

2 Modeling the Effect of Advertising Creative Strategy on Advertising Informativeness and Persuasiveness

2.1 Modeling Framework

Consider a consumer, indexed by i, that at each period t purchases *y* volume equivalent units (VEQ) of product j. At each period t, y_{ijt} can take three different kinds of values: a positive value if consumer i has bought product j, zero if the consumer has bought a competing product in the category, and *NA* (a missing value), if the consumer did not make any purchase in the product category at that time. Formally, defining y_{it} as consumer i's the total purchases in the product category at time t:

$$y_{ijt} = \begin{cases} y_{ijt}^{*} & if \quad y_{ijt}^{*} > 0 \\ 0 & if \quad y_{ijt}^{*} \leq 0 \\ NA & if \quad y_{it} = 0 \end{cases} \tag{3.1}$$

This formulation of y_{ijt} is very similar to the way the dependent variable is expressed in censored regression models, also known as Tobit models (Tobin 1958). This class of models is used when a variable cannot be observed beyond a certain level while the underlying latent variable is believed not to be bounded by the censoring threshold. In this case, the censoring point is zero which makes it similar to a so-called Tobit II model. A classical interpretation of Tobit II models is that the latent variable, y^*_{ijt} in this case, is considered to be a consumer's latent utility (Amemiya 1984). I will justify the inclusion of the missing value case later in this section.

I assume the latent utility of consumer i for product j at time t to be a linear function of consumer-specific taste and preference for the product, usually referred to as goodwill (Nerlove and Arrow 1962), product price, and other potential elements captured by a normally distributed error term:

$$y^*_{ijt} = G_{ijt} + \alpha_{ijt} P_{jt} + \epsilon_{ijt}, \quad \epsilon_{ijt} \sim N(0, \sigma^2_\epsilon) \tag{3.2}$$

Here, G_{ijt} represents consumer i's goodwill towards product j at time t, P_{jt} product j's price at time t, and ϵ_{ijt} is a random shock from a Gaussian distribution with mean zero and variance σ^2_ϵ.

Goodwill towards a product is usually considered to be a dynamic process which is sustained by advertising and would otherwise exponentially decay over time in its absence. The typical formulation for this process is derived from the Nerlove and Arrow (1962) model of advertising awareness (Bass et al. 2007; Bruce 2008; Naik, Mantrala, and Sawyer 1998) which captures the long-term effect of advertising:

$$G_{ijt} = \beta_{ij} A^*_{ijt} + \lambda_{ij} G_{ijt-1} + \nu_{ijt}, \quad \nu_{ijt} \sim N(0, \sigma^2_\nu) \tag{3.3}$$

In the equation above, A^*_{ijt} represents consumer i's advertising exposure for product j at time t, β_{ij} is the contemporaneous effect of advertising on goodwill, and λ_{ij} is a carry-over parameter capturing the long-term effect of advertising spending. Also, ν_{ijt} is a random shock from a Gaussian distribution with mean zero and variance σ_{ν}^2.

Consumer-level advertising exposure is usually hard to observe, and researchers often have only access to data about the aggregate level of advertising spending. A common approach to derive individual-level advertising exposure from aggregate advertising spending data is to treat it as a random Normal deviation centered on the aggregate-level value (Ackerberg 2003; Ackerberg 2001). Similar to Dubois, Griffith, and O'Connell (2017), I enhance this approach with data on consumer i's household characteristics as follows:

$$A_{ijt}^{*} = \pi_i A_{jt} + \kappa_{ijt}, \quad \kappa_{ijt} \sim N(0, \sigma_{\kappa}^2) \tag{3.4}$$

where A_{jt} represents product j's television advertising spending at time t, κ_{ijt} is a normally distributed error term with mean zero and variance σ_{κ}^2, and π_i is a parameter indicating the fraction of advertising reaching consumer i such that

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \rho H_i + \upsilon_i, \quad \upsilon_i \sim N(0, \sigma_{\upsilon}^2) \tag{3.5}$$

where υ_i is normally distributed error term with mean zero and variance σ_{υ}^2. Here, H_i is a variable indicating consumer i's household characteristics that can affect the individual level of advertising exposure and ρ is its associated parameter. In this case, I use information about the number of television sets present in consumer i's household.

As mentioned earlier in the thesis, I use the effect of advertising on price sensitivity to discriminate between informative and persuasive advertising. Therefore, the modeling of consumer i's price sensitivity α_{ijt} occupies a central role. Similarly to the modeling of goodwill, I model consumer i's price sensitivity as a function of advertising in such a way to capture long term advertising effects (Ataman et al. 2016):

$$\alpha_{ijt} = \alpha_{ij} + \gamma_{ijt}A^{*}_{ijt} + \lambda_{ij}\alpha_{ijt-1} + \eta_{ijt}, \quad \eta_{ijt} \sim N\left(0, \sigma^2_{\eta}\right) \tag{3.6}$$

where α_{ij} is consumer i's baseline sensitivity to brand j's price, and η_{ijt} is a normally distributed error term with mean zero and variance σ^2_{η}. The parameter γ_{ijt} represents the effect of advertising on price sensitivity, which is the focus of this investigation.

In order to assess how ACS affects the interaction between advertising and price, I model γ_{ijt} as a linear function of its elements:

$$\gamma_{ijt} = \delta_{1ij}E + \delta_{2ij}A + \delta_{3ij}C + \delta_{4ij}Ex + \delta_{5ij}TEx + \omega_{ijt}, \quad \omega_{ijt} \sim N(0, \sigma^2_{\omega}) \tag{3.7}$$

where *E, A, C, Ex, TEx* indicate Experience, Affect, Cognition, Execution, and the interaction of Template and Execution, namely Templated Execution, respectively. ω_{ijt} is a normally distributed error term with mean zero and variance σ_{ω}^2.

I model heterogeneity among the individual parameters of ACS as a function of two product category characteristics: category competition, and category involvement. Formally:

$$\underbrace{\begin{bmatrix}\delta_{1ij}\\ \vdots \\ \delta_{5ij}\end{bmatrix}}_{\Theta_{\mathrm{ij}}} = \underbrace{\begin{bmatrix}\psi_1^{(\delta_1)} & \cdots & \psi_3^{(\delta_1)}\\ \vdots & \ddots & \vdots \\ \psi_1^{(\delta_5)} & \cdots & \psi_3^{(\delta_5)}\end{bmatrix}}_{\Psi} \underbrace{\begin{bmatrix}1\\ Com_j \\ Inv_j\end{bmatrix}}_{X_j} + \Sigma, \quad \Sigma \sim \mathrm{MVN}\left(0, \mathrm{diag}\begin{pmatrix}\sigma_{\delta_1}^2\\ \vdots \\ \sigma_{\delta_5}^2\end{pmatrix}\right) \tag{3.8}$$

where Σ is a matrix of independent normally distributed error terms.

