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Research Article I Araştırma Makalesi

The Short-Term Effect of TV Advertisements on Digital Traffic

TV Reklamlarının Dijital Trafik Üzerindeki Kısa Vadeli Etkisi

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Öz

Bu makale, farklı sektörden şirketlerin verdiği televizyon (TV) reklamlarının dijital platformlar üzerindeki kısa vadeli etkilerini incelemektedir. Reklamın zamanlaması, program türü ve sektörü gibi faktörlerin dijital trafik üzerindeki etkisi t-testi, ANOVA ve Tukey HSD testi gibi istatistiksel analiz yöntemleriyle değerlendirilmiştir. Bulgular, prime time (öne çıkan saat dilimi) reklamlarının web trafiği üzerinde önemli bir etkiye sahip olduğunu ancak bu etkinin sektörlere ve program türlerine göre değişiklik gösterdiğini ortaya koymuştur. Çalışma, stratejik medya planlamasının önemine dikkat çekerken, saat dilimi, program türü ve şirkete özgü faktörler arasındaki önemli etkileşimleri de gözler önüne sermektedir. Sonuçlar, reklam etkinliğinin sektörlere göre farklılık gösterdiğini ve sektöre özel stratejilerin gerekliliğini vurgulamaktadır. Ayrıca, geleneksel TV reklamcılığının dijital medya stratejileriyle entegrasyonunun önemi vurgulanarak, çapraz platform etkileşiminin en üst düzeye çıkarılması önerilmektedir. Önerilen istatistiksel model sonuçları, reklamcılar ve medya planlayıcıları için reklam kampanyalarının etkisini optimize etme konusunda değerli içgörüler sunmaktadır.

Anahtar Kelimeler: Çapraz Medya Pazarlama, Televizyon Reklamcılığı, Medya Planlama, Tv Reklam Etkisi Ölçümü, İstatistiksel Analiz, Web Trafiği, Anova, T-Testi, Faktör Analizi.

Abstract

This study investigates the short-term effects of television advertisements (TV ads) on digital platform engagement across companies from diverse sectors. Utilizing statistical analysis methods including t-test, ANOVA, and Tukey's HSD test, we examined the impact of factors such as ad timing, program type, and sector on web traffic. Our findings reveal that prime time advertisements significantly influence web traffic, with effects varying across different sectors and program types. The study demonstrates the importance of strategic media planning, highlighting significant interactions between prime time, program types, and company-specific factors. Results indicate that advertising effectiveness differs among industries, suggesting the need for sector-specific strategies. The findings underscore the importance of integrating traditional TV advertising with digital media strategies to maximize cross-platform engagement. These insights provide valuable guidance for advertisers and media planners in optimizing TV ad campaigns and their impact on digital platforms in an evolving media landscape.

Keywords: Cross-Media Marketing, Television Advertising, Media Planning, Tv-Ad İmpact Measurement, Statistical Analysis, Web Session Traffic, Anova, T-Test, Factor Analysis.

Introduction

In today's rapidly evolving digital landscape, the intersection of traditional media and digital platforms presents a unique opportunity for advertisers to maximize their impact. Television advertising, despite being a long-standing and powerful tool, is now often scrutinized for its effectiveness in driving digital engagement. This has led to a growing interest in understanding the short-term effects of television advertisements (TV ads) on digital traffic, particularly how these ads influence consumer behavior on digital platforms immediately following their broadcast.

Previous studies have explored various facets of TV advertising effectiveness, such as its impact on sales, brand awareness, and consumer engagement (Becker et al., 2019). However, the specific relationship between TV ad timing, program type, and the resulting digital traffic remains underexplored.

Building on the gaps identified in literature, this study aims to explore the short-term effects of TV ads on digital engagement, with a particular focus on how these effects vary across company sectors, ad timing, and program types. While prior research has examined individual factors such as ad timing (Hinz et al., 2022; Joo et al., 2014) or program type (Chandrasekaran et al., 2018), no studies to date have combined these variables to assess their joint impact on digital traffic. This research addresses this gap by investigating the combined influence of these factors, aiming to provide a more comprehensive understanding of how they interact to drive digital engagement. To achieve this, we propose the following research questions (RQs):

- **RQ1:** Do the features such as program type, broadcast channel, timing, and advertising company of TV ad have an impact on the digital traffic?
- **RQ2**: If any of those features have an impact, what is the impact difference between different entities of same feature (such as impact difference between different companies.)

