ASSESSING THE IMPACT OF AFFILIATE MARKETING ON E-COMMERCE PERFORMANCE: A TIME SERIES ANALYSIS

Lukáš Veverka*
Prague University of Economics and Business, Czech Republic.

ABSTRACT

This paper presents an empirical study on the effect of an affiliate campaign on an e-commerce website. The study compares two methods for time series decomposition – smoothing splines and Fourier transformation and uses a finite distributed lag model to analyze data on brand awareness (expressed as organic web page visits) and transactions from 2019 to 2022. The results indicate that the affiliate campaign has a strong initial impact on sales but also leads to a decrease in organic sales later. However, the overall effect of the campaign is positive, with an increase in total sales. On the contrary, no statistical evidence exists that the affiliate campaign increases brand awareness. The study provides insight into the performance of affiliate marketing as a strategy for driving sales and conversions.

KEYWORDS: Fourier Transformation, Smoothing Splines, Finite Distributed Lag, Affiliate Marketing, Data-driven Marketing.

MSC: 91B84

RESUMEN

Este artículo presenta un estudio empírico sobre el efecto de una campaña de afiliación en un sitio web de comercio electrónico. El estudio compara dos métodos de descomposición de series temporales – smoothing splines y transformación de Fourier y utiliza un modelo de lag finito distribuido para analizar datos sobre el conocimiento de la marca (expresado como visitas orgánicas a la página web) y transacciones entre 2019 y 2022. Los resultados indican que la campaña de afiliación tiene un fuerte impacto inicial en las ventas, pero también provoca una disminución de las ventas orgánicas más adelante. Sin embargo, el efecto global de la campaña es positivo, con un aumento de las ventas totales. Por el contrario, no existen pruebas estadísticas de que la campaña de afiliación aumente el conocimiento de la marca. El estudio proporciona información sobre el rendimiento del marketing de afiliación como estrategia para impulsar las ventas y las conversiones.

PALABRAS CLAVE: Transformada de Fourier, splines de suavizado, retardo distribuido finito, marketing de afiliación, marketing basado en datos

*lukas.veverka@vse.cz.

1. INTRODUCTION

Affiliate, as well as influencer marketing, is a swiftly growing industry that has gained significant attention in recent years. It is a performance-based marketing strategy in which a business rewards one or more publishers (affiliates) for referring customers to their site. Affiliates typically promote a business through their own personal networks, websites, or social media channels, earning a commission on any resulting sales. The focus of affiliate marketing is on driving sales and conversions. Influencer marketing is based on the effort of a business to partner with an individual with a significant online presence and influence over a specific target audience. The influencer promotes the business's products or services to its audience through sponsored posts, videos, or other forms of content. Influencer marketing focuses on increasing brand awareness and building trust with the audience. In summary, affiliate marketing focuses more on sales, while influencer marketing focuses more on building brand awareness among the target audience.

The empirical study presented in this paper aims to provide insights into the impact of an affiliate campaign on transactions and revenue. The results of this analysis can significantly affect businesses and their marketing strategies, providing them with valuable information to inform decision-making and planning. This highlights the importance of considering both the short and long-term outcomes of marketing initiatives to maximize their impact and drive business growth. By understanding the effect of affiliate campaigns, businesses can optimize their sales and marketing strategies, increasing revenue and boosting transactions.

The structure of this paper is as follows. Section 2 presents a comprehensive literature review that summarizes current knowledge and findings in the study area. Section 3 showcases the data sample that has been analyzed in this study. Section 4 provides a theoretical overview of the methods that have been employed in this study. In Section 5, the methods are applied to real data and the results are presented in a clear and concise manner. Finally, the paper concludes with a summary of its findings in Section 6.

2. LITERATURE REVIEW

Most retailers spend more to acquire customers than they will ever receive in revenue from them. Hoffman and Novak [7] represent a case of the company CDnow, whose key strategy is affiliate marketing. It benefits from the voiding of wasting money on ineffective advertising. Moreover, they collect data, and based on them, they can calculate a customer's lifetime value. The growth of the Internet has created new marketing opportunities, including affiliate marketing, banner ads, and click-through. Rowley [13] describes these opportunities and how to benefit from them. The concept of affiliate marketing is well defined by Duffy [4], who perceives it as a principal mainstream marketing strategy. Based on his work, the key to successful affiliate marketing is building a mutually beneficial relationship between the advertiser and the affiliate. According to Libai et al. [8], pay-per-lead is more profitable when the merchant has a separate agreement with the affiliate, while pay-per-conversion is more profitable for merchants working with multiple affiliates under the same terms. The study by Lobel et al. [9] focuses on the right choice of the payment function that defines the affiliate's reward.

The most important finding is that the optimal function is non-linear and not necessarily monotonic. Edelman and Brandi [5] note that finding suitable affiliates can be challenging. The company's staff are likely to overlook their ineffectiveness but can determine inappropriate practices. However, outside specialists are very capable of identifying just the responsible affiliates. Mariussen et al. [11] studied unintended consequences in affiliate marketing networks and suggested that these consequences can highlight areas for improvement (e.g. successful formation of affiliate marketing networks).
Instagram influencers are very popular affiliate partners, leading to several studies on the topic. Lou and Yuan [10] examine whether brand awareness and purchase intentions are possible to be increased by influencers. They found out that several factors are key to success. Among those factors belong to the influencer's trustworthiness and attractiveness. This study is extended by Casaló et al. [2], who identify that an influencer has to be original and unique to become an opinion leader. Only then is it possible to affect consumer behavioural intentions positively. A study by Sokolova and Kefi [14] investigates para-social interaction with the audience. They found that physical attractiveness has no significant effect on the interactions. Moreover, De Veirman et al. [3] looked at the impact of the influencer's followers and the number of accounts followed by the influencer. They found that if an influencer follows very few accounts, it can negatively impact the influencer's popularity.

