Synergy and Antagonism in Advertising: Exploring the Interplay Between Television Ad Content and Program Context in Driving Brand Sales

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Dedicated to:

All those who stood by me through every challenge and hardship—this work is as much yours as it is mine. Your unwavering support made this journey possible.

Preface

This thesis represents the culmination of a challenging yet profoundly rewarding odyssey, fueled by an enduring passion for data analytics, quantitative research, and marketing. My academic and professional background in these disciplines ignited a fervent desire to unravel the complexities of consumer behavior, particularly within the intricate realm of television advertising. This work is an intricate synthesis of scholarly inquiry and a personal quest to explore the confluence of data and marketing strategy.

Throughout this journey, I have been extraordinarily fortunate to receive unwavering support and encouragement from many remarkable individuals. I am deeply indebted to all those who stood by me during this arduous process. My siblings, whose steadfast support was an unfailing source of strength, enabled me to persevere through the most trying times. I am equally grateful to my friend, Hojjat Barati—who has been more than just a friend, truly a brother in every sense—for his unyielding encouragement and companionship.

I must also express my profound gratitude to my managers and colleagues, whose understanding and flexibility were invaluable as I navigated the delicate balance between professional obligations and the relentless demands of this thesis. Above all, my heartfelt thanks go to my supervisor, Dr. Filippo D., for his patient guidance and unwavering support throughout this endeavor. I extend my warmest wishes for his swift recovery and express my deep appreciation for the mentorship he provided.

The path to completing this thesis was nothing short of Herculean, particularly in the final few months. During this period, I often found myself working up to 16 hours a day, immersed in the painstaking process of writing and debugging thousands of lines of code, running complex models, and redoing the entire process with each new insight. The intellectual rigor required, coupled with some certain personal challenges that happened during the same period, tested the very limits of my mental and emotional endurance, yet I pressed on with unwavering determination.

This work, then, stands as a testament to the indomitable power of perseverance and the paramount importance of resilience. As I present this thesis, I do so with a profound sense of accomplishment and deep gratitude to those whose support made this journey possible.

Abstract

In the intricate landscape of television advertising, where billions of dollars are spent annually to capture the fleeting attention of consumers, understanding the nuanced relationship between ad content and the context in which it is presented is paramount. This thesis delves into this complex interplay, focusing on how the effectiveness of advertisements—categorized as informational or emotional—is influenced by the type of television program during which they are broadcast.

Drawing on rich datasets from Nielsen AdIntel Advertising and NielsenIQ Retail Measurement Services (RMS), this study meticulously analyzes weekly brand sales across various program categories. These include Entertainment, Special Programming, Information and Education, and Sports. The research is underpinned by a series of econometric models, progressing from Linear Models, Lagged Linear Models, Generalized Least Squares (GLS) with ARMA correlation structures to a Dynamic Linear Model (DLM), each model designed to capture both immediate and lingering effects of advertising on sales.

The findings paint a picture of how the synergy between ad type and program context drives sales outcomes. Informational advertisements, with their focus on factual content, exhibit a heightened effectiveness when paired with program categories that are inherently educational or informational. Conversely, emotional advertisements, which appeal to viewers' feelings and moods, thrive in entertainment-driven environments, where the emotional tone of the program aligns with the ad's message. These insights underscore the importance of strategic ad placement, suggesting that the alignment of ad content with program context is not merely beneficial but essential for maximizing advertising returns.

Beyond the practical implications for marketers, this thesis contributes to the broader academic discourse by offering a rigorous analysis of the interaction effects between advertisement content and broadcast context—a topic that, while explored in various forms, remains relatively underexamined in the context of television advertising. By employing advanced statistical modeling to address issues of autocorrelation and heteroscedasticity, this research not only provides robust empirical findings but also sets a methodological precedent for future studies in the field.

Keywords: advertisement, television, sales, context

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2. The Research

The primary objective of this research is to investigate the interaction between advertisement type—whether informational or emotional—and the category of television programs during which these advertisements are broadcasted, with a specific focus on how these interactions influence brand sales. This study is rooted in the understanding that while the individual effects of ad type on sales have been extensively explored, the nuanced interplay between ad content and its contextual placement within different program categories remains under-examined. This research aims to fill this gap by providing empirical insights into how these interactions drive sales outcomes.

Central to this research is the exploration of how program categories, such as news, drama, comedy, and sports, moderate the relationship between ad type and sales. Television program categories create distinct viewing contexts that can either amplify or diminish the effectiveness of advertisements. This study posits that the alignment, or lack thereof, between the nature of the program and the content of the ad—whether informational or emotional—plays a crucial role in determining the ad's impact on consumer purchasing behavior. By examining these interaction effects, the research seeks to uncover patterns that can inform more strategically targeted advertising campaigns.

The research further aims to quantify the impact of these interaction terms on sales at the brand-week level. By analyzing how different combinations of ad type and program category influence sales, the study will identify the most effective pairings that result in optimal sales performance. This focus on interaction effects, rather than the main effects of ad type alone, reflects a more sophisticated approach to understanding the dynamics of advertising effectiveness in real-world settings.

In addition to providing a theoretical contribution to the advertising literature, this research is committed to translating its findings into practical recommendations. By elucidating the conditions under which certain ad types are more effective within specific program contexts, the study will offer actionable insights for advertisers looking to optimize their ad placements to maximize sales. These insights will be particularly valuable for practitioners seeking to allocate advertising budgets more efficiently and achieve better returns on investment.

2.1. Research Questions

To achieve this objective, the research is guided by the following specific questions:

1. **Does the category of television programs have a significant impact on the effectiveness of advertisements?**
2. **Are certain types of advertisements (informational vs. emotional) more effective in specific program categories?**
3. **How do the interactions between ad type and program category influence overall advertising effectiveness?**

These research questions will guide the study in examining the nuanced relationship between media context and ad content, contributing to a more sophisticated understanding of how to optimize advertising strategies for maximum impact.

2.2. Contributions of the Study

This thesis contributes to the advertising effectiveness literature by examining the nuanced interplay between ad type (informational vs. emotional) and the media context in which these ads are broadcasted. Unlike prior studies that have largely focused on the individual effects of informational and emotional advertisements, this research explores how these ad types interact with the category of television programs to influence sales outcomes. This approach offers a more comprehensive understanding of how the effectiveness of different advertising strategies can vary depending on the context in which they are delivered.

Leveraging data from NielsenIQ's Retail Measurement Services (RMS) and Nielsen AdIntel Advertising datasets, the study provides an empirical analysis at the week-brand level, enabling precise measurement of the impact of advertising on sales. By focusing on the interactions between ad type and program category, the research extends existing frameworks and contributes to a deeper understanding of advertising elasticity. This work also introduces the concept of interaction effects between ad type and program category, suggesting that the congruence between an ad’s content and the media environment can significantly enhance or diminish its effectiveness.

Additionally, the findings of this study offer practical implications for marketers seeking to optimize their advertising strategies. By understanding how different combinations of ad type and media context influence consumer behavior, advertisers can make more informed decisions about where and how to allocate their ad spend to maximize return on investment. This research thus provides valuable insights for both academic scholars and industry practitioners interested in the strategic deployment of informational and emotional advertisements.

3. Theoretical Background

This research is grounded in the intersection of advertising content and its contextual placement, particularly within the framework of television programming. While previous studies have extensively explored the direct effects of advertisement types—whether informational or emotional—on consumer behavior and sales, the intricate interplay between ad content and the surrounding media environment remains less understood. This study seeks to address this gap by investigating how the alignment between advertisement type and television program category influences brand sales, offering new insights into the strategic deployment of advertising.

Television program categories, such as news, drama, comedy, and sports, create distinct viewing contexts that shape how audiences perceive and react to advertisements. These contexts can either enhance or detract from the effectiveness of an ad, depending on the congruence between the program's nature and the ad's content. For instance, an informational ad might resonate more in a news program, where viewers are primed to receive factual information, whereas an emotional ad might be more impactful during a drama, where the narrative is designed to evoke feelings. This research posits that the effectiveness of an advertisement is not only a function of its content but also of the context in which it is placed. The study's focus on interaction effects rather than isolated main effects represents a more nuanced approach to understanding advertising dynamics in real-world settings.

The theoretical foundation of this research draws on several key advertising and consumer behavior theories that underscore the importance of contextual relevance in advertising. The **Elaboration Likelihood Model (ELM)**, developed by Cacioppo and Petty (1986, 1989), provides a framework for understanding how different types of advertisements are processed by viewers depending on their involvement with the program content. According to ELM, viewers in a high-involvement context, such as during a news program, are more likely to engage in central processing, making them more receptive to informational ads. Conversely, in low-involvement contexts, like during a light-hearted comedy, peripheral processing may dominate, making emotional ads more effective (Cacioppo & Petty, 1986; Cacioppo & Petty, 1989).

Similarly, **Dual Coding Theory** emphasizes the benefits of leveraging both verbal and visual channels in advertising. This theory suggests that presenting information in a diverse and complementary manner can enhance message retention and understanding (Sherman, 2014). By combining verbal and visual elements, advertisements can create more robust cognitive associations, thereby increasing their impact.

Adaptation-Level Theory suggests that exposure to varied execution types may prevent audience adaptation or habituation. This theory proposes that individuals respond more favorably to stimuli that deviate from their current level of exposure, keeping advertising content fresh and novel (Worchel, 1998). Thus, varied executions can maintain audience interest and engagement over time.

Information Integration Theory supports the use of diverse execution types by allowing for the integration of multiple sources of information. According to this theory, individuals form judgments based on the aggregation of diverse information, which can enhance the persuasiveness of advertising messages (Dahlen, 2010). By providing a comprehensive view through varied executions, advertisements can appeal to a wider range of cognitive processes.

Conversely, **Consistency Theory** argues that individuals prefer consistency in information and may be uncomfortable with conflicting messages. Utilizing too many varied execution types might create confusion or cognitive dissonance, leading to less favorable responses (Brock, 2005). This theory underscores the potential risk of diluting the core message of an advertisement through excessive variation.

Signal Detection Theory adds that individuals have a limited capacity to process information. Introducing varied execution types may overload cognitive resources, making it challenging for individuals to focus on and absorb the main message (Martin et al., 1981; Batailler et al., 2022; Watts, 1998). This perspective highlights the importance of balancing diversity in execution with the clarity of the primary message.

The **Incompatibility Hypothesis** suggests that incongruent information may lead to negative outcomes. If varied execution types are not carefully integrated, they might result in incongruency, diminishing the overall impact on advertising effectiveness (Pratkanis, 1989). This hypothesis warns of the potential pitfalls of mismatched advertising elements, which can undermine the coherence and persuasiveness of the campaign.

Given the empirical nature of this study, the investigation is framed in terms of expectations rather than hypotheses. It is anticipated that combining different advertising types will increase effectiveness up to a certain threshold, beyond which further variation may begin to have a detrimental effect. Furthermore, this relationship is expected to be influenced by the advertising platform, suggesting that the optimal level of execution variance may vary depending on the medium used. This empirical approach allows the study to explore these expectations in a real-world context, providing practical insights into the dynamic interplay between execution variance and advertising effectiveness across different media platforms.

4. Literature Review

The advertising landscape thrives on a dynamic interplay between diverse media platforms and the execution styles employed within them. This literature review delves into this intricate relationship, examining how various ad execution types – from comparative advertising to celebrity endorsements – influence sales outcomes across a spectrum of media channels. Our focus lies in understanding how these execution types synergistically or antagonistically interact with specific media platforms to create a powerful advertising effect. By drawing on existing research, we aim to illuminate the multifaceted impact of advertising strategies on consumer behavior and ultimately, sales success.

The interplay between different advertisement execution types across diverse media platforms has garnered significant attention from both researchers and marketers. This literature review aims to delve into the multifaceted impact of various advertisement execution types on sales outcomes across a spectrum of media channels. Additionally, we seek to explore the synergistic and antagonistic effects that arise from strategically combining different execution types with specific media platforms (Kolsarici 2018, Kolsarici 2020).

Dall'Olio and Vakratsas (2023) contribute to our understanding of advertising elasticity by investigating the impact of creative strategy. The study reveals that more creative advertisements exhibit higher elasticity, with a notable emphasis on the informative versus entertaining dimension. This finding underscores the nuanced relationship between creativity, informativeness, and the effectiveness of advertisements, laying the groundwork for our exploration of how these factors may interact in combination across diverse media.

The study by Kolsarici and Vakratsas (2018) provides valuable insights into the interactions between different media types. By uncovering synergistic, antagonistic, and asymmetric effects, the authors highlight the importance of strategic media planning. This exploration of media interactions aligns with our research focus on understanding how specific execution types, when combined with particular media platforms, can either enhance or diminish advertising effectiveness and subsequent sales outcomes.

Building on the decision-making processes in advertising, Kolsarici, Vakratsas, and Naik (2020) delve into the role of analytics and heuristics in advertising budget decisions. Their findings indicate that analytics-based decision-making is associated with better sales performance. This insight underscores the importance of strategic decision-making in allocating advertising budgets, setting the stage for our investigation into how specific execution types, when strategically combined, contribute to sales performance.

Tsai and Honka (2021) distinguish between informational and non-informational advertising content, revealing that non-informational content is more effective at driving sales. This distinction serves as a foundation for our exploration into the impact of various execution types, each carrying different informational and emotional content, on sales outcomes.

Shapiro, Hitsch, and Tuchman (2021) conducted a comprehensive study on the effectiveness and ROI of television advertising for 288 consumer packaged goods (CPG) brands. Their findings indicate that advertising elasticities are generally smaller than previously reported, with many brands showing negative or statistically insignificant ROI. The study highlights that over 80% of brands over-invest in advertising, though some may benefit from optimized advertising strategies. This foundational work informs the current thesis by providing a critical perspective on advertising effectiveness and resource allocation.

Several studies have explored the impact of specific execution types: Comparative Advertising (Lee & Kim, 2018): Comparative advertising emerges as an effective strategy, particularly for new products entering the market. Visual Imagery (Kalyanaraman & Sundar, 2006): Visual imagery in advertising is linked to greater recall and recognition of the advertised product. Mnemonic Devices: The use of mnemonic devices contributes to increased recall and recognition, highlighting the cognitive impact of specific execution types. Celebrity Endorsements (Dahlen et al., 2010): Celebrity endorsements, explored by Dahlen et al. (2010), enhance recall and recognition, emphasizing the persuasive power of influential figures.

Voorveld et al. (2019) investigate how consumers' engagement with social media platforms influences their evaluation of advertising within these platforms. This aligns with our interest in understanding how different execution types may resonate with engaged audiences across various media channels. Kumar et al. (2016) delve into the synergistic effects of social media and traditional marketing on brand sales. Their findings contribute to our exploration of how the combination of execution types across diverse media, including social media, may amplify sales outcomes.

Jing and Calder (2009) emphasize the carryover effects of engagement with magazines, TV programs, and websites on advertising evaluation. This provides a basis for our investigation into how execution types interact within these mediums, influencing overall advertising effectiveness and sales outcomes. Mafael et. al. (2021) mentions advertising consistency which refers to maintaining a uniform message, tone, and brand identity across different marketing channels. When advertising content is consistent, it reinforces brand recognition and builds trust with consumers. Consistent messaging ensures that consumers receive a coherent brand experience, regardless of whether they encounter the ad on TV, social media, or other platforms.

There is a stream of research related to cross-media advertising effect. Lobschat et al. (2017) identified cross-channel effects for companies primarily operating in offline markets. They found that non-recent online customers, who had not recently visited the company's website, showed increased website visits following exposure to banner and TV advertisements. This heightened web traffic indirectly contributed to offline sales.

According to Chen (2016), integrating multiple channels can lead to operational efficiencies, such as economies of scale and scope, as well as cross-channel synergies. These benefits stem from the ability to interact with customers through various channels, both for transactions and communication, which can enhance the overall customer experience and firm performance. Multichannel marketing also responds to the evolving landscape of information and communication technology, making it a strategic choice for firms looking to maintain relevance and grow their market presence.

Variety effects within media are intricately tied to the notion of synergy, which has emerged as a focal point in cross-media investigations (Voorveld et al., 2019). Synergy, in this context, posits that the presence of one medium can enhance the effectiveness of another, resulting in a combined effect that surpasses the individual contributions of each medium (Naik & Raman, 2003). Media synergy's positive effect has been proven by several studies such as Dong et al.'s (2018) and Dens et al. (2018) works.

Huang (2020) found that participants who encountered diverse social media messages across multiple platforms reported greater levels of enjoyment compared to those exposed to content from a single platform. Tapping into new demographic segments characterized by diverse media consumption habits and preferences is facilitated by leveraging multiple communication channels. This approach enables organizations to continuously introduce fresh and engaging content while also enriching existing narratives through innovative cross-platform storytelling techniques. Ultimately, such strategies serve to amplify the effectiveness of communication efforts (Assael, 2011).