By concentrating on each RQ, we aim at not only highlighting the importance of strategic media planning but also underscoring the need for tailored approaches based on industry-specific dynamics and program characteristics. The contributions of our work can be listed as follows:

- Exploration of the potential significance of ad timing, particularly focusing on the short-term impact of prime time versus non-prime time slots.
- Investigation of whether ad effectiveness varies across companies from different sectors.
- Exploration of potential interaction between program types and ad effectiveness, and the relationship between traditional TV ads and digital platform engagement.

The rest of the article is structured as follows: Section 2 provides a literature review on the influence of TV ads. Section 3 details the research framework, including the dataset and methodology. Section 4 presents the evaluation results, and finally, Section 5 includes the discussion and conclusions.

1. Related Work

This section reviews the existing literature on the effects of TV ads. Lodish et al. conducted one of the pioneering analyses on ad effectiveness (Lodish et al., 1995). They compared the behaviors of individuals exposed to TV ads with those of a control group that had not encountered these ads. Their findings indicated that increased advertising budgets did not necessarily lead to higher sales; however, changes in brand, copy, and media strategies could positively impact them. Another study by Martin et al. focused on the genre of infomercial ads, examining their specific effects on sales (Martin et al., 2002). This research focused solely on a single type of TV advertisement. A study on attention and interest generation demonstrated the effectiveness of TV ads in capturing viewers' attention, sparking interest, creating desire, and driving purchasing actions, as evidenced by the outcomes observed in control groups (Ebrahimian Jolodar & Ansari, 2011).

In 2014, Kitts et al. investigated the lagged effects of ads, noting how they induce immediate spikes in web traffic and keyword searches after a specific duration (Kitts et al., 2014). In their 2014 study, Joo et al. found that product searches on search engines increased due to TV ads, particularly for branded products (Joo et al., 2014). They observed that the influence was more pronounced during morning hours.

Lewis and Rao highlighted the inherent challenges in assessing the effectiveness of ad campaigns (Lewis & Rao, 2015). Their research delves into the ad campaigns of 25 different firms, focusing on their ROI from their ad expenditures. The authors highlighted the high costs and impracticality of conducting ad experiments for many companies. A study in 2015 examined how different factors, such as the ad's content and its place in the media, can affect its influence (Liaukonyte et al., 2015). Tirunillai and Tellis provided a novel perspective on the diversity of the impact of TV ads across digital channels (Tirunillai & Tellis, 2017). Their study contributed to the literature by assessing the effects in both short-term and long-term contexts.

Chandrasekaran et al. examine how the content of television advertisements affects online brand search, using Super Bowl ads from 2004 to 2012 as their empirical context. Their findings reveal that informational content in TV ads significantly increases online brand search, while emotional content shows no significant effect (Chandrasekaran et al., 2018). In 2019, Hill et al. used TV ad campaigns data from iSpot TV, including when and where ads were shown; and search query data from Microsoft Bing, which included raw search queries with timestamps (Hill et al., 2019). By combining these datasets, the researchers were able to analyze how search behavior changed in the minutes following TV ad airings compared to control periods. They observed statistically significant spikes in search queries related to the advertised brands and products in the minutes following TV ad airings. Similary, Hinz et al. combined TV ads and user browsing data to analyze offline ads effect on online shopping behaviour (Hinz et al., 2022). They categorized products based on their complexity. Low-complexity goods included items like beverages, food, and detergents, while high-complexity goods encompassed financial products and consumer electronics. For low-complexity goods such as beverages, food, and detergents, second screening leads to higher sales. Conversely, for high-complexity goods like financial products and consumer electronics, second screening results in lower sales.

Arslan et al. introduced a comprehensive framework named TV-Impact, which employs a Bayesian structural time series model (Arslan et al., 2024). A key innovation of TV-Impact is its dynamic algorithm for selecting control variables, which are supporting data sources presumed to be unaffected by TV ads. Additionally, we introduced the concept of Group Ads, which combines overlapping ads into a unified structure. The TV-Impact framework was subsequently applied to the dataset provided by iLab. The results demonstrate that the proposed model effectively influenced companies' strategies in allocating their TV ad budgets and increasing website traffic, establishing it as a valuable decision support tool.

