Retail Marketing and Analytics

Individual Assignment

Omnichannel Marketing and the VAR Model

Table of Contents

Introduction

The digitisation and development of online channels have shaken up retailers' business models in recent years. This first initiated the advancement of marketing strategies towards multi-channel methods with the integration of new channels into the current marketing mix to cater to customers' evolving media consumption. Nevertheless, further digitisation complexified the customer journey and promoted the move to a new phase, omnichannel marketing, which put more emphasis on the "interplay between channels and brands" (Verhoef, Kannan & Inman, 2015). Shankar and Kushwaha define this marketing strategy as the "practice of simultaneously offering shoppers information, products, services, and support through two or more synchronised distribution channels in a seamless manner" (Shankar & Kushwaha, 2021). The move from multi-channel to omnichannel marketing thus focuses on integrated rather than separated channels and how to create the best experience as the customer moves across channels. Such a form of marketing allows brands to enhance user experience, create a cohesive brand image, and obtain higher revenues. However, this requires continuous testing of the efficacy of the approach and of different marketing mediums to optimise the customer's route and, as such, campaign spending (YR, 2020).

This report will explore omnichannel marketing and how a company can optimally allocate their budget across marketing channels to maximise sales. First, we will outline the context of this report to understand the marketing opportunity at hand as well as the data used to leverage such opportunity. Then, we will build a vector autoregressive (VAR) model to outline the interaction between the variables and analyse the impulse response functions (IRF) and Granger causality tests to identify the intermediate and long-term effects for each channel. Finally, the budget will be optimally reallocated to maximise marketing outcomes.

Understanding the context

Data description and transformation

The 3051 rows and 10 columns of data used follow the marketing spending of a company over 113 weeks and 26 regions from January 2018 to February 2020. The current budget is distributed across 6 channels: paid views, organic views, Google impressions, email impressions, Facebook impressions and affiliate impressions. Paid views and organic views refer to views achieved through Youtube, with paid views being the number of views that a campaign received through paid advertising, and organic views the number of views that a campaign obtained through non-paid means (search, browsing). Google, email, Facebook, and affiliate impressions refer to the number of times an ad was displayed on a platform or sent to a recipient via email. Note that although organic views are not directly controllable through paid marketing efforts, they may still represent an essential source of traffic and engagement. The budget allocated to this channel can then be used to increase the company's organic reach through initiatives such as influencer partnerships, referral marketing, or social media engagement.

The dataset's remaining 4 columns are division, calendar week, overall views, and sales. 'Division' represents different states or regions where the marketing campaigns were run. Here, we focus on one of the regions, region A. Subsetting the data to said region, we further transform it and replace the inputs in the calendar week column with a number from 1 to 113, corresponding to the weeks recorded. The 'division' and 'overall views' columns are dropped to ease analysis. Indeed, the 'overall views' column represents the total number of views received across all channels. However, because we want to analyse the relationships and interactions between the individual marketing channels, excluding it from our dataset is appropriate.

Data analysis is conducted on log-transformed variables to stabilise their variance over time. In the remainder of this report, variables referred to with an 'L', such as 'LPaid_Views', specify a log-transformed variable.

Marketing opportunity

Despite being in a world where companies are presented with a growing variety of channels to market their products, these channels remain unequal in their reach. Therefore, there exists an opportunity for the company to optimise their marketing spend and avoid over or under-investing in relevant channels. The use of the VAR model to analyse the relationship between channels and sale outcomes can help identify which channels are most effective, and thus whether increasing spending necessarily drives sales.

Omnichannel marketing analysis through the VAR model also allows for obtaining a holistic view of the customer journey by visualising the interaction between channels. Indeed, one can use this analysis to understand how spending on one channel affects the outcomes of other channels and thus increase the efficiency of the company’s marketing efforts. This can help them identify areas where they can improve the synergy between channels and maximise combined impact.

The VAR model for optimal budget allocation

Stationarity of the data

The VAR model assumes the time series variables are stationary and that their statistical properties do not change over time. Prior to implementing such a model, one needs to ensure the stationarity of each input by first analysing the seasonal decomposition of the data and then conducting stationarity tests.

The seasonal decomposition of the data will allow to determine whether we need to apply first-order or seasonal differencing to further stationaries the data. To do this, we create time series objects for each parameter in the dataset, specifying that data is in a weekly format (i.e., setting the frequency to 52). Let us detail the process for the LSales data.