Further corroborating the effectiveness of cross-platform advertising, Steele (2013) investigates the synergy between television and online advertising in fostering brand engagement. The study leverages consumer neuroscience to elucidate how audiences interact with content across these platforms. Findings suggest that the combination enhances brand engagement, particularly when content maintains thematic coherence. Steele posits that television offers a more immersive experience, fostering a sustained emotional connection with the brand message.

Hartnett et al. (2016) examines how over 150 creative devices influence short-term sales effectiveness, using a large sample of 312 television ads across various product categories and countries. It reveals that while the original codebook for categorizing ads remains relevant, the effectiveness of specific creative devices has changed since the original study. No single device guarantees sales effectiveness, indicating the complexity of creating effective advertising.

Building on the notion of consistent and unique brand positioning in advertising, Becker and Gijsenberg (2023) examines the long-term sales effects of advertising content consistency and commonality. The study challenges conventional wisdom by demonstrating a differentiated impact based on brand size. Findings reveal that for smaller brands, both internal consistency (similarity within their own ads over time) and external commonality (similarity to competitor ads) contribute positively to long-term sales. Conversely, larger brands seem to experience negative consequences from an excess of internal consistency in their advertising content. This suggests a need to revisit the one-size-fits-all approach to brand messaging, particularly for established players, who may benefit from strategic variation within their advertising strategies.

Since this study utilizes television advertisement data and retail point-of-sale (POS) data, it is essential to discuss the related literature that examines the interplay between advertising and retail sales. Previous research has extensively explored the impact of TV advertising on consumer behavior and sales outcomes, providing valuable insights into how advertisements drive market performance.

Batra and Keller (2016) discuss the evolving role of television within Integrated Marketing Communications (IMC). They highlight that despite the rise of digital media, television remains a crucial component of IMC strategies due to its broad reach and ability to deliver impactful, emotionally engaging content. The authors argue that television's effectiveness lies in its capacity to create strong brand associations and drive consumer behavior.

The study by Bruce, Becker, and Reinartz (2020) investigates the impact of various branding cues in TV advertisements on brand sales. The authors develop a dynamic model to quantify the effects of TV advertising, incorporating 17 different branding cues such as logos and brand attributes. They find that visual salience cues, like the duration and frequency of logo and product displays, are primary drivers of ad effectiveness.

Guitart and Stremersch (2020) examine how the content of television advertisements—whether informational or emotional—affects online search activity and sales. Their study, which looked at over 2,000 ads for 144 car models over four years, found that emotional content significantly boosts online search activity, while informational content does not have the same effect. However, both types of content positively influence sales, though in different ways. Informational content is more effective for lower-priced, lower-quality cars, while emotional content works better for higher-priced vehicles. The research highlights the need for marketers to tailor their ad content according to the product's market positioning to maximize advertising impact.

Consumers often avoid TV advertisements by changing channels, a behavior known as "zapping." This phenomenon poses significant challenges for advertisers and broadcasters, as it reduces the effectiveness of ads and the overall reach of commercial breaks. Becker et al. (2022) investigate the impact of ad content on zapping behavior. Their findings indicate that ad creativity reduces zapping, while a strong information focus and early branding increase it. The study also reveals that the effects vary based on product type, with utilitarian products and search goods experiencing different zapping patterns compared to hedonic products and experience goods3. Additionally, the authors identify irritation as a key psychological mechanism driving zapping behavior, highlighting the importance of ad content in mitigating ad avoidance.

In their study, Becker and Gijsenberg (2023) explore the impact of consistency and commonality in advertising content on long-term sales. They analyze 247 television ads from 33 brands across six consumer packaged goods categories over four years. The findings reveal that small brands benefit from both consistency in their own advertising and commonality with competitors' advertising, while large brands tend to suffer from increased consistency. This suggests that the effectiveness of advertising strategies varies significantly based on the size of the brand.

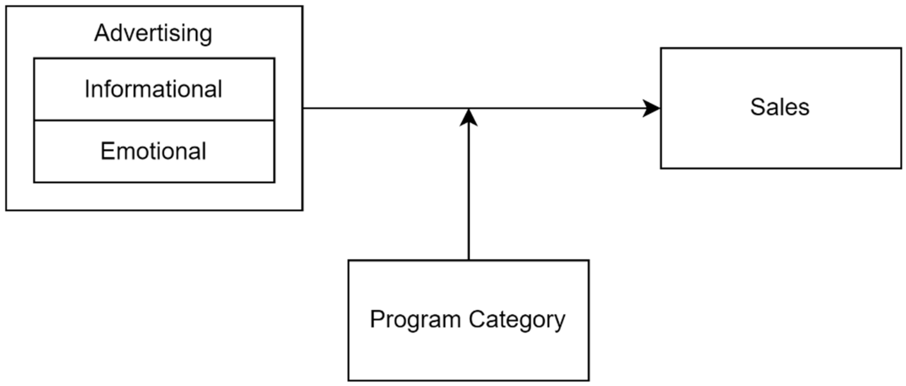
Williams, Hartnett, and Trinh (2022) apply modern data analysis techniques to investigate the creative elements that drive advertising effectiveness. By analyzing television ads with multiple analytical methods, they highlight the importance of visual branding elements, particularly the timing of brand and product introductions, in driving sales success. Their findings emphasize the limitations of traditional single-method approaches and advocate for using diverse analytical models to obtain more reliable insights into what makes advertisements effective.

In their comprehensive meta-analysis, Van Berlo and colleagues (2024) delve into the comparative effectiveness of creative media advertising versus traditional media advertising. Unlike conventional methods, creative media advertising leverages unconventional physical objects as advertising mediums, which can create more potent brand associations and enhance persuasion. The study underscores the positive influence of creative media on various persuasive outcomes, including attitudes toward the ad and brand, purchase intentions, and the likelihood of electronic word of mouth (eWOM).

Building on previous research in the field of program–ad congruity, Bellman, Wooley, and Varan (2015) further investigate the nuanced relationship between television program contexts and the effectiveness of advertisements. Their results reveal that while positive advertisements maintain consistent performance across various program contexts, nonpositive advertisements benefit significantly from being matched with nonpositive programs. These findings highlight the critical role of contextual factors in shaping advertising strategies, especially for informational and negative ads, reinforcing the nuanced interplay between the emotional tone of program content and the corresponding effectiveness of television advertisements.

5. Conceptual Framework

The effectiveness of advertising is a critical factor in driving sales and brand success, particularly in a highly competitive market. This empirical study investigates how the interaction between the type of advertisement (informational vs. emotional) and the category of the television program it is broadcasted during impacts sales outcomes. Furthermore, the study examines how ad spending and Gross Rating Points (GRP) mediate this relationship at the brand-week level, providing actionable insights into optimizing advertising strategies.



5.1. Advertising Types

Informational Advertising

Informational ads focus on delivering factual, detailed content about a product or service, such as features, benefits, pricing, and availability. These ads appeal to the consumer's cognitive processing, aiming to persuade through logical reasoning. In this study, informational ads are identified based on their content's emphasis on product information and explicit calls to action that encourage rational decision-making.

Emotional Advertising

Emotional ads are designed to evoke an emotional response, using imagery, music, and narratives to create strong associations with the brand. These ads aim to influence consumer behavior by appealing to feelings such as joy, nostalgia, or excitement. Emotional ads are categorized based on their ability to generate these affective responses, making the brand more memorable and fostering consumer loyalty.

Program Categories

The category of the television program during which an advertisement is broadcasted significantly influences how the ad is received by viewers. Programs can be broadly categorized into types such as news, drama, comedy, and sports, each attracting different audience segments and creating varying levels of cognitive and emotional engagement. For instance, news programs may enhance the effectiveness of informational ads due to their focus on facts and logical processing, while dramas or comedies may heighten the impact of emotional ads by engaging viewers on an emotional level.

Interaction Between Ad Type and Program Category

This study posits that the effectiveness of an advertisement is not solely determined by its content (whether informational or emotional) but also by the context provided by the program category. The hypothesis is that the interaction between ad type and program category influences key metrics like ad spending and GRP, which in turn affect sales outcomes. Specifically, emotional ads are expected to perform better in emotionally engaging program categories such as drama and comedy, whereas informational ads may be more effective in cognitively engaging categories like news.

5.2. Variables

Gross Rating Points (GRP)

GRP measures the exposure level of an advertisement within a specific period, representing the sum of the ratings for all programs in which the ad appeared. It is an essential metric for understanding the reach of an advertising campaign. The study will explore how different combinations of ad type and program category influence GRP, thereby affecting sales.

Ad Spending

Ad spending reflects the financial investment made in promoting the brand through advertisements. This variable is crucial as it directly impacts the reach and frequency of ads, which can significantly influence consumer behavior and sales. The study examines how the interaction between ad type and program category influences ad spending, which in turn affects sales.

Dependent Variable: Sales

Sales serve as the primary dependent variable in this study, capturing the ultimate impact of the advertising strategies on brand performance. The study hypothesizes that the interaction between ad type and program category, mediated by ad spending and GRP, will significantly influence sales at the brand-week level. The analysis will focus on quantifying this relationship to provide empirical evidence on how advertisers can optimize their ad placements to maximize sales.

5.3. Expectations

Based on the conceptual framework, the following expectations are proposed:

- **E1**: The interaction between informational ads and cognitively engaging program categories (such as news) will lead to higher ad spending, and subsequently higher sales.
- **E2**: The interaction between emotional ads and emotionally engaging program categories (such as drama or comedy) will result in higher ad spending, increase, and subsequently higher sales.

6. Methodology

6.1. Research Design

This study investigates the interaction effects between different types of advertisements—whether informational or emotional—and the category of television programs during which these advertisements are broadcasted, with a specific focus on their impact on brand sales. To achieve this, a quantitative research design is employed, utilizing data from two primary sources: the NielsenIQ (NIQ) Retail Measurement Services (RMS) dataset and the Nielsen AdIntel Advertising Dataset. These proprietary datasets provide a unique opportunity to explore the intricate dynamics between advertising content, contextual placement, and sales outcomes at an unprecedented level of detail. The NIQ RMS dataset offers comprehensive measurements of market activity, while the Nielsen AdIntel dataset provides granular insights into advertising exposure.

The core analytical tool employed in this study is regression analysis, which will be used to examine the relationships between advertisement types, program categories, and sales outcomes. By focusing on interaction effects rather than just main effects, this research aims to uncover how the alignment or misalignment between advertisement content and program context influences consumer purchasing behavior. The regression models will incorporate interaction terms to quantify how different combinations of ad types and program categories affect sales at the brand-week level.

This design allows for a robust empirical investigation into how the interaction between advertisement type and program category impacts sales, offering both theoretical contributions and practical insights for optimizing advertising strategies.

6.2. Ad Classification

In advertising, emotional appeals evoke emotions through mood and music, while informational appeals provide objective brand information (Yoo & MacInnis, 2005). Emotional content is more engaging and shareable (Berger & Milkman, 2012), enhancing social transmission and self-image (De Angelis et al., 2012).

To classify the advertisements into **Informational** and **Emotional** types, this study utilized a systematic process involving independent coders and a structured classification scheme, specifically adapted for categorizing ad descriptions. The scheme was informed by a robust stream of research focused on measuring the informational and emotional value of advertisements (van Reijmersdal, Smit, & Neijens, 2010; Bellman, Wooley, & Varan, 2015; Yoo & MacInnis, 2005).

Coding Process

Three independent coders were engaged to categorize the advertisements based on their descriptions. Each coder was trained using a detailed classification scheme that guided the identification of key elements within the ad descriptions that would determine whether the ad was classified as Informational or Emotional:

- **Informational Ads**: Descriptions in this category were characterized by a focus on delivering factual, product-specific information. These descriptions often highlighted product features, technical specifications, pricing, and other declarative content intended to inform the consumer and facilitate decision-making.
- **Emotional Ads**: Descriptions in this category were aimed at evoking feelings or emotional responses. These ads typically utilized storytelling, evocative imagery, and emotional appeals rather than direct product information, aiming to connect with the audience on an affective level.

Training Scheme

The coders were trained using a comprehensive scheme developed from established methodologies in the field (van Reijmersdal et al., 2010; Bellman et al., 2015; Yoo & MacInnis, 2005). The scheme included:

- **Detailed Descriptions**: Definitions and characteristics of Informational versus Emotional ad descriptions, providing a clear distinction between the two.

- **Examples**: Annotated examples of ad descriptions that had been previously classified, with explanations as to why they were categorized as either Informational or Emotional.
- **Guidelines**: Specific criteria for identifying the presence of factual versus emotional content within ad descriptions, assisting coders in making accurate classifications.

Ensuring Consistency and Accuracy

To ensure consistency across the coders, a calibration phase was implemented where the coders classified a sample set of ad descriptions under supervision. Any discrepancies in their classifications were discussed and resolved, ensuring a uniform understanding of the classification criteria.

After the coding process was complete, the results were reviewed to identify and resolve any inconsistencies. Inter-coder reliability was assessed to confirm that the classifications were consistent and reliable across the different coders.

Application in Analysis

The classified ad descriptions were then used in the study's analysis of the interaction effects between ad type (Informational or Emotional) and the television program category in which the ads were broadcasted. This classification was essential for examining how different types of advertisements performed in various program contexts, directly supporting the study's goal of optimizing advertising strategies to enhance brand sales.

By employing this rigorous classification process, the study ensured that the empirical analysis was grounded in well-defined and consistently applied criteria, contributing to the robustness and validity of the research findings.

6.3. Program Category

The initial dataset from the Nielsen AdIntel Advertising Database included a wide range of television program categories, reflecting the diverse content available across different networks. To facilitate a more focused and meaningful analysis, these categories were aggregated into broader, more analytically manageable groups. This aggregation process was essential for examining the interaction between advertisement type and program context, with a specific focus on how these interactions influence brand sales.

The categorization process began with a comprehensive review of the original program categories, assessing each one based on its content, intended audience, and the typical engagement it generates. The goal was to group similar categories together in a way that would allow for the analysis of distinct viewing contexts that could potentially interact with the type of advertisement being broadcasted. The final broader categories were as follows:

1. **Entertainment**:
   - This category encompasses programs primarily designed to entertain the audience, including dramas, comedies, reality TV shows, and other narrative-driven content. These programs are typically characterized by their emotional appeal, engaging viewers through storytelling, humor, or dramatic tension.
2. **Sports**:
   - Sports programming was maintained as a distinct category due to its unique content and the specific viewer engagement it generates. Sports broadcasts are typically live events with high viewer involvement, making them a critical area of analysis in understanding the interaction between program context and ad type.
3. **Information and Education**:
   - Programs focused on delivering factual or educational content were grouped into this category. This includes news broadcasts, documentaries, educational shows, and talk shows that are primarily information-driven and cater to viewers seeking knowledge and insights.
4. **Children's Programming**:
   - This category includes all content specifically designed for children, such as animated series, educational shows for young audiences, and family-oriented programming. These programs often have a unique style and content focus, which necessitated their separation from other categories.
5. **Special Programming**:
   - Special Programming includes one-off events, specials, or unique broadcasts that do not fit into regular programming schedules. This

category was created to capture the distinct nature of these programs, which may include award shows, holiday specials, or major live events.

6. **Religious**:

    - Religious programming was categorized separately to account for its unique content and target audience. This category includes religious sermons, discussions, and other faith-based broadcasts that have a specific and often highly engaged viewer base.

This aggregation into broader categories allowed the study to simplify the analysis without losing the essential distinctions between different types of television content. By organizing the program types into these categories, the research was better equipped to analyze how different ad types—whether informational or emotional—perform in various viewing contexts, leading to more targeted insights into optimizing advertising strategies for enhanced brand sales.

7. Data Sources

7.1. RMS Dataset

The NielsenIQ Retail Measurement Services (RMS) dataset is a comprehensive source of data on retail sales and market share. This dataset is widely used in marketing research to analyze consumer behavior, market dynamics, and competitive positioning. The RMS dataset provides detailed information on several key aspects.

The dataset encompasses comprehensive sales data for various product categories, sourced from a multitude of retail channels including supermarkets, hypermarkets, convenience stores, and online platforms. It provides a granular view of sales performance, allowing for in-depth analysis at the product, brand, and store levels. Key metrics such as sales volume and sales value are included, enabling a comprehensive assessment of overall market performance.

Furthermore, the dataset offers invaluable insights into market share dynamics, providing a comparative analysis of brand and product performance within specific categories. Pricing information, encompassing regular and promotional prices, as well as discounts, is also included. This data is instrumental in understanding pricing strategies and their impact on sales.

Promotional activities, including in-store promotions, discounts, and special offers, are detailed within the dataset. This information allows for an evaluation of the effectiveness of promotional strategies in driving sales. Additionally, the dataset provides information on product availability and distribution across different retail outlets and regions, facilitating an assessment of market reach and penetration. With a temporal coverage spanning multiple years, the dataset enables longitudinal analysis of sales trends and the evaluation of advertising impact over time.