2. Research Framework

Rather than tracking individual user data, our study focuses on analyzing aggregate user behaviors. This approach aims to minimize privacy concerns while revealing general user trends objectively. We also explore patterns in web traffic, such as differences between day and night and platform-specific behaviors. A key question is whether each company has a unique user behavior model or if similar behavior patterns are observed across different platforms. The findings will offer valuable insights for marketing professionals and researchers on integrating conventional and digital media strategies. Additionally, by enhancing the understanding of cross-media interactions the paper will help develop more effective media planning strategies.

To systematically investigate first RQ, we concentrate on different features individually and test the following hypotheses:

- **H1:** Advertisements aired during prime time have a higher mean impact on digital traffic compared to those aired outside of prime time.
- **H2:** The type of program significantly affects the mean impact of TV ads on digital traffic.
- **H3:** The broadcast channel significantly affects the mean impact of TV ads on digital traffic.
- **H4:** The ads company affects the mean impact of TV ads on digital traffic.

Each hypothesis will be tested to evaluate the effects of ad company, ad timing, channel and program type on digital traffic. H1 will be examined using a T-test to compare ads aired during prime time and non-prime time. H2, H3 and H4 will be tested using ANOVA, comparing pre- and post-advertising data to measure the effects of program type, broadcast channel, and company. We also tested prime time factors with ANOVA besides T-test as well. Here, the company will also be used as an indicator of sectors.

For RQ2, we concentrate on post-hoc tests of ANOVA results. Therefore, we aim to reveal which program types, channel or companies have more impact and vice versa. We apply for Tukey's Honestly Significant Difference (HSD) test. By validating these hypotheses, this study aims to provide insights that help advertisers and media planners optimize TV ad campaigns for enhanced digital engagement.

2.1. Dataset

This work used data from four companies within iLab, a prominent advertiser in Türkiye's digital market. iLab, with over 2000 employees and a reach of more than 65% of the Turkish internet audience, employs various advertising methods, including social media analysis, marketing mix modeling, and brand tracking tools.

For data privacy concerns, companies are anonymized as A, B, C, and D. Company A operates in the real estate sector, B in vehicle sales, C in discount tracking and cheap retail shopping, and D in insurance services. The dataset covers one month from January 1 to January 31, 2022, recording minutely web session counts for each company resulting in 44,640 data points per company. The sample structure of the session data can be seen in Table 1.

Session data is categorized into four types: direct (visits from users who directly enter the URL or use bookmarks), paid (visits through paid online ads), organic (visits from organic search engine results), and referral (visits referred from other websites). This study focuses on organic session data because it best reflects the impact of ads on users' search behaviors, indicating users' active interest after exposure to TV ads.

TV ad data for the same period (January 1-31, 2022) was also collected, including the broadcast date and time, TV channel, program, and program type (Table 2). Although the dataset initially contains 34 program types, for statistical robustness, these were grouped into 7 main categories as shown in Table 3. The number of ads during this period was 1,463 for Company A, 7,462 for Company B, 8,435 for Company C, and 3,215 for Company D.

Table 1 provides a sample of the session data, where each column represents the session values for the website at a specific minute. These sessions are categorized into direct sessions, paid sessions, organic sessions, and referral sessions.

Table 1. *Sample of Session Data*

Date	sum_direct	sum_paid	sum_organic	sum_referral
2022-01-01 00:00:00 UTC	13	287	131	35
2022-01-01 00:01:00 UTC	13	135	60	20
2022-01-01 00:02:00 UTC	15	143	43	22
2022-01-01 00:03:00 UTC	11	128	42	20
2022-01-01 00:04:00 UTC	11	132	53	20

Table 2. *Sample of Advertising Data*

Date	Channel	Program	Program Type
2022-01-05 | 08:11:34	DMAXTV	ED STAFFORD YABAN MACERASI	Reality Show
2022-01-05 | 09:37:03	TEVE 2	TEVE2 MAGAZIN MASASI	Entertainment Programs
2022-01-05 | 10:09:41	TLC	TALIHIMDEKI EV	Lifestyle and Trends
2022-01-05 | 10:36:23	TEVE 2	AKASYA DURAĞI	Local Series

Table 3. *Program Types and Their Corresponding Original Types*

New Type	Original Types
News	News Programs, Commentary / Discussion Programs, Weather / Traffic Reports, Economy, Daily News - Live Broadcasts
Documentary	Documentary
Sports	Sports Programs, Sports, Match
Series	Series, Local Series, Turkish Series
Film	Films, Turkish Films, Foreign Films, Cinema
Entertainment	Competition, Reality Show, Comedy, Entertainment Programs, Lifestyle and Trends, Decoration / Home Furnishing Programs, Cooking, Real Lives, True Life Stories, Entertainment, Magazine, Women
Culture	Travel Programs, Information and Skill Programs, Culture Programs, Educational Programs, Cultural, Knowledge and Culture Competitions

2.2. Methodology

For our quantitative analysis, we employed statistical methods that are increasingly vital in communication research. These methods enable the measurement and analysis of media effects using numerical data. Below, we outline the main approaches used in our study and their relevance to communication sciences.

