Dean&Francis
ISSN 2959-6130

Optimizing Advertisement Spend Timing for Personal E-Commerce: The Critical Role of Weekends in Driving Page Views

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Abstract:
Personal e-commerce operators face significant challenges in optimizing limited advertising budgets, necessitating precise understanding of how temporal factors moderate ad effectiveness. This study addresses this gap by examining the joint influence of advertising expenditure and time-based variables—specifically weekends and holidays—on daily page views, leveraging a dataset from a personal e-commerce platform. Using a stepwise regression framework, this paper first established a baseline model testing ad spend in isolation, followed by an additive model incorporating binary weekend and holiday indicators. Results demonstrate that advertising expenditure alone fails to explain traffic variation; however, when temporal context is controlled, weekends emerge as a dominant predictor of heightened page views, while holiday effects remain statistically undetectable due to data constraints. Critically, ad spend exhibits a weak but significant effect only after accounting for weekend timing, revealing that prior models overlooking temporal confounders underestimate advertising's marginal impact. These findings advocate reallocating budgets toward weekend periods and highlight the imperative for richer temporal data collection to refine targeting strategies.

Keywords: Advertising spending, temporal factors, page view

1. Introduction

With the rapid development of digital economy in the internet ego, the way of advertisements is placed has shifted from the previous traditional wide-net model to precise customized placement [1, 2]. However, fragmentation of traffic and user activity periods are controversy with this trend. Some companies did not receive an effective result after placing advertisement blindly, even causing some issues such as high cost or low page view. For individual operators with limited budgets, how to allocate advertisement spend reasonably and select optimal time windows for promotion to maximize page views has become a key

ISSN 2959-6130

operational challenge. Therefore, solving those problems and making firms create maximum profit margin with limited resources are essential.

In the last decades, there have been some online studies and analysis about this topic. Oğuzhan Karahan focused on the science of advertisement Timing in Campaign Success [3]. By analyzing data from multiple e - commerce platforms during holiday seasons, they demonstrated that well - crafted holiday - themed advertisements significantly enhanced consumer engagement. However, most previous studies either focused solely on the impact of advertisement spend (ignoring temporal factors) or conducted fragmented analyses of single temporal dimensions (e.g., only discussing holiday effects), lacking a systematic exploration of the combined effects of advertisement spend and multi-dimensional temporal factors. Against this backdrop, this study introduces stepwise regression analysis to screen key influencing factors from advertisement spend and various temporal variables, quantify their contribution to page views, and clarify the priority order of factors. This not only enriches the empirical research on e-commerce operational efficiency but also provides actionable strategies for personal e-commerce operators to improve page view conversion efficiency. In this academic research, there are four models been created by using R language [4, 5]: a linear regression model with only advertising expenditure, an additive linear regression model with weekend and holiday variables, an additive linear regression model with day and holiday variables, and a linear regression model for the interaction between advertising expenditure and working days. The primary objective of this study is to construct models to find out the most influenced factors, measuring the coefficient of each factor and verify the predictive performance of the model.

Despite growing interest in e-commerce performance drivers, critical gaps exist in literature: isolated factor analysis and limited focus on personal e-commerce. This study aims to address these via systematic analysis, using Kaggle data (1,096 daily observations, 2022–2024) with variables like advertisement spend, time periods, weekends, and holidays. It employs stepwise regression to identify significant factors, examining interactions and advertisement efficiency to find optimal strategies. Contributions include integrating factors to validate a theory, showcasing stepwise regression's value, and offering insights for operators (e.g., budget allocation).

2. Methods

2.1 Dataset Preparation

The dataset, sourced from Kaggle, simulates daily web analysize for a personal e-commerce website, covering 1,096 observations from 2022/1/1 to 2024/12/31.

Key variables include the dependent variable Page Views (daily website traffic) and independent variables such as advertisement Spend (daily advertising cost), Day of the Week, Weekend (binary), and Holiday (binary). The Timestamp column was excluded due to the presence of derived temporal variables. No explicit preprocessing steps like normalization or string-to-numerical conversion are noted. Temporal variables were structured as categorical or binary (e.g., Weekend and Holiday as 1/0; Day of the Week as a seven-level factor), enabling direct use in regression models.

2.2 Regression models

Model 1 is a baseline linear regression with Advertisement Spend as the sole predictor [6], examining its direct effect on Page Views via the formula:

$$PageView = \beta 0 + \beta 1\left(AdSpend\right) + \epsilon \tag{1}$$

This was constructed as a foundational baseline, implementing a simple linear regression structure where daily page views were expressed solely as a function of advertising spend. This univariate model intentionally excluded temporal confounders to establish whether advertising investment alone could explain variability in traffic patterns absent temporal considerations. Its minimalist design served as a critical reference point for evaluating the necessity of incorporating time-based variables in subsequent models.

Building upon this baseline, Model 2 introduced an additive multivariate framework that integrated binary temporal indicators alongside advertising spend. Specifically, the model incorporated two categorical predictors: a *Weekend* variable distinguishing weekend days (coded as 1) from weekdays (coded as 0), and a *Holiday* variable flagging public holidays (coded as 1) against regular days (coded as 0).

$$\begin{aligned} PageView = \beta 0 + \beta 1\left(AdSpend\right) + \\ \beta 2\left(Weekend\right) + \beta 3\left(Holiday\right) + \epsilon \end{aligned} \tag{2}$$

The expanded specification allowed simultaneous estimation of three distinct effects: the partial association between advertisement spend and page views while statistically controlling for inherent traffic differences attributed to weekends and holidays. This additive structure inherently assumed that the impact of advertising expenditure remained constant regardless of day type, while the temporal variables captured baseline shifts in traffic volume independent of advertising investment. The inclusion of the holiday variable, despite anticipated data limitations, was deliberate to mitigate potential omitted-variable bias in parameter estimation.