7.2. AdIntel Dataset

The Nielsen AdIntel dataset provides detailed information on advertising activities, expenditures, and creative executions across various media channels. This dataset is instrumental in understanding the competitive advertising landscape and the effectiveness of different advertising strategies. Key features of the AdIntel dataset include:

The AdIntel dataset offers a comprehensive repository of advertising data, providing invaluable insights into industry trends and competitive landscapes. Central to the dataset is a detailed breakdown of advertising expenditures across various brands, companies, and product categories. These expenditures are meticulously categorized by media channel, encompassing traditional outlets like television, radio, and print, as well as digital platforms such as online, social media, and outdoor advertising. This granular level of detail facilitates a nuanced understanding of advertising budget allocation strategies employed by different market players.

Beyond financial metrics, the dataset delves into the creative core of advertising campaigns. Through in-depth analysis of ad formats, durations, visuals, and messaging, researchers can gain a comprehensive perspective on the creative strategies and execution styles adopted by different brands. This information is essential for evaluating the effectiveness of creative concepts and identifying emerging trends in advertising.

The dataset's coverage extends across a wide spectrum of media types, enabling researchers to compare and contrast the performance of traditional and digital channels. By examining the media mix employed by different advertisers, valuable insights can be derived regarding the optimal allocation of advertising resources to achieve desired campaign objectives.

Moreover, AdIntel provides a competitive intelligence advantage by offering detailed information on the advertising strategies of rival companies. By benchmarking advertising expenditures, media channel preferences, and creative approaches, businesses can gain a competitive edge by identifying opportunities for differentiation and improvement.

The dataset's longitudinal nature allows for the tracking of advertising campaigns over time, facilitating the assessment of campaign reach, frequency, and overall impact. This temporal perspective is crucial for understanding the long-term effects of advertising on brand awareness, market share, and sales.

Finally, the dataset's geographical coverage enables researchers to analyze regional variations in advertising strategies and their corresponding outcomes. This geographic dimension is essential for understanding the nuances of consumer behavior and tailoring advertising campaigns to specific markets.

8. Data Cleaning and Integration

The datasets employed in this empirical study are characterized by their substantial size, encompassing numerous tables, observations, parameters, geographic locations, and an extensive temporal scope. The sheer magnitude of these datasets necessitated a rigorous data cleaning and preparation process which involved thousands of hours. These steps were conducted in strict adherence to the access and publication restrictions imposed by the dataset providers.

8.1. AdIntel

The data preparation process starts with AdIntel. The data encompasses national and local television, radio, newspapers, magazines, digital media, and cinema. Detailed ad impressions and universe estimates are included, facilitating the calculation of Gross Rating Points (GRPs). Advertising impressions are segmented by age and gender, with National TV impressions further delineated into 50 demographic classifications. To enrich the analysis, the dataset incorporates reference files pertaining to advertisers, brands, product categories, creative executions, television programs, and distributors. For the purpose of the current work, however, two media are selected: national and spot television.

The initial dataset comprised two primary components: TV occurrence and impression data. Occurrence records detailed the specific airing of an advertisement, including date, time, and media type. Impression data provided estimates of the number of individuals exposed to each advertisement based on demographic breakdowns.

National TV encompassed Network TV, Cable TV, and Syndicated TV, while local TV included Spot TV, Network Clearance Spot TV, Syndicated Spot TV, and Local/Regional Cable TV. Nielsen provided impression data for various demographic groups across these media types.

The first challenge is that an important discrepancy exists between national and local TV occurrences. While representing identical advertising events, the latter is measured at the local level, enabling alignment with local impression data. Conversely, national TV occurrences are measured nationally, primarily serving two purposes: estimating the nationally purchased ad cost and validating the accuracy of the clearance data by identifying potential instances where local stations might override national ad placements. It is essential to recognize that these two data types do not represent distinct advertising forms but rather different measurement perspectives of the same event.

Local affiliates possess a degree of autonomy to modify or relocate nationally scheduled advertisements. Furthermore, potential inaccuracies in Nielsen's local measurement device data can contribute to discrepancies between national and local records. Consequently, not all Network TV advertising occurrences perfectly align with corresponding local occurrences, even when representing identical ad buys. Instances where national occurrences lack associated local occurrences within a specific market are defined as discrepancies. We will address this issue by analyzing schedule gaps. We can infer whether a missing National TV ad represents a recording error or a deliberate replacement by the local station.

Local impression data availability varied significantly across markets. A subset of 25 markets, designated as Local People Meter (LPM) markets, provided continuous monthly impression measurements through set-top box technology. In contrast, the remaining markets relied on diary-based data collection restricted to four specific months annually, commonly referred to as "sweeps" periods. To address the substantial gaps in impression data for non-LPM markets, an imputation method was employed. A weighted average of the adjacent sweep month values was calculated to estimate impressions for intervening months.

The process of aligning national and local television advertising data was intricate and multifaceted. Initially, detailed information was gathered for each local station, encompassing market, network affiliation, and distributor identification. To accommodate temporal discrepancies and ensure accurate data alignment. Subsequently, a meticulous comparison between national and local advertising occurrences was undertaken. National advertisements were categorized based on their correspondence with local data: direct matches, indirect matches allowing for temporal variations, replacements by other advertisements, or instances of complete absence in local markets.

To account for time zone variations and potential broadcast delays, particularly in mountain and pacific time zones, adjustments were made to the analysis. A systematic approach was employed to identify instances where national advertisements might have been delayed in their broadcast. Impression data for these time zones was subsequently averaged across potential airtimes to mitigate the impact of time zone differences.

8.2. RMS

To make the scope of this thesis feasible, we concentrated on the general merchandise department from the RMS dataset. The general merchandise department includes 23 groups, 281 modules, and around 204,000 UPCs. Here are some of the groups:

- Automotive
- Batteries and Flashlights
- Books and Magazines
- Cookware
- Electronics, Records, Tapes
- Light Bulbs, Electric Goods
- Floral, Gardening
- Glassware, Tableware
- Hardware, Tools
- Housewares, Appliances
- Kitchen Gadgets
- Photographic Supplies
- Stationery, School Supplies
- Toys & Sporting Goods

The next stage of the data cleaning involves wrangling the retail data. The Retail Measurement System (RMS) dataset provided granular sales information at the Universal Product Code (UPC) level, necessitating aggregation to the brand level for subsequent analysis. The complexity of this process was exacerbated by the heterogeneity of UPCs within a given brand, which often represented varying product sizes, packaging formats, and quantities.

The initial phase of the data processing pipeline involved the construction of metadata and the subsequent formation of the movement dataset. Metadata generation commenced with a comprehensive scan of the Nielsen extracts folder to identify product modules and their corresponding file locations. For each module, annual movement files were processed to compute summary statistics at the UPC level. These individual yearly summaries were then consolidated into a unified dataset, enriched with UPC version and product module identifiers.

Leveraging the generated metadata, the movement dataset was constructed. UPCs were ranked based on annual revenue, and those achieving a top ranking at any point were selected for in-depth analysis. Movement data for these high-performing UPCs were extracted and stored separately, while the remaining data was compiled into a distinct dataset. Owing to the extensive data volumes involved, this step presented computational challenges, necessitating efficient memory management strategies which will be discussed for educational purpose later on.

8.3. Top Brands Sampling

The stratified sampling approach ensures a representative and proportional selection of top brands based on their revenue contributions within various product groups. By calculating each product group's total revenue and its percentage contribution to the overall revenue, the methodology guarantees that groups with higher financial impact are adequately represented in the sample. This proportional representation is critical for understanding market dynamics and the influence of leading brands.

Within each product group, the sampling is further refined by considering the revenue contributions of individual modules, ensuring a balanced and comprehensive selection process. Ranking brands based on their revenue ensures that the most impactful brands are prioritized, which is essential for analyzing market leaders and the effectiveness of different advertising strategies. This approach provides a structured and meaningful selection of brands, reflecting the true financial landscape of the market and enabling a thorough analysis of advertising executions' effects on sales.

The process began with an initial dataset containing 204,655 UPCs. To ensure the reliability and relevance of the data, we filtered out any UPCs with low store presence and limited year-round availability. This filtering step was crucial to focus on products with consistent market presence and significant revenue impact.

The following figure illustrates the contribution of each module to the total revenue. The sampling methodology is based on this revenue distribution, ensuring a representative selection of top brands from each module. The table also details the number of top brands selected from each module, totaling 209 brands. However, after accounting for duplicate brands across modules, we identified 161 unique top brands.

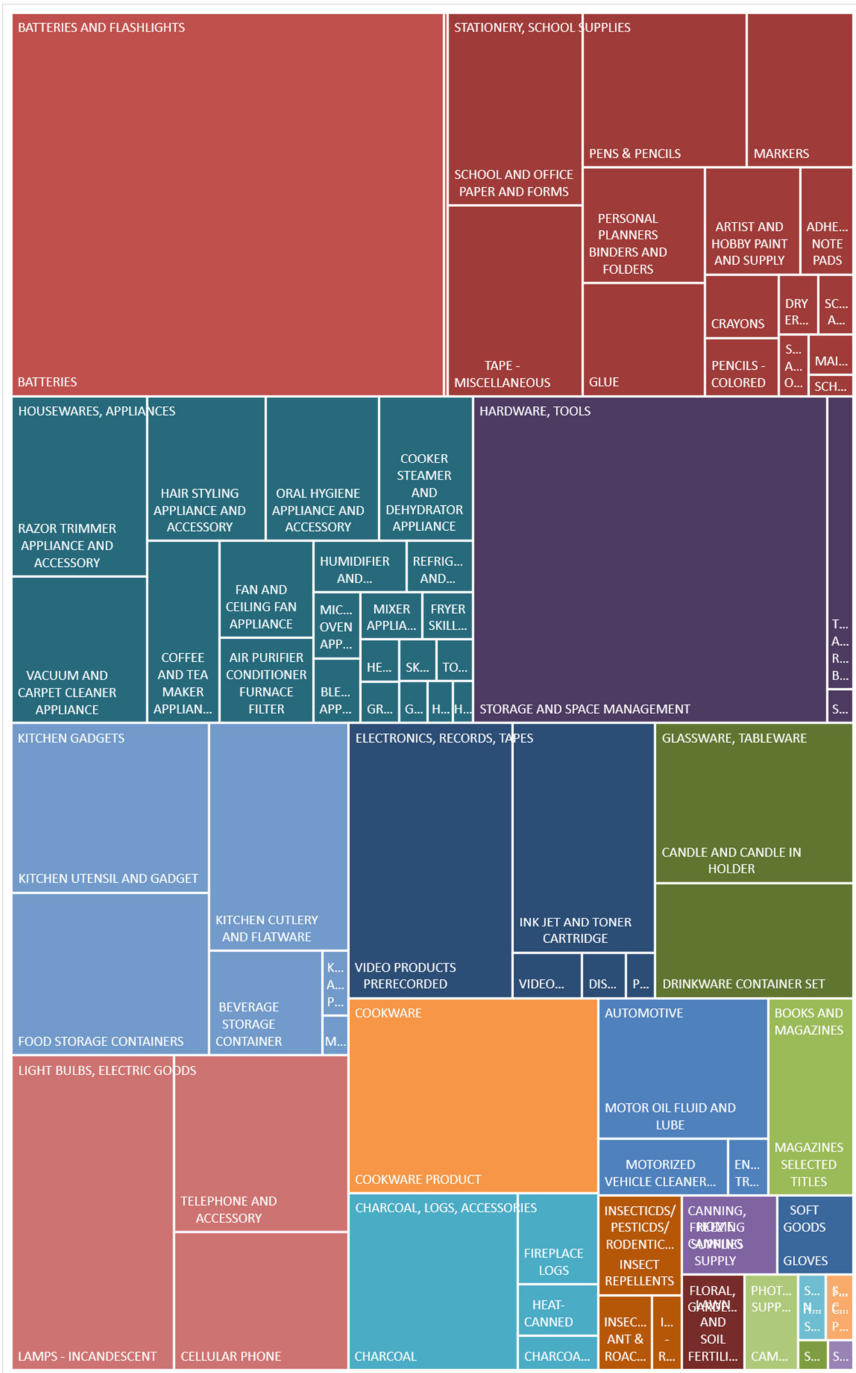
This approach ensures that the sample accurately reflects the financial impact of each module, maintaining the integrity and representativeness of the analysis. The selection process prioritizes high-revenue brands within each module, providing a comprehensive view of the market's leading brands.

Table 1: Proportional Representation of Product Groups

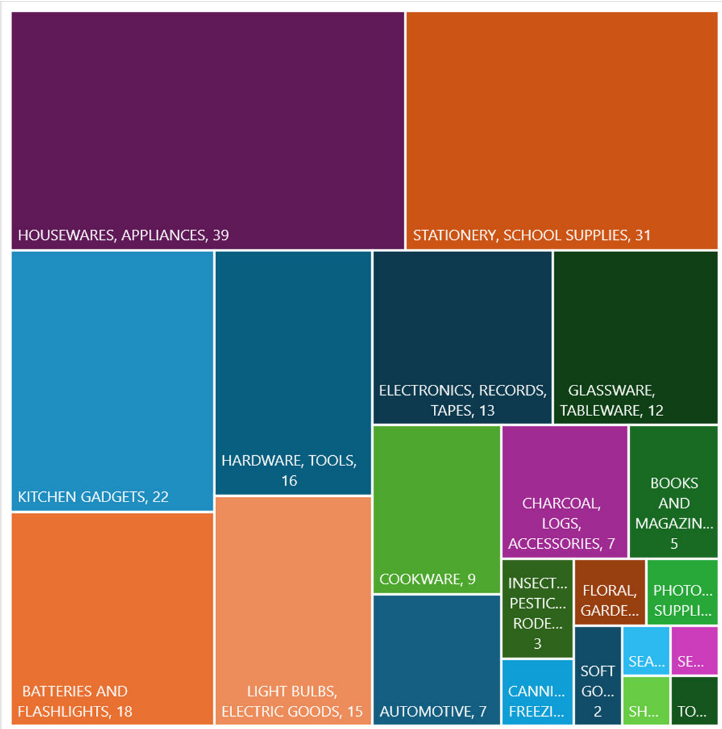
Product Group Code	Product Group	Total Revenue	No. of Selected Top Brands
5501	AUTOMOTIVE	$ 220,077,077	7
5502	BATTERIES AND FLASHLIGHTS	$ 1,100,220,801	18
5503	BOOKS AND MAGAZINES	$ 110,702,567	5
5504	CANNING, FREEZING SUPPLIES	$ 49,974,642	2
5505	CHARCOAL, LOGS, ACCESSORIES	$ 289,706,627	7
5506	COOKWARE	$ 320,519,177	9
5507	ELECTRONICS, RECORDS, TAPES	$ 555,459,151	13
5508	FLORAL, GARDENING	$ 39,319,381	2
5509	GLASSWARE, TABLEWARE	$ 358,794,179	12
5511	HARDWARE, TOOLS	$ 818,787,541	16
5513	HOUSEWARES, APPLIANCES	$ 992,516,676	39
5514	INSECTICDS/PESTICDS/RODENTICDS	$ 95,837,210	3
5515	KITCHEN GADGETS	$ 736,302,887	22
5516	LIGHT BULBS, ELECTRIC GOODS	$ 589,795,479	15
5517	PHOTOGRAPHIC SUPPLIES	$ 33,520,433	2
5518	SEASONAL	$ 4,979,335	1
5519	SEWING NOTIONS	$ 11,983,707	1
5520	SHOE CARE	$ 11,756,483	1
5521	SOFT GOODS	$ 40,038,122	2
5522	STATIONERY, SCHOOL SUPPLIES	$ 1,023,558,992	31
5524	TOYS & SPORTING GOODS	$ 5,845,035	1

TOTAL		**$ 7,409,695,500**	**209**

Distribution of revenue by module



Distribution of number of sampled brands:



8.4. Integration Methodology

Matching brand names across datasets presented a substantial challenge due to the inherent variability of string data.

Joining datasets based on brand titles that are close but not identical presents several significant challenges. One primary issue is string variability, where differences in spelling, abbreviations, or formatting can hinder accurate matching. For instance, variations such as “Coca-Cola” versus “Coca Cola” or “McDonald’s” versus “McDonalds” can lead to mismatches. Additionally, typographical errors are common in large datasets, where simple mistakes like “Nike” versus “Nkie” can cause discrepancies. Case sensitivity further complicates the process, as strings like “apple” and “Apple” may be treated as distinct entities. Moreover, whitespace and special characters can introduce errors; for example, “Procter & Gamble” versus “Procter and Gamble” or “L’Oréal” versus “Loreal”.

Another challenge is the presence of synonyms and acronyms, where different terms or abbreviations refer to the same brand, such as “P&G” for “Procter & Gamble” or “IBM” for “International Business Machines”. Partial matches also pose a problem, where only a portion of the string matches, leading to incorrect joins, such as “Johnson & Johnson” versus “Johnson”. These issues are compounded by performance concerns, as string matching algorithms can be computationally intensive, especially with large datasets.