I also allow for heterogeneity in the other individual-level parameters $(\alpha_{ij}, \beta_{ij}, \lambda_{ij})$:

$$\begin{bmatrix}\alpha_{ij}\\ \beta_{ij} \\ \lambda_{ij}\end{bmatrix} \sim MVN\left(\begin{bmatrix}\alpha\\ \beta \\ \lambda\end{bmatrix}, \begin{bmatrix}\sigma_\alpha^2 & 0 & 0\\ 0 & \sigma_\beta^2 & 0 \\ 0 & 0 & \sigma_\lambda^2\end{bmatrix}\right). \tag{3.9}$$

2.2 Modified Dynamic Tobit Model

As per the addition of missing values into the typical Tobit II formulation, the rationale is to accommodate the mismatch between purchase occasions, that is when the customer purchases in the product category, and calendar time periods (e.g. days, weeks, months depending on the granularity of the data, weeks in our case). Usually this difference can be dealt with in two alternative ways: removing the observations in which the customer does not purchase in the product category or assigning a value of zero to those observations as well.

The first approach does not pose any problem in the case observations are not serially correlated. In this case, both goodwill and price sensitivity are dynamic processes for which the effect of advertising builds up over time, which is usually referred to as adstock (Broadbent 1984). Removing observations, would then lead to severe bias in the estimation of these processes since the effect of advertising for the time periods that have been removed would not be accounted for. Conversely, assigning a value of zero to the observations in which a consumer is not observed purchasing in the product category, a relatively common approach in marketing applications (Ackerberg 2001; Erdem, Keane, and Sun 2008), implies that each calendar period is a potential purchase occasion. This is not a problem when a consumer could potentially buy at each point in time (Zantedeschi, Feit, and Bradlow 2016). However, in the case of frequently purchased consumer goods, timing considerations are fundamental (e.g. stockpiling). The vast literature on consumer timing decisions shows that its appropriate modeling is a complicated and delicate endeavor (Fok, Paap, and Franses 2012; Vakratsas and Bass 2002a; Vakratsas and Bass 2002b) which would severely complicate this investigation.

Since neither of the typical approaches are suitable in this case, the solution must be found in a third method. Luckily, a state-space approach offers the perfect tool for this task since it allows observations to be unequally spaced (i.e. purchase occasions vs. calendar weeks) by adding missing values to make the time-series equally spaced. The state-space approach can also easily handle the lack of information coming from such missing observations while still being able to estimate the evolution of the latent processes (Durbin and Koopman 2012; Leeflang et al. 2017). I provide a discussion of the way the state space approach allows for the handling of missing values in Appendix B.

I rewrite the model for the latent consumer utility in its state-space form as follows. First, the observation equation can be expressed as:

$$y_{ijt}^{*} = \begin{bmatrix} 1 & P_{jt} & 0 \end{bmatrix} \begin{bmatrix} G_{ijt} \\ \alpha_{ijt} \\ A_{ijt+1}^{*} \end{bmatrix} + \epsilon_{ijt}, \tag{3.10}$$

then the state equations can be expressed as:

$$\begin{bmatrix} G_{ijt} \\ \alpha_{ijt} \\ A_{ijt+1}^{*} \end{bmatrix} = \begin{bmatrix} \lambda_{ij} & 0 & \beta_{ij} \\ 0 & \lambda_{ij} & \gamma_{ijt} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} G_{ijt-1} \\ \alpha_{ijt-1} \\ A_{ijt}^{*} \end{bmatrix} + \begin{bmatrix} 0 \\ \alpha_{ij} \\ \pi_i A_{jt+1} \end{bmatrix} + \begin{bmatrix} \nu_{ijt} \\ \eta_{ijt} \\ \kappa_{ijt} \end{bmatrix}. \tag{3.11}$$

2.3 *Estimation Procedure*

Given the complex probabilistic structure of the modeling framework, I adopt a Hierarchical Bayesian procedure to estimate all the parameters of interest. The lowermost layer of the hierarchy includes the individual consumer-level parameters, while the upper layer (hyperparameters) include the cross-sectional parameters.

In this section, I will present an overview of the Gibbs sampling procedure used for estimation. The sampling procedure involves cycling through each step of the sampler holding all other elements constant at the previously drawn value (or at a given initial value in the case of the first sampling step). To ease exposition, I mark previously drawn values with a hat symbol (e.g. $\hat{G}_{ijt}$). It proceeds as follows:

1. Sampling of the latent utility values for censored observations (y^*_{ijt}). The first step of the sampler involves simulating the latent utility data points for the censored observations. That is, those observations reporting a value of zero. This can be done by drawing from a truncated normal distribution with left truncation at 0 having expected value $\hat{G}_{ijt} + \hat{\alpha}_{ijt} P_{jt}$ and variance $\hat{\sigma}^2_{\epsilon}$ (Chib 1992).
2. Sampling of the latent time-varying states ($G_{ijt}, \alpha_{ijt}, A^*_{ijt}$). Given the latent utility $\hat{y}^*_{ijt}$ and all individual-level parameters ($\widehat{\Theta}_{ij}$, $\hat{\gamma}_{ijt}$, $\hat{\pi}_i$, and model variances), a sample of the individual-level time-varying latent states can be drawn using the forward filtering backward sampling (FFBS) algorithm for linear Gaussian state-space models (Carter and Kohn 1994; Frühwirth-Schnatter 1994).
3. Sampling of (γ_{ijt}). Given the latent time-varying states $\hat{G}_{ijt}, \hat{\alpha}_{ijt}, \hat{A}^*_{ijt}$, the individual level parameters $\widehat{\Theta}_{ij}$ and model variances, I can construct an auxiliary state space model composed of observation equation

$$\hat{\alpha}_{ijt} - \hat{\alpha}_{ij} - \hat{\lambda}_{ij}\hat{\alpha}_{ijt-1} = \hat{A}^*_{ijt}\gamma_{ijt} + \eta_{ijt}$$

and state equation

$$\gamma_{ijt} = \hat{\delta}_{1ij}E + \hat{\delta}_{2ij}A + \hat{\delta}_{3ij}C + \hat{\delta}_{4ij}Ex + \hat{\delta}_{5ij}TEx + \omega_{ijt}.$$

As before, it is possible to draw γ_{ijt} via FFBS (Shephard 1994).

4. Sampling of (α_{ij}). The model for α_{ij} can be rewritten as

$$\left(\hat{\alpha}_{ijt} - \hat{\lambda}_{ij}\hat{\alpha}_{ijt-1} - \hat{\gamma}_{ijt}\hat{A}^{*}_{ijt}\right) \sim N\left(\alpha_{ij}, \hat{\sigma}^2_{\eta}\right)$$

$$\alpha_{ij} \sim N(\hat{\alpha}, \hat{\sigma}^2_{\alpha})$$

so that it is possible to draw directly from the posterior distribution of α_{ij} due to conjugacy.