2.2.1. T-Test

The T-test is a parametric hypothesis test method used to compare the means of two different groups, determining whether the observed difference is statistically significant or likely due to chance (Ewens & Brumberg, 2023). For example, in pharmaceutical research, a T-test could be used to evaluate the effectiveness of a new headache medication by comparing pain levels in an experimental group receiving the drug versus a control group receiving a placebo. If the T-test results show a significant difference (low p-value), it can be concluded that the difference is not random and that the medication is indeed effective. Similarly, a T-test could be employed by a fast-food chain to assess whether different packaging colors impact sales. If the test results do not show a significant difference (high p-value), it can be concluded that packaging color does not significantly have a significant impact on affect sales, and any observed small differences are likely due to random variation.

In order to apply the T-test reliability, certain assumptions must be met. First, the data should be normally distributed. Secondly, the observations between groups must be independent, meaning that the assignment of one observation to a group should not affect the assignment of others (Kim & Park, 2019). Finally, the homogeneity of the variance condition must be satisfied, meaning that the variances between the groups should be similar to ensure accurate interpretation of the results (Kim, 2015). After confirming that our data set these conditions, we applied for a T-test in our study.

2.2.2. Analysis of Variance

Analysis of Variance (ANOVA) is a parametric statistical test used to determine whether the average differences among more than two groups are statistically significant (Siegel & Wagner, 2022). ANOVA compares the variance between groups to the variance within groups, allowing for the simultaneous examination of multiple factors. For instance, an agricultural expert might use ANOVA to evaluate the effects of three different fertilizers on wheat yield across four soil types. This analysis not only assesses the main effects of each fertilizer and soil type but also reveals potential interactions between these factors. simultaneously. This way, we can understand complex relationships, such as which fertilizer type produces the best results in which soil type or how the factors modify each other's effects.

In our research, ANOVA was used to compare the effects of TV ads on web traffic on different program types, channels, broadcast times, and companies. This approach helps determine whether these variables have a significant impact on web traffic. Through ANOVA, we can determine which factors significantly influence web traffic and reveal the complex relationships between these factors.

2.2.3 Post-Hoc Tests

Tukey's Honestly Significant Difference (HSD) test was applied to examine the ANOVA test results in more detail and to determine the specific differences between the groups. Tukey's test is a post-hoc test that is used to determine between which groups when a significant difference is found as a result of ANOVA. This test compares all possible pairs of groups to determine which groups are statistically significantly different from each other.

In our study, we applied the Tukey test in two distinct approaches. First, pre- and post-advertising web traffic differences were analyzed by grouping them according to companies. This analysis allowed us to identify which companies' ads had a more pronounced effect on web traffic. In the second approach, we combined company and program type information to create more specific groups, allowing us to analyze the differences between these groups. This method helped us understand how effective a particular company's ads were for specific types of programs.

The results of the Tukey test reveal which companies or company-program type combinations differ significantly from others, providing a detailed assessment of advertising effectiveness.

3. Evaluation Results

We began by applying a T-test to assess the impact of prime-time ads on each company individually and to determine whether these ads statistically differed from those aired outside of prime time. Specifically, we analyzed whether there was a significant difference in session values 1 minute before and 1 minute after the ad during prime time. T-test is used to test H1, examining whether ads aired during prime time have a higher mean impact on digital traffic compared to those aired outside of prime time.

In T-tests and other statistical tests such as ANOVA, the p-value is a key metric for evaluating whether the differences between groups are statistically significant. The p-value represents the probability that the observed differences occurred by random chance. A lower p-value indicates that the differences are less likely to be due to chance and more likely to reflect a true effect (Kestenbaum, 2019). In our study, we set the significance threshold at 0.05. If the calculated p-value is below this threshold, we conclude that the difference between the groups is statistically significant, meaning that there is strong evidence against the null hypothesis (which states that there is no difference between the groups).

