Evaluating the Impact of Television Advertising on Quick Service Restaurant Visits: A Causal Analysis Using DMA Border Strategy

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1. Introduction

The impact of television advertising on consumer behavior has been a subject of extensive research across various industries. However, the effectiveness of such ads, particularly in driving physical store visits, remains a complex and nuanced area of study. This paper seeks to contribute to this ongoing discussion by focusing on the Quick Service Restaurant (QSR) industry, a sector where consumer behavior is directly tied to in-person visits, with limited online-shopping options. Unlike other consumer goods industries, where advertisements may influence purchases across multiple retail outlets, QSR ads are uniquely positioned to drive traffic to specific restaurant locations. This distinct characteristic makes the QSR industry an ideal context for studying the causal effects of TV advertisements on consumer visits.

The core objective of this research is to analyze how TV advertisements influence foot traffic (visit) to QSR POI (Point of Interest, i.e. store locations) using a DMA (Designated Market Area) border strategy. The DMA borders, determined by Nielsen Company, create natural advertising discontinuities between neighboring counties, where populations are similar in demographics and live in similar geography but are exposed to different advertisements due to their placement in different DMAs. This setup offers a quasi-experimental design that allows for robust causal inference, as we can compare the behavior of consumers in bordering counties who are subjected to varying levels and brands of advertisement exposure.

This study is particularly relevant given the growing importance of data-driven marketing strategies in the QSR industry. With the increasing availability of granular data on consumer behavior and advertising exposure, marketers could tailor their campaigns better to maximize impact. However, the challenge remains in understanding which specific aspects of advertisement videos are most effective in driving desired outcomes, such as increased visits to physical locations.

To address this challenge, our research utilizes data from the Vivvix TV advertisement tracking platform, which provides detailed information on TV ads aired for QSR brands, including the number and cost of ads and airing times. This data is complemented by visit data from the Advan dataset, which tracks consumer visits to QSR locations using cell phone PINs. By integrating these datasets, we can map TV ad exposure to subsequent consumer behavior, offering insights into the effectiveness of different advertising strategies.

Our empirical strategy involves a fixed effects model that controls for firm(brand)-border-time and firm(brand)-county effects, allowing us to isolate the impact of TV advertisements on consumer visits. Preliminary results indicate a positive relationship between the number of ads and consumer visits, with a 0.18 lift in visits observed on average. However, further analysis reveals significant heterogeneity across different QSR brands, with some brands experiencing stronger positive effects and others showing negative or non-significant results.

Moreover, by examining the specific ad creatives (ad videos), we identify that certain features within the ads are more effective in driving consumer behavior. Using machine learning techniques such as visual feature extractions and XGBoost, we explore how different visual and content-related elements contribute to the overall effectiveness of an ad. These findings suggest that not all ads are created equal, and that the content and design of an ad creative can significantly influence its impact on consumer visits.

In summary, this paper aims to shed light on the complex dynamics of TV advertising in the QSR industry, attempting to offer both theories validations and creations in the field of marketing and practical insights for industry practitioners. By leveraging a robust empirical strategy and data analytics, we aim to provide a comprehensive analysis of how TV ads drive consumer behavior.

In the following sections, we will detail the literature review, empirical strategy, data preparation, preliminary results, and the implications of our findings.

2. Literature Review

The literature review for this study is divided into two primary sections. The first section provides a broad overview of the existing literature on the analysis of TV ads and video content, with a particular focus on the empirical methodologies employed to assess their impact. The second section delves into specific TV ad features relevant to building recommendation or prediction systems, providing a detailed discussion of how various elements of video content can influence consumer behavior and ad effectiveness.

2.1. General Analysis of TV Ads and Video Content

2.1.1 DMA-Border Strategy in TV Ad Analysis

The DMA-border empirical strategy is a crucial methodological tool in analyzing the causal effects of TV ads. This strategy leverages the natural discontinuities at the borders of Designated Market Areas (DMAs), allowing researchers to isolate the effects of TV ads by controlling for various confounders related to the brand, advertisement, time, and geographic area. This approach is particularly valuable in overcoming the challenges posed by endogenous factors such as ad spending rates and fundraising activities, as demonstrated in the work by Wang, Lewis, and Schweidel (2018) [11]. Although their focus was on political ads, the methodological insights are directly applicable to our analysis of Quick Service Restaurant (QSR) brands, where we aim to assess the impact of TV ads on foot traffic.

In their study, Wang et al. (2018) [11] explored the effectiveness of political ads on vote shares and voter turnout by exploiting the advertising discontinuities along DMA borders. Their findings highlighted that negative ads sponsored by candidates were more effective in increasing vote shares than those sponsored by Political Action Committees (PACs), underscoring the nuanced effects of ad sponsorship on political outcomes. While our study differs in context, where we focus on QSR brands rather than political campaigns, the DMA-border strategy remains a powerful and popular tool for causal inference in TV ad effectiveness studies.

Similarly, the work by Shapiro, Hitsch, and Tuchman (2021) [9] extended the use of the DMA-border strategy to analyze the return on investment (ROI) of TV advertising for a wide range of consumer packaged goods (CPG) brands. Their findings, which revealed a significant over-investment in TV advertising by most brands, are particularly relevant to our study. Although the CPG industry differs from the QSR sector, both industries share the commonality of relying heavily on TV ads to drive consumer behavior. Our study aims to build on this work by applying the DMA-border strategy to the QSR industry, focusing on different outcomes, specifically visit volumes, using unique datasets at the video-day/week-county level.

2.2. TV Ad Features in Prediction and Recommendation Systems

The second part of this literature review shifts focus to the specific features of TV ads that are crucial for building effective prediction and recommendation systems. Recent studies have demonstrated the value of analyzing video content and ad features to predict consumer responses and optimize ad targeting.