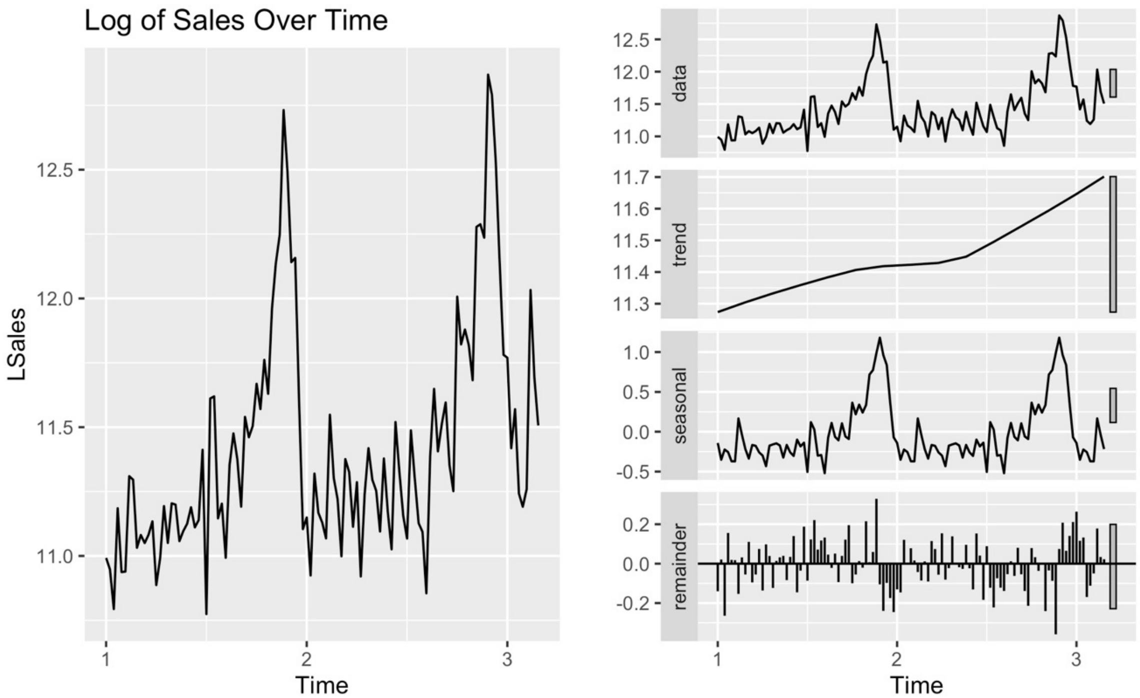

Figure 3 – Seasonal decomposition of LSales

The grey bars to the right of each panel of the seasonal decomposition in Figure 3 showcase the relative scales of each component. A longer bar indicates that the variation in the component is small compared to the variation in the data. Therefore, the above output shows a clear trend (despite likely being insignificant due to the long grey bar), and a significant seasonal component. We can check whether our analysis is correct by conducting several stationarity tests, notably the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS tests, along with using the *nsdiffs* function to test for seasonal stationarity.

The ADF and PP tests check for the presence of unit roots in the data. The ADF test gives a p-value of 0.1649, greater than the 5% significance level. Therefore, we fail to reject the null hypothesis of the presence of a unit root. The PP test has a p-value of 0.01143, suggesting there is sufficient evidence to reject the null, and so that the time series is stationary. Nevertheless, the KPSS test (which looks at whether the data is trend-stationary) supports the non-stationarity of the data, with a p-value of 0.02196, leading us to reject the null that the data is stationary. Taking the majority rule and our prior analysis, we apply first-order differencing to LSales. Finally, the *nsdiff*s function gives an output of 1, indicating that it is also necessary to apply seasonal differencing. The log-transformed sales data thus first undergoes first-order differencing, then seasonal differencing with a lag of 52 (for a yearly pattern with weekly data).

A similar analysis applies first-order differencing to the LPaid_Views, LOrganic_Views, LGoogle_Impressions, LFacebook_Impressions and LAffiliate_Impressions variables (which take the suffix 'diff', for example, LPaid_Views.diff). Further detail of this process can be found in Appendix 1. Note that the differenced variables will be interpreted as growth, while the non-differenced ones (here only LEmail_Impressions) will be interpreted as percentages.

Construction of the model and identification of the different effects

As previously outlined, this strategy goes beyond the direct effects and considers phenomena such as the cross effects between different touchpoints or channels, carryover effects, performance feedback effects, and the direct impact of channels on sales. Carryover effects assign value to the idea that past touchpoints can influence what the customer will do next on that channel. Performance feedback effects assign value to the idea that a customer's past purchases will affect their interaction with different touchpoints in the future. These effects can be identified in the output of the VAR model in Figure 4.

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LPaid_Views.diff.l1	-0.078	0.093	-0.041	-0.026	0.096	-0.015	-0.0002
	(0.143)	(0.060)	(0.071)	(0.064)	(0.139)	(0.038)	(0.066)
LOrganic_Views.diff.l1	-0.043	-0.007	-0.056	-0.094	-0.067	-0.044	-0.075
	(0.334)	(0.139)	(0.165)	(0.151)	(0.326)	(0.088)	(0.154)
LGoogle_Impressions.diff.l1	0.103	0.087	0.054	0.131	-0.004	0.034	0.001
	(0.265)	(0.110)	(0.130)	(0.119)	(0.258)	(0.070)	(0.122)
LEmail_Impressions.l1	0.217	-0.034	-0.019	0.390***	0.571*	-0.063	-0.036
	(0.292)	(0.122)	(0.144)	(0.132)	(0.285)	(0.077)	(0.135)
LFacebook_Impressions.diff.l1	-0.086	0.013	-0.044	0.036	-0.058	0.058	0.079
	(0.149)	(0.062)	(0.074)	(0.067)	(0.146)	(0.039)	(0.069)
LAffiliate_Impressions.diff.l1	0.333	0.070	0.103	0.191	0.316	-0.482***	-0.127
	(0.497)	(0.208)	(0.245)	(0.224)	(0.485)	(0.131)	(0.230)
LSales.diff.l1	0.083	0.005	-0.446***	-0.144	0.049	0.060	-0.429***
	(0.282)	(0.118)	(0.139)	(0.127)	(0.275)	(0.074)	(0.130)
const	-2.758	0.467	0.253	7.795***	-7.273*	0.800	0.461
	(3.739)	(1.560)	(1.844)	(1.686)	(3.644)	(0.982)	(1.728)
Observations	59	59	59	59	59	59	59
R2	0.040	0.064	0.184	0.183	0.085	0.245	0.220
Adjusted R2	-0.091	-0.064	0.071	0.071	-0.041	0.142	0.113
Residual Std. Error (df = 51)	0.630	0.263	0.310	0.284	0.613	0.165	0.291
F Statistic (df = 7; 51)	0.306	0.502	1.637	1.637	0.677	2.370**	2.054*