As shown in Table 4, the results indicate that for Companies A and B, ads aired during prime time resulted in significantly different session values compared to those aired outside of prime time, with p-values of 0.0098 and 0.0011, respectively. However, this distinction was not observed for Companies C and D, suggesting that prime-time advertising had a varying impact across different sectors. Thus, H1 is concluded as, the session number is significantly different between prime-time and other times for company A and B. We had a finding that ads broadcasted at prime-time results in a significantly higher number of sessions for those companies. But, for company C and D, there is no significant difference.

Table 4. *T-Test Results Comparing Session Values Before and After Ad, Grouped by Prime- Time*

Company	prime_time	p-value
A	YES	0.0098
A	NO	0.42
B	YES	0.0011
B	NO	0.79
C	YES	0.32
C	NO	0.94
D	YES	0.41
D	NO	0.74

Various factors and their interactions may influence the success of an ad. To assess these effects, we applied an ANOVA test, focusing on both individual and joint effects. The dependent variable was defined as the difference in session values 1 minute before and

1 minute after the advertisement, which serves as the primary measure of ad impact. Independent variables included company information, broadcast time (prime time vs. non-prime time), TV channel, and program type. ANOVA is used to test H2, H3 and H4 as it evaluates the effect of program type (H2), broadcast channel (H3) and company (H4) on digital traffic. We also analyzed the interactions between these variables to capture more complex effects.

As in previous tests, our evaluation criterion was the p-value. The ANOVA results, presented in Table 5, revealed that prime time ($p < 0.0001$), the interaction between program type and prime time ($p < 0.01$), and the interaction between prime time and company ($p < 0.0001$) were the most significant factors affecting ad impact. These results indicate that while prime time significantly enhances ad effectiveness, its influence varies depending on program type and advertiser company. On the other hand, no significant effect was found for channel, program type, or company as isolated factors. We conclude H2, as the type of program in which ads are broadcasted has no individual effect on online traffic. H3 concluded that the broadcast channel also does not have individual effect on online traffic. Finally, our conclusion for H4 is that the advertising company also has no individual effect on online traffic. Even though a separate hypothesis test was not written, the effects of variable pairs on online traffic were also examined with ANOVA and are presented in Table 5.

In addressing RQ2, we applied Tukey HSD on the ANOVA test results. The findings are presented in Table 6. The session differences were grouped by company, and the Tukey HSD test was applied to determine whether significant differences existed between these groups. The analysis revealed statistically significant differences between Companies B and C ($p = 0.02$) and between Companies C and D ($p = 0.01$).

Table 5. *ANOVA Test Results for the Impact of Program Type, Channel, Prime Time, and Company on Web Traffic.*

Variable	P-Value
Program Type	1.000
Channel	0.999
Prime Time	< 0.0001
Company	1.000
Program Type and Channel	0.999
Program Type and Prime Time	0.004
Program Type and Company	0.982
Channel and Prime Time	0.954
Channel and Company	0.999
Prime Time and Company	< 0.0001

In addition to the p-value, the analysis incorporated a metric known as the 'mean difference,' which quantifies the average change in session values between pairs of companies. This metric helps quantify the magnitude of differences observed between groups. A positive mean difference indicates that the post-advertising session value for the company in Group1 is, on average, higher than that of the company in Group2, while a negative mean difference indicates the opposite.

In our study, Company B exhibited an average ad impact 1.47 units higher than Company C, and Company D showed an average impact 1.98 units higher than Company C. No significant differences were observed between the other pairs of companies. These results in Table 6 suggest that ad effectiveness varies among companies, with Companies B and D demonstrating notably higher impacts compared to Company C. This indicates that sector-specific or company-specific factors may play a significant role in influencing advertising performance.

Table 6. *Tukey HSD Test, Analyzing Pairwise Comparisons Between Companies to Determine Significant Differences in Web Traffic. Column Names: Group1 (First Company in Comparison), Group2 (Second Company in Comparison)*

Group1	Group2	Mean Difference	P-Value
A	B	-0.016	1.0
A	C	1.45	0.36
A	D	-0.53	0.95
B	C	1.47	0.02
B	D	-0.51	0.86
C	D	-1.98	0.01

To investigate the relationship between the type of program and the effectiveness of ads, we categorized ads by program type for each company. Then, a Tukey HSD test was applied based on the session differences before and after the ads. With 7 distinct program types and 4 companies, this resulted in 378 unique combinations. Out of these combinations, only 9 showed statistically significant differences that are given in Table 7.