2.2.1 Temporal Analysis of Video Content

Zhang, Wang, and Chen (2020) [14] introduced the concept of in-consumption social listening, highlighting the importance of temporal variations in video content and consumer engagement. Their study, which analyzed live comments during online movie watching, demonstrated that temporal synchronicity between content variations and viewer reactions could predict post-consumption appreciation. This finding is relevant to our study as it underscores the potential of analyzing temporal patterns in TV ads—such as scene cuts, transcript content, and viewer engagement metrics—to predict consumer behavior, such as foot traffic to QSR locations.

2.2.2 Product Engagement and Ad Effectiveness

In their forthcoming paper, Yang, Zhang, and Zhang [13] developed a novel metric called the Product Engagement Score (PE-score) to measure the effectiveness of influencer video advertising. By training a deep learning model to analyze pixel-level engagement with products in videos, they were able to predict sales lift associated with the ads. While their study focused on short-form videos on platforms like TikTok, the underlying principle of assessing product engagement is highly applicable to TV ads. Our study could similarly benefit from evaluating how different ad features—such as the number of scene cuts or the clarity of the product presentation—affect consumer visits to QSR locations.

2.2.3 Personalized Ad Recommendations

Xiao, Wu, and Ding (2024) [12] proposed a smart ad display system that uses real-time facial expression and eye gaze tracking to personalize video ad delivery. Their system links consumer responses to specific visual elements in the ad, enabling more targeted and effective ad recommendations. This approach, while developed in a lab setting, offers valuable insights for our study, particularly in understanding how consumer reactions to specific ad features might influence their likelihood of visiting a QSR after viewing the ad.

2.2.4 Content Factors Affecting Ad Avoidance

The study by Becker et al. (2023) [1] on ad zapping behavior provides another critical perspective by exploring how ad content influences the likelihood of consumers actively avoiding ads. They found that ad creativity reduces zapping, while an early integration of branding elements increases it. Although our study focuses on foot traffic rather than zapping, understanding the factors that lead to ad avoidance can inform our analysis of which ad features drive or deter consumer visits to QSRs.

2.2.5 Informational vs. Emotional Content

Guitart and Stremersch (2021) [5] analyzed the effects of informational and emotional content in TV ads on consumer behavior, particularly online searches and sales. Their findings suggested that while emotional content generally drives more online searches, both informational and emotional content positively impact sales, albeit in different ways depending on the product category. This distinction between informational and emotional content is crucial for our study, as it can guide the selection of ad features that are likely to resonate most with QSR consumers.

2.2.6 Visual Elements in Ad Effectiveness

Finally, studies such as those by Lu et al. (2016) [6] and Pan (2011) [7] emphasize the importance of visual elements in ads. Lu et al. (2016) [6] developed a video-based automated recommender system for garments that used visual cues to predict consumer preferences, while Pan (2011) [7] explored how visual elements in tourism TV commercials influenced destination image formation. These insights highlight the potential of using visual elements—such as scene composition, color schemes, and object prominence—to predict the effectiveness of QSR ads in driving foot traffic.

3. Empirical Strategy - DMA Border Analysis

3.1 Introduction to DMA Border Strategy

The Designated Marketing Area (DMA) border strategy is a robust empirical tool employed to assess the effectiveness of TV advertisements. This approach leverages the natural advertising discontinuities created by DMA borders, which are created by Nielsen Company, the entity responsible for managing TV advertisement airing in the United States. Each

DMA represents a specific geographic region, mostly consist of counties, where the local TV stations broadcast their content. The borders between these DMAs create a unique setting where neighboring counties, despite being demographically and geographically similar, are exposed to different sets of advertisements due to their placement in different DMAs.

This discrepancy in ad exposure across DMA borders allows us to construct a quasi-experimental design. By comparing the outcomes, such as visit volumes, of populations residing on either side of the DMA border, we can isolate the causal impact of advertising. This method has been widely used in previous research, particularly in studies examining political campaigns, where ads for different parties might be broadcasted on either side of a DMA border. The underlying principle is that, while the populations on either side of the border are similar, the variation in ad exposure, especially in different political parties, serves as the treatment effect that can be analyzed.

Figure 1. Illustration of Atlanta–Macon DMA Border in Georgia

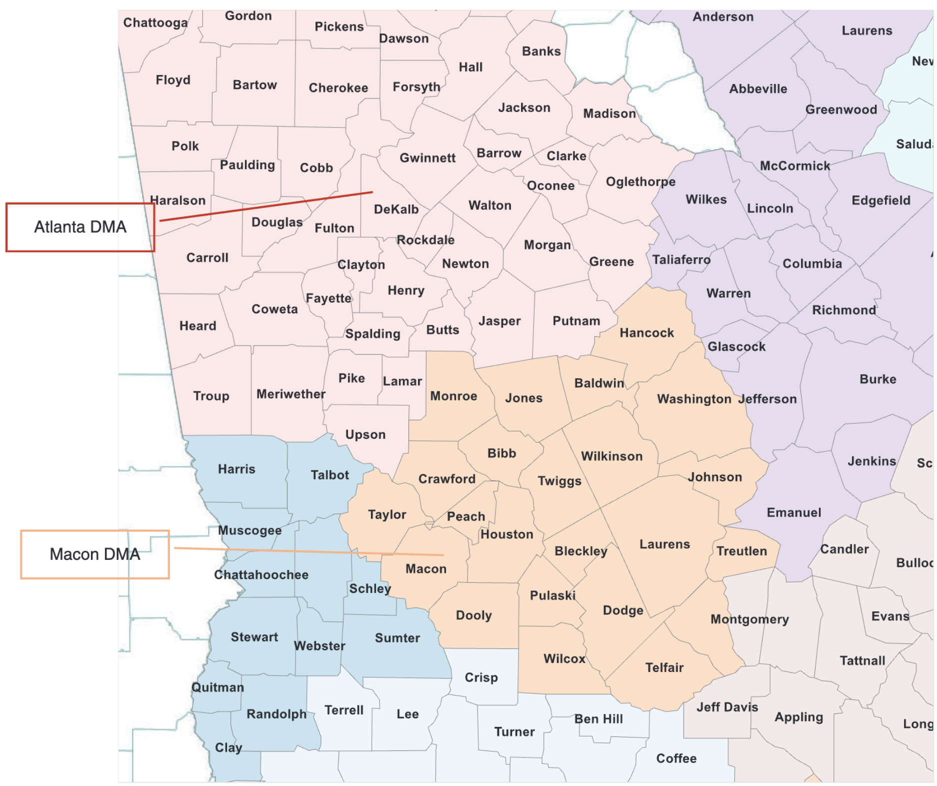


Figure 1: DMA Borders in Georgia, by Wang et al. (2018)