Figure 4 – Output of the VAR model

Carryover effects

From the above output, one can identify a majority of negative carryover effects created by marketing spending. Thus, if there is an increase in a channel's views or impressions in one period, it will see a decrease in the next. Specifically, a unit increase in paid views in this period will decrease them by 0.078 units in the next, similarly for organic views, Facebook impressions, and affiliate impressions, which will be reduced by 0.007, 0.058, and 0.482 units respectively. Nevertheless, a unit increase in Google impressions will increase them by 0.054 units, and a 1% increase in email impressions will increase them by 0.390% in the next period. Only the effects of email and affiliate impressions are significant at the 1% level.

Cross-over effects

Spending on one marketing channel can also affect others. Positive cross-over effects indicate there may be complementarity between channels where customers who engage with one channel are more likely to engage with another. On the contrary, negative cross-over effects indicate there may be a substitution, where customers who engage with one are less likely to engage with another.

Although most carryover effects are significant at the 1% level, few cross-over effects are significant. Indeed, in numerical terms, only email impressions have a significant positive effect on Facebook impressions, where a 1% increase in email impressions increases Facebook impressions by 0.571 units. The company should therefore be particularly mindful of the impact investing in a channel will have on another channel in the above-described case.

Feedback Effects

Sales can also impact channel growth in the next period through feedback effects. Here, a unit increase in past sales growth impacts paid views, organic views, Facebook impressions positively, and affiliate impressions in the following period by 0.083 units, 0.005 units, 0.049 units, and 0.060 units, while it negatively impacts Google and email impressions by 0.446 units and 0.144%. The effect of sales on Google impressions is significant at the 1% level. The company may therefore want to optimise their Google impressions to mitigate the negative feedback effects.

Direct Impact

None of the channels have a significant impact on sales.

Explanatory power of the model

Overall, the VAR model is a good fit for predicting sales. Its residuals analysis is also satisfactory, with a mean of 0. However, its explanatory power remains low, with adjusted R^2 values ranging from -0.091 to 0.142. This is not a major issue here, as this is likely due to insufficient variables. Indeed, there are important factors other than marketing channels affecting sales, such as macroeconomic factors, competitors, or external events, which are not accounted for here.

Analysis of the IRF plots

We can analyse the impact or shock of the impulse series on the response series and how it progresses over time, here 7 periods ahead, through an analysis of the IRF plots below.