Addressing these challenges requires a combination of techniques, including string normalization, fuzzy matching, tokenization, and phonetic matching. String normalization involves standardizing strings by converting them to lowercase, removing extra spaces, and handling special characters. Fuzzy matching algorithms, such as Levenshtein distance, can identify strings that are close in terms of character edits. Tokenization breaks strings into tokens (words) and matches based on these tokens, while phonetic matching algorithms like Soundex match strings based on their pronunciation. These methods, when applied effectively, can significantly improve the accuracy of joining datasets based on brand titles with close but unequal strings.

String Matching Across Datasets

To address the challenge of matching brand information between two distinct datasets—RMS and AdIntel—we employed a hybrid string matching approach. This approach was necessitated by the inconsistencies in brand naming conventions across the datasets, including variations in spelling, punctuation, and abbreviations.

Data Preprocessing

Initially, the data underwent a preprocessing phase to standardize the brand descriptions. This involved converting all text to lowercase, removing punctuation and common suffixes (e.g., "ltd," "inc"), and eliminating stop words. This preprocessing ensured that the comparisons were not biased by trivial differences in text format.

Hybrid Similarity Measure

Given the need for robust matching, we developed a hybrid similarity measure that integrates multiple distance metrics: Jaccard similarity, Jaro-Winkler distance, and Levenshtein distance. The Jaccard similarity assessed the overlap of word sets between brand descriptions, thus capturing the semantic similarity of multi-word brand names. The Jaro-Winkler distance was employed to give more weight to matches at the beginning of the strings, and the Levenshtein distance accounted for simple typographical errors by measuring the minimum number of edits required to transform one string into another.

These measures were combined using a weighted approach, with exponential decay applied to emphasize stronger matches. This hybrid measure allowed for a flexible yet rigorous comparison across varying brand descriptions.

Pre-filtering and Matching Process

To enhance the efficiency of the matching process, a pre-filtering step was implemented. This step identified potential matches by checking if all or any words from an RMS brand description were present in the AdIntel brand data across multiple descriptive fields. This reduced the candidate set of AdIntel brands, thus focusing computational resources on more likely matches. The filtered candidates were then subjected to the hybrid similarity measure. For each RMS brand, the best-matching AdIntel brands were identified based on a similarity threshold, ensuring that only highly probable matches were retained.

Results and Output

The matching process generated a set of potential brand matches, ranked by their computed similarity scores. The results were subsequently ordered and exported for further analysis. This approach not only improved the accuracy of brand matching but also minimized false positives, thereby ensuring the reliability of subsequent analyses.

8.5. Big Data Challenges

The analysis of massive datasets, characterized by trillions of rows and terabytes of data, presented formidable computational challenges. To address these complexities, R was employed as the primary analytical tool due to its rich ecosystem of statistical and data manipulation packages. However, the sheer scale of the data necessitated the exploration of novel approaches to circumvent memory limitations inherent to traditional data processing frameworks.

Central to the analysis was the efficient management and manipulation of multiple, interconnected tables. Standard data manipulation operations, such as calculations, concatenations, filtrations, and joins, became computationally intensive and often resulted in memory exhaustion. To overcome these hurdles, we integrated specialized libraries like Apache Arrow and DuckDB into the R environment.

Apache Arrow, renowned for its columnar in-memory format, significantly enhanced data processing speeds and memory efficiency. By representing data in a columnar layout, Arrow optimized data access patterns, reduced memory footprint, and accelerated computational operations. This was particularly advantageous when dealing with repetitive calculations across large datasets.

DuckDB, a high-performance in-process relational database management system, provided a robust foundation for managing and querying large-scale datasets within the R environment. By offloading data processing to DuckDB, we could exploit its optimized query engine and parallel processing capabilities, thereby improving performance and scalability. This was crucial for complex join operations and aggregations that would have been prohibitively expensive in traditional R data frames.

The combination of R, Apache Arrow, DuckDB and other libraries such as dplyr and data.table enabled us to execute analyses that would have been infeasible using traditional R data structures. By adopting an out-of-memory approach, we were able to process and analyze datasets of unprecedented size and complexity. This integration of tools and methodologies proved instrumental in extracting valuable insights from the massive dataset.

The successful execution of this analysis would have been virtually impossible without the invaluable contributions of the developers of Apache Arrow and DuckDB. These libraries represent groundbreaking advancements in data management and processing, offering unparalleled efficiency and scalability. Their innovative approaches to data storage and manipulation have redefined the boundaries of what is computationally feasible, enabling us to tackle datasets of unprecedented size and complexity. We extend our sincere gratitude to these brilliant minds whose work has been instrumental in pushing the frontiers of data science.

For instance, the integration of AdIntel impression and occurrence data presented significant computational challenges due to the dataset's immense size and complexity. The presence of numerous duplicate records within both datasets, often in the thousands, exacerbated the problem. Traditional join operations, reliant on exact key matches, produced an exponential increase in data volume, resulting in a Cartesian product that overwhelmed computational resources. To address these challenges, a non-equi join methodology was implemented. By relaxing the strict matching criteria, this approach allowed for more flexible comparisons between records, identifying potential matches based on approximate or conditional relationships. This strategy effectively reduced the dataset's size while preserving essential information, enabling subsequent analysis.

9. Model Preprocessing

9.1. Handling of Categorical Variables

To incorporate the categorical variables into the regression model, each categorical variable was converted into a set of binary (dummy) variables. This transformation allows the model to include categorical predictors by representing each category as a separate binary variable (0 or 1), indicating the presence or absence of that category. For example, the categorical variable representing different types of television programs (TVProgCatID) was transformed into multiple dummy variables, each corresponding to a specific program category. Similarly, the ad type (CreativeType) was also converted into dummy variables.

This approach ensures that the model can assess the impact of each specific category while avoiding issues of multicollinearity by omitting one category as a reference group. The resulting coefficients for the dummy variables indicate how much each category deviates from the baseline (omitted) category in terms of its effect on the dependent variable, brand revenue.

9.2. Aggregation to the Weekly Level

Given that advertising effects are often observed over time, the data was aggregated to the weekly level to facilitate a more coherent analysis of temporal trends. Aggregation was performed by summing or averaging the relevant variables for each brand-week combination.

Variables such as Spend and GRP were summed across all instances within the same week for each brand. This aggregation captures the total advertising effort and exposure for each brand during that specific week, reflecting the cumulative effect of multiple advertising activities.

For dummy variables representing categories like Informational, ENT (Entertainment), and other program categories, averages were computed to reflect the proportion of ads that fell into each category within a week. For instance, if 70% of a brand's ads in a given week were informational, the Informational variable would have an average of 0.7 for that week.

9.3. Transformation

In the analysis, we applied the Box-Cox transformation to both the GRP and revenue variables to address potential issues of non-normality and heteroscedasticity in the data. The Box-Cox transformation helps to stabilize variance and make the data more normally distributed, which is important for meeting the assumptions of linear regression models. By transforming these variables, we aim to improve the accuracy and reliability of the model estimates, ensuring that the relationships between the predictors and the dependent variable are more linear and that the residuals are homoscedastic. This transformation ultimately leads to a more robust and interpretable model.

10. Model Development

10.1. Model 1: Base Model

The first model in this study was developed to examine the immediate impact of advertising efforts on brand revenue. Unlike the second model, which incorporates lagged variables to account for delayed effects, this model focuses on capturing the direct, contemporaneous relationship between advertising exposure and revenue within the same period.

Rationale for the Model

Advertising campaigns are often designed with the expectation of generating an immediate response from consumers, such as increased awareness, interest, and ultimately, purchases. Therefore, it is crucial to assess how advertising efforts, specifically within the same time period, influence revenue outcomes. This model aims to quantify the direct effects of advertising variables on revenue, providing insights into the immediate effectiveness of different advertising strategies.

Structure of the Model

The model includes key advertising variables, such as Gross Rating Points (GRP) and informational advertising averages (inf_avg and its interaction terms), to capture the immediate effects on revenue. The specific structure of the model is as follows:

- **GRP_boxcox:** This variable represents the Gross Rating Points, a standard measure of the reach and frequency of an advertising campaign. Including GRP in the model allows for the analysis of how advertising exposure within a specific period directly influences revenue.

- **Informational Ad Variables (inf_avg and Interaction Terms):** The model also incorporates the average level of informational advertising (inf_avg) and its interaction terms with different types of programming categories (inf_ENT_avg, inf_INF_avg, inf_SPC_avg, inf_SPR_avg). These variables enable the examination of how different types of informational ads impact revenue immediately.

By focusing on the contemporaneous effects of these variables, the model aims to capture the direct impact of advertising strategies on revenue during the same period in which the advertisements are aired. The inclusion of these variables in the model serves several key purposes:

1. **Quantifying Immediate Impact:** The model provides a clear understanding of how advertising efforts directly influence revenue within the same period. This immediate effect is crucial for advertisers who need to evaluate the effectiveness of their campaigns in real-time and make timely adjustments.
2. **Informing Advertising Strategy:** By analyzing the immediate effects, the model helps identify which types of advertisements and programming categories are most effective in driving sales. This information is valuable for making strategic decisions about ad content and placement to maximize revenue impact.
3. **Establishing a Baseline for Comparison:** This first model serves as a baseline for understanding the direct effects of advertising. It provides a point of comparison for the second model, which includes lagged effects, allowing for a more comprehensive analysis of both immediate and delayed impacts.

Model Equation:

$$Revenue_{boxcox} = GRP\_boxcox + inf\_avg + inf\_ENT\_avg + inf\_INF\_avg + inf\_SPC\_avg + inf\_SPR\_avg$$

10.1.1. Results

Variable	Estimate	Std. Error	t value	Pr(>|t|)
GRP_boxcox	3815.9	187.2	20.385	< 2e-16 ***
inf_avg	-1481888.2	187678.5	-7.896	4.83e-14 ***
inf_ENT_avg	1481344.9	187556.0	7.898	4.76e-14 ***
inf_INF_avg	1496945.3	187823.8	7.970	2.94e-14 ***
inf_SPC_avg	1520778.5	188336.2	8.075	1.45e-14 ***
inf_SPR_avg	1482701.5	187441.9	7.910	4.39e-14 ***

Significance Codes:

***: $p < 0.001$
**: $p < 0.01$
*: $p < 0.05$
. : $p < 0.1$
' ' : $p \geq 0.1$

Notes:

- Residual standard error: 14180 on 315 degrees of freedom
- Multiple R-squared: 0.6705, Adjusted R-squared: 0.6642
- F-statistic: 106.8 on 6 and 315 DF, p-value: < 2.2e-16

10.1.2. Discussion

The linear regression model under consideration demonstrates a robust relationship between the transformed revenue (Revenue_boxcox) and several predictor variables, including the transformed Gross Rating Points (GRP_boxcox) and various averages of informational advertising expenditure across different program categories (inf_avg, inf_ENT_avg, inf_INF_avg, inf_SPC_avg, inf_SPR_avg). The model accounts for approximately 67.05% of the variance in revenue, as indicated by the multiple R-squared value, with an adjusted R-squared of 66.42%. Furthermore, the overall model is highly significant, as evidenced by an F-statistic of 106.8 and a p-value less than 2.2e-16.

The coefficient for GRP_boxcox is both highly significant (p < 2e-16) and positive, with an estimated value of 3815.9. This suggests a strong association between increases in Gross Rating Points— a measure of advertising exposure intensity— and increases in transformed revenue. This finding reinforces the established understanding that heightened advertising exposure positively correlates with consumer response and sales, underscoring the importance of advertising intensity in driving sales outcomes.

Conversely, the coefficient for inf_avg is negative and highly significant, with an estimated value of -1481888.2 (p < 4.83e-14). This result indicates that general informational advertising, when averaged across all program categories, exerts a negative impact on revenue. This finding could potentially reflect issues such as oversaturation or a misalignment between the general content of informational advertisements and consumer needs, leading to a decline in advertising effectiveness when such ads are deployed broadly.

In contrast to the general inf_avg, the coefficients for informational advertising within specific program categories— including Entertainment, Information, Special Programming, and Sports— are all positive and highly significant, with estimates ranging from approximately 1.48 to 1.52 million. These results suggest that when informational advertisements are strategically targeted within specific program categories, they can exert a substantial positive effect on revenue. The high significance and magnitude of these coefficients imply that the contextual alignment between advertising content and program category is crucial in enhancing advertising effectiveness.

The findings from the first model yield several critical insights into the immediate effects of advertising on brand revenue. These results hold significant implications for understanding the relationship between different types of advertising and sales performance, as well as for guiding strategic decisions in advertising planning and execution.

1. The Strong Positive Impact of GRP on Revenue

The coefficient for GRP_boxcox is highly significant ($p < 2e-16$), with a positive estimate of 3815.9. This finding indicates a strong and direct relationship between Gross Rating Points (GRP) and revenue, suggesting that higher levels of advertising exposure are associated with increased sales within the same period.

This result confirms the effectiveness of maximizing advertising reach and frequency in driving immediate sales outcomes. Advertisers should prioritize increasing GRP during campaign periods to boost sales, as the impact on revenue is both substantial and statistically significant.

2. Significant Effects of Informational Advertising Variables

The informational advertising variables (inf_avg and its interaction terms with various program categories) exhibit strong statistical significance, with p-values all below 0.001. Notably, while the coefficient for inf_avg is negative (-1481888.2), the interaction terms (e.g., inf_ENT_avg, inf_INF_avg, inf_SPC_avg, inf_SPR_avg) are associated with positive coefficients.

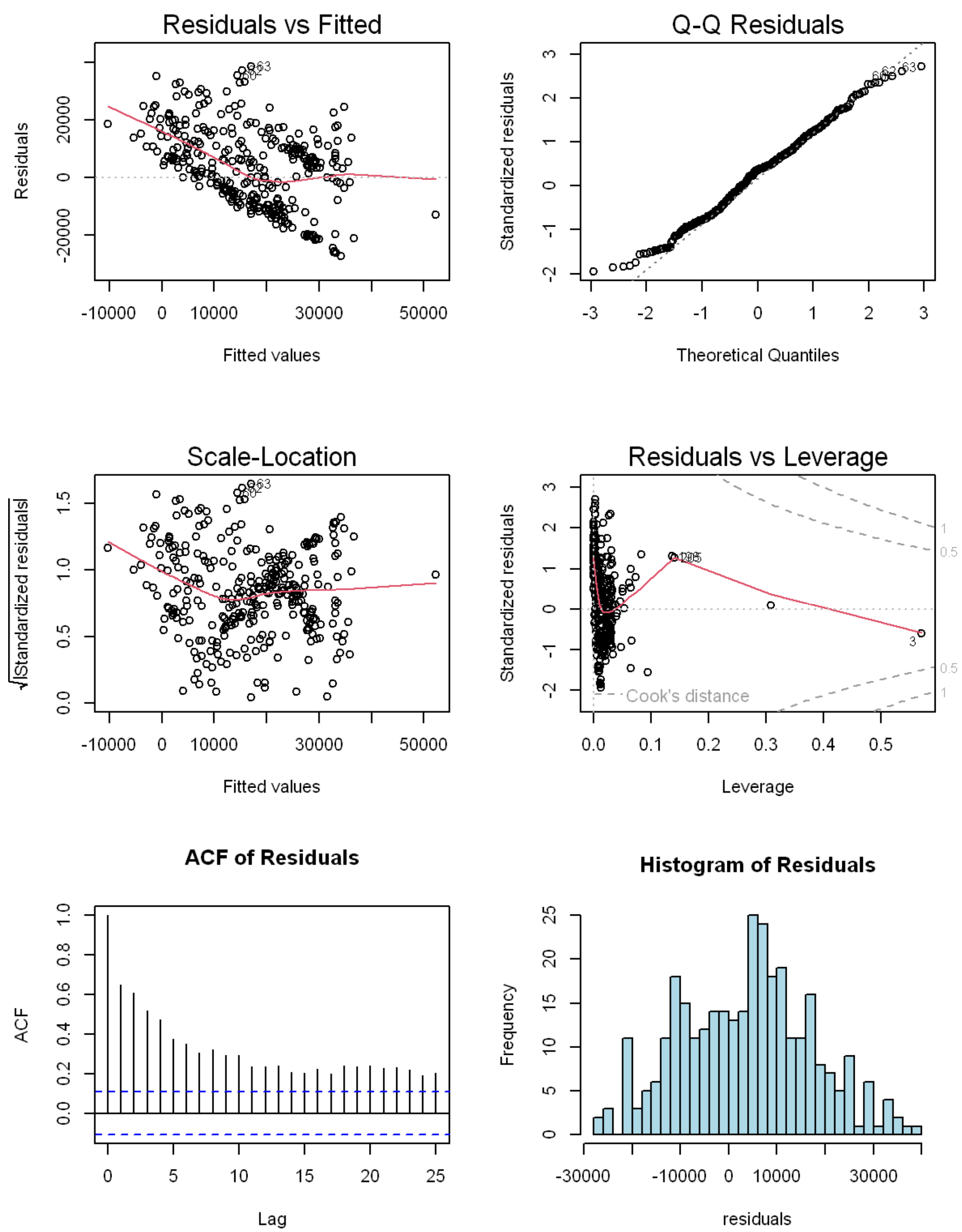
The negative coefficient for inf_avg suggests that, in isolation, a higher average level of informational advertising may be ineffective or even detrimental to revenue. However, when combined with certain types of programming, as indicated by the positive interaction terms, the impact becomes positive. This highlights the critical importance of contextual factors in determining advertising effectiveness— informational advertisements must be carefully tailored to the programming environment to achieve positive results. Advertisers should consider both the content of their advertisements and their placement within specific program categories to optimize effectiveness.