3. ANALYZED DATA SAMPLE

The data for this empirical study was obtained from Google Analytics for a Fast Moving Consumer Goods (FMCG) company that sells clothes in the Central and Eastern Europe (CEE) region. The dependent variable is the daily transactions. The data sample contains 1161 observations, covering a period from 28.10.2018 to 31.12.2021. The sample of the data is possible to see in Table 1, which includes the first ten rows of the data frame.

Table 1: Data sample of the first ten rows emerging into the model

Transactions	Pageviews	Course of the year	Course of the month	Discount 25 %	After Christmas	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Affiliate campaign	Covid positive	Lockdown
78	8141	0.820	0.871	0	0	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	0	FALSE
96	9485	0.822	0.903	0	0	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	0	FALSE
107	10189	0.825	0.935	0	0	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	0	FALSE
116	10651	0.828	0.968	0	0	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	0	FALSE
81	9053	0.831	1.000	0	0	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	0	FALSE
72	7599	0.833	0.032	0	0	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	0	FALSE
54	7437	0.836	0.065	0	0	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	0	FALSE
85	8491	0.839	0.097	0	0	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	0	FALSE
96	11521	0.842	.129	0	0	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	0	FALSE
134	12797	0.844	0.161	0	0	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	0	FALSE

To analyze the impact of the affiliate campaign on transactions, additional variables were created based on the date of the transactions. The variables created from the date include *After Christmas*, *Course of the month*, *Course of the year*, and dummy variables for days in a week. These variables provide important information about the seasonality and trends in the transactions, which can have an impact on the business.
The *Affiliate campaign* is a boolean variable that represents the beginning of the discount event communicated through the affiliate partners. The event was valid for five days and is expected to impact the transactions positively. The *Discount 25 %* is another boolean variable that represents dates

when there was a yearly special discount event, which usually significantly impacts the transactions. The *After Christmas* variable represents the time after the Christmas shopping fever, which usually occurs after the weekend prior to Christmas Day. This variable provides important information about Christmas shopping patterns.

Covid positive and *Lockdown* variables are connected to the Covid crisis, which began in 2020. *Covid positive* variable represents the total amount of people with a positive test based on the data from the national health statistics institute. *Lockdown* is a boolean variable indicating days when the national government has ordered a lockdown, and people were unable to go shopping physically, but they were still able to buy goods online.

4. METHODOLOGY

4.1. Decomposition of time series using smoothing splines

Splines are a combination of polynomial and piecewise constant regression. They provide both benefits: they are locally adaptable, like piecewise constant regression and smooth, like polynomial regression. This allows for the capture of unusual local trends while reducing the complexity of polynomial regression.

Determining the number and location of knots is crucial in spline regression. Knots are often placed on identified breakpoints by domain experts. However, this may be challenging when expert knowledge is limited. The regression function is defined as a piecewise polynomial that is continuous at each knot. Mathematically, it is represented as a series of polynomials joined at knots. Mathematically it can be written as

$$y_i = \beta_0 + \beta_1 b_1(x_i) + \beta_2 b_2(x_i) + \cdots + \beta_{K+3} b_{K+3}(x_i) + u_i, \tag{4.1}$$

where the number of knots is represented by K and the basis functions are denoted by b_k. The basis functions used in spline regression are polynomials. As an example, a cubic spline (which is the third degree of a polynomial) can be represented mathematically as

$$b_{k+3}(x_i) = (x_i - \xi_k)^3_+, \quad \forall k. \tag{4.2}$$

Splines can be extended to polynomials of various degrees, depending on the complexity of the data. Cubic splines are commonly used and sufficient for most cases. The representation of a spline starts with a polynomial basis and then includes one truncated power basis function for each knot. In equation (4.2), the truncated power basis function is $(x_i - \xi_k)^3_+$ where ξ_k are the values of the knots and the $()_+$ indicates the positive part, which results in a truncated representation.

$$(x_i - \xi_k)^3_+ = \begin{cases} (x_i - \xi_k)^3 & \text{if } x_i > \xi_k \\ 0 & \text{otherwise.} \end{cases} \tag{4.3}$$

This ensures that the function is continuous at each knot. Additionally, the degree of continuity is one less than the degree of the polynomial. For example, a cubic polynomial (3rd degree) is continuous at each knot and its first and second derivatives.

Determining the number and location of knots requires specialized knowledge, making it challenging to obtain. To address this, smoothing splines were developed. Unlike traditional splines, smoothing splines do not require the determination of knots. Instead, a knot is placed at each training point x_i. The general problem of smoothing splines is defined mathematically as:

$$\sum_{i=1}^{n}(y_i - g(x_i))^2 + \lambda \int g''(t)^2 dt \rightarrow \text{MIN}, \tag{4.4}$$

where the minimized function in this problem is made up of two components: the residual sum of squares (RSS) and a penalty for complexity. The penalty for complexity is calculated by summing (integrating) the variability in the function g. The square is used to eliminate the sign, and the second derivative represents how much the function changes (the rate of change of slope). Lastly, λ is a tuning parameter for the roughness penalty. A value of $\lambda = 0$ would allow the function g to interpolate, while a value of $\lambda = \infty$ would result in a linear function (equivalent to linear regression) since the second derivative of a linear function is zero and the penalty would be irrelevant.