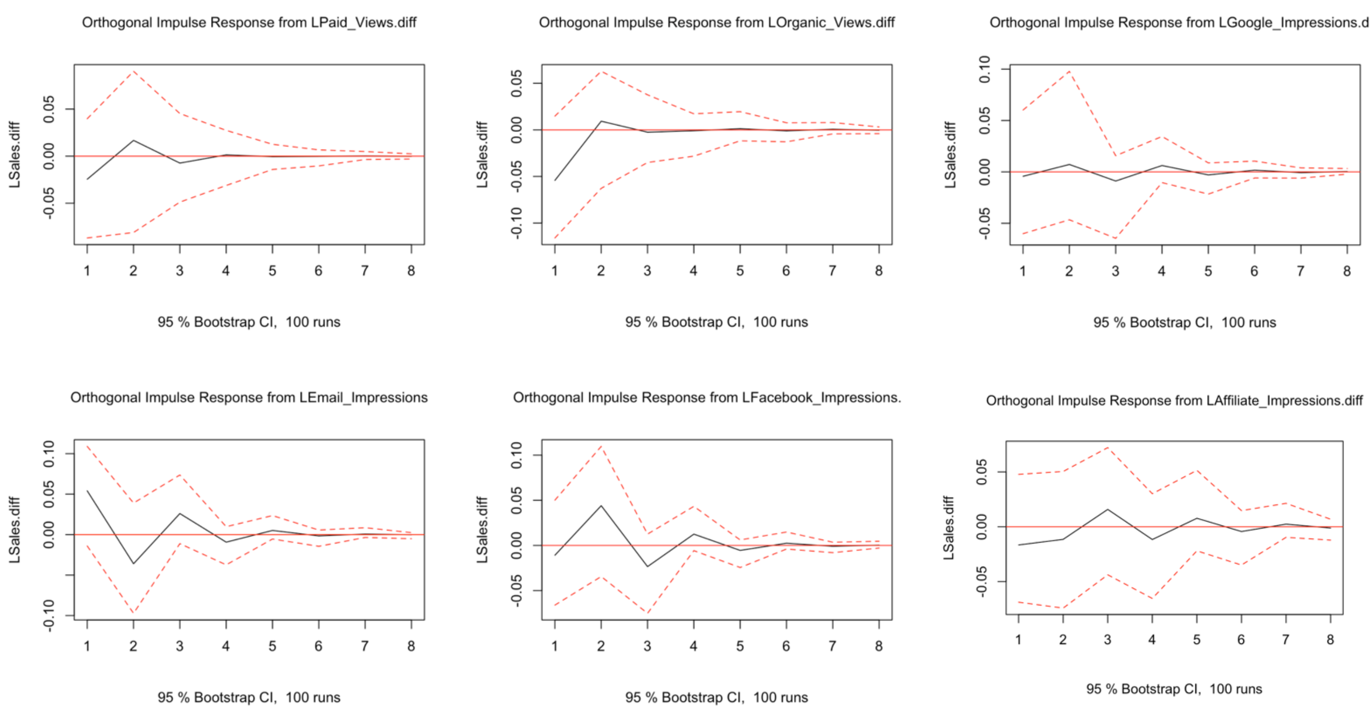

Figure 5 – IRF plots

Although the long-term effect of all channels tends to 0, an increase in email impressions will cause an immediate boost in revenue. An increase in Facebook impressions, on the other hand, will have a delayed positive effect, increasing revenues in the short term. The limited positive effect of the other channels asks for cautious allocation of resources to said channel.

Tests of Granger Causality

The predictive power of the marketing channels on sales, and thus whether there is a causal relationship between variables, can be tested through Granger causality tests. These tests show there is no evidence that any channel Granger-cause sales. The sales do not Granger-cause marketing channels. Indeed, if sales were to Granger-cause marketing channels, this would imply the company's marketing efforts are only reactive to changes in sales, thus limiting their ability to optimise their strategy and reach desired outcomes.

The outcomes of these tests are important information as it sets the expectation for the optimal budget allocation of the company.

Evaluating the intermediate and long-term effects

We can then apply the t>1 criteria to determine coefficient significance and calculate the long-term elasticities of the different advertising spending. This statistical test states that the absolute value of the t-statistic for a coefficient must be greater than 1 for it to be considered statistically significant.

Table 1 – Table summarising the t>1 criteria

Period	Paid Views	Organic Views	Google Impressions	Email Impressions	Facebook Impressions	Affiliate Impressions
1	0	0	0	0.054	0	0
2	0	0	0	0	0.044	0
3	0	0	0	0.026	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0
7	0	0	0	0	0	0
8	0	0	0	0	0	0
Sum	0	0	0	0.080	0.044	0

Paid views, organic views, Google impressions, and affiliate impressions advertising have no significant and positive impact on the periods studied. Email impressions advertising has a significant and positive impact in periods 1 and 3; Facebook impressions in period 2.

Reallocation of the budget

Current budget allocation

Finally, using all the prior analyses, one can define optimal budget allocation. This, however, starts with understanding how the company currently allocates their budget across different marketing channels, showcased in the pie chart below.

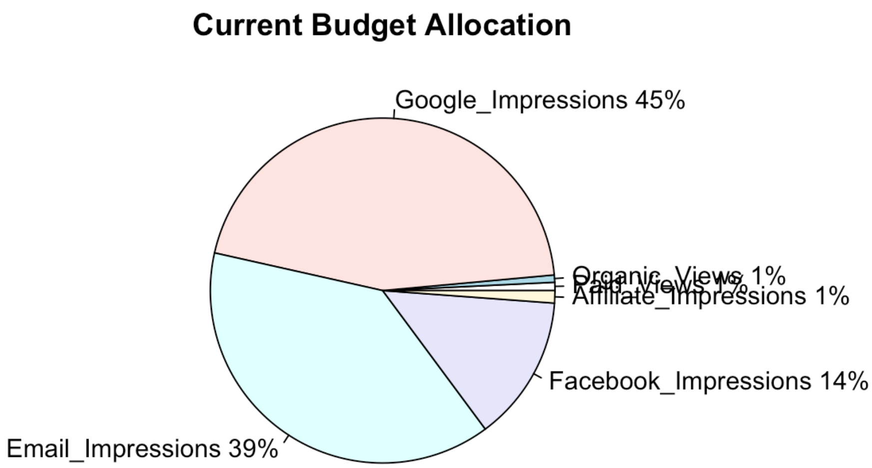

Figure 6 – Pie chart of the current budget allocation

Currently, the company focuses on Google, email, and Facebook impressions, making up 45%, 39%, and 14% of the budget respectively. The remaining three channels, i.e., paid views, organic views, and affiliate impressions, each take 1% of the overall budget.

Optimal budget allocation

The optimal resource allocation is calculated based on the channels' estimated long-term elasticities from the IRF analysis. Indeed, optimal resource allocation is computed by dividing the elasticity of each channel by the sum of all elasticities. This assigns 65% of the budget to email impressions and 35% to Facebook impressions.