3. High R-squared Value Indicates Good Model Fit

The model explains approximately 67.05% of the variability in revenue, as indicated by the R-squared value, with an adjusted R-squared of 66.42%, accounting for the number of predictors included in the model.

The relatively high R-squared value suggests that the model effectively captures a significant portion of the variation in revenue, indicating that the selected variables are appropriate for modeling the immediate effects of advertising on sales. However, approximately 33% of the variability remains unexplained, potentially due to other factors not included in the model, such as pricing, promotions, or competitive actions. Future research could explore these additional variables to further enhance the model's explanatory power.

10.1.3. Model Diagnostic Plots



10.2. Model 2: Lagged Variables Model

The development of the second model was driven by the need to explore the temporal dynamics between advertising efforts and their impact on brand revenue. While the first model primarily addressed the immediate effects of advertising, this model extends the analysis by incorporating lagged variables to capture the delayed influence of advertisements over time. This approach acknowledges that consumer responses to advertising are often not instantaneous but may unfold gradually across subsequent periods.

Rationale for the Model

Advertising strategies are frequently designed to influence consumer behavior over an extended timeframe. Consumers may not immediately act upon seeing an advertisement; instead, they may take time to process the information before making a purchase decision. This delayed response suggests that the effect of advertising on sales may not be immediate but could manifest across several subsequent periods. To accurately capture this phenomenon, it becomes essential to include lagged variables in the analytical model.

Lagged variables represent the values of independent variables from previous time periods, thereby enabling the model to account for the cumulative and delayed effects of advertising. By integrating these lagged terms, the model offers a more nuanced and comprehensive understanding of how advertising strategies influence revenue over time, beyond the immediate impact captured by the first model.

Structure of the Model

The structure of this model is designed to reflect the temporal nature of advertising effects. It includes lagged versions of key variables such as Gross Rating Points (GRP) and informational advertising averages (inf_avg) along with their interaction terms. Specifically, the model incorporates lagged GRP variables, which are lagged by up to four periods, allowing the analysis to assess how previous levels of advertising exposure influence current revenue. GRP, as a standard measure of advertising exposure, is pivotal in determining whether the impact of such exposure is immediate or whether it persists and accumulates over time.

In addition to GRP, the model also includes lagged informational ad variables. The incorporation of these lagged informational ad averages and their interaction terms facilitates an investigation into how previous informational advertisements affect current revenue. This approach enables the examination of whether the effects of informational ads are sustained over time or if they diminish quickly after their initial deployment.

Importance of Investigating Lagged Effects

The inclusion of lagged effects in the model serves several critical purposes that are essential for a deeper understanding of advertising dynamics. Firstly, by examining lagged variables, the model provides valuable insights into the delayed impact of advertising efforts. This understanding is crucial for advertisers who need to anticipate whether their campaigns will yield immediate results or if the benefits will accumulate over a more extended period.

Secondly, the model allows for the identification of cumulative effects, wherein advertisements from previous weeks combine with current efforts to influence revenue. This is particularly relevant for campaigns that rely on repeated exposure to build brand awareness and reinforce messaging. The cumulative nature of these effects can provide a more accurate assessment of an advertising campaign's overall effectiveness.

Lastly, understanding the lagged effects of advertising carries significant strategic implications. Insights gained from this model can inform more effective ad scheduling and budgeting decisions. Advertisers can optimize their campaigns by strategically timing their advertisements to maximize their impact on sales, taking into consideration the delayed response patterns of consumers. This approach ensures that advertising efforts are not only well-targeted but also well-timed to achieve the desired outcomes in terms of revenue generation.

Model Equation

```
Revenue_boxcox ~
lag(GRP_boxcox, 3) +
lag(GRP_boxcox, 4) +
lag(inf_avg, 3) +
lag(inf_avg, 4) +
lag(inf_ENT_avg, 3) +
lag(inf_INF_avg, 3) +
lag(inf_SPC_avg, 3) +
lag(inf_SPR_avg, 3) +
lag(inf_ENT_avg, 4) +
lag(inf_INF_avg, 4) +
```

lag(inf_SPC_avg, 4) +
lag(inf_SPR_avg, 4)

10.2.1. Results

Residuals:

Min	1Q	Median	3Q	Max
-30042	-6640	1910	10485	38264

Coefficient	Estimate	Std. Error	t value	Pr(>t)	Sign. Level
lag(GRP_boxcox, 1)	1193.9	367.2	3.251	0.001281	**
lag(GRP_boxcox, 2)	900.3	385.7	2.334	0.02024	*
lag(GRP_boxcox, 3)	923.4	379.9	2.431	0.015656	*
lag(GRP_boxcox, 4)	1307	363.9	3.591	0.000385	***
lag(inf_avg, 1)	-202.2	3148.9	-0.064	0.948836	
lag(inf_avg, 2)	-796378	306220.1	-2.601	0.00977	**
lag(inf_avg, 3)	-428416	362686.3	-1.181	0.238457	
lag(inf_avg, 4)	-712601	307399.1	-2.318	0.02112	*
lag(inf_ENT_avg, 2)	794107.4	306158.1	2.594	0.009963	**
lag(inf_INF_avg, 2)	796076.1	306187.6	2.6	0.00979	**
lag(inf_SPC_avg, 2)	816623.1	306604.4	2.663	0.008157	**
lag(inf_SPR_avg, 2)	796093.8	306194.3	2.6	0.009789	**
lag(inf_ENT_avg, 3)	428133.2	362499.2	1.181	0.238524	
lag(inf_INF_avg, 3)	425901.2	362539.8	1.175	0.241027	
lag(inf_SPC_avg, 3)	447270.3	362868	1.233	0.218701	
lag(inf_SPR_avg, 3)	426914.1	362618.4	1.177	0.240015	
lag(inf_ENT_avg, 4)	716033	307363.7	2.33	0.020498	*
lag(inf_INF_avg, 4)	716876.6	307424	2.332	0.020375	*
lag(inf_SPC_avg, 4)	731850.9	307767.8	2.378	0.018043	*
lag(inf_SPR_avg, 4)	712432.2	307404.5	2.318	0.021152	*

Significance Codes: ***: p < 0.001 **: p < 0.01 *: p < 0.05 . : p < 0.1 ' ' : p ≥ 0.1

Notes:

- Residual standard error: 12630 on 297 degrees of freedom
- Multiple R-squared: 0.7535, Adjusted R-squared: 0.7369
- F-statistic: 45.39 on 20 and 297 DF, p-value: < 2.2e-16

10.2.2. Discussion

The results of the regression analysis, as presented in Table 1, reveal a statistically significant relationship between the independent variables and the dependent variable, which is the Box-Cox transformed brand revenue at the weekly level. The overall model demonstrates its robustness by explaining a substantial portion of the variance in brand revenue, with an adjusted R-squared value of 0.7369. This indicates that approximately 73.69% of the variance in revenue is accounted for by the model. The F-statistic of 45.39, accompanied by a p-value of less than 2.2e-16, further substantiates the statistical significance of the model.

The coefficients for the lagged Gross Rating Points (GRP) variables, particularly at lags 1, 3, and 4, indicate a positive and significant impact on revenue. This suggests that increased advertising exposure has a delayed but positive effect on sales. Specifically, the coefficient estimates for lag(GRP_boxcox, 1), lag(GRP_boxcox, 3), and lag(GRP_boxcox, 4) are 1193.9 ($p = 0.0013$), 923.4 ($p = 0.0157$), and 1307.0 ($p = 0.0004$) respectively, underscoring that the effects of advertising are not immediate but rather unfold over several weeks.

The relationship between the average informational ad spend (inf_avg) and revenue is more complex. The lagged values of inf_avg at lags 2 and 4 exhibit significant negative impacts on revenue, with coefficient estimates of -796377.9 ($p = 0.0098$) and -712601.1 ($p = 0.0211$), respectively. This negative association may suggest the presence of diminishing returns or oversaturation effects when informational advertisements are consistently present across multiple weeks.

The second model, which incorporates lagged effects, provides a deeper understanding of how advertising impacts brand revenue over time. By including lagged variables, this model allows for the exploration of not only the immediate effects of advertising but also how these effects unfold and persist across subsequent periods. The findings from this model have several important implications for advertising strategy and decision-making.

Significant Lagged Effects of GRP on Revenue

The lagged GRP variables, ranging from 1 to 4 periods, all demonstrate statistically significant positive coefficients, with p-values spanning from 0.001281 to 0.000385. This finding indicates that the impact of advertising exposure, as measured by GRP, extends beyond the period in which the ads are aired and continues to influence revenue in subsequent weeks. The persistence of GRP's impact over multiple periods suggests that advertising exerts a lasting effect on consumer behavior. This insight implies that advertisers should consider the cumulative impact of their campaigns, planning for sustained exposure over time rather than relying solely on short bursts of high GRP. The results also imply that the benefits of advertising may continue to accrue even after the campaign has concluded, emphasizing the importance of consistent, ongoing advertising efforts.

Delayed and Sustained Effects of Informational Ads

The lagged informational advertising variables, including lag(inf_avg, 2) and lag(inf_avg, 4), along with their interactions, also show significant coefficients, with several variables exhibiting p-values below 0.01. This suggests that informational advertising exerts a delayed effect on revenue, with significant impacts materializing several periods after the ads are aired. The delayed effects of informational ads indicate that consumers may require time to process and act on the information provided in these advertisements. This finding supports the strategy of maintaining informational campaigns over extended periods to ensure that the message resonates with consumers and translates into sales over time. Advertisers should exhibit patience with informational campaigns, recognizing that the benefits may not be immediately apparent but can emerge in the following weeks.

Differential Impact Based on Program Context

The interaction terms between lagged informational advertising and various program categories, such as lag(inf_ENT_avg, 2), lag(inf_INF_avg, 2), and lag(inf_SPC_avg, 2), reveal significant positive effects. This suggests that the effectiveness of informational ads varies depending on the type of programming in which they are placed. These effects are observed not only in the immediate period but also across several lagged periods. The results indicate that the effectiveness of informational advertising is context-dependent, and its impact can vary based on the type of program with which it is associated. Advertisers should carefully select the programming environment for their informational ads, aiming to align the content of the ad with the interests and expectations of the audience. The sustained positive effects observed in lagged periods further emphasize the importance of strategic ad placement in maximizing long-term revenue impact.

Strategic Timing and Scheduling of Advertising Campaigns

The significant lagged effects identified in this model provide critical insights into the optimal timing and scheduling of advertising campaigns. The results suggest that the benefits of advertising extend beyond the initial period and can influence consumer behavior over an extended timeline. Advertisers should consider a staggered approach to their campaigns, where the timing of ads is planned to ensure continuous or overlapping exposure that maximizes the cumulative impact over time. This approach can help sustain brand awareness and influence purchasing decisions long after the initial ad exposure.

Impact of Advertising Pressure (GRP)

The coefficients for the lagged GRP variables are positive and statistically significant across all four lags, with the first lag showing a particularly strong effect (Estimate = 1193.9, $p < 0.01$). This suggests that advertising pressure, as measured by GRP, exerts a sustained positive impact on brand revenue, with effects lasting up to four weeks. The consistent significance across lags underscores the importance of ongoing advertising efforts in maintaining brand sales over time.

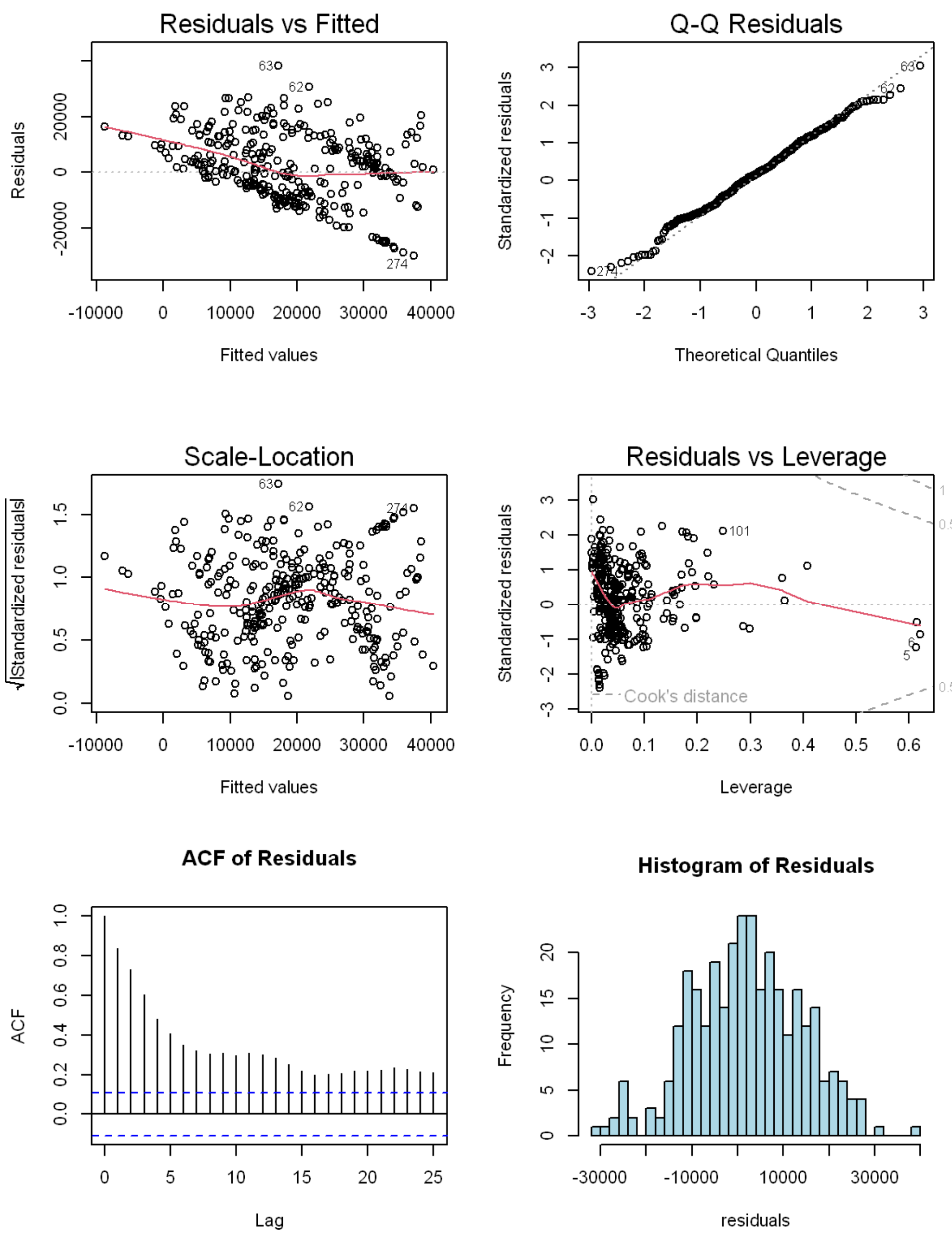
Effect of Informational Advertising

The impact of informational advertising, as measured by inf_avg, is mixed. While the first lag shows a non-significant effect, the second and fourth lags reveal large negative coefficients (e.g., -796377.9 for the second lag, $p < 0.01$), indicating a potential detrimental effect on revenue after a certain delay. This could suggest that informational ads, if overexposed or not refreshed, might lead to diminishing returns or even adverse effects on brand revenue.

Interaction Effects Between Informational Ads and Program Categories

The interaction terms between informational advertising and program categories (ENT, INF, SPC, SPR) exhibit positive and statistically significant coefficients, particularly at the second lag (e.g., lag(inf_ENT_avg, 2) Estimate = 794107.4, $p < 0.01$). This indicates that the effectiveness of informational ads is enhanced when placed within certain program categories, suggesting a synergy between the ad content and the programming context. These findings emphasize the strategic importance of ad placement in maximizing the impact of informational advertising.

10.2.3. Model Diagnostics Plots



10.3. Model 3: GLS AR(1)

Model 3 was introduced as a response to the limitations identified in Models 1 and 2. Model 1, serving as the base model, examined the direct relationship between revenue and various advertising metrics without accounting for the temporal dynamics inherent in the data. Although this model provided an initial understanding, it revealed significant issues with autocorrelation and homoscedasticity, meaning that the residuals were correlated over time and the variance of the errors was constant across observations, which violated key assumptions of the model.

Model 2 sought to improve upon this by introducing lagged variables to capture the effects of previous weeks' advertising metrics on current revenue. While this model added temporal depth to the analysis, it still suffered from autocorrelation in the residuals, indicating that the model did not fully account for the time-series nature of the data. Additionally, homoscedasticity remained an issue, suggesting that the model did not appropriately capture the varying levels of variability across brands.