A natural spline, with a knot placed at each unique x_i value, solves the smoothing spline problem. This method uses all available degrees of freedom, but the roughness penalty reduces the actual effective degrees of freedom. The effective degrees of freedom are estimated using the stated formula:

$$df_\lambda = \sum_{i=1}^{n}\{\boldsymbol{S_\lambda}\}_{ii}. \tag{4.5}$$

The smoother matrix $\boldsymbol{S_\lambda}$ can be obtained using the formula in Hastie et al. [6]. The fitted values of smoothing spline ($\hat{\boldsymbol{g}}_{\boldsymbol{\lambda}}$) can be expressed as $\hat{\boldsymbol{g}}_{\boldsymbol{\lambda}} = \boldsymbol{S_\lambda y}$, where g is the solution to (4.4) based on training points $x_1, \ldots, x_n$.

The effective degrees of freedom can be calculated from the roughness parameter λ, or λ can be calculated from the required degrees of freedom. A cross-validation is also an option, including the efficient *leave-one-out* cross-validation error.

4.2. Fourier transformation

Even though Fourier transformation was developed to solve the heat equation, it is used in many other disciplines. Primarily it is used for signal processing, electrical engineering, and econometrics. In this paper, we will use it for the approximation of seasonality. It works similarly to Taylor polynomial, which combines power series to approximate a difficult function around a certain point. Fourier transformation is based on combining trigonometric functions, which are able to converge to any periodical function. An extreme example is square or sawtooth waves which are, in fact, angular. Fourier transformation is able to converge even to them [12]. The black line in figure 1 represents the above-mentioned square wave. It is possible to see that with a growing degree of the Fourier series, the resulting function is converging towards it [12].

Fourier transformation is based on combining trigonometric series. The principal thought is based on assembling an anisochronous (i.e. having different frequencies) harmonic motion having the same direction with such frequencies so that the resulting function would be periodical. thus $T_1 = nT_n$, where n is integer. The equation for such a function is:

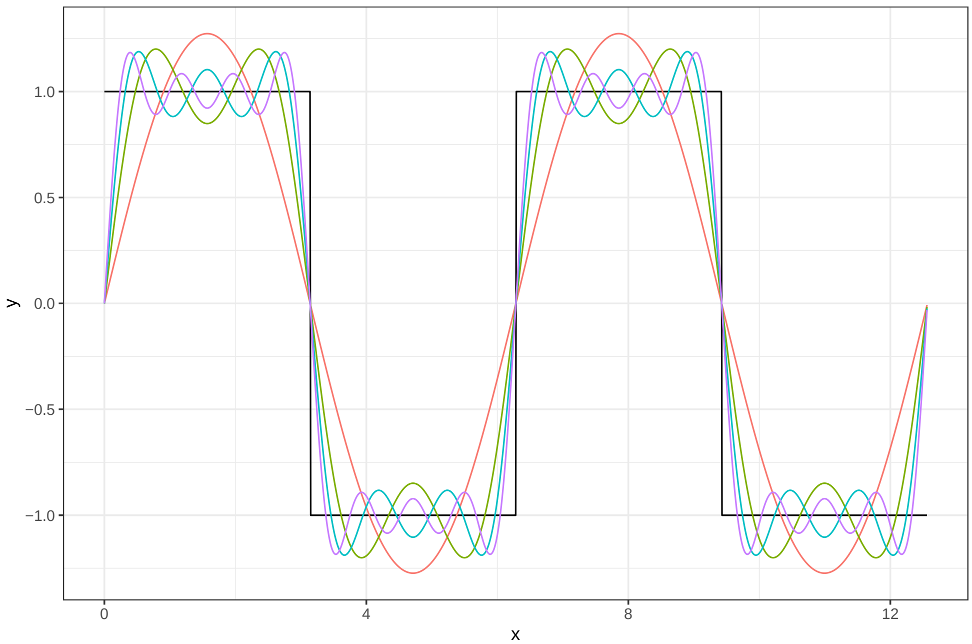


Figure 1: Fourier transformation converging to a square wave

$$f(t) = \beta_0 + \sum_{n=1}^{\infty} A_n \sin(\omega n t) + \sum_{n=1}^{\infty} B_n \cos(\omega n t), \tag{4.6}$$

where ω represents how many times the seasonal wave appears in one time period (e.g. $\omega = 2\pi$ in case of one wave in a year) and t is a linearly increasing vector containing the same number of elements as observations and its values are in the range of 0 and length of time periods (e.g. years). Finally, A_n and B_n are coefficients creating a spectrum of the function. These coefficients are then estimated with OLS (ordinary least squares) so the resulting function would approximate the seasonality of a given time series.