In our study, we apply this strategy to analyze the effectiveness of TV ads for around 150 Quick Service Restaurant (QSR) brands. For example, the Atlanta DMA (shown in pink) might broadcast 3 McDonald's ads, while the neighboring Macon DMA (shown in orange) might broadcast 5 McDonald's ads. By examining the counties that lie along these borders—such as Jasper County in the Atlanta DMA and its neighboring county Jones in the Macon DMA—we can compare the effectiveness of these advertisements in driving foot traffic to QSR locations. In addition, we will assign a unique DMA border to each county. For example, Jasper and Jones will share the Atlanta-Macon DMA border. If a county has multiple borders, such as Upson (in Pink) neighboring two DMAs (in Blue and Orange), we will randomly assign a unique border to it.

3.2 Data Utilization and Sample Selection

Our Advan Foot Traffic dataset includes a comprehensive list of QSR POI locations (latitude and longitude) across the United States, with half of these located in the DMA bordering counties. The DMA-border strategy allows us to utilize around half of our available shops, after removing GU (Guam), HI (Hawaii), AK (Alaska), PR (Puerto Rico) and VI (U.S. Virgin Islands). Further processing details will be discussed in section 4, Data Collection and Preparation.

This natural experiment setting enables us to compare the advertising effectiveness in border counties, where the population and other external factors (such as weather or economic conditions) are similar, yet the ad exposure varies due to the DMA assignment. This approach maximizes the use of our dataset, allowing for a robust analysis of the impact of TV ads on QSR visit volumes and spending patterns.

3.3 Model Specifications and Fixed Effects

Our empirical model incorporates two primary fixed effects to capture the impact of TV ads: (1) firm-border-time fixed effects and (2) firm-county fixed effects. These fixed effects are essential for controlling various unobserved factors that could influence the outcomes. The full model specification is as follows:

$$y_{f,c,t} = \beta_{f,b,t} + \beta_{f,c} + \beta_1 \cdot x_{f,c,t} + \epsilon_{f,c,t}$$

Where:

- $y_{f,c,t}$ represents the VISIT outcomes of customer shopping for firm f in county c at time t.
- $\beta_{f,b,t}$ is the firm-border-time specific fixed effect, explained in Section 3.3.1.
- $\beta_{f,c}$ is the firm-county specific fixed effect, explained in Section 3.3.2.
- $x_{f,c,t}$ represents the advertisement treatment for firm f in county c at time t, which could either be a scalar or a more detailed summation of specific ad creatives, as discussed in Section 3.3.3.
- $\epsilon_{f,c,t}$ is the error term, capturing unobserved factors not explained by the fixed effects or treatment.

The following subsections provide detailed explanations of each component of the model:

3.3.1 Firm-Border-Time Fixed Effects

The firm-border-time fixed effects, denoted as $\beta_{f,b,t}$, control for the influence of a specific QSR brand within a given DMA border during a specific time period. This allows us to isolate the effect of a particular brand's advertisements within the context of a specific border region across different time periods.

For example, consider McDonald's advertisements aired along the Atlanta-Macon border during a specific week in 2023. By fixing the firm (McDonald's), the border (Atlanta-Macon), and the time (a specific week), we can capture the unique impact of McDonald's ads on consumer behavior in this particular border region. This approach allows us to determine how effective McDonald's ads are in driving foot traffic within the counties that lie along the DMA border.

This fixed effect ensures that we account for any temporal changes in the brand's advertising strategy, the weather, as well as regional differences, such as overall ad exposure volume and economic status, due to the DMA border. By controlling for these factors, we can more accurately assess the differential impact of McDonald's (or any other QSR brand) ads on consumer outcomes within the border regions.

3.3.2 Firm-County Fixed Effects

The firm-county fixed effects, denoted as $\beta_{f,c}$, control for the influence of specific QSR brands within each county. This allows us to account for any unobserved factors that are specific to the interaction between a brand and a county, such as the number of QSR locations, local brand loyalty, or county-specific economic conditions.

For example, McDonald's might have more locations or a stronger brand presence in one county compared to another, which could influence the effectiveness of its TV advertisements. By including firm-county fixed effects, we ensure that our analysis accurately captures these local variations, isolating the effect of TV ads on consumer visits.

3.3.3 Treatment and Outcome Variables

The primary outcome variables in our analysis are the number of visits at QSR locations during each week.

The treatment variable, $x_{f,c,t}$, represents the advertisement treatment for firm f in county c during time t. This can be represented in two ways:

- **Scalar Case:** When $x_{f,c,t}$ is treated as a scalar, it represents the total number of ads aired for firm f in county c during time t. In this case, β_1 is a scalar coefficient that captures the overall effect of the total number of ads on the visit outcomes. This approach allows us to measure the general impact of ad exposure on consumer behavior across the entire set of ads aired.