5. Sampling of (β_{ij}). Similarly, the same can be done for β_{ij}:

$$\left(\hat{G}_{ijt} - \hat{\lambda}_{ij}\hat{G}_{ijt-1}\right) \sim N\left(\beta_{ij}\hat{A}^{*}_{ijt}, \hat{\sigma}^2_{\nu}\right)$$

$$\beta_{ij} \sim N\left(\hat{\beta}, \hat{\sigma}^2_{\beta}\right)$$

6. Sampling of ($\delta_{1ij}, \dots, \delta_{5ij}$). Again, conjugacy for the Bayesian regression model (Rossi, Allenby, and McCulloch 2012) can be used to sample from the posterior of $\delta_{1ij}, \dots, \delta_{5ij}$ using the model:

$$\hat{\gamma}_{ijt} \sim N\left(\delta_{1ij}E + \delta_{2ij}A + \delta_{3ij}C + \delta_{4ij}Ex + \delta_{5ij}TEx, \hat{\sigma}^2_{\omega}\right)$$

$$\begin{bmatrix} \delta_{1ij} \\ \vdots \\ \delta_{5ij} \end{bmatrix} \sim MVN\left(\begin{bmatrix} \hat{\psi}_1^{(\delta_1)} & \cdots & \hat{\psi}_3^{(\delta_1)} \\ \vdots & \ddots & \vdots \\ \hat{\psi}_1^{(\delta_5)} & \cdots & \hat{\psi}_3^{(\delta_5)} \end{bmatrix}\begin{bmatrix} 1 \\ Com_j \\ Inv_j \end{bmatrix}, \hat{\Sigma}\right)$$

7. Sampling of (λ_{ij}). In order to take advantage of conjugacy, I sample from the posterior of λ_{ij} using the following model:

$$stack\left(\begin{matrix} \dfrac{\hat{G}_{ijt} - \hat{\beta}_{ij}\hat{A}^{*}_{ijt}}{\hat{\sigma}_{\nu}} \\ \dfrac{\hat{\alpha}_{ijt} - \hat{\alpha}_{ij} - \hat{\gamma}_{ijt}\hat{A}^{*}_{ijt}}{\hat{\sigma}_{\eta}} \end{matrix}\right) \sim N\left(stack\left(\begin{matrix} \dfrac{\hat{G}_{ijt-1}}{\hat{\sigma}_{\nu}} \\ \dfrac{\hat{\alpha}_{ijt-1}}{\hat{\sigma}_{\eta}} \end{matrix}\right)\lambda_{ij}, 1\right)$$

$$\lambda_{ij} \sim N\left(\hat{\lambda}, \hat{\sigma}^2_{\lambda}\right).$$

Here, the function $stack(.)$ concatenates its elements in a single column vector.

8. Sampling of (π_i). Since π_i is supposed to be between 0 and 1, conjugacy is not viable. Therefore, I need to resort to a metropolis-within-gibbs step in order to sample from its posterior given the following model:

$$\hat{A}^*_{ijt} \sim N\left(\pi_i \hat{A}_{jt}, \hat{\sigma}_\kappa\right)$$

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) \sim N(\hat{\rho} H_i, \hat{\sigma}_\upsilon)$$

9. Sampling of (Ψ). In order to sample from the posterior of Ψ, I adopt the conjugate procedure for multivariate regression highlighted in Rossi, Allenby, and McCulloch (2012). The model is as follows:

$$\begin{bmatrix} \hat{\delta}_{1ij} \\ \vdots \\ \hat{\delta}_{5ij} \end{bmatrix} \sim MVN\left(\begin{bmatrix} \psi_1^{(\delta_1)} & \cdots & \psi_3^{(\delta_5)} \\ \vdots & \ddots & \vdots \\ \psi_1^{(\delta_5)} & \cdots & \psi_3^{(\delta_5)} \end{bmatrix} \begin{bmatrix} 1 \\ Con_j \\ Inv_j \end{bmatrix}, \hat{\Sigma}\right),$$

$$\Psi \sim MVN(0,10I)$$

where I is an identity matrix.

10. Sampling of ($\rho, \alpha, \beta, \lambda$). Similarly, I use a conjugate model with weakly informative priors for sampling from the posterior distributions of $\rho, \alpha, \beta, \lambda$:

$$\log\left(\frac{\hat{\pi}_i}{1-\hat{\pi}_i}\right) \sim N(\rho H_i, \hat{\sigma}^2{}_\upsilon), \quad \rho \sim N(0, 10)$$

$$\hat{\alpha}_{ij} \sim N(\alpha, \hat{\sigma}_\alpha^2), \quad \alpha \sim N(0, 10)$$

$$\hat{\beta}_{ij} \sim N\left(\beta, \hat{\sigma}_\beta^2\right), \quad \beta \sim N(0, 10)$$

$$\hat{\lambda}_{ij} \sim N\left(\lambda, \hat{\sigma}_\lambda^2\right), \quad \lambda \sim N(0, 10)$$

For brevity, I do not report the sampling steps for the variances in the model since they all follow standard conjugate models with weakly informative priors (Gelman et al. 2013).

To ensure that the sampler reaches stationarity, I allow for a burn-in of 25000 iterations and collect one sample each 35 iterations to ensure no autocorrelation in the posterior samples for a total of 5000 posterior samples for each parameter.

3 *Empirical Study*

3.1 *Data*

The data for this empirical study includes 104 weeks of individual-level data from January 2010 to December 2011 for 16 brands across 8 Consumer Packaged Goods (CPG) product categories from the IRI Marketing Dataset (Bronnenberg, Kruger, and Mela 2008). Data for each brand includes an average of approximately 2000 panelist households, for each of which weekly sales in terms of Volume Equivalent Units (VEQ) and price in terms of dollars per VEQ are reported. From the same dataset, I also retrieve the number of TV sets owned by each household, which I use as a way to treat individual-level heterogeneity of exposure to advertising. As in the empirical study in the previous section of this thesis, advertising data comes from the Kantar Media Stradegy database and includes weekly national advertising spending for each brand. The ACS data is also obtained as in the previous section, together with category-level data on Competition and Involvement.

Given the individual-level nature of the data, which includes zero sales for those weeks in which a panelist has purchased in the category but not the focal brand, it is not possible to resort to a log-

log formulation which would allow for the parameters for the covariates to be interpreted directly as elasticities. The advantage of using elasticities is that they are a standardized measure of effectiveness. In this case, in order to make parameters comparable across brands and categories, I need to resort to a different standardization method of the advertising spending at the category level. I opt for the z-score standardization. That is subtracting the sample mean and dividing by the sample standard deviation. Price and Advertising Creative Strategy variables do not require standardization as they are already standardized by construction. Price is defined as dollars per VEQ, which is already a standardized measure, and Advertising Creative Strategy variables are transformed between zero and one with respect to the content of all advertisements in the data. I simply center these variables so that their mean is zero in order to ease the computations of the filtering procedure and aid the interpretation of results. That is, each parameter can be interpreted as the marginal effect of the corresponding variable when all other variables are at their average level. Ultimately, I also standardize (z-score) the values of the category-specific variables.

Table 9 below reports the summary statistics of the data used in this study in their original scale.