To address these shortcomings, Model 3 was developed using Generalized Least Squares (GLS). This model was designed to explicitly correct for the autocorrelation by incorporating an AR(1) correlation structure, which models the influence of past revenue on current revenue. Furthermore, GLS allows for heteroscedasticity by incorporating a variance function that permits different variances across brands. By resolving the issues of autocorrelation and homoscedasticity present in the previous models, Model 3 provides a more accurate and reliable framework for analyzing the impact of advertising metrics on revenue, leading to more robust and credible conclusions.

10.3.1. Results
Generalized Least Squares Fit by REML
Model:

```
Revenue_boxcox ~
  GRP_boxcox +
  inf_avg +
  inf_ENT_avg +
  inf_INF_avg +
  inf_SPC_avg +
  inf_SPR_avg
```

Data:
df_weekly

AIC	BIC	logLik
6385.592	6460.644	-3172.796

Correlation Structure:
AR(1)
Formula:
~1 | week_end

Parameter estimate(s):
Phi: 0.9552295

Variance Function:
Structure: Different standard deviations per stratum
Formula: ~1 | brand_code_uc

Parameter estimates:

544907	548436	560405	710197	617480	569063	599631	558929
1.0000000	1.0930385	0.2688458	0.1343923	0.4235435	0.6222469	0.3774674	0.7100098

581335	500426	545320	635032	617497
0.7841691	0.2577837	0.3054187	0.4665658	0.4554535

Coefficients:

	Value	Std. Error	t-value	p-value
GRP_boxcox	438.30	34.835	12.582016	0.000
inf_avg	79192.54	22807.978	3.472142	0.0006
inf_ENT_avg	-81364.26	22886.791	-3.555075	0.0004
inf_INF_avg	-78585.70	22878.461	-3.434921	0.0007
inf_SPC_avg	-66352.74	22897.008	-2.897878	0.004
inf_SPR_avg	-82260.16	22749.567	-3.615900	0.0003

Correlation:

	GRP_boxcox	inf_avg	inf_ENT_avg	inf_INF_avg	inf_SPC_avg
inf_avg	-0.701				
inf_ENT_avg	0.698	-1.000			
inf_INF_avg	0.689	-0.996	0.995		
inf_SPC_avg	0.696	-0.996	0.996	0.991	
inf_SPR_avg	0.701	-1.000	1.000	0.996	0.996

Standardized Residuals:

Min	Q1	Med	Q3	Max
0.4437053	0.8455107	0.9511092	1.0664801	2.3214105

Residual Standard Error:
32339.54
Degrees of Freedom:
321 total; 315 residual

10.3.2. Discussion

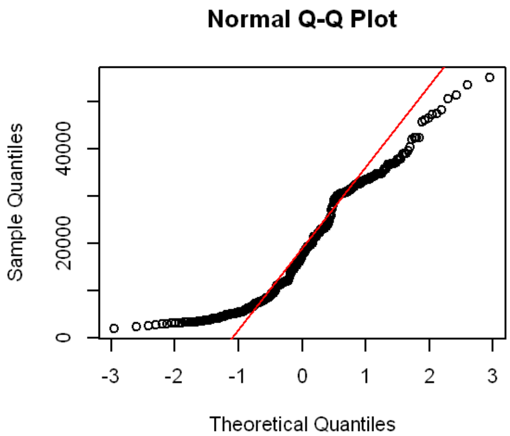
The results from Model 3, estimated using Generalized Least Squares (GLS), provide a deeper understanding of how advertising variables influence brand revenue while addressing the issues of autocorrelation and heteroscedasticity that were present in the earlier models. By incorporating an AR(1) correlation structure, Model 3 effectively accounts for the temporal dependence in the data, where revenue in one week is influenced by the revenue from the previous week. This temporal autocorrelation is significant, as indicated by the high AR(1) parameter estimate (Phi = 0.955), suggesting a strong persistence in revenue trends over time. This persistence could be attributed to factors such as brand loyalty or the cumulative impact of advertising, where the effects of advertisements carry over from one week to the next.

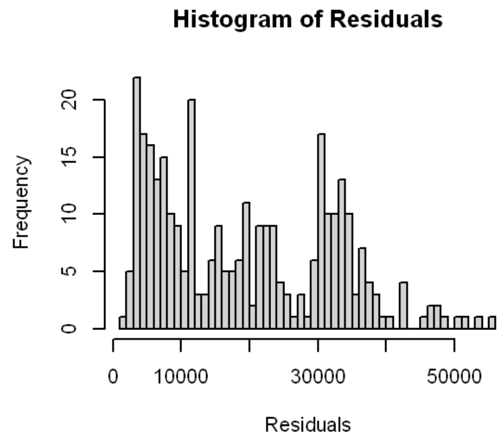
The GLS model also allows for different variances across brands, addressing the issue of heteroscedasticity that was observed in the earlier models. The variance function reveals that the variability in revenue differs across brands, with some brands exhibiting higher or lower variability. This suggests that the impact of advertising on revenue is not uniform across all brands, and that some brands are more sensitive to advertising efforts than others. This variance should be considered when planning advertising strategies, as it indicates that different brands may require tailored approaches to maximize their revenue impact.

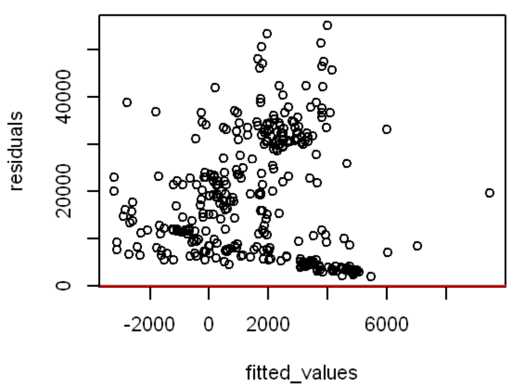
The estimated coefficients from Model 3 provide valuable insights into the effectiveness of various advertising strategies. The coefficient for GRP (Gross Rating Points) is positive and highly significant, indicating that an increase in GRP is associated with a substantial rise in revenue. This finding underscores the importance of maintaining high levels of GRP in advertising campaigns, as it directly contributes to higher sales. However, the effects of informational advertisements, when averaged across different program categories, present a more nuanced picture. While the overall effect of informational ads on revenue is positive, the interaction terms between informational ads and specific program categories—such as entertainment, informational/educational, special programming, and sports—are negative and significant. This suggests that informational ads may not perform equally well across all types of programming. In fact, in some contexts, these ads may even have a detrimental effect on revenue.

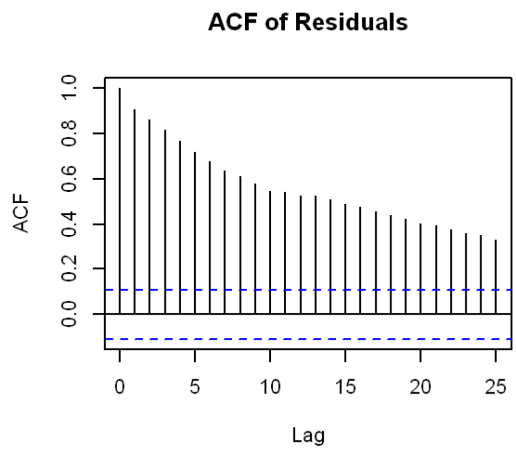
The implications of these findings are significant for advertising strategy. Advertisers should carefully consider the context in which their ads are placed, as the effectiveness of informational ads varies depending on the type of program in which they are embedded. For example, while informational ads may be effective in certain contexts, they may be less successful or even counterproductive in entertainment or sports programs, where viewers might be seeking more emotional or engaging content rather than factual information. These results suggest that advertisers should tailor their ad content to the nature of the program to maximize its effectiveness and avoid potential negative impacts on revenue.

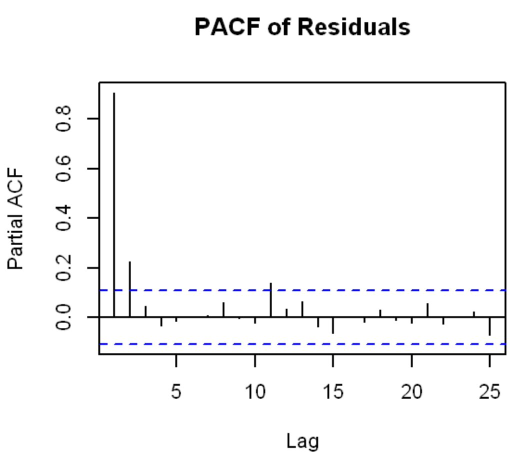
10.3.3. Diagnostics Plots











10.4. Model 4: GLS ARMA(2,2)

Model 3 employed a Generalized Least Squares (GLS) regression with an AR(1) correlation structure and a Box-Cox transformation of the revenue and GRP variables. Despite this, the model exhibited some limitations, particularly in terms of persistent autocorrelation and challenges with heteroscedasticity, as indicated by the residual diagnostics.

Model 3, while providing a solid initial framework, revealed significant issues that suggested the need for further refinement. The AR(1) structure used in Model 3 was designed to capture first-order autocorrelation, but the residuals still exhibited patterns of autocorrelation that were not fully addressed. The AIC and BIC values for Model 3 were relatively high (6385.592 and 6460.644, respectively), indicating that the model's fit could be improved. Additionally, the variance function in Model 3, while allowing for different variances across brands, suggested the presence of significant heteroscedasticity, further complicating the model's reliability.

In response, Model 4 introduced several key modifications. Firstly, the correlation structure was expanded to an ARMA(2,2) model, which incorporates both autoregressive and moving average components to more effectively capture the complex temporal dependencies in the data. This change was intended to better account for the residual autocorrelation that was inadequately addressed by the AR(1) structure in Model 3. Secondly, both the revenue and GRP variables were log-transformed in Model 4, rather than using the Box-Cox transformation. This log transformation aimed to stabilize the variance and address the skewness observed in the residuals, providing a more normalized distribution of errors.

10.4.1. Results

Model:
Revenue_log ~ GRP_log + inf_avg + inf_ENT_avg + inf_INF_avg + inf_SPC_avg + inf_SPR_avg

Data:
df_weekly

AIC	BIC	logLik
435.4978	525.4832	-193.7489

Correlation Structure:
ARMA(2,2)

Formula:
~1 | week_end

Parameter estimate(s):
Phi1: 0.94156896
Phi2: 0.05609251
Theta1: -0.46627929
Theta2: -0.09985474
Variance Function:
Structure: Different standard deviations per stratum
Formula: ~1 | brand_code_uc

Parameter estimates:

544907	548436	560405	710197	617480	569063	599631	558929
1.0000000	0.8814988	2.9817324	3.1937603	2.6943469	1.8422222	3.5628313	1.5209606

581335	500426	545320	635032	617497
1.6671183	3.2983408	3.4233790	2.0781895	2.6889955

Coefficients:

	Value	Std. Error	t-value	p-value
(Intercept)	16.770301	0.053033	316.22158	0.0000
GRP_log	0.026312	0.011830	2.22415	0.0268
inf_avg	-15.746169	6.877993	-2.28935	0.0227
inf_ENT_avg	15.656741	6.876108	2.27698	0.0235
inf_INF_avg	15.693825	6.862343	2.28695	0.0229
inf_SPC_avg	16.675235	6.875172	2.42543	0.0159
inf_SPR_avg	15.802214	6.865419	2.30171	0.0220

Correlation:

	(Intercept)	GRP_log	inf_avg	inf_ENT_avg	inf_INF_avg	inf_SPC_avg
GRP_log	-0.850					
inf_avg	0.363	-0.280				
inf_ENT_avg	-0.363	0.280	-1.000			
inf_INF_avg	-0.361	0.277	-0.999	0.999		
inf_SPC_avg	-0.368	0.288	-0.999	0.999	0.999	
inf_SPR_avg	-0.364	0.282	-1.000	1.000	0.999	0.999

Standardized Residuals:

Min	Q1	Med	Q3	Max
-1.4618217	-1.0883974	-1.0042634	-0.9225285	-0.2637588

Residual Standard Error:
1.022698

Degrees of Freedom:
321 total; 314 residual

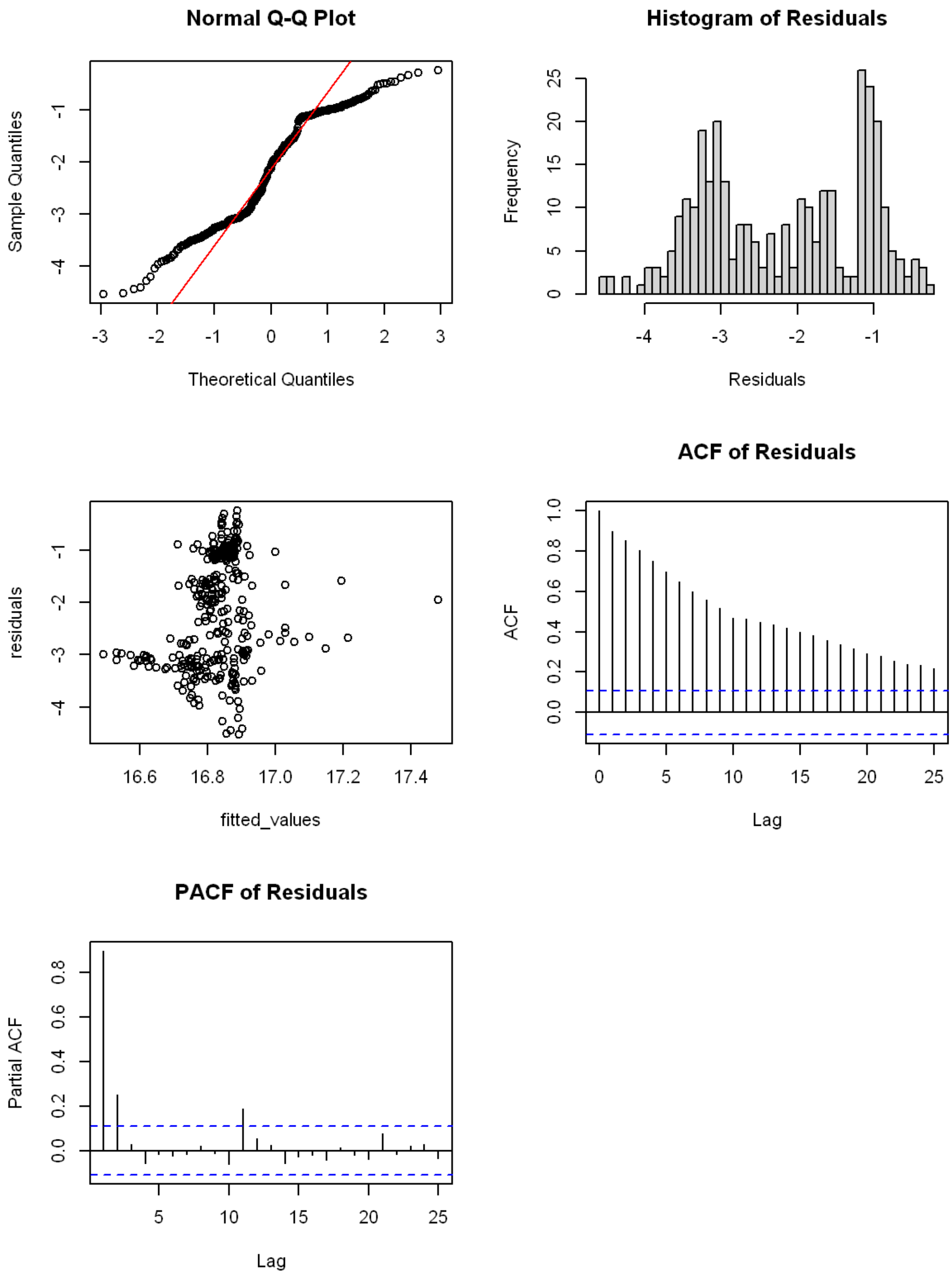
10.4.2. Discussion

The results from Model 4 demonstrate a marked improvement over Model 3, both in terms of model fit and the interpretability of the coefficients. The AIC and BIC values for Model 4 (435.4978 and 525.4832, respectively) are significantly lower than those for Model 3, indicating that the model provides a better fit to the data. The log-likelihood has also improved, suggesting that the modifications made in Model 4 more accurately capture the underlying patterns in the data.

In terms of coefficient estimates, Model 4 reveals a positive and significant relationship between the log-transformed GRP and revenue, with a coefficient of 0.026312 ($p = 0.0268$). This finding aligns with economic expectations, suggesting that a percentage increase in GRP leads to a corresponding percentage increase in revenue. The interaction terms between inf_avg and various program categories (inf_ENT_avg, inf_INF_avg, inf_SPC_avg, and inf_SPR_avg) also show statistically significant relationships, with the coefficients indicating that the effectiveness of informational ads varies depending on the context in which they are aired. Notably, while inf_avg alone has a negative impact on revenue, this effect is moderated or reversed in certain program categories, such as entertainment, where the interaction term is positive and significant.