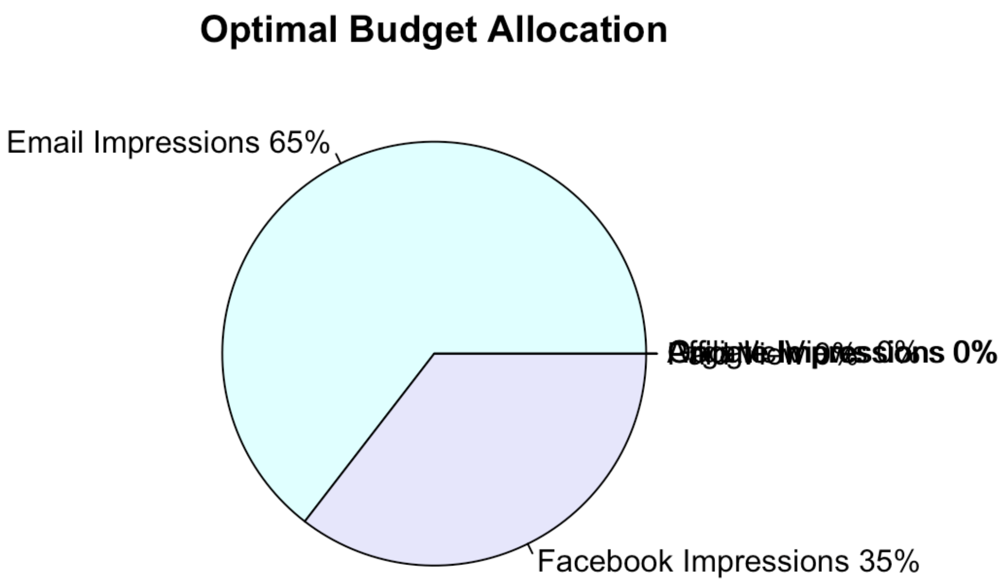

Figure 7 – Pie chart of the optimal budget allocation

Conclusion

To conclude, we used the VAR model with IRF and Granger causality analysis to optimally reallocate company marketing resources. Email and Facebook impressions make up all of the reallocated budget. Nevertheless, this analysis remains limited to region A, with little generalisability to other regions or the company as a whole.

References

Agrawal, Y. (2021) Sample Media Spends Data. Version 1. Kaggle. https://www.kaggle.com/datasets/yugagrawal95/sample-media-spends-data

Eric. (2021) *The Intuition Behind Impulse Response Functions and Forecast Error Variance Decomposition.* https://www.aptech.com/blog/the-intuition-behind-impulse-response-functions-and-forecast-error-variance-decomposition/ [Accessed April 18 2023]

Eloriaga, J. (2020) *A Deep Dive on Vector Autoregression in R.* https://towardsdatascience.com/a-deep-dive-on-vector-autoregression-in-r-58767ebb3f06 [Accessed April 17 2023]

Marketing Evolution. (no date) *What is Omnichannel marketing? Definition, Tips, and Examples.* https://www.marketingevolution.com/knowledge-center/topic/marketing-essentials/omnichannel [Accessed April 14 2023]

Verhoef, P. C., Kannan, P. K. & Inman, J. J. (2015) From Multi-Channel Retailing to Omni-Channel Retailing: Introduction to the Special Issue on Multi-Channel Retailing. *Journal of Retailing.* 91 (2), 174-181. 10.1016/j.jretai.2015.02.005.

Shankar V. & Kushwaha, T. (2021) Omnichannel Marketing: Are Cross-Channel Effects Symmetric? *International Journal of Research in Marketing*. 38 (2). 290-310. 10.1016/j.ijresmar.2020.09.001.

YR, Y. (2020) *Omni-Channel Marketing: How Can We Evaluate Its Impact?* https://towardsdatascience.com/omni-channel-marketing-how-can-we-evaluate-its-impact-922949458682 [Accessed April 14 2023]

Appendix

Appendix 1: Stationarity tests

Paid views:

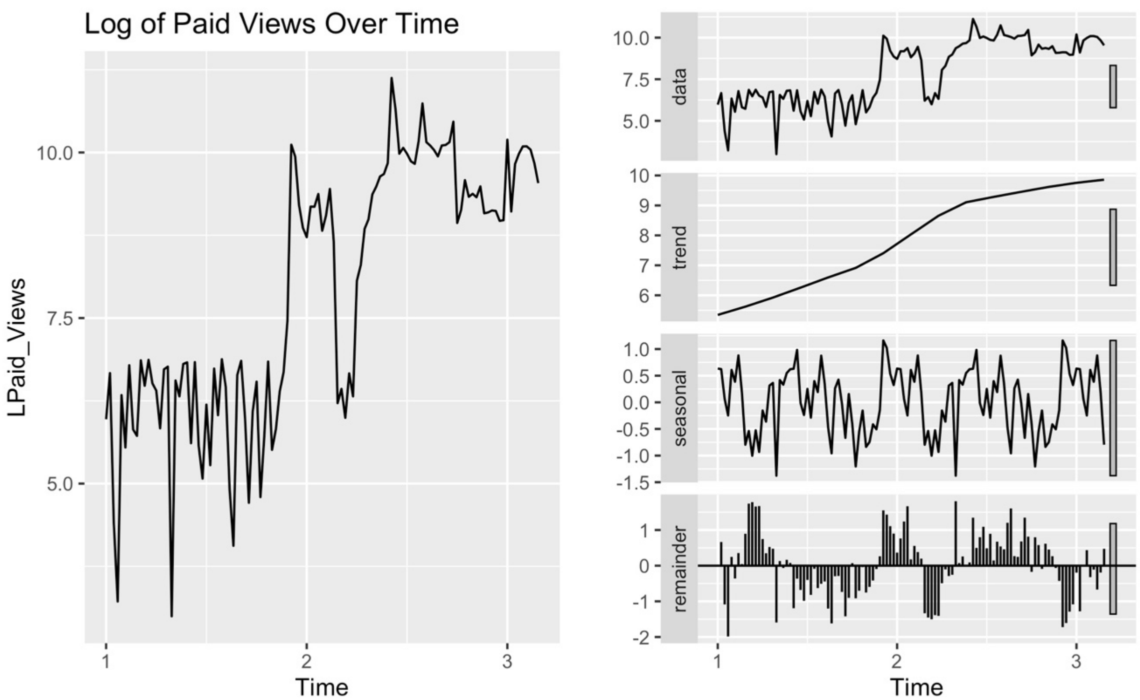

Figure 8 – Seasonal decomposition of LPaid_Views

There doesn't seem to be a significant seasonal component, although there may be a trend component (shown by the shorter grey bar), which we can check with stationarity and seasonal stationarity tests.