- **Vector Case as Summation:** In more detailed analyses, $x_{f,c,t}$ can be expressed as a summation of specific ad creatives. In this case, the model is written as:

$$y_{f,c,t} = \beta_{f,b,t} + \beta_{f,c} + \sum_{k=1}^{K} \beta_1^{(k)} x_{f,c,t}^{(k)} + \epsilon_{f,c,t}$$

Here, each element $x_{f,c,t}^{(k)}$ represents the number of times a specific ad creative k for firm f was aired in county c during time t, and each $\beta_1^{(k)}$ represents the effect of that specific ad creative on the visit outcomes.

This summation approach allows us to analyze the differential impact of each creative on consumer behavior, providing a more nuanced understanding of how various ad elements contribute to driving visits or spending.

By using both the scalar form and the summation representation of the vector case, our analysis can capture a broad range of advertising impacts, from aggregate effects to more granular insights into the performance of individual ad creatives.

3.4 Conclusion of the Empirical Strategy

The DMA border strategy, combined with the fixed effects model, provides a powerful framework for analyzing the effectiveness of TV ads in driving QSR visits. By controlling for local variations and using the natural experiment setting created by DMA borders, we can isolate the impact of the ads and provide robust insights into the causal relationship between TV ad exposure and consumer behavior. This approach not only leverages the strengths of our dataset but also builds on the existing literature that has successfully employed similar strategies in other contexts.

4. Data Collection and Preparation

4.1 Selection of the Quick Service Restaurant (QSR) Industry

The decision to focus on the Quick Service Restaurant (QSR) industry is driven by two key considerations.

First, our outcome variable is consumer visits, which requires an industry where customers primarily visit physical locations to obtain the product. Unlike other retail sectors where online shopping plays a significant role, online shopping options for QSRs are naturally limited, with the exception of delivery platforms such as Ubereats and Grubhub. This makes QSRs an ideal choice, as the data will primarily reflect in-person visits, aligning directly with our research objectives.

Second, focusing on QSRs helps minimize confounding factors related to cross-retailer purchases. For instance, in industries such as grocery stores, advertisements for a specific product (e.g. Coca-Cola) might lead consumers to purchase that product at various retail outlets, making it challenging to attribute store visits directly to the advertisement. In contrast, a QSR advertisement is more likely to result in a visit to a specific restaurant location, providing a clearer link between the ad and consumer behavior.

Additionally, our choice is reinforced by the robustness of the data available from the Vivvix platform, which extensively tracks QSR brands, particularly McDonald's. This platform's detailed and comprehensive tracking of TV advertisements for QSRs ensures that we have high-quality data for our analysis.

4.2 Overview of the Vivvix TV Advertisement Tracking Platform

The Vivvix TV advertisement tracking platform is a critical data source for this study, providing detailed information on TV ads aired for QSR brands. The platform tracks around 400 brand advertisers in the QSR industry, of which approximately 200 are active. Each advertisement is identified by a unique creative name and is associated with specific airing times, allowing us to match the raw video files with their corresponding broadcast times.

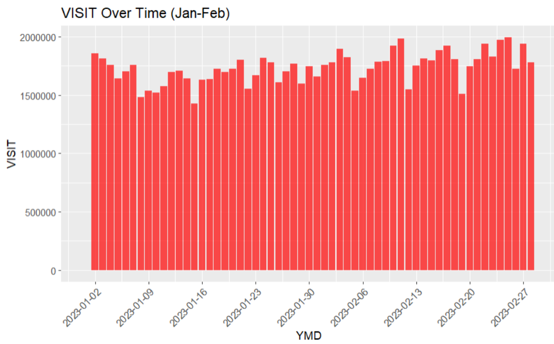
Vivvix also provides data at multiple levels. Advertisements can be classified as either national (covering the entire U.S.) or local, identified by specific DMAs, which are crucial for our analysis. Each advertisement entry includes its length in seconds, the cost of the ad, and the airing time to the precision of seconds, providing valuable metrics for assessing the intensity and investment in each campaign.

This granular data allows us to accurately map TV advertisements to their respective airings time (week) and geographic locations (DMA), allowing for a detailed analysis of their impact on QSR visits.

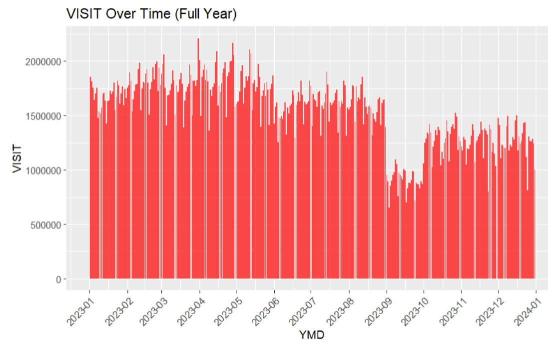
4.3 Description of the Visit Data (Dewey Advan Dataset)

The visit data, which serves as our primary outcome measure, is sourced from the Advan dataset provided by Dewey Dataset. This data is derived from users' cell phone PINs, which track visits to physical stores. A visit is recorded when a user's PIN is detected within the polygon of a Point of Interest (POI), which in this case, represents a QSR location (e.g. a McDonald's restaurant). The POI polygons are defined by sequences of latitude and longitude, ensuring precise identification of visits. Some POIs have their open and/or close date recorded, which is taken into account when preprocessing the data for the period between 2023 and 2024.

Importantly, the Advan platform does not apply a dwell time threshold when recording visits, which enhances the accuracy and stability of visit counts by avoiding the potential cannibalization of visits from neighboring POIs. Advan has tested its own data on 1,500 publicly traded tickers versus (a) top line revenue as reported from the companies and (b) credit card transaction counts on physical locations, and has determined consistently that in the vast majority of cases filtering for dwell time reduces the signal and makes the correlation/forecasting worse. This results in a slightly higher median visit count but significantly reduces the risk of misattribution of visits. (Dewey Data Community (2024))



(a) 2023 Jan Feb



(b) 2023 Whole Year

Figure 2: Top 10 QSR Visit

Here are two graphs illustrating the distribution of visits across the top 10 QSR brands throughout 2023. The drops in each week are Sunday-Monday drops.