4.3. Finite distributed lag

In a finite distributed lag (FDL) model, it is considered the effect of one or more variables (e.g. x_t on y_t) with a time delay. There are many reasons for the lagged effect of the change in x_t – it might be biological, economic or behavioural reasons (e.g. the dependency between central interest rates and inflation). Equation (4.7) represents an example of an FDL model of order k (allowing up to k lags).

$$y_t = \beta_0 + \delta_0 x_t + \delta_1 x_{t-1} + \delta_2 x_{t-2} + \dots \delta_k x_{t-k} + u_t, \tag{4.7}$$

where δ_0 represents the immediate change in y_t resulting from a one-unit increase of x_t. It is commonly referred to as the impact propensity. δ_1, δ_2 and δ_k indicate the changes in y_t that occur one, two and k periods after the temporary change, respectively. The graph of all the δ parameters as a function of lag (k) results in the lag distribution. It displays the dynamic impact of a temporary increase in x_t on y_t. Such a distribution has no assumptions and is not restricted in any way (on the contrary with, e.g. generalised gamma distribution) [1]. The sum of the estimated δ parameters ($\sum_{i=0}^{k} \delta_k$) for the current and lagged effect of change in x_t represents the long-term change in y_t. This is known as the long-run propensity (LRP) and is often the most interesting value studied in distributed lag models. Even though the estimations of individual δ parameters might be imprecise due to the multicollinearity, the estimation of the LRP is often good.

5. RESULTS

In this academic study, we propose the development of four distinct models to analyze two key dependent variables: Pageviews and Transactions. These models will incorporate various factors, such as seasonality decomposition, special events, the prevailing Covid situation, and the focal point of interest, which is the affiliate campaign.

Two approaches for each dependent variable will be employed to address seasonal variations: smoothing splines and Fourier transformation. The smoothing spline adjustment will comprise two components, one for the annual trend and the other for the monthly trend. On the other hand, the Fourier transformation is expected to be capable of handling these trends effectively due to its higher-order nature. We will determine the optimal order for the Fourier transformation using cross-validation of the Akaike Information Criterion (AIC) across orders up to 50.

Notably, the affiliate campaign is of particular significance in this study, and it has communicated a discount event that spanned five days. We will include four lagged variables in the model to account for this temporal influence. Subsequently, we will estimate and evaluate the finite distributed lag based on this information.

To comprehensively understand the highly seasonal dependent variables, Figure 2 presents an overview of their behaviour over a period slightly exceeding three years. This visualization will aid in comprehending the fluctuations and patterns exhibited by the variables under investigation.

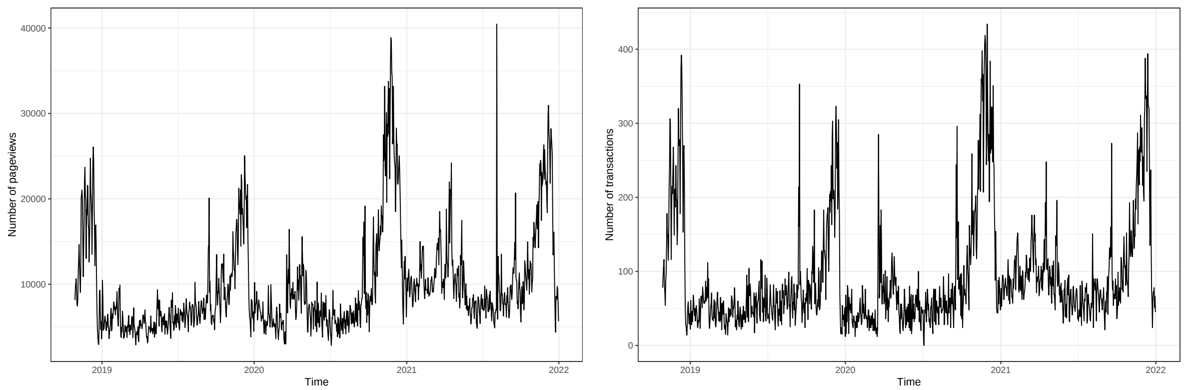
The proposed models for analyzing Pageviews and Transactions with smoothing splines and Fourier transformation seasonality adjustments are formulated as follows:

1. Smoothing Splines Model:

   The model with smoothing splines seasonality adjustment takes the form:

$$y_t = \beta_0 + s(yr_t) + s(mo_t) + \sum_{i=1}^{n} \beta_i x_{it} + \sum_{l=0}^{4} \delta_l c_{t-l} + u_t, \tag{5.1}$$

   where y_t represents either pageviews or transactions and $s()$ denotes the smoothing spline functions for the course of the year (yr_t) and the course of the month (mo_t). The variables x_{it} are control variables necessary for the model's completeness. The affiliate campaign's time series c_t is incorporated, considering up to 4 lagged versions denoted as c_{t-l}. Parameters β and δ are to be estimated.



(a) Pageviews

(b) Transactions

Figure 2: Course of the dependent variables is very similar. The correlation is 93.7 %.

2. Fourier Transformation Model:

   The model with Fourier transformation seasonality adjustment is represented as follows:

$$y_t = \beta_0 + f(\phi_n, \theta_n, yr_t) + \sum_{i=1}^{n} \beta_i x_{it} + \sum_{l=0}^{4} \delta_l c_{t-l} + u_t, \tag{5.2}$$

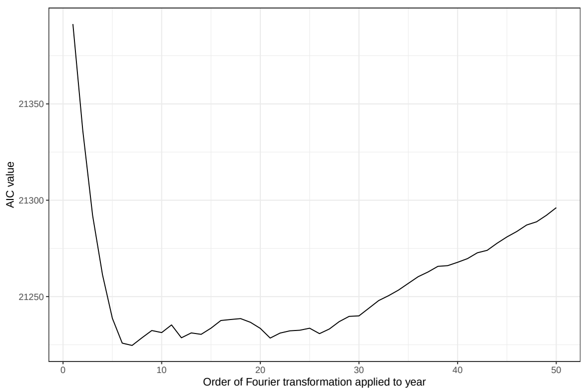
   where y_t represents pageviews or transactions, in this model, $f(\phi_n, \theta_n, yr_t)$ corresponds to the Fourier transformation, which is explained in detail in equation (5.3). The parameters ϕ_n and θ_n will be estimated during Ordinary Least Squares (OLS) estimation. The variable c_t represents the affiliate campaign's time series, with up to 4 lagged versions (c_{t-l}), and the control variables x_{it} are included for model completeness. Parameters β and δ are to be estimated.

