



# SPOTIFY

MARKETING ANALYTICS TEAM PROJECT  
MSC STRATEGIC MARKETING 2023-24

SYNDICATE TEAM C18

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# INTRODUCTION



## SPOTIFY

Spotify was established in Stockholm, Sweden in 2006 with the platform launched in 2008 (Spotify AB., 2023), a response to the growing problem of piracy (Newsbeat, 2018). Spotify is an online streaming service relying on subscription fees (Premium) and advertising (free account) as revenue (Wlömert & Papies, 2016). Today, Spotify AB, 2023, states that “Spotify offers over 100 million tracks, 5 million podcast titles, and 350,000 audiobooks on one platform to its users. We are the world’s most popular audio streaming subscription service with more than 551 million users, including 220 million subscribers in more than 180 markets.” Since its inception, Spotify has been able to continue to grow and achieve success through offering users convenience and accessibility, and by creating features people are willing to pay for (Alonso, 2023.)



## MARKETING OPPORTUNITY

Spotify generates revenue through its monthly subscription-based structure and advertising for non-subscription-based accounts. The report’s research questions will address:

1. The comparative profitability between free and premium accounts.
2. The effective business strategies for increasing revenue and gross profit whilst attracting Premium and Ad MAUs.

# METHODOLOGY

## *Dataset*

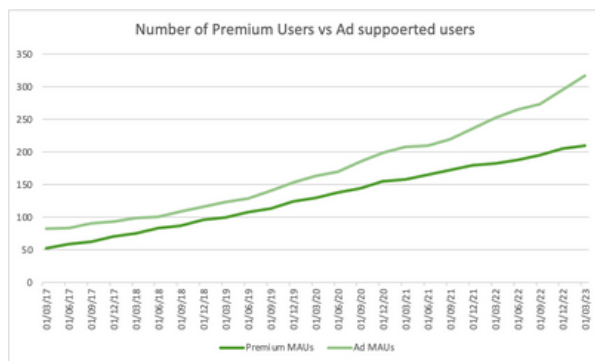
To conduct this research, the relevant dataset was collected from Kaggle (Maurya, 2023) containing Spotify’s quarterly earnings from Mar. 2017 to Mar. 2023. It was chosen to analyse Spotify’s growth. To address data quality and to perform proper analysis, the date column was cleaned from object data types to date data types and the last row was omitted due to missing information. All numerical data as well as user data has been described in millions of Euros. The tables below define the dataset variables as follows:

Dependent Variables	Definition
Premium MAUs	Users that are registered with Spotify for its premium services (e.g., monthly active users)
Ad MAUs	Users that are registered with Spotify for free and therefore have ad supported content (e.g., monthly active users)
Independent Variables	Definition
Sales and Marketing Cost (S&M)	The total amount spent quarterly on sales and marketing (in millions of euros)
Research and Development Cost (R&D)	The total amount spent on quarterly research and development (in millions of euros)
General and Administrative Cost (G&A)	The total amount spent quarterly on general and administrative (in millions of euros)

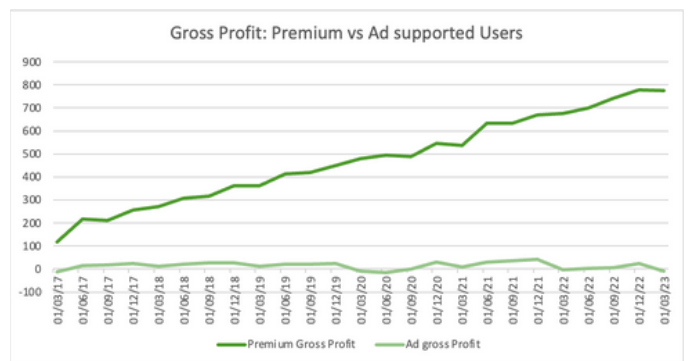
Table 1: Definitions of Variables

To effectively answer the research questions, two dependent variables were chosen for analysis, namely Premium and Ad MAUs. The predictor/independent variables against which these variables were regressed are S&M, R&D and G&A. The project performed multiple regression models, linear regression model, log-log regression model and mean-centred log-log regression model to find the most statistically significant results and the highest adjusted R squared to yield the best-fitted model to devise relevant recommendations. An initial graphical comparison was made using the dataset to understand the growth of Premium MAUs and Ad MAUs over time, highlighting the relationships between the gross profits, revenue and business costs (Appendix, Exhibit A).