Table 9: ACS, Information, and Persuasion - Summary Statistics

Category	Brand	Panelists	Volume (VEQ) Mean	Volume (VEQ) SD	Price ($ per VEQ) Mean	Price ($ per VEQ) SD	Advertising (1000$) Mean	Advertising (1000$) SD
Coffee (1)	Folgers (1)	2001	1.090	0.956	6.562	0.823	427.752	228.796
	Maxwell House (2)	1433	1.131	0.875	6.592	1.273	246.874	143.536
Cold Cereals (2)	Honey Nut Cheerios (1)	1584	2.754	1.947	3.978	0.265	183.715	140.777
	Honey Bunches of Oats (2)	1051	3.121	2.886	3.744	0.319	347.494	294.918
Facial Tissue (3)	Kleenex (1)	2087	4.422	3.189	1.380	0.123	160.113	53.281
	Puffs (2)	884	4.032	2.946	1.320	0.285	352.412	216.538
Frozen Dinners (4)	Marie Callenders (1)	681	1.851	1.261	4.159	0.428	194.936	136.588
	Stouffers (2)	1586	4.825	3.498	4.017	0.343	428.578	418.429
Paper Towels (5)	Bounty (2)	1601	1.113	0.944	3.349	0.205	383.048	223.077
	Scott (2)	783	2.154	1.886	2.509	0.284	178.432	120.691
Salty Snacks (6)	Doritos (1)	2264	3.096	0.560	4.823	0.419	1137.940	1715.502
	Lays (2)	2675	2.625	1.996	5.234	0.631	45.760	15.217
Soup (7)	Campbell's (1)	3427	7.333	7.000	2.057	0.125	772.196	566.072
	Progresso (2)	2436	5.622	6.964	1.667	0.215	342.678	341.690
Yogurt (8)	Dannon Light and Fit (1)	1784	3.134	1.593	1.783	0.108	202.841	124.043
	Yoplait Light (2)	2302	3.897	2.044	1.874	0.191	374.474	205.628

Category	Brand	Experience Mean	Experience SD	Affect Mean	Affect SD	Cognition Mean	Cognition SD	Execution Mean	Execution SD	% Templated
(1)	(1)	0.577	0.131	0.495	0.000	0.124	0.088	0.532	0.237	18%
	(2)	0.500	0.215	0.464	0.311	0.124	0.568	0.340	0.237	0%
(2)	(1)	0.654	0.233	0.330	0.200	0.767	0.176	0.863	0.218	25%
	(2)	0.394	0.236	0.144	0.128	0.814	0.249	0.641	0.114	28%
(3)	(1)	0.961	0.256	0.910	0.435	0.216	0.192	0.177	0.154	100%
	(2)	0.621	0.189	0.086	0.021	0.587	0.466	0.681	0.423	0%
(4)	(1)	0.961	0.355	0.910	0.344	0.587	0.356	0.455	0.234	5%
	(2)	0.763	0.175	0.668	0.214	0.124	0.113	0.681	0.576	0%
(5)	(1)	0.621	0.199	0.266	0.200	0.945	0.335	0.177	0.154	0%
	(2)	0.961	0.235	0.086	0.112	0.945	0.127	0.681	0.114	100%
(6)	(1)	0.126	0.081	0.495	0.287	0.124	0.155	0.681	0.566	100%
	(2)	0.621	0.165	0.495	0.266	0.587	0.389	0.177	0.175	0%
(7)	(1)	0.544	0.130	0.499	0.244	0.546	0.153	0.189	0.063	18%
	(2)	0.305	0.189	0.666	0.164	0.341	0.158	0.681	0.632	100%
(8)	(1)	0.603	0.089	0.116	0.149	0.914	0.148	0.177	0.164	0%
	(2)	0.324	0.237	0.559	0.385	0.587	0.499	0.417	0.242	5%

3.2 Results

In this section, I discuss the main estimation results for the model proposed previously. While estimates for each individual panelist might be useful for practical marketing purposes such as targeting or segmentation, here I focus on the estimates of the parameters of the upper layer of the hierarchical model. These parameters are, in fact, the ones governing the heterogeneity across brands and panelists, and are the most central to this investigation.

Results in Table 10 report the posterior mean, standard deviation, and Highest Density Intervals (HDI) of the Advertising Creative Strategy parameters. The intercept for Experience is positive and significant (0.2768) indicating that experiential cues mitigate price sensitivity. This effect holds constant across categories regardless of the level of category competition. However, this mitigating effect is less strong in categories characterized by a high level of involvement. For categories characterized by high involvement (i.e. one standard deviation above the mean), for example, the mitigating effect of experiential cues drops to 0.2117 (0.2768 – 0.0651). This is likely due to the fact that consumers in high involvement categories are more aware of the relevant characteristics of the product and are hence less affected by the persuasive effect of advertising content.

Unexpectedly, affective cues do not seem to have an effect, regardless the level of competition or involvement. Conversely, as expected, cognitive cues reinforce price sensitivity. Overall, Cognition has a negative effect (-0.7053) which is further strengthened for brands in high involvement categories (-0.7053 – 0.0482 = -0.7535). As per Experience and Affect, the level of competition in the product category does not seem to have an impact.

With respect to the Form component of ACS, the executional richness of an advertisement, as captured by the Execution element of the framework, does not have an impact on price sensitivity, regardless of the level of the category competition or involvement. However, its effect becomes significant if the advertisement is structured according to a creative template resulting in a lowering of price sensitivity (0.6114). This effect is mitigated for categories characterized by higher competition (0.5699 = 0.6114 - 0.0415). Also, for product categories characterized by higher involvement, the effect of Templated Execution results lower as well (0.5705 = 0.6114 – 0.0409).

Table 10: ACS, Information, and Persuasion - Results

Variable	Mean	SD	95% HDI Lower	95% HDI Upper
Experience	**0.2768**	**0.1247**	**0.0331**	**0.5244**
x Competition	0.0748	0.0550	-0.0325	0.1836
x Involvement	**-0.0651**	**0.0324**	**-0.1281**	**-0.0004**
Affect	0.2884	0.2575	-0.2164	0.7847
x Competition	-0.0702	0.0453	-0.1624	0.0187
x Involvement	0.0361	0.0269	-0.0164	0.0888
Cognition	**-0.7053**	**0.2170**	**-1.1315**	**-0.2744**
x Competition	-0.0344	0.0310	-0.0939	0.0277
x Involvement	**-0.0482**	**0.0242**	**-0.0953**	**-0.0001**
Execution	0.0125	0.0076	-0.0021	0.0275
x Competition	-0.0608	0.0347	-0.1292	0.0086
x Involvement	0.0851	0.0587	-0.0291	0.2026
Templated Execution	**0.6114**	**0.2870**	**0.0601**	**1.1708**
x Competition	**-0.0415**	**0.0204**	**-0.0804**	**-0.0008**
x Involvement	**-0.0409**	**0.0185**	**-0.0764**	**-0.0038**

Bold indicates parameters for which the 95% Highest Density Interval (HDI) does not include zero.

Results in Table 11 report the posterior mean, standard deviation, and HDI for the overall effect of Price, Advertising, and Advertising carry-over parameters, as well as the effect of the number of TV sets on the fraction of advertising exposure each panelist receives. As expected, the parameter for price sensitivity is negative and relatively large compared to the effectiveness of advertising, -1.4845 vs. 0.1311, and as previously found in this thesis the overall advertising carry-over is considerable: 0.6736. Ultimately, results indicate that the number of TV sets a panelist's household owns increases the proportion of advertising that household is likely to be exposed to. This indicates that it is a good instrument for treating heterogeneity in individual-level advertising exposure.

Table 11: ACS, Information, and Persuasion - Other Results

			95% HDI	
Variable	**Mean**	**SD**	**Lower**	**Upper**
Price	**-1.4845**	0.7460	-2.9228	-0.0174
Advertising	**0.1311**	0.0588	0.0171	0.2441
Carry-Over	**0.6736**	0.0914	0.4938	0.8541
Household TV Sets	**0.0038**	0.0011	0.0017	0.0058

Bold indicates parameters for which the 95% Highest Density Interval (HDI) does not include zero.