The improved residual diagnostics in Model 4 further support the robustness of the model. The standardized residuals are more symmetrically distributed, with fewer extreme values, indicating that the log transformation and ARMA(2,2) structure have effectively addressed the heteroscedasticity and non-normality issues observed in Model 3. The inclusion of both autoregressive and moving average components has also successfully mitigated the residual autocorrelation, as evidenced by the more stable residual standard error.

10.4.3. Diagnostics Plots



10.5. Model 5: GAM

Model 5 represents a further refinement in the analysis by incorporating lagged effects of both the GRP_log and inf_avg variables, as well as their interactions with various program categories. The rationale for including these lagged variables stems from the understanding that the impact of advertising is often not immediate. Advertising effects, particularly in terms of influencing consumer behavior and sales, can manifest over several weeks. Therefore, by including lagged variables, this model aims to capture the delayed effects of advertising on revenue, providing a more comprehensive view of how advertising influences sales over time.

The inclusion of smooth terms for GRP_log and inf_avg without lags allows the model to account for the immediate effects of these variables, while the lagged terms (both first and second lags) help in understanding how these effects persist or change over subsequent weeks. The tensor product smooths for the lagged interactions between inf_avg and program categories (ENT_avg, INF_avg, SPC_avg, and SPR_avg) further explore how these delayed effects vary depending on the context in which the ads are aired.

10.5.1. Results

Family:
Gaussian

Link Function:
Identity

Formula:
Revenue_log ~
  s(GRP_log) +
  s(inf_avg) +
  te(inf_avg, ENT_avg) +
  te(inf_avg, INF_avg) +
  te(inf_avg, SPC_avg) +
  te(inf_avg, SPR_avg) +
  s(lag(GRP_log, 1)) +
  s(lag(inf_avg, 1)) +
  te(lag(inf_avg, 1), lag(ENT_avg, 1)) +
  te(lag(inf_avg, 1), lag(INF_avg, 1)) +
  te(lag(inf_avg, 1), lag(SPC_avg, 1)) +

te(lag(inf_avg, 1), lag(SPR_avg, 1)) +
te(lag(inf_avg, 2), lag(ENT_avg, 2)) +
te(lag(inf_avg, 2), lag(INF_avg, 2)) +
te(lag(inf_avg, 2), lag(SPC_avg, 2)) +
te(lag(inf_avg, 2), lag(SPR_avg, 2))

Parametric Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	14.66438	0.02817	520.6	<2e-16 ***

Approximate Significance of Smooth Terms:

Term	edf	Ref.df	F	p-value
s(GRP_log)	5.2396	6.3700	3.863	0.000907 ***
s(inf_avg)	0.9985	0.9985	20.906	8.77e-06 ***
te(inf_avg, ENT_avg)	20.7819	21.9375	4.308	< 2e-16 ***
te(inf_avg, INF_avg)	6.0456	7.3837	7.101	< 2e-16 ***
te(inf_avg, SPC_avg)	7.2724	7.4887	11.050	< 2e-16 ***
te(inf_avg, SPR_avg)	3.5326	4.3704	10.580	< 2e-16 ***
s(lag(GRP_log, 1))	1.0000	1.0000	2.665	0.104016
s(lag(inf_avg, 1))	0.9985	0.9985	21.974	5.34e-06 ***
te(lag(inf_avg, 1), lag(ENT_avg, 1))	3.0296	3.4278	13.278	< 2e-16 ***
te(lag(inf_avg, 1), lag(INF_avg, 1))	13.9575	16.0988	4.830	< 2e-16 ***
te(lag(inf_avg, 1), lag(SPC_avg, 1))	7.3075	7.5170	9.306	< 2e-16 ***
te(lag(inf_avg, 1), lag(SPR_avg, 1))	5.2086	6.1420	8.644	< 2e-16 ***
te(lag(inf_avg, 2), lag(ENT_avg, 2))	4.0674	4.7667	12.559	< 2e-16 ***
te(lag(inf_avg, 2), lag(INF_avg, 2))	11.9367	14.0166	5.154	< 2e-16 ***
te(lag(inf_avg, 2), lag(SPC_avg, 2))	3.2567	3.7663	11.047	2.60e-07 ***
te(lag(inf_avg, 2), lag(SPR_avg, 2))	4.4540	4.9609	15.608	< 2e-16 ***

Significance Codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Model Summary:

	Value
Rank	309/314
R-sq.(adj)	0.778

Deviance explained	84.7%
GCV	0.36884
Scale est.	0.25312
n	319

10.5.2. Discussion

The results from Model 5 indicate a substantial improvement in model fit compared to previous models. The adjusted R-squared has increased to 0.778, and the deviance explained is now at 84.7%. These metrics suggest that Model 5 captures a significant portion of the variance in Revenue_log, making it the most robust model in the series. The Generalized Cross-Validation (GCV) score has also decreased to 0.36884, reflecting a better balance between model complexity and predictive accuracy. The enhanced model fit suggests that the incorporation of lagged effects and their interactions has successfully captured the delayed impact of advertising on revenue, which previous models may have overlooked.

In examining the smooth terms, the non-linear relationship between GRP_log and Revenue_log remains complex, as indicated by the effective degrees of freedom (edf) of 5.2396. This complexity suggests that the impact of GRP on revenue is not straightforward and may vary at different levels of GRP. On the other hand, the smooth term for inf_avg shows an edf close to 1, indicating a nearly linear relationship with Revenue_log. This finding contrasts with earlier models where more complex non-linear effects were observed, suggesting that the immediate impact of inf_avg might be more predictable and less variable.

The introduction of lagged effects in Model 5 yields important insights. The first lag of GRP_log was not statistically significant, suggesting that the immediate effect of GRP on revenue does not persist into the following week. This could imply that the influence of advertising exposure, as measured by GRP, is largely confined to the week in which the ads are broadcast. Conversely, the first lag of inf_avg is statistically significant, indicating that the impact of informational ads extends beyond the initial week. This finding aligns with expectations, as informational content may require additional time for consumers to process, leading to delayed purchasing decisions.

The tensor interaction terms for the first and second lags of inf_avg with program categories are all statistically significant, underscoring the importance of the context in which ads are aired. The varying effects across different program categories suggest that the effectiveness of informational ads not only differs by context but also changes over time. These results highlight the nuanced nature of advertising effectiveness, where both the content of the ad and the environment in which it is presented play critical roles in driving consumer behavior.

The residual diagnostics for Model 5 further affirm its robustness. The normal Q-Q plot shows that the residuals are approximately normally distributed, with only slight deviations at the tails, indicating a well-fitted model. The residuals versus fitted values plot shows no obvious patterns, suggesting that heteroscedasticity is not a concern. Moreover, the ACF and PACF plots of residuals indicate that autocorrelation has been adequately addressed, with no significant autocorrelation remaining. These diagnostics confirm that Model 5 successfully overcomes the limitations observed in previous models.

Compared to earlier models, Model 5 represents a significant advancement in capturing the dynamics of advertising effects on revenue. Model 3, which employed an AR(1) correlation structure and a Box-Cox transformation, struggled with residual autocorrelation and heteroscedasticity issues. Model 4, which introduced a log transformation and an ARMA(2,2) structure, improved the fit but still left some variance unexplained, particularly regarding delayed effects. Model 5 builds on these earlier models by explicitly modeling the delayed effects of advertising through lagged variables and their interactions. This approach provides a more nuanced understanding of how advertising works over time and in different contexts, making it the most comprehensive and accurate model to date.

10.6. Model 6: DLM

The Dynamic Linear Model (DLM) was selected as an advanced analytical tool in this thesis to investigate the temporal dynamics of advertising effects on revenue. Unlike traditional regression models, which assume static relationships over time, the DLM offers the flexibility to capture evolving relationships, which is critical given the dynamic nature of consumer behavior and the fluctuating market environment.

In the context of this research, the DLM is particularly valuable due to its ability to model time-varying effects, a key consideration when studying the impact of advertising. Advertising effectiveness can fluctuate over time due to factors such as consumer saturation, shifts in market conditions, or changes in competitive strategies. By allowing the coefficients associated with advertising metrics—such as Gross Rating Points (GRP) and informational ad averages across various program categories—to vary over time, the DLM provides a more accurate and nuanced understanding of these dynamics.

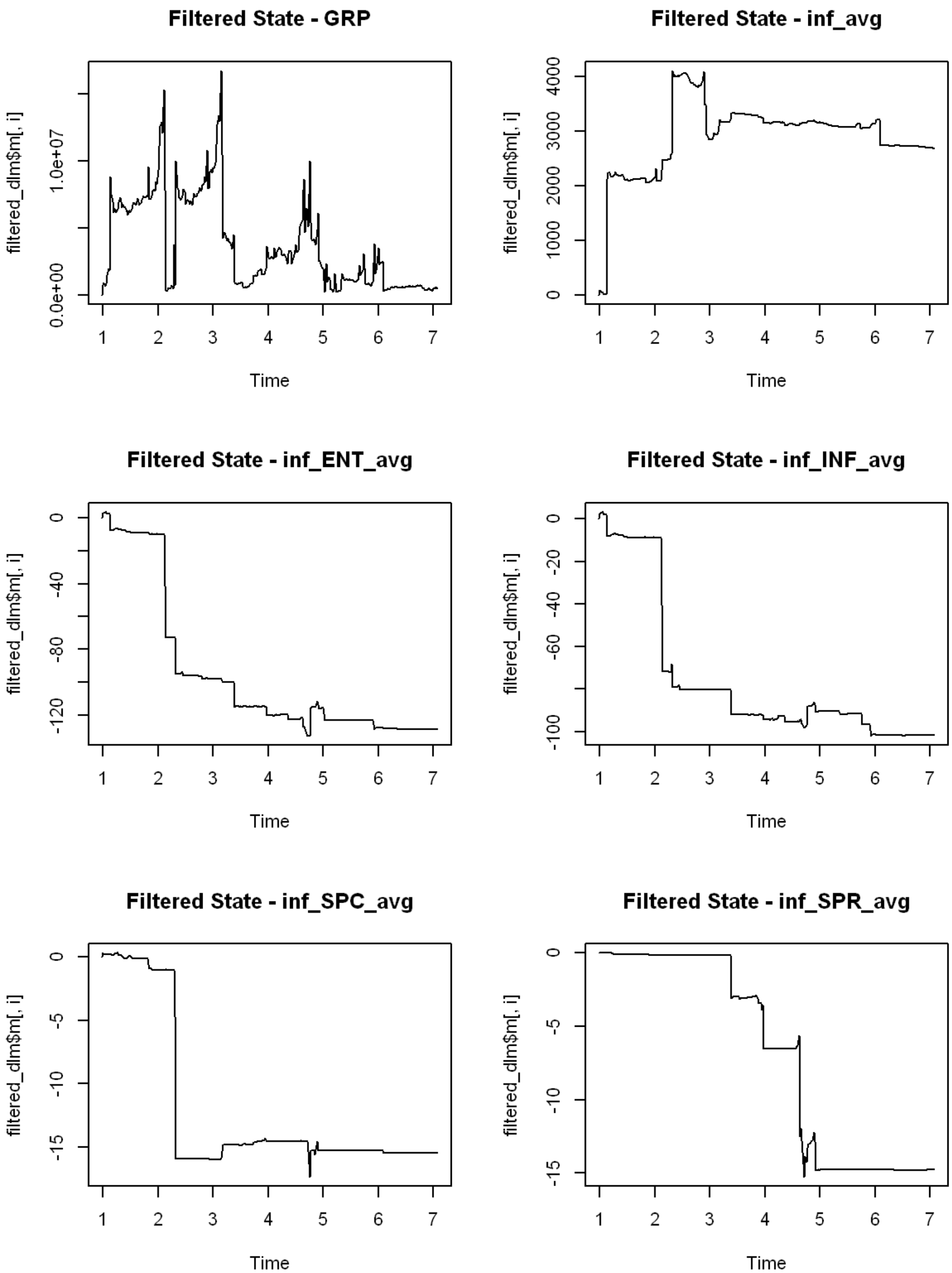
Moreover, the DLM's structure inherently accommodates lagged effects, recognizing that the impact of advertising is not always immediate. For instance, the influence of an advertising campaign may extend over several weeks, a phenomenon that static models might overlook. The inclusion of lagged variables within the DLM framework allows for a more comprehensive analysis, capturing both the immediate and delayed effects of advertising on revenue.

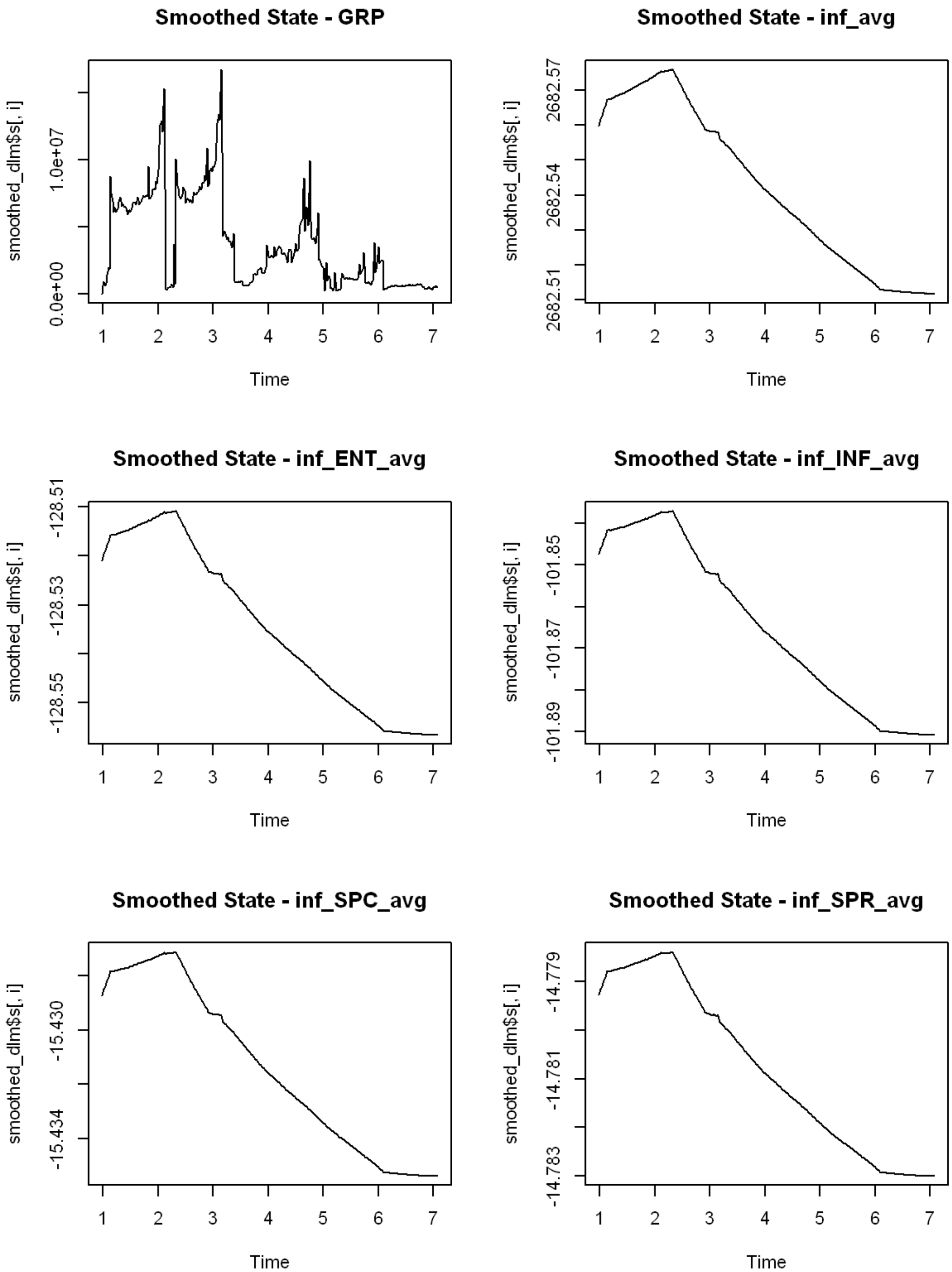
Another advantage of the DLM lies in its capacity to manage multicollinearity and interactions among advertising metrics. In real-world data, advertising activities often interact in complex ways, and traditional models might struggle to disentangle these effects. The state-space representation in DLMs helps mitigate these issues, providing clearer insights into how different types of ads and their combinations influence revenue over time.

The ability of the DLM to handle non-stationarity is also crucial. In dynamic market environments, revenue data often exhibit non-stationary behavior, where statistical properties like mean and variance change over time. The DLM is designed to model such non-stationary processes, making it a robust tool for forecasting and analysis in contexts where traditional models might fail.

In Model 6, the DLM was specified with a local level component and multiple regressors, including GRP and average informational ad metrics across different program categories—Entertainment, Informational, Special, and Sports. This specification allows the model to dynamically assess the impact of each type of advertising on revenue, considering both immediate and delayed effects, while also accounting for the potential interactions and multicollinearity among the predictors.