4.4 Mapping QSR Locations to Counties and DMAs

To conduct our analysis, we need to map each QSR location to the appropriate county and DMA. This process involves several steps:

1. **County Boundary Information**: We obtained the boundary lines and corresponding latitude and longitude coordinates for each county from the U.S. Census Bureau's 2023 official data. This information allows us to accurately assign each QSR location to its respective county.

2. **DMA Boundary Information**: Similarly, we gathered the boundary lines for each DMA, which are composed of multiple counties. This data is essential for identifying which DMA each QSR POI location belongs to.

3. **County Adjacency Information**: We obtained a list of neighboring counties from the U.S. Census Bureau's 2023 official data. This information allows us to later identify all the neighboring counties that lie on DMA borders.

4. **Identifying Bordering POIs**: We then created a list of neighboring county pairs, with each pair having different DMA, indicating that the neighboring county pairs lie on the borders of two DMAs. These bordering POIs are of particular interest, as they allow us to leverage the DMA border strategy to assess the effectiveness of TV advertisements.

4.5 Bordering Counties and Physics of Broadcasting

Figure 1. Illustration of Atlanta–Macon DMA Border in Georgia

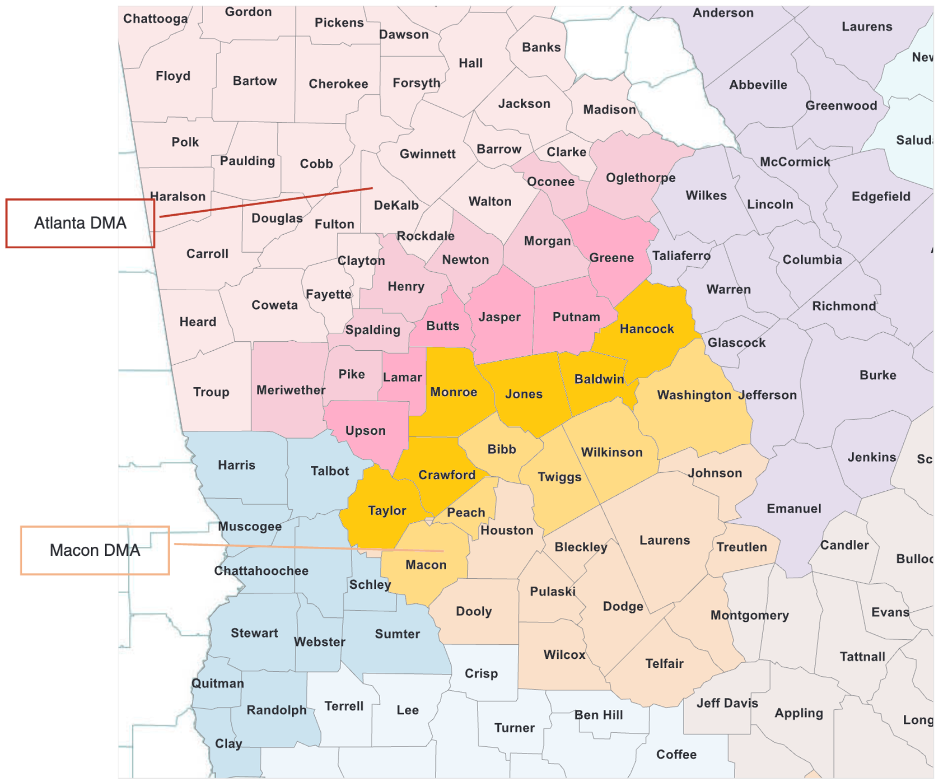


Figure 3: DMA Borders in Georgia, by Wang et al. (2018) - Highlighted Bordering Counties and Secondary Bordering Counties

We focus specifically on counties along DMA borders. For example, let us reexamine the example provided by Wang et al. (2018). For the Atlanta-Macon (Pink-Orange) border analysis, we only include the counties Upson, Lamar, Butts, Jasper, Putnam, and Greene from the Atlanta DMA, shown in brighter pink, and the counties Taylor, Crawford, Monroe, Jones, Baldwin, Hancock from the Macon DMA, shown in brighter orange. The non-bordering counties are excluded from the analysis.

This bordering strategy assumes that no significant signal spillover occurs into counties on the other side of the border. To understand why this assumption holds, it is important to examine how broadcasting works. Due to the physical limitation of OTA (Over-the-Air) broadcasting, or the limitation of a signal's reach, major TV networks such as CBS, NBC, ABC or FOX need multiple affiliates to cover a local area. However, the cost of setting up affiliates - covering equipment, maintenance, payments to local news and production teams, etc. - limits the number of affiliates that can be established. For example, the Tampa-St. Pete area is served by a single station, covering not only these two cities but also hundreds of smaller towns [8].

The division of the 210 DMA markets is largely influenced by the physical range of signal coverage, ensuring that home antennas can pick up the signal. Other important factors include local interests, such as news and weather, which are only meaningful to a small enough DMA, and the cost of maintaining affiliates.

Overspill occurs rarely and only on the geographic edge of two DMAs. These ”fuzzy zones” where two DMAs meet are typically sparsely populated, and it’s just as likely for these areas to have signal dead zones as overlap. For example, a person might not be close enough to receive signals from Denver or Phoenix stations.

Cable television (CATV) further reduces the chance of overspill, as CATV companies only offer the affiliate that is local to the viewer, preventing channel switching between networks from different DMAs .

For robustness checks, we could include secondary boundary counties, such as Meriwether, Pike, Spalding, Henry, Newton, Morgan, Oconee, and Oglethorpe from the Atlanta DMA, shown in less bright pink, and Macon, Peach, Bibb, Twiggs, Wilkinson, and Washington from the Macon DMA, shown in less bright orange. However, this approach would weaken the assumption that populations on both sides of the border are geographically and demographically similar.