4 *Discussion and Implications*

The results presented in the previous section shed some light on the effect of an advertisement's creative strategy on its informativeness or persuasiveness. As expected, Cognition increases price sensitivity, which indicates that the higher the level of cognitive cues the more an advertisement is informative. This result is consistent with the "advertising as information" theory (Nelson 1974; Stigler 1961) since cognitive cues are designed to make consumers more aware of a product's characteristics as well as of competitors', hence providing consumers with economically relevant information.

Results also show that Experience makes consumers less sensitive to price, which indicates that the experiential elements of an advertisement's creative strategy contribute to making it more persuasive. This is consistent with the "market power" theory of advertising (Bain 1956; Comanor and Wilson 1967) as well as the predictive framing theory (Deighton, Henderson, and Neslin 1994) since advertising is expected to prepare consumers to the product experience, so that when it happens it is evaluated more favorably. This would make consumers more familiar with the product, which in turn makes them more likely to implicitly associate higher prices with better quality (Rao and Monroe 1988). This would hence create "artificial" differentiation since this change in perception would not be based on physical or objective characteristics. Interestingly, I would have expected affective cues to play a role in shaping price sensitivity, as they are usually perceived to be the opposite of cognitive cues, and hence the perfect candidates for supporting the "market power" theory of advertising (Bain 1956; Comanor and Wilson 1967). However, affective cues do not seem to alter consumers' price sensitivity. Therefore, I cannot associate the Affect dimension of an advertisement's creative strategy to informativeness nor persuasiveness.

A major result is represented by the Templated Execution taming price sensitivity, and hence contributing to an advertisement's persuasiveness. This results provide empirical validation to the findings in the behavioral literature since creative templates have been associated with increased creativity perceptions (Goldenberg, Mazursky, and Solomon 1999) which have in turn been associated with a higher persuasive power of advertising (Smith, Chen, and Yang 2008; Smith et al. 2007; Yang and Smith 2009). Overall results regarding the Form component of ACS show that executional elements do not play a significant role in shaping price sensitivity, unless they are structured according to a creative template. This is likely due to the fact that creative templates might increase consumer liking and preference, which represents the very definition of advertising persuasiveness.

Results also show that the level of product category involvement consistently moderates the effect of ACS in the direction of informativeness (increased price sensitivity). That is, it lowers the effect of those elements contributing to persuasiveness, i.e. Experience and Templated Execution, and enhances the effect of the elements contributing to informativeness, i.e. Cognition. This is likely due to the fact that for products in high involvement categories consumers are more involved with the purchase (Vaughn 1980; Vaughn 1986) and information is considered more carefully due to this higher engagement (Petty and Cacioppo 1986).

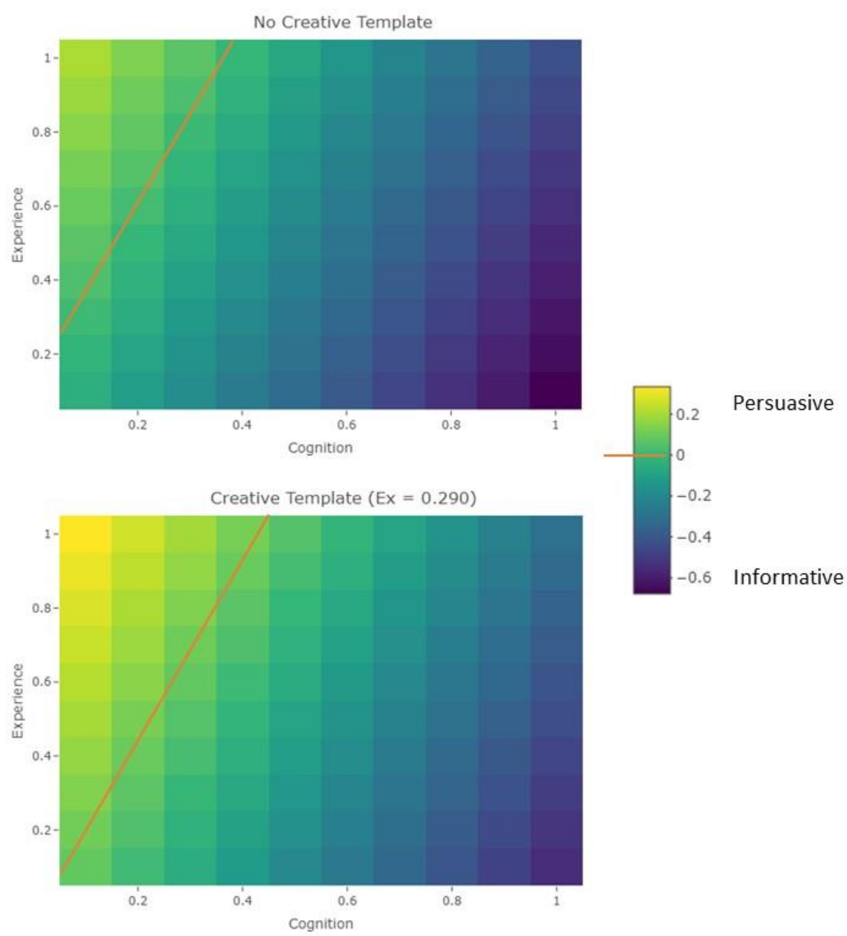
The implications of my findings are both theoretical and practical. From a theoretical standpoint, these results shed some light on the nature and drivers of advertising informative and persuasive effects, the latter being of particular importance given the lack of scholarly research. First, they show that advertising effects are not strictly dichotomous, i.e. just persuasive or informative, but can potentially be both depending on the mix of the components of an advertisement's content and structure. This implies that the distinction between national and local advertising used by researchers to proxy the type of advertising content (Ataman et al. 2016; Ataman, Van Heerde, and Mela 2010; Gatignon 1984; Leszczyc and Rao 1990; Mitra and Lynch Jr 1995; Schroeter, Smith, and Cox 1987; Wittink 1977) is not a reliable approximation. This is also supported by the conflicting results in the literature as well as by the empirical results of this study which show that national advertising has the potential to be both informative and persuasive. As per the identification of the drivers of the persuasive effects of advertising, results show that persuasiveness stems mostly from experiential cues in the content of an advertisement as well as from the structuring of the executional elements according to a creative template. Ultimately, these results are consistent with the marketing and advertising literature, which I believe to be further evidence of the validity of ACS as a framework for comprehensively and parsimoniously evaluating the content and structure of advertisements.

These results also provide general directions to marketers and advertisers who wish to align their ACS to their stated advertising goals. Assume, for example, that the managers of a brand have decided to update their product line and to reposition it at a higher price point. This kind of strategy would work best with persuasive advertising as it tends to make consumers less price sensitive. However, assume also that the updated product line features some new characteristics (e.g. a new formula) that it is fundamental to make consumers aware of in order to differentiate the updated product line from the old one. Advertising the new formula would surely represent a cognitive cue in terms of the brand's ACS, which has been shown to drive informativeness rather than persuasiveness. Since results show that advertising is not only informative or persuasive, but its nature depends on the mix of its ACS, it would be still possible for the brand to offset the informativeness created by the necessary cognitive element with high levels of experiential cues.