   The Fourier transformation function is represented as follows:

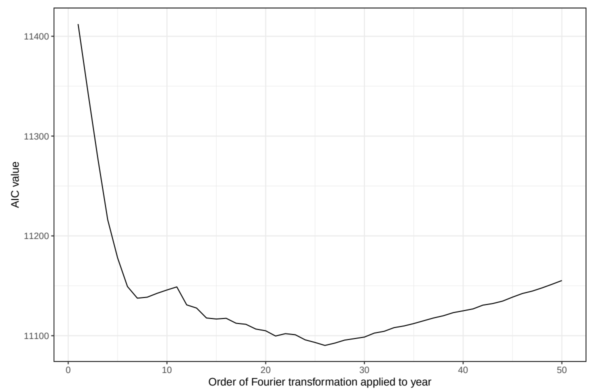
$$f(\phi_n, \theta_n, yr_t) : \sum_{n=1}^{O_{yr}} \phi_n \sin(\omega n yr_t) + \sum_{n=1}^{O_{yr}} \theta_n \cos(\omega n yr_t), \tag{5.3}$$

   where ϕ_n and θ_n are parameters to be estimated during OLS estimation. yr_t represents the part of the year (see Table 1), and O_{yr} and represent the number of orders for the Fourier transformation – this is going to be chosen by cross-validation later. In this case, ω is set to 2π since the seasonal wave occurs only once within one period.

To decompose the time series, both models incorporate dummy variables for days of the week. This choice is made to avoid overly interpolated decompositions, thus enhancing the models' robustness. The reference day for this decomposition is set as Monday, based on the results shown in the Appendix, where it is found to have the second-highest estimated activity.
However, both models exhibit significant autocorrelation, as determined by the Breusch-Godfrey test for correlation of orders up to 7, possibly indicating weekly serial correlation. The models are adjusted to address this issue by adding a lagged dependent variable (y_{t-1}), eliminating the autocorrelation.



(a) Pageviews

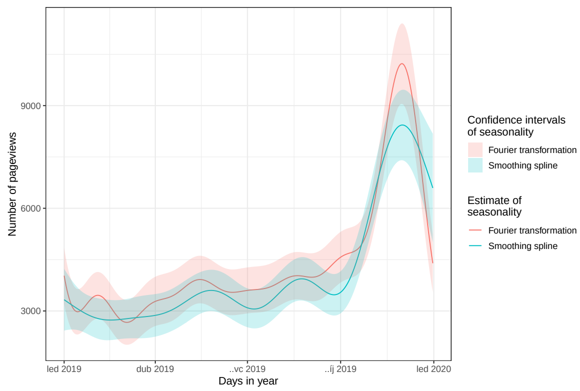


(b) Transactions

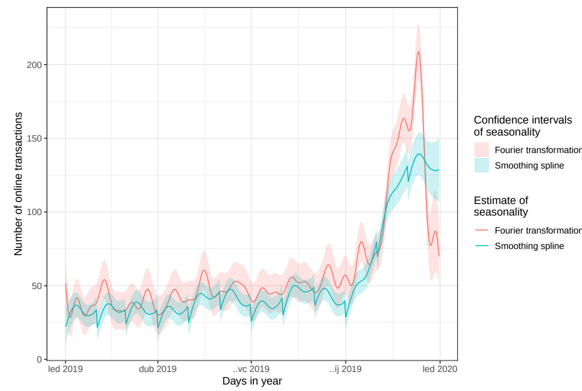
Figure 3: Model selection using Akaike Information Criterion (AIC) for Fourier transformation orders 1–50

The Fourier transformation model is fitted with different orders (O_{yr}) ranging from 1 to a predetermined maximum value (in this study, it is 50). The model's performance is assessed for each order using an appropriate evaluation metric, such as the Akaike Information Criterion (AIC). The order that yields the lowest AIC value indicates the best model fit for the data (as shown in Figure 3). The cross-validation process helps to prevent overfitting and ensures that the selected order generalizes well to unseen data, providing a robust and optimal Fourier transformation model for capturing the seasonal patterns in the time series.

The application of the smoothing spline method to the pageviews data does not yield a significant monthly pattern, while for the transactions data, a significant monthly course is retained. This comparative analysis is visually presented in Figure 4, which illustrates the estimates of seasonality obtained through both the Fourier transformation and the smoothing spline approaches. Notably, when applying the smoothing spline technique to the transaction data, the resulting seasonality estimate exhibits non-smooth behaviour. This characteristic arises from the presence of two additive splines, each contributing distinct components, as evidenced in Figure 5. Specifically, the individual splines demonstrate a pronounced payday effect and a pre-Christmas peak. It is evident that the highest shopping activity happens before Christmas time. Figure 5b displays the monthly transaction trends. It is clearly visible that the majority of transactions occur around payday. This trend highlights the importance of considering payroll schedules and their impact on consumer spending habits. Businesses can use this information to understand their target audience better and optimize their sales and marketing strategies to align with these patterns. Additionally, by considering the payday cycle, businesses can make informed decisions about discounts, promotions, and other marketing initiatives to drive sales and increase revenue. The only disadvantage of the smoothing splines is that it is not periodically continuous – meaning it does not start at the same value it ends, while Fourier transformation is. That is one of the key reasons for choosing a Fourier transformation over smoothing splines.