3. Results and Discussions

The study's four stepwise regression models progressively integrate temporal variables to explore how advertisement spend and timing factors influence personal e-commerce page views, with key findings and implications as follows:
For the model 1 which includes only advertisement spend as a predictor, exhibits negligible explanatory power, with $R^2 \approx 0$ and a non-significant p-value ($p=0.909$). The coefficient for advertisement spend is small and negative ($\beta=-0.013$), indicating no meaningful relationship between advertisement spend alone and daily page views. The lack of explanatory power suggests that advertisement spend, in isolation, cannot account for variations in page views. This aligns with the study's premise that timing plays a critical role in advertising effectiveness—without controlling for temporal patterns, the effect of advertisement spend is obscured by other unmeasured factors (e.g., user behavior differences across days). The model highlights the necessity of incorporating temporal variables to accurately assess advertisement spend's impact.
For model 2, adding binary weekend and holiday variables modestly improves the model's explanatory power. Weekend emerges as a significant positive predictor , reflecting higher median page views on weekends (consistent with exploratory analysis). Advertisement spend becomes significant but with a weaker effect than weekends. Holiday, however, remains non-significant. The improvement in R^2 confirms that temporal factors (specifically weekends) contribute to page view variation. The significance of weekends aligns with intuitive user behavior—leisure time on weekends likely increases browsing activity. Advertisement spend's significance, though weaker, suggests it has a measurable effect when paired with temporal controls. The non-significance of holidays is attributed to the small sample size (only 12 holiday observations), which reduces statistical power and prevents detection of consistent effects. Notably, retaining holidays as a control avoids omitted-variable bias, enhancing model robustness despite its lack of significance.
Together, these results emphasize that advertising cannot be evaluated in isolation; rather, it must be understood in conjunction with consumers' temporal patterns. The insignificant result in Model 1 suggests that raw spending provides little insight into user engagement when the rhythm of consumer activity is ignored. The significant increase in ad spending once weekends are included suggests that time modulates advertising effectiveness, allowing its true impact to emerge. In other words, ads resonate more strongly when users are naturally more active, highlighting the synergy between spending and temporal opportunities.
The limited explanatory power of holidays reflects not only sample size limitations but also the heterogeneity of holiday behavior. Unlike weekends, which follow a predictable weekly cycle, holidays vary in cultural significance, length, and associated consumer habits. This makes it more difficult to capture consistent patterns in small datasets. This also points to a potential avenue for future research: larger datasets spanning multiple years and regions can more effectively measure the impact of holidays, especially during periods like Black Friday, Singles' Day, or Christmas, when consumer behavior shifts dramatically.
From a management perspective, these findings have practical implications for e-commerce operators, particularly small and medium-sized enterprises. Rather than evenly distributing advertising budgets across all days, businesses should prioritize weekends or other high-traffic periods to maximize return on investment. Even a small amount of advertising during these times can result in higher exposure than during weekdays. Conversely, treating all days as equal opportunities risks wasting resources and diminishing advertising effectiveness.
In summary, this study confirms that the explanatory power of advertising depends on context. Without time controls, advertising appears ineffective, but once time factors (particularly weekends) are accounted for, the impact becomes measurable and significant. This evidence suggests that advertising strategies should not be evaluated solely based on spending levels but must incorporate timing as a fundamental design dimension. Future research should expand the dataset to incorporate seasonality and consumer demographics, and explore advanced modeling techniques to uncover deeper interactions between advertising, timing, and user engagement. Ultimately, the findings emphasize that in e-commerce, timing is not just a contextual factor but a key determinant of advertising success.

4. Conclusion

This study demonstrates that weekends drive significantly higher traffic independent of advertising spend, establishing their critical role in personal e-commerce engagement. Furthermore, while advertising expenditure alone showed negligible impact, its effectiveness became contingent on controlling for temporal variables—revealing a weak but statistically significant relationship only when weekend timing was explicitly modeled. However, holiday effects remain inconclusive due to data scarcity, as limited observations prevented robust statistical detection despite preliminary evidence of elevated traffic. Therefore, this paper recommends redirecting advertising budgets toward weekends to leverage inherent user activity peaks, while advising against holiday-focused allocations until richer temporal data is obtained. Ultimately, these findings underscore that strategic resource allocation must prioritize temporal context over mere spending increases

ISSN 2959-6130

to optimize page view outcomes. These findings contribute to both theory and practice by demonstrating that consumer engagement in e-commerce depends not only on a company's advertising spending but also on the timing of advertising. The observed weekend effect highlights the importance of aligning marketing efforts with natural behavioral rhythms, suggesting that consumer availability and browsing habits fundamentally determine advertising effectiveness. For managers, this implies a clear strategy: optimize advertising campaigns around high-traffic periods to ensure the greatest return on limited budgets. For researchers, these results suggest the need to incorporate temporal dynamics into models of online consumer behavior, rather than assuming its homogeneity over time.

At the same time, the inconclusive results for holiday research highlight the challenges of limited datasets and the complexity of consumer heterogeneity. Holidays vary in length, cultural significance, and shopping motivations, making generalization difficult without larger sample sizes. This limitation offers several promising avenues for future research. Larger, multi-year datasets could better capture holiday cycles, while cross-platform analyses could assess whether the weekend effect consistently holds across different e-commerce environments. Furthermore, employing nonlinear or machine learning methods may reveal interactions between advertising, consumer demographics, and temporal factors that linear models cannot fully capture. By addressing these gaps, future research can further refine the understanding of how time, advertising, and consumer behavior are intertwined in the digital economy.

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