Figure 4 provides a graphical representation of the trade-off between information and persuasion for the case in which the executional elements of ACS are not structured according to a creative template (panel above) as well as for the case in which they are structured according to a creative template (panel below) for a product category with an average level of competition and involvement. I have chosen the value of 0.290 for the level of executive elements as it represents the overall average value of Execution across all brands (Table 2). The orange line represents the cut-off between information and persuasion, i.e. the point in which an advertisement cannot be considered neither informative nor persuasive. With respect to the example reported previously, it is possible to note that for low levels of cognitive cues, say C = 0.2, levels of Experience above approximately 0.5 would still produce persuasive advertising, so it would be possible to reach the desired goal of a persuasive ad while at the same time conveying the necessary cognitive information.

To illustrate the extent to which changes in informativeness and persuasiveness can produce significant marketplace results, I will use the limiting values reported in Figure 4 as examples. For the case in which executional elements are not structured according to a creative template, a creative strategy featuring the maximum along the experiential dimension and no cognitive cues would decrease price sensitivity (by making it less negative) by approximately 0.2, while in the case of a templated execution it would decrease it by approximately 0.35. Given the average sales volume and price per volume across categories of 3.64 and 3.39 respectively, these changes in price sensitivity would amount to a 19% increase in sales for the non-templated execution case and 33% increase in sales for the templated execution case while maintaining the price level unchanged. Conversely, a creative strategy featuring no experiential cues and the highest level of cognitive elements would increase price sensitivity by approximately 0.65 and 0.55 in the cases of non-templated and templated execution respectively. For a common promotional tool such as a 25% price cut, this would lead to respectively a 15.1 percentage points (from 34.5% to 49.6%) and a 12.8 percentage points (from 34.5% to 47.3%) increase in sales response.

Figure 4: ACS, Information, and Persuasion - Information Persuasion Trade-Off



In Table 12, I report the cut-off values between informative and persuasive advertising in the cases of high and low competition and high and low involvement product categories (± one standard deviation from their respective averages). The table can be interpreted as follows taking the case of low competition as an example. In product categories characterized by a low level of competition, the level of cognitive cues should be at least 0.04 for an advertisement to be informative given a level of experiential cues equal to 0.1 in case the advertisement does not feature a templated execution. It should be at least 0.08 for a level of experiential cues equal to 0.02, 0.12 for 0.03, and so on. In case the advertisement features a templated execution, the level of cognitive cues should be equal to 0.31 given a level of experiential cues equal to 0.1, 0.35 for 0.2, 0.39 for 0.3 and so on. Similarly, for an ad to be persuasive given a level of cognitive cues equal to 0.1, the level of experiential cues should be at least 0.25 in case of non-templated execution. In case of templated execution, the ad would always be persuasive if cognitive cues amount to a level of 0.1. However, the table also shows that the trade-off between information and persuasion is not always possible. For example, if an ad features a level of cognitive cues equal to 0.7, there is no level of experiential cues that could turn it into a persuasive advertisement, neither in the case of non-templated execution nor in the case of templated execution.

Table 12: ACS, Information, and Persuasion - Information Persuasion Trade-Off

Low Competition											
Information											
Experience		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Cognition >	NTE	0.04	0.08	0.12	0.16	0.20	0.23	0.28	0.31	0.35	0.39
	TE	0.31	0.35	0.39	0.42	0.46	0.50	0.54	0.58	0.62	0.66
Persuasion											
Cognition		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Experience >	NTE	0.25	0.51	0.76	X	X	X	X	X	X	X
	TE	V	V	0.08	0.33	0.59	0.84	X	X	X	X
High Competition											
Information											
Experience		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Cognition >	NTE	0.04	0.08	0.12	0.16	0.20	0.23	0.28	0.31	0.35	0.39
	TE	0.27	0.31	0.35	0.39	0.43	0.47	0.51	0.55	0.59	0.63
Persuasion											
Cognition		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Experience >	NTE	0.25	0.51	0.76	X	X	X	X	X	X	X
	TE	V	V	0.17	0.42	0.68	0.93	X	X	X	X
Low Involvement											
Information											
Experience		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Cognition >	NTE	0.05	0.10	0.15	0.21	0.26	0.31	0.36	0.41	0.46	0.52
	TE	0.34	0.39	0.44	0.49	0.54	0.60	0.65	0.70	0.75	0.80
Persuasion											
Cognition		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Experience >	NTE	0.19	0.38	0.58	0.77	0.96	X	X	X	X	X
	TE	V	V	0.02	0.21	0.41	0.60	0.79	0.98	X	X
High Involvement											
Information											
Experience		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Cognition >	NTE	0.03	0.06	0.08	0.11	0.14	0.17	0.20	0.23	0.25	0.28
	TE	0.25	0.28	0.31	0.33	0.36	0.39	0.42	0.45	0.48	0.50
Persuasion											
Cognition		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Experience >	NTE	0.36	0.71	X	X	X	X	X	X	X	X
	TE	V	V	0.29	0.64	X	X	X	X	X	X

NTE = No Templated Execution, CT = Templated Execution, V = always, X = Never

5 *Summary and Conclusions*

In this chapter, I studied the way the composition of a brand's ACS affects the informativeness or persuasiveness of an advertisement. To empirically distinguish informative and persuasive advertising effects I examined the way ACS influences the interaction between advertising spending and price. According to the "advertising as information" theory, informative advertising should make consumers more price sensitive. Therefore, I consider the elements of ACS that allow advertising spending to increase price sensitivity as drivers of informativeness. Conversely, I consider the elements of ACS that allow advertising spending to make consumers less price sensitive as drivers of advertising persuasiveness, in accordance to the "market power" theory of advertising. I estimate these effects via a modified individual-level Bayesian Dynamic Tobit Model. As expected, cognitive cues make an advertisement more informational, while results show that persuasiveness stems mostly from experiential cues in the content of the advertisement as well as from the structuring of its executional elements according to a creative template. In product categories characterized by high involvement, all elements of ACS tend to be more informative. I also provide examples of how advertisers can use the composition of ACS to match their intended advertising goals.

This study is not free of limitations. First of all, the sample of data includes only CPG product categories Including a more diverse set of products would definitely help making results more robust. Also, I can only infer individual advertising exposure instead of observing it. Data about actual individual advertising exposure, possibly even from different media channels, would definitely allow for a more precise assessment of advertising effects.

Conclusions

In this thesis I analyze the role and effects of the advertising creative. I first propose an integrative framework to evaluate the advertising creative that is grounded in marketing and advertising theory: Advertising Creative Strategy (ACS). It is based on a synthesis of the advertising literature and consists of two components: Function, i.e. what message the advertisement is conveying to consumers (the content of the advertisement), and Form, i.e. how this message is conveyed (the execution of the ad). The proposed framework provides a comprehensive and parsimonious structure for the evaluation of the advertising creative, both in terms of content and execution, which can be used by both researchers and advertisers.