Graph 1 compares the number of Premium users vs Ad-supported users. The number of Ad-supported and Premium users both increased, while throughout the time frame in discussion, there were more Ad-supported users overall.



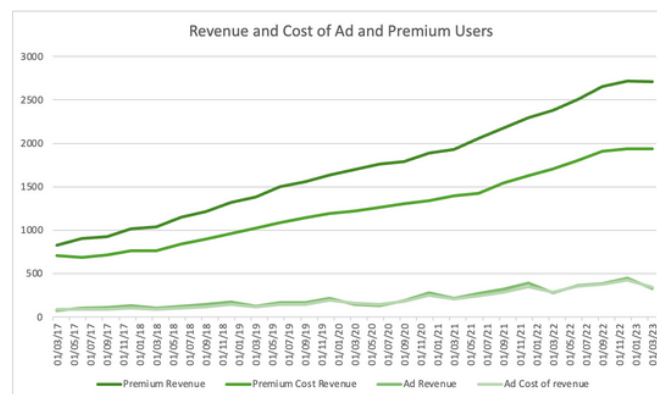
*Graph 1: Number of Premium vs. Ad supported users*



*Graph 2: Gross Profit: Premium vs. Ad supported users*

Graph 2 portrays the comparative Gross Profit for Premium vs Ad-supported users over time. It can be established that Spotify’s Gross Profit generated from Premium users is higher than Ad-Supported Users, even though Ad Users are far higher in number.

Graph 3 captures the relationship between Absolute Revenue vs Cost of Revenue for Premium and Ad-supported users. By analysing Graphs 1, 2 and 3 we can interpret that Spotify’s Ad-supported user base is larger than their Premium subscription user base, however, the majority of the company’s income is derived from its Premium members. In Graph 3, it can be seen that the cost of revenue for Premium Users is high in comparison to Ad-supported users but the overall revenue generated is also higher for the Premium users. Thus, strategies pertaining to proper budget allocation for business costs can be suggested.



*Graph 3: Revenue and Cost of Ad and Premium users*

# DATA ANALYSIS AND INTERPRETATION

## ***A. Linear Regression***

To begin an assessment of the data and describe Spotify's subscriptions, two types of regression models were used: linear regression and log-log regression. This was necessary to determine which regression was the best fit for the dataset.

Two linear regressions were implemented to examine the relationship between Spotify's dependent and independent variables. The first linear regression assessed the dependent variable Premium MAUs and independent variables S&M cost, R&D cost, and G&A cost. The second linear regression assessed Ad MAUs and the same independent variables. The adjusted R-squared for Premium MAUs was 0.8625, and only S&M cost had a statistically significant p-value. The adjusted R-squared for Ad MAUs was 0.9027, whilst two of the coefficients, S&M and R&D, had p-values below 0.05 (Appendix, Exhibit C). Although both regressions showed high R-squared values and were technically good fits, to test the dataset further the study took the log-log regression to see if the findings were a better fit for the dataset.

## ***B. Log-Log Regression***

Before running a log-log regression model, it was imperative to ensure zero-value identification to avoid errors and missing values. Summarising the variables of the dataset illustrated that there were no zero values present. The results showed that the adjusted R-squared for Premium MAUs was 0.9465, which was an increased fit compared to the linear regression model, while only one of the coefficients had a p-value below 0.05. The coefficient G&A displayed a negative relationship to Premium MAUs. The results for Ad MAUs presented an adjusted R-squared of 0.9195 which displayed a slightly better fit from the linear regression model. The coefficient S&M and G&A showcased negative relationships to Ad MAUs (Appendix, Exhibit D). Although the adjusted R-squared for both log-log regression models had improved, the coefficients displayed negative relationships when compared to the dependent variables. To further analyse its validity, mean-centred log-log regression models were tested to determine if mean-centring variables had any effect on the relationship between the dependent and independent variables.