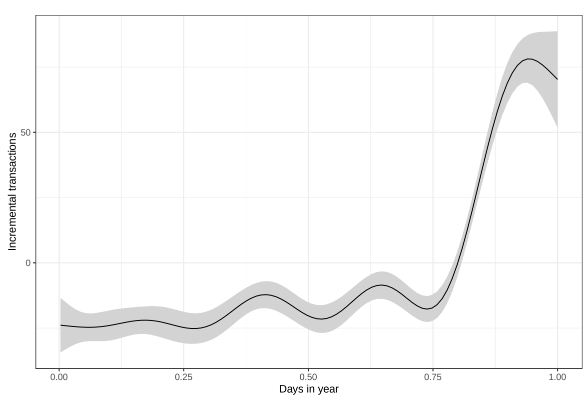


(a) Pageviews

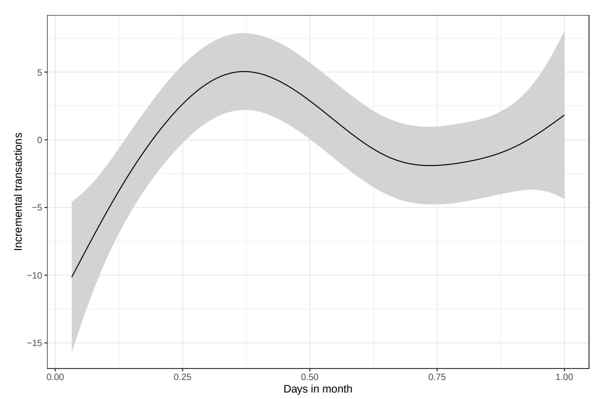


(b) Transactions

Figure 4: Estimation of the seasonality throughout the year. Note that the transaction model had a significant monthly course spline; therefore, the seasonal adjustment is not smooth.



(a) Yearly



(b) Monthly

Figure 5: Estimation of the seasonality with smoothing splines for Transactions. The estimated monthly course is significant because most transactions occur after the common payday.

Table 2: Significance testing of the affiliate campaign based on ANOVA comparison of models including Fourier transformation for Transactions with and without the affiliate campaign.

Model for Transactions	RSS	Res.Df	Sum of Sq	F	Pr(>F)
Including affiliate campaign	$848,211$	1092			
Without affiliate campaign	$882,369$	1097	-34158	8.7952	3.409×10^{-8}

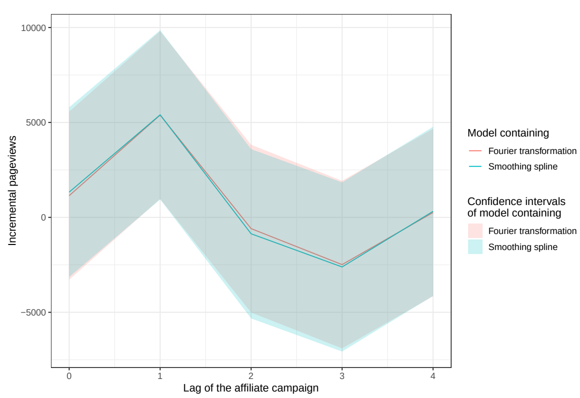
The model's most noteworthy findings are the estimated parameters for the impact of the affiliate campaign (δ parameters). As shown in the Appendix in Tables 4 and 5, the immediate response to the campaign, reflected in the δ_0 (*Affiliate campaign* variable) known as the impact propensity, is a significant increase in transactions but insignificant increase in brand awareness (expressed as pageviews). This suggests that the discount promotion through affiliate partners immediately affects only transactions on the launch date. The subsequent δ parameters indicate that the campaign also has a substantial impact on both pageviews and transactions the following day. Although the discount code is valid for five days, the campaign appears to have negative consequences on both transactions and pageviews after the second day. However, this is not conclusive as the effect on Pageviews may not be significant and could even be zero (based on the significance testing using ANOVA to compare models with Fourier transformation with and without affiliate campaign in Table 2). On the other hand, the effect on transactions is undoubtedly positive, as confirmed by the statistical testing in Table 3. Figure 6 visually compares the estimated evolution of transactions and pageviews after the initiation of the affiliate campaign. Notably, the estimation is very similar for both of the methods used for the seasonal adjustment.

The campaign's overall impact is determined by the Long Run Propensity (LRP), and it has been calculated to be positive (LRP = approx. 185 transactions and approx. 3,600 pageviews). This means that even though there may be a decline in transactions towards the end of the campaign, it still benefits the business as a whole, as it brings an extra shopping activity. However, to tell exactly whether the affiliate campaign had a significant effect, it is necessary to perform statistical testing. The uplift in pageviews caused by the affiliate campaign is statistically inconclusive because the effect is insignificant (based on the significance testing in Table 2). The affiliate campaign has driven transactions and pageviews and contributed positively to the business's overall growth. The positive LRP in transactions indicates that the affiliate campaign has been a worthwhile investment and should be considered for future marketing strategies.