I then assess the way ACS affects advertising performance, i.e. advertising elasticity, by means of a Bayesian Dynamic Linear Model. Findings show that experiential and cognitive cues positively influence advertising elasticity directly, with the effect of cognitive cues also depending on the level of involvement in the product category. Also, I find the level of executional complexity of an advertisement to have a positive effect on advertising elasticity for high involvement product categories, which is further enhanced in case its executional elements are structured according to a creative template. Furthermore, I show the importance of accounting for the interaction among the dimensions of the Function component of ACS. I show that balanced advertisements, that is advertisements in which the dimensions of creative strategy’s Function are present in similar proportions, perform better in high involvement categories. However, focusing only on some dimensions (high Focus) helps to differentiate advertisements, which results more effective in categories with a high level of competition. I also find that varying the composition of advertising content over time, i.e. Variation, is positively associated with advertising elasticity regardless of the product category.

Finally, I assess which elements of the Advertising Creative Strategy contribute to advertising informativeness or persuasiveness. I find, as expected, that cognitive cues drive advertising informativeness, while results show that persuasiveness stems from experiential cues and the structuring of executional elements according to creative templates. This latter result is particularly important as it provides a direct explanation of the drivers of advertising persuasiveness, which has usually been accounted for in the literature only by exclusion, that is the absence of informative content (i.e. the fewer informative elements, the more an ad is persuasive). These results suggest that advertising is not uniquely informative or persuasive, but it is potentially both depending on the composition of its creative strategy.

The findings of this thesis do not only contribute to the marketing and advertising academic literature, but also provide practitioners with useful guiding directions on how to leverage their creative strategy to increase marketplace success. In Chapter 2, I elaborate on five recommendations for advertisers, one general and four category-specific, based on the results of a simulation study conducted using the results of my empirical investigation. Regardless of the product category, advertisers are be better off changing the content of their advertising over time. In high competition product categories, advertisers should focus their content on cognitive elements, while in low competition categories, advertisers should balance Experience, Affect, and Cognition. In low involvement product categories, advertisers should focus their content on experiential elements, while in high involvement product categories, advertisers should leverage the trade-off between the positive effect of cognition and the positive effect of a balanced creative strategy by alternating their emphasis between cognitive and experiential elements. Brands in high involvement product categories would also benefit from the executional elements of their creative strategy being structured according to creative templates. The results of the simulation study also illustrate the extent to which advertisers could improve the effectiveness of their advertising spending, i.e. advertising elasticity, following the above recommendations. Results range from an increase of 25% in advertising elasticity in the case of high involvement product categories to an almost four-fold increase for low competition product categories.

In Chapter 3, I also discuss how advertisers can use their Advertising Creative Strategy to create informative or persuasive advertisements. The focus on the latter is of particular importance as the drivers of advertising persuasiveness, unlike those of advertising informativeness, were largely unknown. I also illustrate the extent to which an increase in advertising persuasiveness could lead to an increase in marketplace performance. Results show that the increase in persuasiveness due to maximizing experiential cues (the main drivers of persuasiveness) and minimizing cognitive cues (the main drivers of informativeness) could lead up to a 33% increase in sales in the case of an advertisement featuring a templated execution. Conversely, I also illustrate how marketers could leverage informative advertising to increase the effectiveness of price promotions. Results show that maximizing cognitive cues and minimizing experiential cues could improve the performance of a 25% price cut by up to 15.1 percentage points (from 34.5% to 49.6% increase in sales) when the advertisement executional elements are not structured according to a creative template.

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Appendix A: The Advertising Creative Strategy (ACS) Scale

Component	Item	ID	Guidelines
Function	Experience - Usage	E1	Does any of the following apply? (Yes = 1, No = 0) • The ad shows the product being bought, used, or consumed • The ad shows or recommends how or where the product should be bought, used, or consumed
	Experience – Usage Novelty	E2	Does any of the following apply? (Yes = 1, No = 0) • The ad suggests or recommend new types of use for the product • The ad suggests or recommends new ways to purchase the product
	Experience – Behavioral Reinforcement	E3	Does the following apply? (Yes = 1, No = 0) • The ad clearly seeks to reinforce an existing behavior or habit
	Affect – Feeling Generation	A1	Does the following apply? (Yes = 1, No = 0) • The ad is clearly designed to generate feelings in the audience. Feelings could include joy, warmth, nostalgia, fun, etc.
	Affect – Emotional Benefits	A2	Does the following apply? (Yes = 1, No = 0) • The ad mentions emotional benefits gained from purchasing, using, or consuming the product. Emotional benefits could include peace of mind, decreased discomfort, higher confidence, etc.)
	Cognition – Product	C1	Does any of the following apply? (Yes = 1, No = 0) • The ad refers to a new product • The ad mentions novelty regarding objective characteristics of the product. New characteristics could include new flavors, new price, new packaging, etc. • The ad mentions or highlights specific attributes or characteristics of the product. This could include ingredients, composition, production method etc.
	Cognition – Price	C2	Does any of the following apply? (Yes = 1, No = 0) • The ad explicitly mentions the price of the product • Does the ad mention price-related promotions?

Component	Item	ID	Guidelines
	Cognition – Promotion	C3	Does the following apply? (Yes = 1, No = 0) • The ad mentions promotional activities unrelated to price
	Cognition – Place	C4	Does the following apply? (Yes = 1, No = 0) • The ad mentions where it is possible to find or purchase the product
	Cognition – Quality	C5	Does any of the following apply? (Yes = 1, No = 0) • The ad shows how well the product performs • The ad report certifications or research results
Form	Endorsement	F1	Does any of the following apply? (Yes = 1, No = 0) • The ad shows a celebrity endorsing the product • The ad shows an expert endorsing the product • The ad shows a consumer or a layperson endorsing the product
	Format	F2	Does any of the following apply? (Yes = 1, No = 0) • Humor is a key element of the ad • Dramatization is a key element of the ad • The ad tells a story with a clear plot (beginning, unwinding, conclusion) • Is a significant portion of the ad animated
	Visual Device	F3	Does any of the following apply? (Yes = 1, No = 0) • Beauty is a key element of the ad. This involves strikingly beautiful scenery, handsome characters, etc. • Ugliness is a key element of the ad. This involves scenery that evokes disgust, ugly characters, etc. • The ad uses graphic displays. This includes charts, tables, etc.
	Mnemonic Device	F4	Does any of the following apply? (Yes = 1, No = 0) • The ad features a memorable character or a mascot. Examples could be the Duracell bunny, Mr. Clean, etc. • The ad features a memorable catchphrase. Examples could be Budweiser's "what's up", etc. • The ad features a song, or a sound clearly associated with a product. Examples could be Intel Inside sound, etc.
	Template	F5	Does the ad make clear use of any of the following templates? (Yes = 1, No = 0) • Analogy: use of information from a different or unrelated context to perform inference on the

Component	Item	ID	Guidelines
			product. An example could be silk flowing out of a shampoo bottle to illustrate how soft hair can be after using the shampoo • Extremes: the ad depicts an extreme or an absurd situation. An example could be a SUV driving under water to demonstrate its all-terrain capabilities • Consequences: the ad indicates the consequences associated with executing or failing to execute the recommendations of the ad. Recommendations could include buying the product, consuming it in a certain way, etc. • Competition: the ad shows situation in which the product is competing with something of a different class. An example could be a sports car competing with a fighter jet • Interactive Experiment: the ad requires the viewer to engage in an experiment (real or thought) to fully understand the content of the ad. An example of this could be any "think what would happen if" situations • Dimensionality Alteration: the ad manipulates the dimension of the product in relation to its environment. Examples could be portraying the ocean as very small in comparison to an airplane to indicate the speed of a new aircraft, multiplying the product and compare duplicates, depict an ordinary situation only shifted in the future or the past

Operationalization

Experience:	Sum E1 – E3
Affect:	Sum A1 – A2
Cognition:	Sum C1 – C5
Execution:	Sum F1 – F4
Template:	F5

Appendix B: Dynamic Linear Models and the FFBS Algorithm

In this Appendix, I will summarise the nature and properties of state-space models and the Forward Filtering Backward Smoothing Algorithm used in this thesis.