Both the ADF and KPSS tests suggest the data is not stationary with p-values of 0.2756 and 0.01, whereas the PP test suggests the data is stationary with a p-value of 0.01. Taking a majority rule, we apply first-order differencing. Furthermore, the nsdiffs function suggests no seasonal differencing is necessary.

Organic Views:

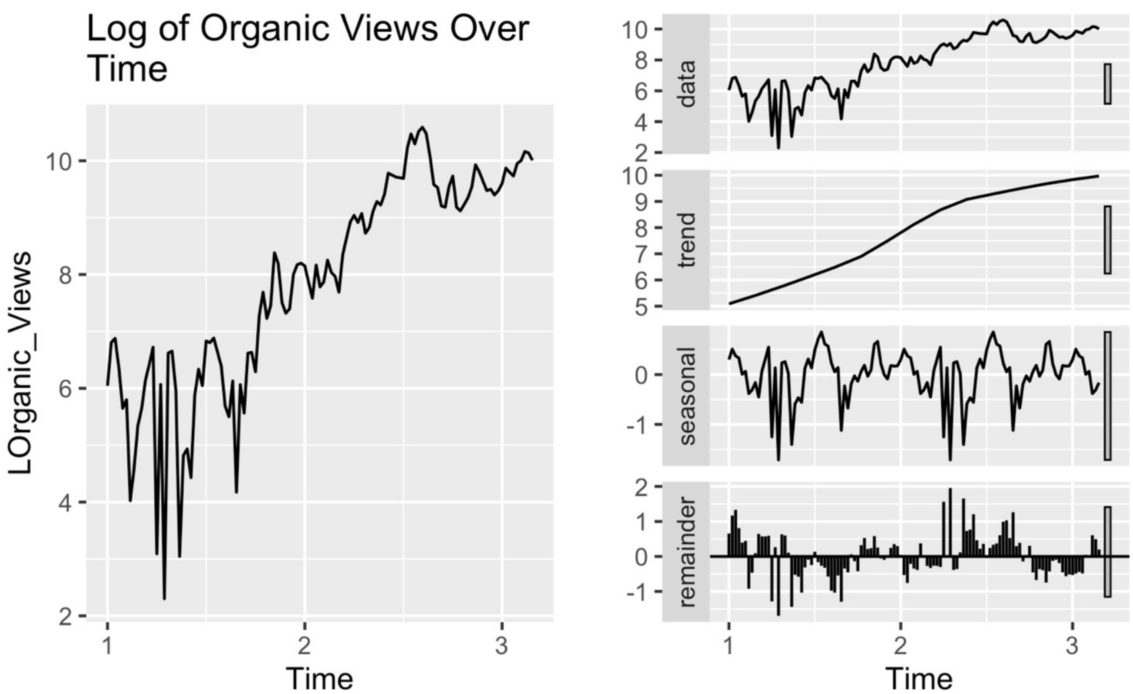

Figure 9 – Seasonal decomposition of LOrganic_Views

There doesn't seem to be a significant seasonal component. However, there may be a trend component, demonstrated by the shorter grey bar on the right side of the 'trend' panel. Therefore, we may need to apply first-order differencing, which we can check with stationarity and seasonal stationarity tests.

With p-values larger than 0.05 for the ADF test and smaller than 0.05 for the PP and KPSS test, the LOrganic_Views data is most likely not stationary. It is however stationary in terms of seasonality. We thus need to apply first-order differencing, but not seasonal differencing to the LOrganic_Views data.

Google impressions:

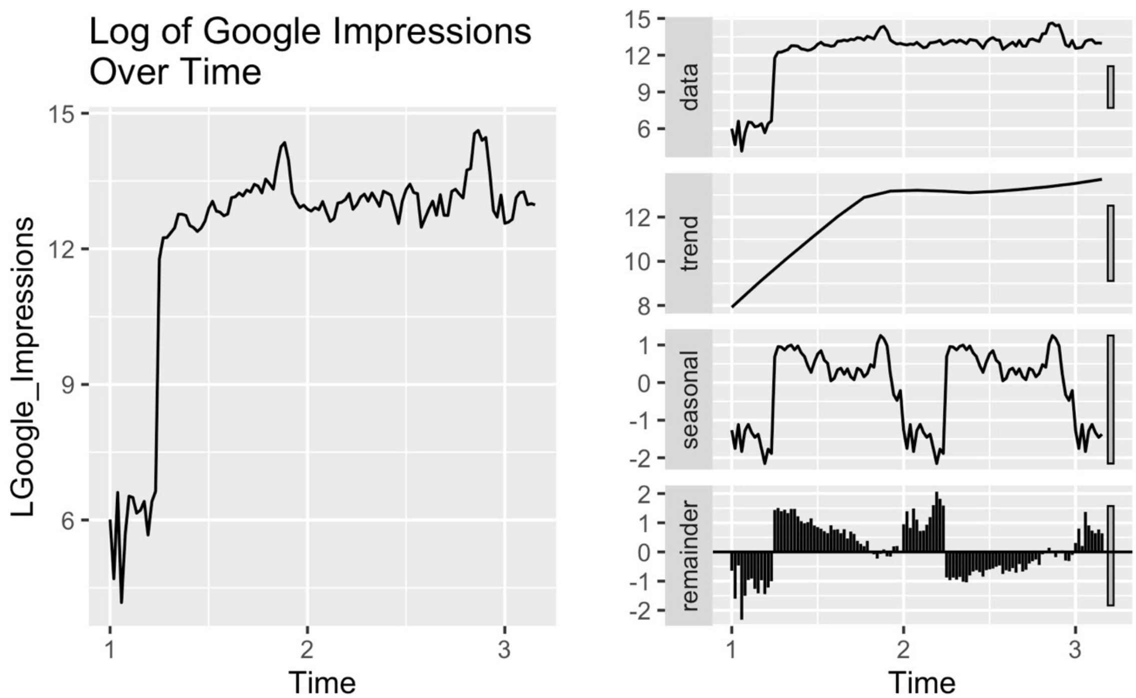

Figure 10 – Seasonal decomposition of LGoogle_Impressions

There seems to be a trend component, but no seasonal component. Therefore, we may need to apply first-order differencing, which we can check with stationarity and seasonal stationarity tests.

The ADF (p-value = 0.1432 > 0.05), PP (p-value = 0.6642 > 0.05), and KPSS (p-value = 0.01 < 0.05) tests all suggest the data is not stationary. Therefore, with our prior analysis, we apply first-order differencing. It is unnecessary to apply seasonal differencing as nsdiffs gives an output of 0.

Email impressions:

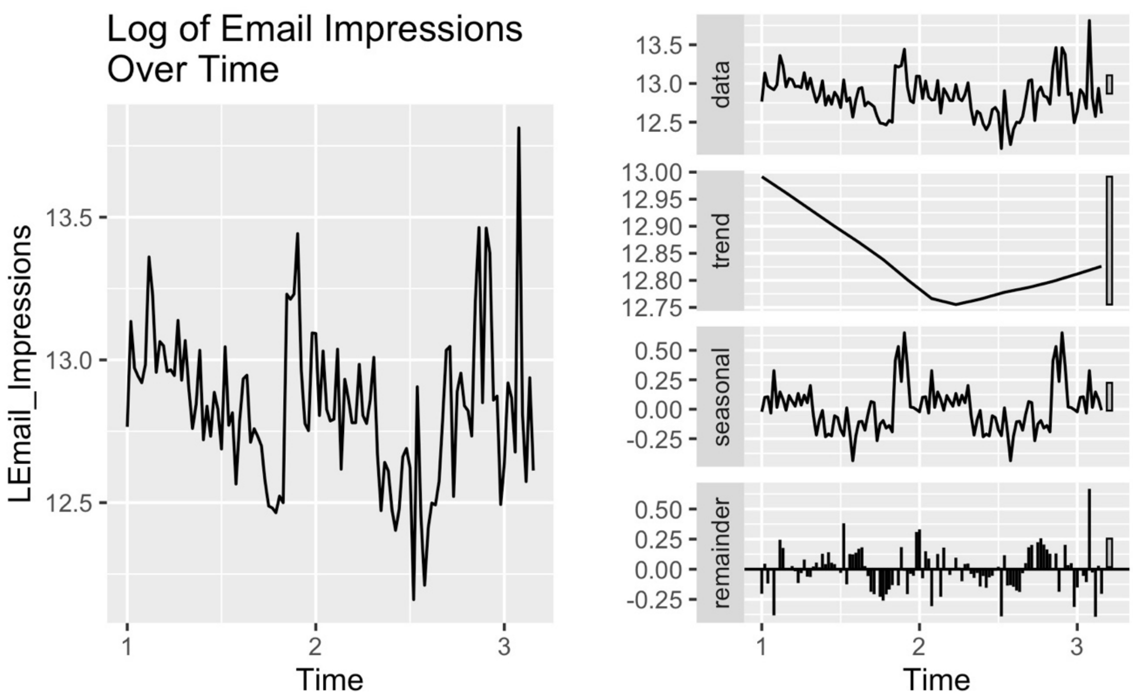

Figure 11 – Seasonal decomposition of LEmail_Impressions

There doesn't appear to be a trend or a seasonal component in the data. Indeed, all further tests (ADF, PP, KPSS, nsdiffs) suggest the data is stationary, thus we do not conduct first-order nor seasonal differencing.