## ***C. Mean-centred Log-Log Regression Model Selection & Result Interpretation***

Mean-centred log-log regression was used to identify non-linear correlations that conventional linear regressions may overlook. Gleman describes mean-centred log-log regression as a common trick in applied regression to 'standardise' each input variable by subtracting its mean and dividing by its standard deviation (Gelman, 2008). Centring the data around the mean allows for the interpretation of coefficients in a straightforward manner.

In the Spotify dataset, it is highly implausible that the costs of S&M, R&D, and G&A would be zero in a real-world business scenario. These are essential operating costs that all businesses must pay, therefore centring around the mean assists in managing that expenses are intrinsically non-zero in the data. It also guarantees that the model is constructed around realistic baseline values, ensuring that the modelling approach is in line with practical considerations while also accurately capturing the realities of the business environment.

While both the Premium and Ad MAUs mean-centred log-log regressions resulted in the exact same R-squared values in the log-log regressions, performing this kind of regression on both of the variables led to higher levels of statistical significance for all the variables when compared to linear or regular log-log regressions. Additionally, the mean-centred log-log regression for Ad MAUs and coefficient of S&M costs displayed a positive correlation, making it a better fit. We can also observe that there are marginally significant synergies between S&M costs and R&D costs for Premium MAUs(Appendix - Exhibit E & F).

Results of the mean-centred log-log regression of **Premium MAUs**:

	<i>Estimate</i>	<i>P-Value</i>
Intercept	4.87557	< 2e-16 ***
SM_Centered	0.61183	0.003092 **
RD_Centered	0.78424	0.000459 ***
GA_Centered	-0.57767	0.021942 *
<b>Adjusted R-Squared: 0.9465</b>		

Results of the mean-centred log-log regression of **Ad MAUs**:

	<i>Estimate</i>	<i>P-Value</i>
Intercept	5.09637	< 2e-16 ***
SM_Centered	0.62614	0.01135 *
RD_Centered	0.74264	0.00431 **
GA_Centered	-0.53300	0.07826
<b>Adjusted R-squared: 0.9195</b>		

Finally, mean-centring reduces multicollinearity between independent variables, which was especially important when analysing the different costs within Spotify. The reason for choosing a mean-centred log-log regression model was to first, achieve more statistically significant correlations between the predictor variables and the dependent variables.

#### ***D. Adstock Predictor Variable Interpretation***

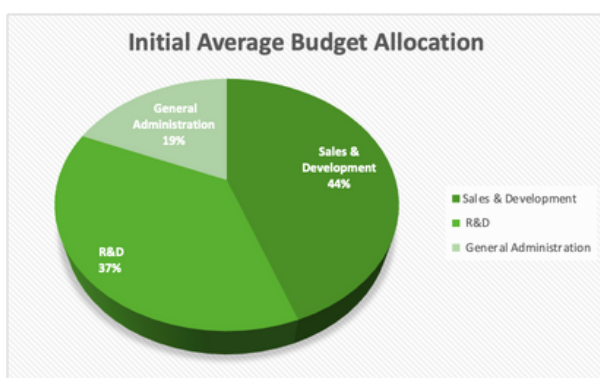
The report discusses the application of Adstock predictor variables because the consumer's response to marketing strategies may be delayed, thus the carryover effect needed to be calculated to ensure that the independent elasticities were not undervalued. This report calculated the Premium MAUs and Ad MAUs model with multiple lambda values (0, 0.3, 0.5, 0.8) to understand the best fit for the predictor variable carryover effect. After running the code for the various lambda values, we concluded that 0.80 lambda value yields the best-fitted model as the adjusted R-squared is 0.9708 for Premium MAUs and 0.946 for Ad MAUs (Appendix, Exhibit G.) Based on the result, S&M had the highest positive carryover effect for Premium MAUs, indicating that the influence of S&M investment continued even if a change in the investment was introduced at a later time. Similarly, R&D showed a positive carryover effect for Premium MAUs. R&D had the highest carryover effect on Ad MAUs as seen in the Adstock regression model for Ad MAUs, followed by the high carryover effect of the S&M on Ad MAUs suggesting the prolonged effect of S&M on overall customer acquisition and revenue.