4.6 Data Overview

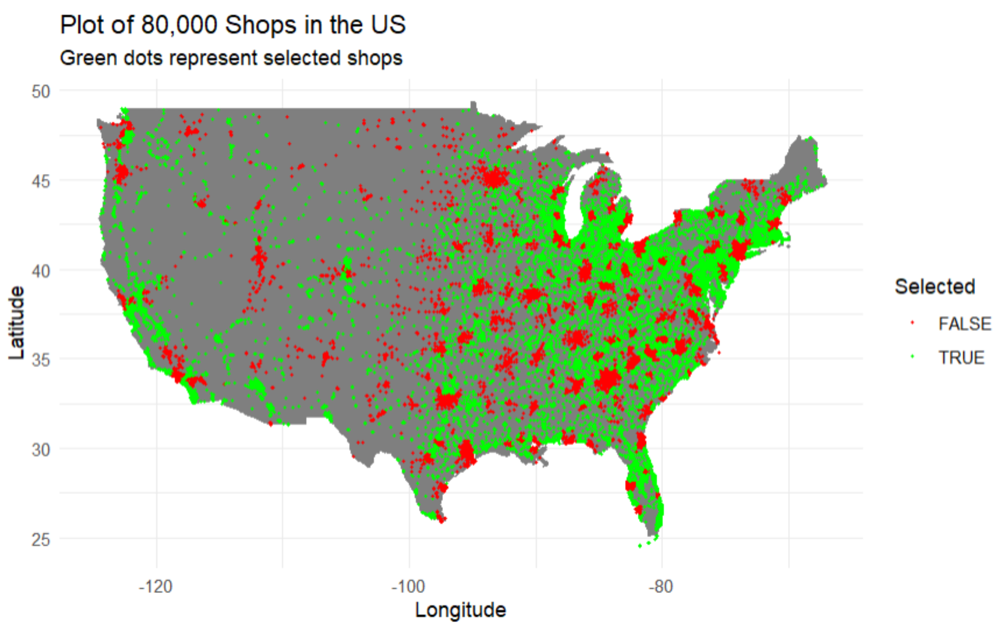


Figure 4: Top 10 QSR POI in DMA Bordering Counties

After completing the mapping process, we analyzed the distribution of QSR locations across the United States. Approximately half of the QSR locations in our dataset are situated in counties that border two DMAs, providing a rich dataset for our analysis. As illustrated in the map, the green markers indicate stores in bordering counties, while the red markers represent stores located in non-bordering counties.

4.7 Conclusion of the Data Section

This section has outlined the data sources and preparation steps necessary for our analysis. By focusing on the QSR industry, we minimize confounding factors and ensure a strong link between advertisements and consumer visits. The Vivvix platform provides detailed advertisement data, while the Advan dataset offers accurate and comprehensive visit records. The mapping of QSR locations to counties and DMAs, together with the county adjacency information, allow us to apply the DMA border strategy effectively in our analysis.

In the next section, we will delve into the data analysis, where we will apply the empirical strategies discussed earlier to assess the impact of TV advertisements on consumer visits to QSR locations.

5. Preliminary Results

5.1 Overall Impact of TV Advertisements on Consumer Visits

Table 1: PanelOLS Estimation Summary

Dep. Variable:	num_visits		
Estimator:	PanelOLS		
No. Observations:	1208872		
R-squared:	6.503e-05	**F-statistic:**	47.723
R-squared (Within):	0.0120	**P-value:**	0.0000
R-squared (Between):	-0.2698	**F-statistic (robust):**	47.723
R-squared (Overall):	0.0015	**P-value:**	0.0000
Log-likelihood:	-9.432e+06	**Distribution:**	F(1,733852)
Entities (Counties):	1800		
Avg Obs:	671.6		
Min Obs:	40		
Max Obs:	3295		
Time periods (Weeks):	53		
Avg Obs:	22810		
Min Obs:	22600		
Max Obs:	23080		

	Parameter	**Std. Err.**	**T-stat**	**P-value**	**Lower CI**	**Upper CI**
intercept	494.86	1.1937	414.54	0.0000	492.52	497.20
num_ads	0.1802	0.0261	6.9082	0.0000	0.1291	0.2313

F-test for Poolability:	12.920
P-value:	0.0000
Distribution:	F(475018,733852)

Included effects: Other Effect (brand_border_time_fe), Other Effect (brand_county_fe)
Model includes 2 other effects
Other Effect Observations per group (brand_border_time_fe):
Avg Obs: 2.6752, Min Obs: 1.0000, Max Obs: 15.000, Groups: 451877
Other Effect Observations per group (brand_county_fe):
Avg Obs: 52.235, Min Obs: 1.0000, Max Obs: 53.000, Groups: 23143

Table 2: Weekly Regressions Results

	Dependent variable:
	VISIT
Num_Ads	0.1802***
Constant	494.86***
Firm-Border-Time Fixed Effect	Yes
Firm-County fixed effect	Yes
Observations	1,208,872
Note:	*p<0.05; **p<0.01; ***p<0.001

Group	Count	Avg Obs	Min Obs	Max Obs
Counties	1800	671.60	40.000	3295.0
Weeks	53	22810	22600	23080
Firm-Border-Time Groups	451877	2.6752	1.0000	15.000
Firm-County Groups	23143	52.235	1.0000	53.000

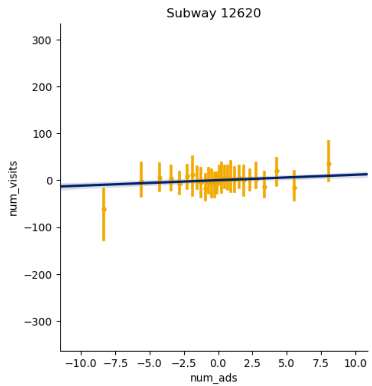
Table 3: Summary Statistics for Different Groups

In the first part of our analysis, we applied the scalar version of the empirical model specification outlined earlier to evaluate the overall impact of TV advertisements on consumer visits.