The ads by Company B differed significantly from those by Company C in series programs. Additionally, Company C's ads in sports and series categories also exhibited statistically significant differences. In addition to this statistical difference, Company C's ads during TV series had a lower impact than Company B's ads in 6 out of 7 categories. Company D also received more efficiency with its ads in the film category compared to Company C's series category.

Table 7. *Tukey HSD Test Results for Investigating Session Differences Before and After Advertisements Based on Company-Program Type Combinations (Only Results with P < 0.05).*

Group1	Group2	Mean Difference	P-Value
B_news	C_series	5.0374	0.0095
B_documentary	C_series	6.7981	0.0035
B_sports	C_series	5.6523	0.0011
B_film	C_series	5.6908	0.0214
B_entertainment	C_series	4.7467	0.0281
B_culture	C_series	5.7338	0.0113
C_sports	C_series	5.9838	0.0011
C_series	C_culture	-5.5722	0.0093
C_series	D_film	-5.4055	0.0383

Conclusion

This research investigates the short-term effects of TV ads on digital engagement, focusing on factors such as timing, program type, and sector across four key sectors: real estate, vehicle sales, discount retail, and insurance services. The findings reveal that the impact of TV ads on digital engagement is heavily influenced by factors like ad timing, program type, and company sector.

Sectoral contributions: The results demonstrate that prime-time ads significantly impact digital traffic, particularly for companies in the real estate and vehicle sales sectors, underscoring the critical role of strategic timing in TV advertising. Prime-time ads drive higher digital engagement compared to non-prime time, especially in sectors like real estate and automotive. This highlights the opportunity for advertisers to capture consumer attention most effectively. However, the effectiveness of TV ads was not uniform across all sectors; while real estate and vehicle sales benefited significantly, the discount retail and insurance sectors showed less pronounced digital engagement even during prime-time ads. This implies that sectors such as discount retail might require a more diverse advertising mix, potentially combining traditional TV ads with other formats to increase overall effectiveness. The analysis also highlights the importance of content alignment; ads aired during news or entertainment programs were more effective for real estate and automotive sectors, while series or documentaries were less effective for discount retail ads. These findings suggest that advertisers should carefully align their ad placements with content that resonates with consumer interests specific to each sector.

Academic contributions: From an academic perspective, this study provides new insights into the interplay between ad timing, program type, and sectoral influence on digital engagement. Unlike previous studies, such as Joo et al. (2014), which emphasized the effectiveness of morning ads, our sector-specific approach reveals that prime-time ads generally yield higher engagement across most sectors. This sector-focused perspective provides more effective insights compared to general findings that do not distinguish between industries. Additionally, our research aligns with and expands upon findings from Chandrasekaran et al. (2018) by demonstrating the influence of content alignment across different industries. Specifically, the study highlights how aligning ad content with relevant programming can drive engagement, especially when content matches viewer interests and the nature of the sector. The findings further support Hill et al. (2019), who noted variability in online engagement based on product complexity. However, our emphasis on sector-specific analysis offers finer-grained recommendations that go beyond generic product categories, providing practical guidelines for advertisers aiming for precision in targeting.

Practical implications: The study emphasizes that integrating traditional TV advertising with sector-specific digital strategies can help maximize cross-platform engagement, enhance brand visibility, and drive consumer actions effectively. Strategically aligning TV ad or other media placements with high-engagement program types and optimal time slots can significantly improve campaign outcomes, helping advertisers achieve both short-term conversion and long-term brand loyalty.

Future work: For future research, extending the dataset to capture a longer timeframe could provide insights into seasonal and cyclical variations in web traffic influenced by TV ads. Moreover, broadening the scope to include diverse forms of web traffic, such as social media and other referral sources, could offer a more comprehensive view of cross-platform engagement patterns. Incorporating machine learning techniques could also allow for dynamic predictions of optimal ad timings and a deeper understanding of interaction effects on digital engagement post-ad exposure. Given that the current study is limited to a single company spanning four sectors, expanding the sample to involve multiple companies across various industries would strengthen the generalizability of the findings and provide broader insights into sectoral differences in ad effectiveness.