The state-space model is a generic and parsimonious framework for the structural specification of time-series models. The peculiarity of this framework lies in the specifications of one or more unobserved (latent) time-series to describe the observed one. It consists of two components. The first is the observation equation, which describes the observed time-series as a function of the latent one(s). The second is the state equation, which describes the dynamics or evolution of the latent states. The most common state-space model is the linear Gaussian state-space model, also known as Dynamic Linear Model (DLM).

A generic matrix representation of a DLM goes as follows:

$$Y_t = F_t\theta_t + C_t + \epsilon_t, \quad \epsilon_t \sim N(0, V_t) \tag{B.1}$$

$$\theta_t = G_t\theta_{t-1} + D_t + \eta_t, \quad \eta_t \sim N(0, W_t) \tag{B.2}$$

where Equation (B.1) is the observation equation and Equation (B.2) is the state equation.

Table 13 reports the names and dimensions of the vectors and matrices involved in a DLM. As for matrix dimensions, m represents the dimensionality of the observed time-series (e.g. m=1 is a univariate time-series, m=2 a bivariate time-series etc.), while n represents the dimensionality of the state vector. Subscript t indicates the observation time which goes from 1 to T.

Table 13: Appendix B - DLM Vectors and Matrices

Notation	Name	Dimension
Vectors		
Y_t	Observation Vector	$m \times 1$
θ_t	State Vector	$n \times 1$
C_t	Observation Drift Vector	$m \times 1$
D_t	State Drift Vector	$n \times 1$
ϵ_t	Observation Error Vector	$m \times 1$
η_t	State Error Vector	$n \times 1$
Matrices		
F_t	Link Matrix	$m \times n$
G_t	Transition Matrix	$n \times n$
V_t	Observation Covariance	$m \times m$
W_t	State Covariance	$n \times n$

The states of a DLM, θ_t, are unobserved and require estimation. In the case of the DLM, given the linearity in the states and the normality of the error terms, the optimal path of the distribution of the states can be estimated via the Kalman Filter. The optimal path of the distribution of θ_t, $\hat{\theta}_t \sim N(M_t, P_t)$ is estimated in three steps: prediction step, measurement step, and update step.

In the prediction step, the mean and covariance matrix of the states are projected one time step ahead:

$$M_{t|t-1} = G_t M_{t-1} + D_t \tag{B.3}$$

$$P_{t|t-1} = G_t P_{t-1} G_t{}' + V_t \tag{B.4}$$

The measurement step assesses the goodness of this prediction by calculating forecast errors and developing a corrective measure called the Kalman Gain (Equation B.6):

$$\nu_t = Y_t - F_t M_{t|t-1} - C_t \tag{B.5}$$

$$K_t = (P_{t|t-1} F_t')(F_t P_{t|t-1} F_t' + V_t) \tag{B.6}$$

Finally, the predictions of the mean and covariance of the states are updated according to the Kalman Gain:

$$M_t = M_{t|t-1} + K_t \nu_t \tag{B.7}$$

$$P_t = P_{t|t-1}(I - K_t Z_t)' \tag{B.8}$$

The Kalman Filter estimates the optimal mean and covariance of the states recursively running forward over time given the initial state of their distribution $\theta_0 \sim N(M_0, P_0)$. Equations (B.3) to (B.8) represent the Forward Filtering (FF) component of the FFBS algorithm.

One of the most interesting features of DLMs and the Kalman Filter, is that it can easily accommodate missing values. This is of fundamental importance for the application in Chapter 3 of this thesis. For those time periods in which values are missing, in fact, it is sufficient to set the Kalman Gain, $K_t = 0$. That is, the updated values of the mean and covariance of the states corresponds to their predicted values. This can be interpreted as follows: in the absence of new evidence (missing values in the observation equation), the estimation of the states relies on the forecasts based on the information up to the last available data.

The Kalman Filter provides the optimal mean and covariance of the states at each time step t based on information up to and including time t. This is generally useful when the goal of the modeling effort is to provide future forecasts of the state vector. However, for normative modeling purposes it is possible to improve the estimates using all available information (i.e. from t = 1 to t = T). This is accomplished via the Kalman Smoother:

$$M_{t|T} = M_t + P_t G'_{t+1} P^{-1}_{t+1|t}(M_{t+1|T} - M_{t+1|t}) \tag{B.9}$$

$$P_{t|T} = P_t + P_t G'_{t+1} P^{-1}_{t+1|t}\left(P_{t+1|T} - P_{t+1|t}\right) P^{-1}_{t+1|t}\, G_{t+1} P_t \tag{B.10}$$

In the equations above, $M_{t|T}$ and $P_{t|T}$ represent the optimal mean and covariance of the states given all the available information. The Kalman Smoother recursions start at time t = T and run backwards. The initial values of the states, $\theta_T \sim N(M_T, P_T)$ are provided by the Kalman Filter recursions. The values of M_t, $M_{t+1|t}$, P_t, and $P_{t+1|t}$ are also provided by the Kalman Filter recursions.

The Kalman Smoother returns the mean and covariance matrix of the unobserved states at each point in time conditional on the information in the whole sample. In Bayesian Inference applications, as it is the case in this thesis, it is necessary to draw samples of the latent states from their distribution taking into account not only their mean and covariance matrix, but also their covariance across time. This is possible via the Simulation Smoother. Several algorithms are available for this, and only differ in terms of their computational speed. For this application I adopt the simulation smoother described by Durbin and Koopman (2002).

The steps of the Simulation Smoother are as follows.

1. Draw θ_t^+ from a normal distribution with mean $G_t\theta_{t-1}$ and covariance W_t, and $Y_t^+$from a normal distribution with mean $F_t\theta_t$ and covariance V_t, with the recursion being initialized with a draw from a normal distribution with mean 0 and covariance P_0. This corresponds to the model in Equation (B.1) and (B.2) with $C_t = D_t = 0$.
2. Construct the artificial time-series $Y_t^* = Y_t - Y_t^+$ and put it through the Kalman Filter and Smoother to compute $M_{t|T}^*$.
3. Then, $\tilde{\theta}_t = M_{t|T}^* + \theta_t^+$ is a draw from the distribution of θ conditional on the information in the whole sample.

Generally speaking, obtaining samples from the distribution of the states requires running the Kalman Filter recursions which run forward in time (Forward Filtering), and then use the Kalman/Simulation Smoother recursions, which run "backwards in time" (i.e. from T to 1). This is the so-called Backward Sampling component of the FFBS algorithm. The algorithm outlined above, although different in form, is mathematically equivalent to the recursions originally derived by Frühwirth-Schnatter (1994) and Carter and Kohn (1994), only faster and computationally more efficient.