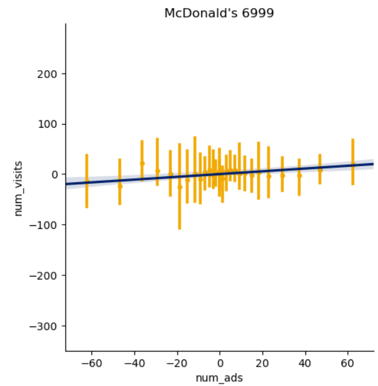
We observed that an increase in the number of advertisements corresponds to a 0.18 lift in the number of consumer visits per week.

5.2 Brand-Specific Analysis

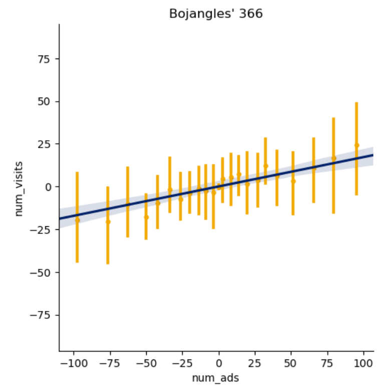
Building on the overall analysis, we further examined the impact of TV advertisements at the individual brand level. This analysis revealed significant heterogeneity in the effectiveness of TV ads across different QSR brands. For each firm (brand), by maintaining controls for firm-border-time fixed effects and firm-county fixed effects (which is equivalent to just border-time and county fixed effects), we observed varying results for different brands:



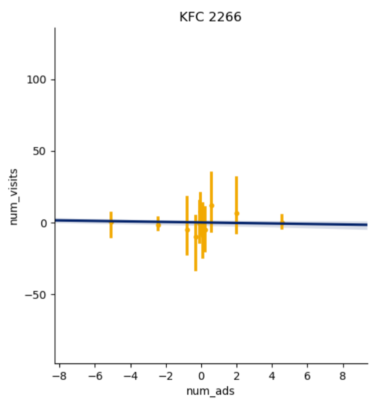
(a) Subway 12620 POIs



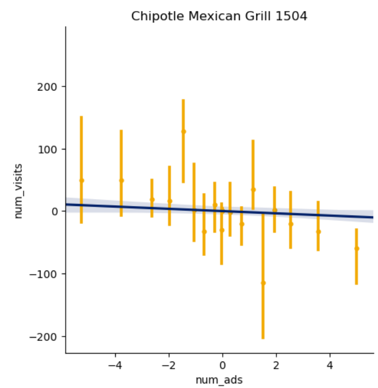
(b) McD 6999 POIs



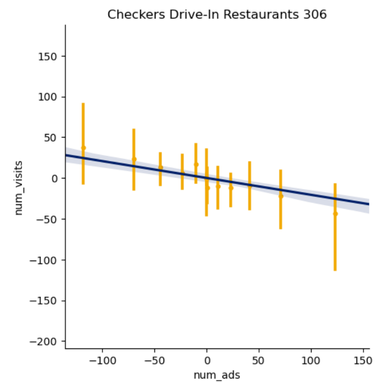
(c) Bojangles 366 POIs



(d) KFC 2266 POIs



(e) Chipotle 1504 POIs



(f) Checkers 306 POIs

Figure 5: QSR Brand and Number of POIs

While some brands, such as Subway, McDonald's and Bojangles, exhibited a positive relationship between ad exposure and visits, others like KFC, Chipotle Mexican Grill and Checker's Drive-in Restaurants showed a non-significant or negative relationship. This variation highlights the importance of considering brand-specific factors when assessing the effectiveness of TV advertisements. The observed heterogeneity could be influenced by various factors, including the nature of the ads, the target audience, and brand reputation.

5.3 Creative-Level Analysis

To gain deeper insights into what drives the differences in ad effectiveness across brands, we conducted a creative-level analysis, which is the vector version of the empirical model specification outlined earlier. In this stage, we regressed the visit outcomes against each brand's unique creative advertisements, while continuing to control for firm-border-time and firm-county fixed effects.