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References

Arslan, A., Tecimer, K., Turgut, H., Bali, Ö., Yücel, A., Alptekin, G. I., & Orman, G. K. (2024). A Comprehensive Framework for Measuring the Immediate Impact of TV Advertisements: TV-Impact. *Entropy*, *26*(2), 109. https://doi.org/10.3390/e26020109

Becker, M., Wiegand, N., & Reinartz, W. J. (2019). Does It Pay to Be Real? Understanding Authenticity in TV Advertising. *Journal of Marketing*, *83*(1), 24–50. https://doi.org/10.1177/0022242918815880

Chandrasekaran, D., Srinivasan, R., & Sihi, D. (2018). Effects of offline ad content on online brand search: insights from super bowl advertising. *Journal of the Academy of Marketing Science*, *46*(3), 403–430. https://doi.org/10.1007/s11747-017-0551-8

Ebrahimian Jolodar, S. Y., & Ansari, M. E. (2011). An Investigation of TV Advertisement Effects on Customers' Purchasing and their Satisfaction. *International Journal of Marketing Studies*, *3*(4). https://doi.org/10.5539/ijms.v3n4p175

Ewens, W. J., & Brumberg, K. (2023). Tests on Means. In *Introductory Statistics for Data Analysis* (pp. 173–203). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-28189-1_13

Hill, S., Colas, A., Schwartz, H. A., & Burtch, G. (2019). TV Ad Events and Digital Search: On the Selection of Outcome Measures. *2019 IEEE International Conference on Big Data (Big Data)*, 3518–3528. https://doi.org/10.1109/BigData47090.2019.9006405

Hinz, O., Hill, S., & Sharma, A. (2022). Second Screening—The Influence of Concurrent TV Consumption on Online Shopping Behavior. *Information Systems Research*, *33*(3), 809–823. https://doi.org/10.1287/isre.2021.1099

Joo, M., Wilbur, K. C., Cowgill, B., & Zhu, Y. (2014). Television Advertising and Online Search. *Management Science*, *60*(1), 56–73. https://doi.org/10.1287/mnsc.2013.1741

Kestenbaum, B. (2019). Hypothesis Tests in Practice. In *Epidemiology and Biostatistics* (pp. 207–216). Springer International Publishing. https://doi.org/10.1007/978-3-319-96644-1_15

Kim, T. K. (2015). T test as a parametric statistic. *Korean Journal of Anesthesiology*, *68*(6), 540. https://doi.org/10.4097/kjae.2015.68.6.540

Kim, T. K., & Park, J. H. (2019). More about the basic assumptions of t-test: normality and sample size. *Korean Journal of Anesthesiology*, *72*(4), 331–335. https://doi.org/10.4097/kja.d.18.00292

Kitts, B., Bardaro, M., Au, D., Lee, A., Lee, S., Borchardt, J., Schwartz, C., Sobieski, J., & Wadsworth-Drake, J. (2014). Can Television Advertising Impact Be Measured on the Web? Web Spike Response as a Possible Conversion Tracking System for Television. *Proceedings of the Eighth International Workshop on Data Mining for Online Advertising*, 1–9. https://doi.org/10.1145/2648584.2648591

Lewis, R. A., & Rao, J. M. (2015). The Unfavorable Economics of Measuring the Returns to Advertising *. *The Quarterly Journal of Economics*, *130*(4), 1941–1973. https://doi.org/10.1093/qje/qjv023

Liaukonyte, J., Teixeira, T., & Wilbur, K. C. (2015). Television Advertising and Online Shopping. *Marketing Science*, *34*(3), 311–330. https://doi.org/10.1287/mksc.2014.0899

Lodish, L. M., Abraham, M., Kalmenson, S., Livelsberger, J., Lubetkin, B., Richardson, B., & Stevens, M. E. (1995). How T.V. Advertising Works: A Meta-Analysis of 389 Real World Split Cable T.V. Advertising Experiments. *Journal of Marketing Research*, *32*(2), 125–139. https://doi.org/10.1177/002224379503200201

Martin, B. A. S., Bhimy, A. C., & Agee, T. (2002). Infomercials and advertising effectiveness: an empirical study. *Journal of Consumer Marketing*, *19*(6), 468–480. https://doi.org/10.1108/07363760210444850

Siegel, A. F., & Wagner, M. R. (2022). ANOVA. In *Practical Business Statistics* (pp. 485–510). Elsevier. https://doi.org/10.1016/B978-0-12-820025-4.00015-4

Tirunillai, S., & Tellis, G. J. (2017). Does Offline TV Advertising Affect Online Chatter? Quasi-Experimental Analysis Using Synthetic Control. *Marketing Science*, *36*(6), 862–878. https://doi.org/10.1287/mksc.2017.1040