10.6.1. Results




Smoothed State - GRP
smoothed_dlm$s[, i]
0.0e+00
1.0e+07
Time
Smoothed State - inf_avg
2682.51
2682.54
2682.57
Time
Smoothed State - inf_ENT_avg
-128.51
-128.53
-128.55
Time
Smoothed State - inf_INF_avg
-101.85
-101.87
-101.89
Time
Smoothed State - inf_SPC_avg
-15.430
-15.434
Time
Smoothed State - inf_SPR_avg
-14.779
-14.781
-14.783
Time

10.6.2. Discussion

The application of the DLM to the data provided significant insights into the dynamics of advertising effects on revenue. The results indicate that the influence of GRP on revenue fluctuates considerably over time, with marked peaks corresponding to periods of intense advertising campaigns. These peaks suggest that GRP's impact is most pronounced during these concentrated advertising efforts but diminishes during off-peak periods. The smoothed states from the DLM also reveal a general downward trend in the long-term effectiveness of GRP, potentially indicating that sustained high levels of GRP may lead to diminishing returns.

The analysis of informational ads across different program categories yielded mixed results. For informational ads within the Entertainment and Special programming categories, the DLM initially detected strong positive effects on revenue. However, over time, these effects began to plateau and, in some cases, declined, as seen in the smoothed states. This pattern suggests that while these ads were initially effective, their impact has waned, likely due to audience saturation or a lack of novelty in the advertising content.

Conversely, the effectiveness of informational ads within the Informational and Sports programming categories showed a consistent decline throughout the study period. This trend may indicate that the audience for these categories has become desensitized to informational ads or that the ads are failing to engage viewers effectively. The observed decline underscores the need for a reassessment of advertising strategies in these categories, potentially calling for a shift towards more engaging or varied content.

The inclusion of lagged variables in the model highlighted the extended influence of advertising activities on revenue. The findings show that the impact of GRP and certain informational ads persists for one to two weeks after the initial exposure, albeit with diminishing intensity. This delayed effect emphasizes the importance of sustaining advertising efforts over time to maximize their cumulative impact on revenue.

The implications of these findings are significant for marketing strategy. The dynamic changes in advertising effectiveness suggest that a static approach to ad planning is suboptimal. Instead, marketers should consider adopting a dynamic strategy that adjusts advertising intensity and content based on real-time feedback and evolving market conditions. This approach could enhance return on investment by aligning advertising efforts with periods of higher responsiveness.

Furthermore, the decline in the effectiveness of informational ads in certain categories points to the need for content diversification. Marketers should explore new ad formats or creative approaches, particularly in categories where the audience appears to be experiencing ad fatigue. For example, integrating more emotional appeals or interactive elements might help reinvigorate the impact of ads in these segments.

The identified lagged effects also suggest that advertising campaigns should be planned with a longer-term perspective, ensuring that their impact is sustained over multiple weeks. This could involve staggered ad releases or continuous engagement strategies to maintain audience interest and maximize revenue impact.

11. Limitations and Further Research

This study, while comprehensive, is not without its limitations. Firstly, the scope of the analysis is constrained by the availability of data, particularly the reliance on NielsenIQ Retail Measurement Services (RMS) and Nielsen AdIntel datasets. These datasets, while robust, are limited to the general merchandise department and specific time frames. The generalizability of the findings to other product categories or time periods may be limited. Additionally, the complexity of the data integration process, especially in matching brand names across datasets, introduces potential inaccuracies despite the implementation of advanced string-matching techniques.

Secondly, the study's focus on the interaction between advertisement types (informational vs. emotional) and program categories is novel but also somewhat reductionist. The categorization of ads into strictly informational or emotional types may overlook the nuanced and often overlapping nature of advertising content. Furthermore, the classification of television programs into broader categories may not fully capture the diversity of viewer engagement and program content.

Another significant limitation is related to the econometric models employed. While the use of Linear Models, Lagged Linear Models, Generalized Least Squares (GLS) with ARMA correlation structures, and Dynamic Linear Models (DLM) provides a robust framework for analysis, these models are subject to the assumptions of normality, linearity, and homoscedasticity. Despite the use of Box-Cox transformations to address some of these issues, the models may still be prone to specification errors or omitted variable biases, particularly given the complexity of consumer behavior and advertising effectiveness.

Finally, the study's approach to handling autocorrelation and heteroscedasticity, while methodologically sound, may not fully account for the dynamic nature of advertising effects, particularly in the presence of external factors such as economic conditions, competitive actions, and consumer trends that were not explicitly modeled. The potential for endogeneity, where ad spending could be influenced by anticipated sales, also remains a concern that could affect the validity of the causal inferences drawn.

Given these limitations, there are several avenues for future research. Firstly, expanding the dataset to include other product categories and time periods would enhance the generalizability of the findings. Additionally, integrating other forms of media, such as digital and social media advertising, could provide a more holistic view of the advertising landscape and its impact on sales.

Future research could also benefit from a more granular approach to categorizing advertisements and television programs. For instance, employing machine learning techniques to classify ads based on content analysis or using viewer engagement metrics to refine program categories could yield more precise insights into the interaction effects studied here.

Moreover, there is potential to explore the long-term effects of advertising by extending the time horizon of the analysis. Incorporating more sophisticated models, such as Vector Autoregression (VAR) or machine learning-based predictive models, could help capture the dynamic interplay between advertising and sales over time.

Finally, addressing the issue of endogeneity more explicitly, perhaps through instrumental variable techniques or natural experiments, would strengthen the causal claims of future studies. This could be particularly valuable in disentangling the complex relationships between ad spending, program context, and sales performance.

In summary, while this study contributes to the understanding of the interaction between ad content and program context, future research should aim to broaden the scope, refine the methodologies, and deepen the analysis to further illuminate the complex dynamics of advertising effectiveness.

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The analyses, conclusions, and interpretations drawn from the NielsenIQ and Nielsen data are solely those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing or preparing the results reported herein.

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13. References

Assael, H. (2011). From silos to synergy. *Journal of Advertising Research, 51*(1 50th Anniversary Supplement), 42–58. https://doi.org/10.2501/jar-51-1-042-058

Becker, M., & Gijsenberg, M. (2023). Consistency and commonality in advertising content: Helping or Hurting? *International Journal of Research in Marketing, 40*(1), 128–145. https://doi.org/10.1016/j.ijresmar.2022.05.004

Bellman, S., Robinson, J. A., Wooley, B., & Varan, D. (2017). The effects of social TV on television advertising effectiveness. Journal of Marketing Communications, 23(1), 73–91. https://doi-org.proxy.library.brocku.ca/10.1080/13527266.2014.921637

Batailler, C., Brannon, S. M., Teas, P. E., & Gawronski, B. (2022). A Signal Detection Approach to Understanding the Identification of Fake News. Perspectives on Psychological Science, 17(1), 78-98. https://doi.org/10.1177/1745691620986135

Batra, R., & Keller, K. L. (2016). Integrating marketing communications: New findings, new lessons, and new ideas. *Journal of Marketing, 80*(6), 122-145. https://doi.org/10.1509/jm.15.0419

Becker, M., & Gijsenberg, M. J. (2023). Consistency and commonality in advertising content: Helping or hurting? International Journal of Research in Marketing, 40(1), 128-145. https://doi.org/10.1016/j.ijresmar.2022.05.004

Becker, M., Scholdra, T. P., & Reinartz, W. J. (2022). The effect of content on zapping in TV advertising. *Journal of Marketing, 87*(2). https://doi.org/10.1177/00222429221105818

Bellman, S., Wooley, B., & Varan, D. (2015). Program–ad matching and television ad effectiveness: A reinquiry using facial tracking software. Journal of Advertising, 45(1), 72-77. https://doi.org/10.1080/00913367.2015.1085816

Berger, J., & Milkman, K. L. (2012). What makes online content viral? *Journal of Marketing Research, 49*(2), 192-205. https://doi.org/10.1509/jmr.10.0353

Brock, T. C., & Green, M. C. (2005). Persuasion: psychological insights and perspectives (2nd ed.). Sage Publications.

Bruce, N. I., Becker, M., & Reinartz, W. (2020). Communicating brands in television advertising. *Journal of Marketing Research, 57*(2). https://doi.org/10.1177/0022243719892576

Cacioppo, J. T. & Petty, R. E. (1986). The Elaboration Likelihood Model of Persuasion. In Advances in Experimental Social Psychology (Vol. 19, pp. 123–205). Elsevier Science & Technology. https://doi.org/10.1016/S0065-2601(08)60214-2

Cacioppo, J. T., & Petty, R. E. (1989). Effects of message Repetition on Argument Processing, Recall, and Persuasion. Basic and Applied Social Psychology, 10(1), 3–12. https://doi-org.proxy.library.brocku.ca/10.1207/s15324834basp1001_2

Calder, B.J. and Malthouse, E.C. (2012). Media Engagement and Advertising Effectiveness. In Kellogg on Advertising & Media, B.J. Calder (Ed.). https://doi-org.proxy.library.brocku.ca/10.1002/9781119198154.ch1

Chen, S., & Lamberti, L. (2016). Multichannel marketing: The operational construct and firms' motivation to adopt. Journal of Strategic Marketing, 24(7), 594–616. https://doi-org.proxy.library.brocku.ca/10.1080/0965254X.2016.1148759

Dahlen, M., Lange, F., & Smith, T. (2010). Marketing Communications: A Brand Narrative Approach. John Wiley & Sons.

Dall'Olio, F., & Vakratsas, D. (2023). The Impact of Advertising Creative Strategy on Advertising Elasticity. Journal of Marketing, 87(1), 26–44. https://doi.org/10.1177/00222429221074960

De Angelis, M., Bonezzi, A., Peluso, A. M., Rucker, D. D., & Costabile, M. (2012). On braggarts and gossips: A self-enhancement account of word-of-mouth generation and transmission. *Journal of Marketing Research, 49*(4), 551-563. https://doi.org/10.1509/jmr.11.0136

Dekimpe, M.G., Franses, P.H., Hanssens, D.M., Naik, P.A. (2008). Time-Series Models in Marketing. In: Wierenga, B. (eds) Handbook of Marketing Decision Models. International Series in Operations Research & Management Science, vol 121. Springer, Boston, MA. https://doi.org/10.1007/978-0-387-78213-3_11

Dens, N., De Pelsmacker, P., Goos, P., Aleksandrovs, L., & Martens, D. (2018). How consumers' media usage creates synergy in advertising campaigns. *International*

Journal of Market Research, *60*(3), 268–287. https://doi.org/10.1177/1470785317751333

Dong, X., Chang, Y. P., Liang, S., & Fan, X. (2018). How online media synergy influences consumers' purchase intention. *Internet Research*, *28*(4), 946–964. https://doi.org/10.1108/intr-08-2017-0298

Guitart, I. A., & Stremersch, S. (2020). The impact of informational and emotional television ad content on online search and sales. *Journal of Marketing Research*, 58(2). https://doi.org/10.1177/0022243720962505

Hartnett, N., Kennedy, R., Sharp, B., & Greenacre, L. (2015). Creative That Sells: How advertising execution Affects sales. *Journal of Advertising*, *45*(1), 102–112. https://doi.org/10.1080/00913367.2015.1077491

Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1993). Emotional Contagion. Current Directions in Psychological Science, 2(3), 96-100. https://doi.org/10.1111/1467-8721.ep10770953

Huang, C. (2020). A meta-analysis of the problematic social media use and mental health. *International Journal of Social Psychiatry*, *68*(1), 12–33. https://doi.org/10.1177/0020764020978434

Jing, W., & Calder, B. J. (2009). Media engagement and advertising: Transportation, matching, transference and intrusion. *Journal of Consumer Psychology*, *19*(3), 546–555. https://doi.org/10.1016/j.jcps.2009.05.005

Kalyanaraman, S., & Sundar, S. S. (2006). The psychological appeal of personalized content in web portals: Does customization affect attitudes and behavior? Journal of Communication, 56(1), 110–132. https://doi.org/10.1111/j.1460-2466.2006.tb01915.x

Keller, K. (2002). Branding and brand equity. In Handbook of Marketing (pp. 151-178). SAGE Publications Ltd, https://doi.org/10.4135/9781848608283

Kolsarici, C., & Vakratsas, D. (2018). Synergistic, Antagonistic, and Asymmetric Media Interactions. Journal of Advertising, 47(3), 282–300. https://doi.org/10.1080/00913367.2018.1471757

Kolsarici, C., Vakratsas, D., & Naik, P. A. (2020). The Anatomy of the Advertising Budget Decision: How Analytics and Heuristics Drive Sales Performance. Journal of Marketing Research, 57(3), 468–488. https://doi.org/10.1177/0022243720907578

Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R., & Kannan, P. K. (2016). From Social to Sale: The Effects of Firm-Generated Content in Social Media on Customer Behavior. Journal of Marketing, 80(1), 7-25. https://doi-org.proxy.library.brocku.ca/10.1509/jm.14.0249

Lee, M., & Kim, Y.-K. (2018). Comparative advertising effectiveness: The role of involvement and source credibility in a new market context. Journal of Business Research, 91(C), 1–9.

Lee, S., Kim, K., & Sundar, S. S. (2015). Customization in mobile app advertising: Effects of content interactivity and device type on ad response. Computers in Human Behavior, 50, 20-26.

Lobschat, L., Osinga, E. C., & Reinartz, W. J. (2017). What happens online stays online? Segment-specific online and offline effects of banner advertisements. Journal of Marketing Research, 54(6), 901–913. https://doi-org.proxy.library.brocku.ca/10.1509/jmr.14.0625

Lopez, S. J., Edwards, L. M., & Marques, S. C. (Eds.). (2016). The Oxford handbook of positive psychology (3rd edition.). Oxford University Press.

Mafael, A., Raithel, S., Taylor, C. R., & Stewart, D. W. (2021). Measuring the Role of Uniqueness and Consistency to Develop Effective Advertising1. Journal of Advertising, 50(4), 494–504. https://doi.org/10.1080/00913367.2021.1883488

Martin, W. W., & Rovira, M. (1981). Signal Detection Theory: Its Implications for Social Psychology. Personality and Social Psychology Bulletin, 7(2), 232-239. https://doi.org/10.1177/014616728172008

Mehta, N., Chen, X., & Narasimhan, O. (2008). Informing, transforming, and persuading: disentangling the multiple effects of advertising on brand choice decisions. Marketing Science, 27(3), 334–355. https://doi.org/10.1287/mksc.1070.0310

Naik, P. A., & Raman, K. (2003). Understanding the impact of synergy in multimedia communications. *Journal of Marketing Research*, *40*(4), 375–388. https://doi.org/10.1509/jmkr.40.4.375.19385

Pratkanis, A.R., Breckler, S.J., & Greenwald, A.G. (Eds.). (1989). Attitude Structure and Function (1st ed.). Psychology Press.

Shapiro, B. T., Hitsch, G. J., & Tuchman, A. E. (2021). TV advertising effectiveness and profitability: Generalizable results from 288 brands. *SSRN*. https://ssrn.com/abstract=3273476

Sherman, J. W., Gawronski, B., & Trope, Y. (Eds.). (2014). *Dual-process theories of the social mind*. Guilford Publications.

Steele, A., Jacobs, D., Siefert, C. J., Rule, R. R., Levine, B. N., & Marci, C. D. (2013). Leveraging synergy and emotion in a Multi-Platform world. *Journal of Advertising Research, 53*(4), 417–430. https://doi.org/10.2501/jar-53-4-417-430

van Berlo, Z. M. C., Meijers, M. H. C., Eelen, J., Voorveld, H. A. M., & Eisend, M. (2024). When the medium is the message: A meta-analysis of creative media advertising effects. *Journal of Advertising, 53*(2), 278-295. https://doi.org/10.1080/00913367.2023.2186986

van Reijmersdal, E., Smit, E., & Neijens, P. (2010). How media factors affect audience responses to brand placement. *International Journal of Advertising, 29*(2), 279-301. https://doi.org/10.2501/S0265048710201154

Voorveld, H. A. M. (2019). Brand Communication in Social Media: A Research Agenda. *Journal of Advertising, 48*(1), 14–26. https://doi-org.proxy.library.brocku.ca/10.1080/00913367.2019.1588808

Williams, J., Hartnett, N., & Trinh, G. (2022). Finding creative drivers of advertising effectiveness with modern data analysis. *International Journal of Market Research, 65*(4), 423-447. https://doi.org/10.1177/14707853221134258

Yoo, C., & MacInnis, D. (2005). The brand attitude formation process of emotional and informational ads[12]. *Journal of Business Research, 58*(10), 1397-1406. https://doi.org/10.1016/j.jbusres.2005.03.011

Young, C., Gillespie, B., & Otto, C. (2019). The Impact of Rational, Emotional, And Physiological Advertising Images on Purchase Intention: How TV Ads Influence

Brand Memory. *Journal of Advertising Research, 59*(3), 329–341.
https://doi.org/10.2501/JAR-2019-010