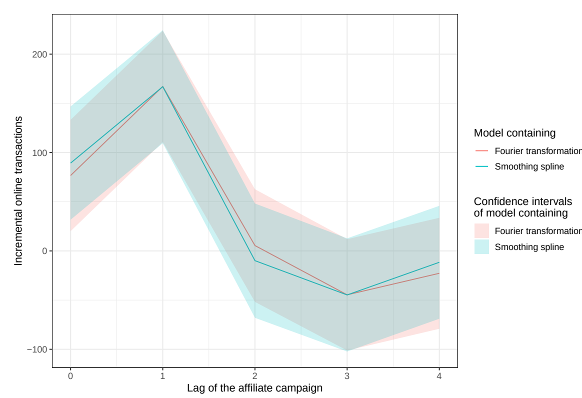
In the final section of the description of the results, our focus shifts towards a set of control variables. The company organizes an annual discount event (variable *Discount 25 %*), akin to Black Friday, but occurring at an entirely different time. This event significantly impacts transactions and is a crucial factor affecting web traffic. On average, transactions during this event increased by more than 180, and web visits surged by over 7000. The Covid pandemic has profoundly influenced market dynamics, as evident from significant variables related to the number of positive cases and lockdown measures.

Table 3: Significance testing of the affiliate campaign based on ANOVA comparison of models including Fourier transformation for Pageviews with and without the affiliate campaign.

Model for Pageviews	RSS	Res.Df	Sum of Sq	F	Pr(>F)
Including affiliate campaign	5.5963×10^9	1130			
Without affiliate campaign	5.6327×10^9	1135	-36380371	1.4692	0.1971



(a) Pageviews



(b) Transactions

Figure 6: Distribution of the lagged effect of the affiliate campaign. The estimation is almost the same regardless of the method of seasonality estimation.

When the government imposed a lockdown, web visits increased by an average of more than 1800 visits, and online transactions rose by over 25. Moreover, as the number of infected individuals grew, both web traffic and transactions escalated, likely due to people's reluctance to shop physically in stores and a preference for online purchases on e-commerce platforms. These findings underscore the profound impact of external factors, such as discount events and pandemic-induced changes in consumer behaviour, on the observed market trends and performance indicators.

6. CONCLUSION

In conclusion, this study presents a comprehensive analysis of Pageviews and Transactions, employing four distinct models that incorporate seasonality decomposition, special events, the prevailing Covid situation, and the affiliate campaign. By adopting two approaches, smoothing splines and Fourier transformation, we effectively address the inherent seasonal variations in the data. The optimal order for the Fourier transformation model is determined via cross-validation of the Akaike Information Criterion (AIC), ensuring a robust fit to the observed patterns in the time series data.

Notably, the affiliate campaign emerges as a significant driver of both transactions and pageviews, eliciting an immediate response on the launch date, followed by subsequent impacts on web traffic and sales. The campaign's Long Run Propensity (LRP) further quantifies its overall positive influence on the business, resulting in an approximate increase of 185 transactions. Although there might be a slight decline in transactions towards the campaign's end, the cumulative effect proves beneficial for the company, driving additional shopping activity.

Furthermore, the study reveals the considerable impact of the annual discount event and the Covid pandemic on web traffic and transactional activity. During the discount event, transactions surge by over 180, and web visits soar by more than 7,000 on average. Similarly, in response to government-imposed lockdown measures, web visits increase by an average of over 1,800, with online transactions experiencing a rise of more than 25. These findings underscore the profound influence of external factors on market dynamics, emphasizing the need for businesses to adapt their strategies to changing consumer behaviours during such events.

This study's analysis provides valuable insights into the complex interplay of factors influencing web traffic and transactional behaviour. By effectively capturing and understanding seasonal patterns and the impact of special events, companies can make informed decisions about marketing strategies, promotions, and overall business growth, thus positioning themselves to thrive in a dynamic and evolving market landscape.

7. DISCUSSION

Future research could consider including other media communications that occur outside the affiliate campaign period to enhance the accuracy of seasonality estimates further. This additional data may refine and modify seasonal adjustment estimates, providing more comprehensive insights into the data. Comparing different seasonal adjustment techniques and acknowledging certain limitations, such as computational resources and data quality, could further validate our findings and improve our understanding of web traffic and transactional behaviour.

FUNDING

This research was supported by the Internal Grant Agency of the Prague University of Economics and Business under grant F4/22/2023.

RECEIVED: NOVEMBER, 2023.
REVISED: FEBRUARY, 2024.

REFERENCES

[1] ALMON, S. (1965): The Distributed Lag Between Capital Appropriations and Expenditures **Econometrica**, 33(1):178–196 Publisher: [Wiley, Econometric Society].

[2] CASALÓ, L., FLAVIÁN, C., and IBÁÑEZ-SÁNCHEZ, S. (2020): Influencers on Instagram: Antecedents and consequences of opinion leadership **Journal of Business Research**, 117:510–519.

[3] DE VEIRMAN, M., CAUBERGHE, V., and HUDDERS, L. (2017): Marketing through instagram influencers: The impact of number of followers and product divergence on brand attitude **International Journal of Advertising**, 36(5):798–828.

[4] DUFFY, D. (2005): Affiliate marketing and its impact on e-commerce **Journal of Consumer Marketing**, 22(3):161–163.

[5] EDELMAN, B. and BRANDI, W. (2015): Risk, information, and incentives in online affiliate marketing **Journal of Marketing Research**, 52(1):1–12.