The Short-Term Effect of TV Advertisements on Digital Traffic

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Extended Abstract

In today's rapidly changing digital world, the convergence of traditional media with digital platforms offers advertisers unique opportunities to increase their effectiveness. Despite its historical importance, television advertising is increasingly being questioned in terms of its impact on digital channels. This situation has increased interest in understanding the impact of TV ads on instant digital consumer behaviors. While past studies have investigated the effects of TV ads on sales, brand awareness, and engagement, less attention has been paid to how factors such as ad timing, program type, and industry sector shape digital traffic. This study aims to address this gap by examining the short-term effects of TV advertising on digital engagement across sectors.

Using statistical methods such as T-tests, ANOVA, and Tukey HSD tests, we aim to uncover insights that can improve digital media plannig. Our findings are expected to guide advertisers in optimizing TV ad placements based on program characteristics and sector dynamics, and to emphasize the importance of tailored approaches for maximum impact.

This study used data from four anonymized companies within iLab, a significant advertiser in Turkey's digital market, reaching more than 65% of Turkish internet users. Labeled as A (real estate), B (vehicle sales), C (discount tracking and retail), and D (insurance), the companies provided web session data containing 44,640 data points per company for January 2022.

Session data was categorized as direct, paid, organic, and referral visits, with a focus on organic sessions to assess the impact of TV ads on users' search behavior. TV advertising data for the same period, including broadcast details, was also collected. Initially, 34 program types were consolidated into 7 categories to increase the reliability of the analysis. The number of ads broadcast during this period showed significant differences among companies, with Company A having 1,463, Company B 7,462, Company C 8,435, and Company D 3,215 ads.

T-tests were used to evaluate the impact of prime-time ads on each company separately and to determine if these ads were statistically different from those aired outside prime time. Analysis of Variance (ANOVA) was applied to examine the effects of various factors (company information, broadcast duration, TV channel, and program type) and their interactions on web traffic. When ANOVA results showed significant effects, the Tukey HSD test was used to conduct post-hoc analyses to identify specific differences between groups.

T-test results revealed that ads broadcast during prime time produced significantly different session values compared to those broadcasts outside prime time for companies A (real estate) and B (vehicle sales) ($p = 0.0098$ and $p = 0.0011$, respectively). However, this distinction was not observed for companies C (discount retail) and D (insurance). This indicates that prime time advertising has a variable effect on different sectors.

ANOVA results showed that prime time ($p < 0.0001$), the interaction between program type and prime time ($p < 0.01$), and the interaction between prime time and company ($p < 0.0001$) were the most important factors determining ad impact. These findings indicate that prime time significantly increases advertising effectiveness, but this effect varies depending on the program type and the advertising company. No significant effect was found for channel, program type, or company as isolated factors. This highlights the need for optimization of advertising strategies, particularly in terms of broadcast time and content.

The Tukey HSD test, analyzing pairwise comparisons between companies, revealed statistically significant differences between companies B and C ($p = 0.02$) and companies C and D ($p = 0.01$). Company B showed a higher average ad impact compared to Company C, while Company D also showed a higher average impact compared to Company C. These results demonstrate that advertising effectiveness varies across companies, with Companies B and D showing significantly higher impacts compared to Company C. This suggests that sector-specific or company-specific factors may play an important role in influencing advertising performance.

Further analyses investigating the relationship between program type and ad impact on session numbers revealed statistically significant differences in only 9 out of 378 unique combinations of program types and companies. In particular, the impact of Company B’s ads differed significantly from Company C’s ads. Additionally, Company C’s ads in the sports and series categories also showed statistically significant differences within themselves. Company C’s ads during TV series showed a lower impact compared to Company B’s ads, while Company D’s ads in the film category achieved more efficiency compared to Company C’s ads in the series category. These results indicate that digital media or ad strategies need to be optimized specifically for program types and companies.

In conclusion, this study sheds light on the complex relationship between TV advertising and digital engagement, providing valuable analyses for optimizing advertising campaigns in the evolving media environment. By emphasizing the importance of factors such as timing, program type, and company-specific strategies, the findings provide a foundation for more effective cross-platform advertising approaches.

Keywords: Cross-Media Marketing, Television Advertising, Media Planning, Tv-Ad İmpact Measurement, Statistical Analysis, Web Session Traffic, Anova, T-Test, Factor Analysis.

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