Facebook impressions:

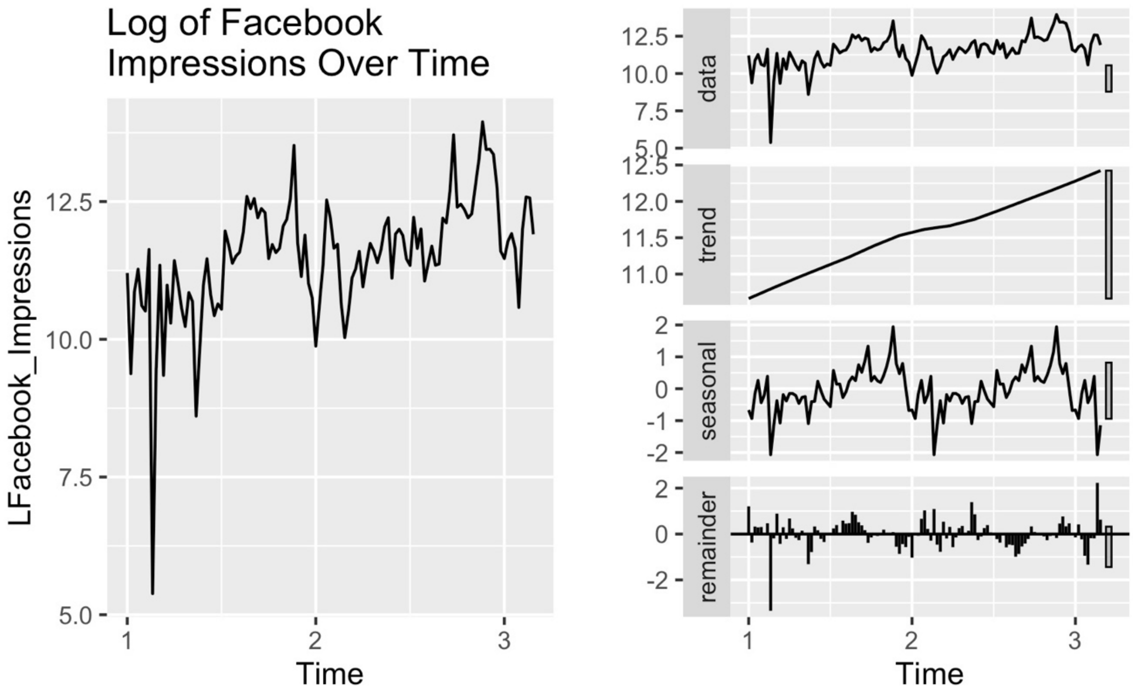

Figure 12 – Seasonal decomposition of LFacebook_Impressions

There is a clear trend in the data although this may not be significant due to the long grey bar. We check this with stationarity tests.

Both the ADF and PP tests suggest the data is stationary, unlike the KPSS test. Taking the majority rule and our prior analysis, here, we choose to apply first-order differencing.

Affiliate impressions:

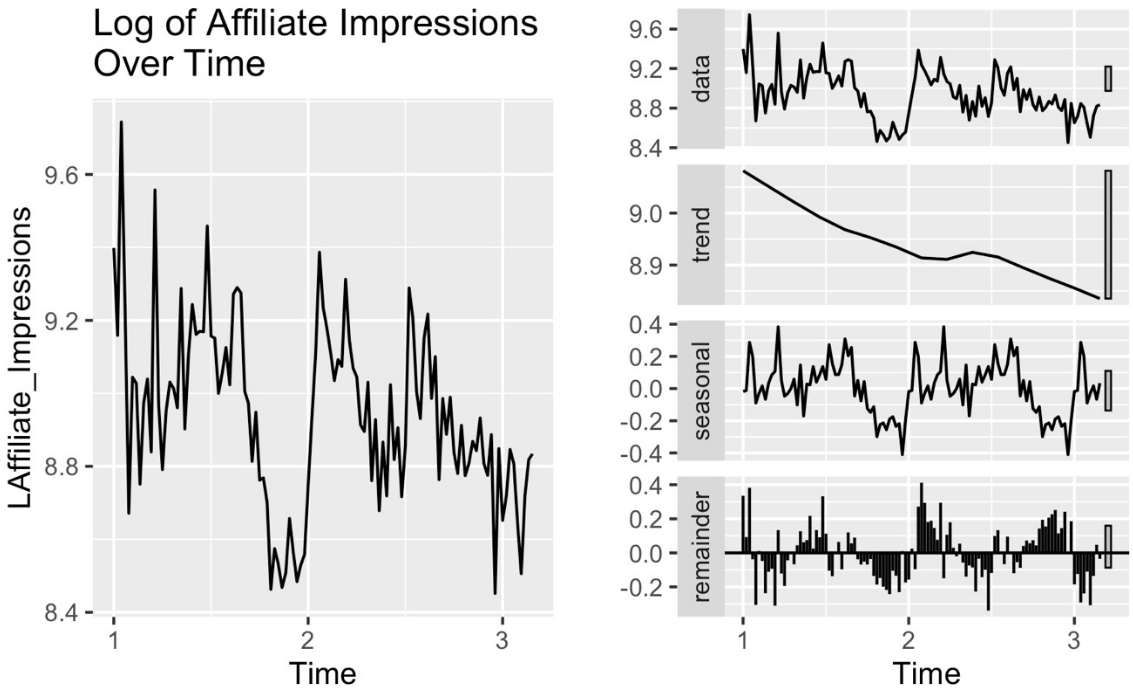

Figure 13 – Seasonal decomposition of LAffiliate_Impressions

There doesn't seem to be a significant seasonal component. However, there is a clear trend component. Therefore, we may need to apply first-order differencing, which we can check with stationarity and seasonal stationarity tests.

Although according to the PP test we should reject the null hypothesis that the data is not stationary, because the ADF and KPSS tests suggest otherwise and we identified a clear negative trend in the data, we apply first-order differencing. We do not need to apply seasonal differencing as the nsdiffs function gives an output of 0.