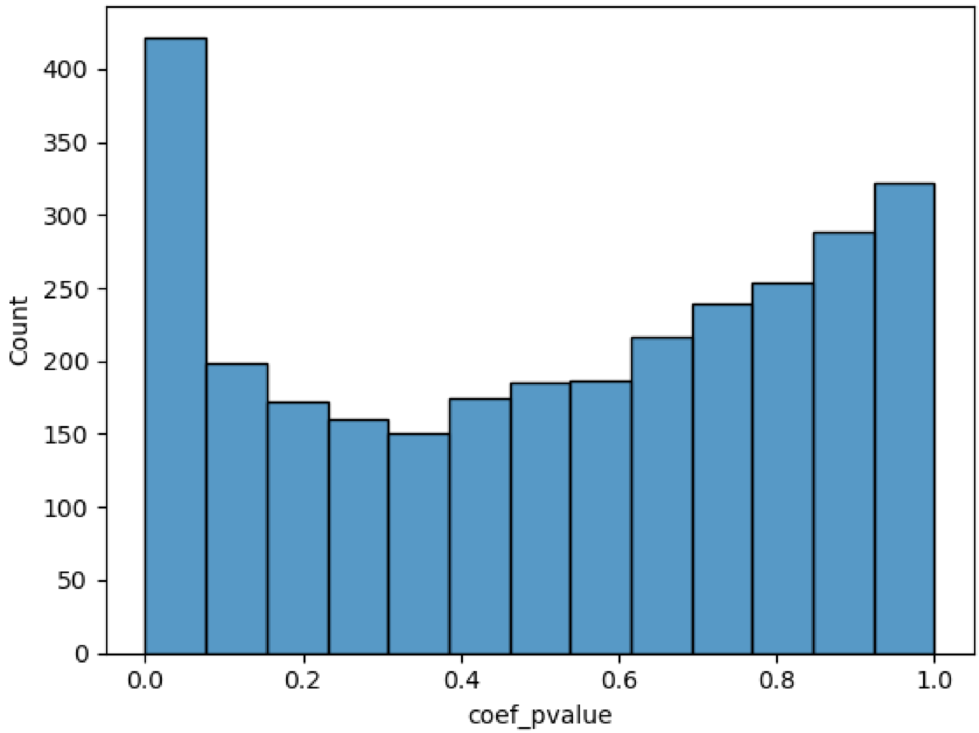


Figure 6: Vector Version Regression: Visit - Number of Each Ad Creative

The preliminary results indicated that 15% to 20% of the coefficients for the creatives were significant or marginally significant. This suggests that certain ad creatives are particularly effective (or ineffective) in driving consumer visits.

5.4 Machine Learning Analysis of Creative Features

5.4.1 BERT Embedding on Labels

To further explore these findings, we utilized Microsoft Azure's video analysis tools to extract detailed frame-by-frame labels for each creative, resulting in approximately 1,000 unique labels. These labels capture a wide range of features, such as visual elements, scene transitions, and content descriptors.

We used BERT to generate embeddings for each label, and find the optimal number of clusters based on the euclidean distance between the embedding vectors.

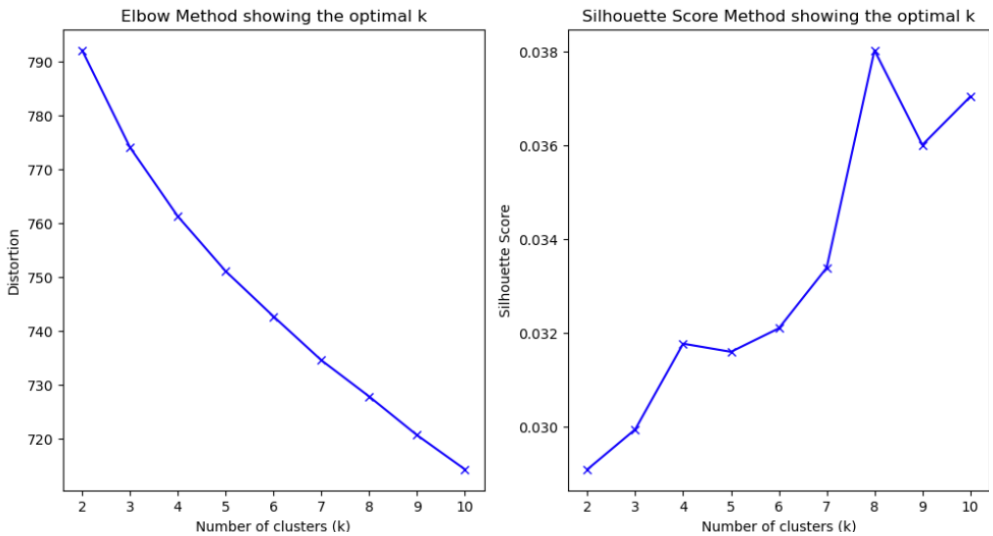


Figure 7: Optimal Clustering based on BERT

An optimal 8 clusters are identified, with centering labels: "electronic device", "beverage", "sport", "food", "clothing", "animal", "wall", "vehicle", each on average containing around 130 labels. However, these labels did not generate helpful insights towards the effectiveness of certain significantly influential creatives.

5.4.2 XGBoost on Labels

An alternative method to analyze the vast amount of data generated from the creative-level analysis is XGBoost, a gradient boosting machine learning algorithm. With a simplified shallow XGBoost, we used labels and advertiser brand (firm) to predict each creative's effectiveness coefficient from the brand-specific analysis (weighted by their standard errors). The goal was to identify specific features or patterns in the ads that correlate with their effectiveness.

Table 4: Feature Importance from XGBoost Model

Feature	Importance
label_bun	0.138349
advertiser_Subway Restaurant	0.090441
label_table	0.073698
advertiser_Braums Ice Cream & Dairy Store	0.048789
total_shots	0.040592
label_Snack	0.040469
label_sandwich	0.029432
label_snack food	0.027778
label_cooking	0.027755
label_wall	0.026046
advertiser_Lees Famous Recipe Chicken Restaurant	0.024963
label_interior	0.023615
label_kitchen	0.023225
label_suit	0.020152
label_Athletic Play	0.020081
advertiser_Pals Sudden Service Restaurant	0.019920
label_smartphone	0.019410
label_Furniture	0.019124
label_local food	0.019090
label_Human Face	0.018392

Preliminary test showed that it could achieve slightly better performance (MSE 189.9) in predicting the effectiveness of ad creatives compared to a baseline model (MSE 222), which uses the simple mean of all the coefficients. This suggests that there are some unidentified features that can help predict the effectiveness of creatives.

5.5 Key Findings and Implications

The preliminary results from our analysis provide several important insights:

1. **Overall Positive Impact**: TV advertisements generally have a positive effect on driving consumer visits to QSR locations, with a 0.18 lift in visits observed on average.

2. **Brand-Specific Variability**: There is significant heterogeneity in ad effectiveness across different QSR brands.

3. **Creative Influence**: Certain ad creatives are significantly more (or less) effective than others in driving visits

4. **Machine Learning Potential**: Machine learning algorithms like XGBoost shows that there are more to explore in each unique creative ad videos.

These findings underscore the complexity of advertising effectiveness and the value of granular analysis at both the brand and creative levels.

Future Research Directions

As this project is ongoing, our future research will focus on a more detailed examination of these creative features. We aim to identify specific visual and content-related elements that contribute to the success of TV ads, by testing existing features discovered in the literatures.

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