[6] HASTIE, T., TIBSHIRANI, R., and FRIEDMAN, J. (2009): Basis Expansions and Regularization In HASTIE, T., TIBSHIRANI, R., and FRIEDMAN, J., editors, **The Elements of Statistical Learning: Data Mining, Inference, and Prediction**, Springer Series in Statistics, pages 139–189. Springer, New York, NY.

[7] HOFFMAN, D. and NOVAK, T. (2000): How to acquire customers on the Web. **Harvard Business Review**, 78(3):179–188, 218.

[8] LIBAI, B., BIYALOGORSKY, E., and GERSTNER, E. (2003): Setting Referral Fees in Affiliate Marketing **Journal of Service Research**, 5(4):303–315.

[9] LOBEL, I., SADLER, E., and VARSHNEY, L. (2017): Customer referral incentives and social media **Management Science**, 63(10):3514–3529.

[10] LOU, C. and YUAN, S. (2019): Influencer Marketing: How Message Value and Credibility Affect Consumer Trust of Branded Content on Social Media **Journal of Interactive Advertising**, 19(1):58–73.

[11] MARIUSSEN, A., DANIELE, R., and BOWIE, D. (2010): Unintended consequences in the evolution of affiliate marketing networks: A complexity approach **Service Industries Journal**, 30(10):1707–1722.

[12] NERLOVE, M., GRETHER, D. M., and CARVALHO, J. L. (1995): Analysis of economic time series. economic theory, econometrics, and mathematical economics. Elsevier ISBN: 0-12-515751-7.

[13] ROWLEY, J. (2004): Just another channel? Marketing communications in e-business **Marketing Intelligence & Planning**, 22(1):24–41.

[14] SOKOLOVA, K. and KEFI, H. (2020): Instagram and YouTube bloggers promote it, why should I buy? How credibility and parasocial interaction influence purchase intentions **Journal of Retailing and Consumer Services**, 53.

APPENDIX

Table 4: The results of the regression models for the dependent variable Transactions.

	Transactions:	
	Smoothing spline	Fourier transformation
Transactions $t-1$	0.489***	0.367***
	(0.024)	(0.026)
Discount 25 %	181.107***	185.826***
	(13.977)	(14.406)
After Christmas	−103.115***	−50.018***
	(9.635)	(11.668)
Tuesday	−10.532***	−9.917***
	(3.198)	(3.073)
Wednesday	−6.346**	−6.852**
	(3.198)	(3.070)
Thursday	−15.641***	−16.093***
	(3.195)	(3.070)
Friday	−20.981***	−22.568***
	(3.195)	(3.073)
Saturday	−29.326***	−31.314***
	(3.211)	(3.092)
Sunday	0.757	−2.262
	(3.273)	(3.160)
Covid positive	0.001**	0.001***
	(0.0003)	(0.0002)
Lockdown	25.658***	31.273***
	(3.099)	(3.105)
Affiliate campaign	89.264***	76.642***
	(29.375)	(28.881)
Affiliate campaign $t-1$	166.943***	167.199***
	(29.320)	(28.850)
Affiliate campaign $t-2$	−9.887	5.461
	(29.640)	(29.223)
Affiliate campaign $t-3$	−44.748	−44.619
	(29.348)	(28.869)
Affiliate campaign $t-4$	−11.537	−22.736
	(29.284)	(28.785)
Spline - course of the year	F=38.066***	–
Spline - course of the month	F=4.406***	–
Fourier transformation	–	F=10.160**
Constant	112.644***	60.798***
	(3.051)	(3.056)
Observations	1,161	1,161
Adjusted R^2	0.854	0.865
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5: The results of the regression models for the dependent variable Pageviews.

	Pageviews:	
	Smoothing spline	Fourier transformation
Pageviews $t-1$	0.614***	0.568***
	(0.023)	0.024)
Discount 25 %	7,160.566***	7,135.237***
	(1,079.721)	(1,084.120)
After Christmas	−4,373.211***	−2,610.752***
	(694.802)	(479.325)
Tuesday	−512.850**	−503.372**
	(248.357)	(245.188)
Wednesday	−663.959***	−668.927***
	(248.930)	(245.512)
Thursday	−1,158.580***	−1,172.711***
	(248.404)	(245.062)
Friday	−1,643.787***	−1,684.590***
	(248.127)	(244.993)
Saturday	−1,940.815***	−1,996.568***
	(249.185)	(246.273)
Sunday	270.419	201.337
	(252.723)	(249.892)
Covid positive	0.057***	0.076***
	(0.020)	(0.020)
Lockdown	1,896.777***	2,066.337***
	(248.071)	(249.880)
Affiliate campaign	1,330.564	1,143.426
	(2,280.896)	(2,259.532)
Affiliate campaign $t-1$	5,403.076**	5,389.401**
	(2,274.716)	(2,253.316)
Affiliate campaign $t-2$	−862.724	−590.928
	(2,274.818)	(2,253.974)
Affiliate campaign $t-3$	−2,610.457	−2,486.322
	(2,272.702)	(2,251.260)
Affiliate campaign $t-4$	319.112	255.418
	(2,272.426)	(2,250.627)
Spline - course of the year	F=22.300***	–
Spline - course of the month	–	–
Fourier transformation	–	F=17.310***
Constant	4,281.299***	4,424.932***
	(279.377)	(269.990)
Observations	1,161	1,161
Adjusted R^2	0.857	0.864
Note:		*p<0.1; **p<0.05; ***p<0.01