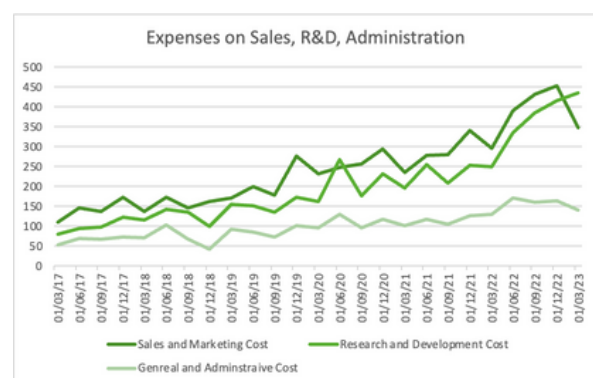
However, the negative coefficient for G&A investment suggested that the impact of the investment in these services diminished over time. The investment had a stronger impact immediately and then the effect weakened over time. Another reason for a negative adstock coefficient for G&A could be the saturation effect, which suggests that after a certain level, the investments made in the G&A category will not have any direct impact on the growth of Premium MAUs or revenue. The high adjusted R-squared and significant p-values ( $<0.05$ ) support the reliability of these results. A similar observation can be made for Ad MAUs (Appendix, Exhibit G.)

### ***E. Ratio of Elasticities & Budget Allocation***

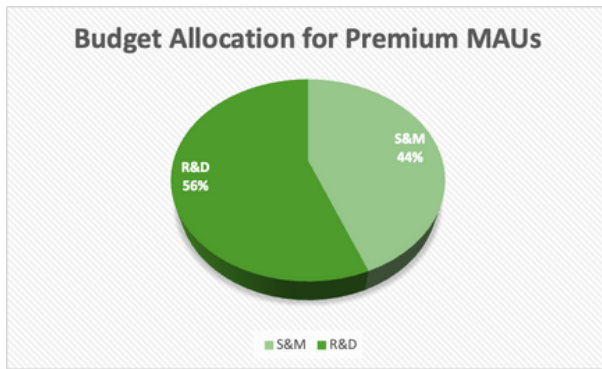
Elasticity can be quantified as the ratio of the percentage change in one variable to the percentage change in another variable when the latter has a causal influence on the former and all other conditions remain the same (Wikipedia, 2023). To be able to suggest budget allocation for these recurring business costs, the report examined the ratio of elasticities between S&M, R&D and G&A for both Premium and Ad supported users. The budget allocation recommendations differ for the two categories as the revenue, profit and the number of users are different for each of these categories. As calculated from the dataset, the ratio of elasticities for Premium users was 0.44 for S&M and 0.56 for R&D. A similar need for budget reallocation can be observed for the Ad MAUs. By calculating the ratio of elasticities for the Ad MAUs we observed that the suggested division of budget is 0.46 for S&M and 0.54 for R&D. This result suggests that in order to increase Spotify's revenue there is a need for budget reallocation between the three recurring costs of S&M, R&D and G&A. The following graphs depict the original budget allocation within the organisation (Graph 1) in contrast with the new recommended budget allocation for both Premium MAUs (44% to S&M and 56% to R&D) as depicted in Graph 3 and Ad MAUs (46% for S&M and 54% for R&D) in Graph 4. Consequently, it can be interpreted from the regression model that G&A did not contribute directly or significantly to the profit and revenue maximisation. Thus, in the new budget allocation, the maximum budget was redistributed to the two main driving factors for growth of the business. In a real-world scenario, it is impossible to have the overall G&A budget be zero, so, for this reason, the recommended allocation hypothetically describes the best revenue-maximising technique. By comparing the individual ratio of elasticities for both Premium MAUs and Ad MAUs we can conclude that budget allocation for both users is more or less the same, even though a larger share of revenue is derived from the Premium MAUs. Thus, a suggestive finding can be to optimise the budget allocation for both the Premium MAUs and Ad MAUs for an optimal allocation value.



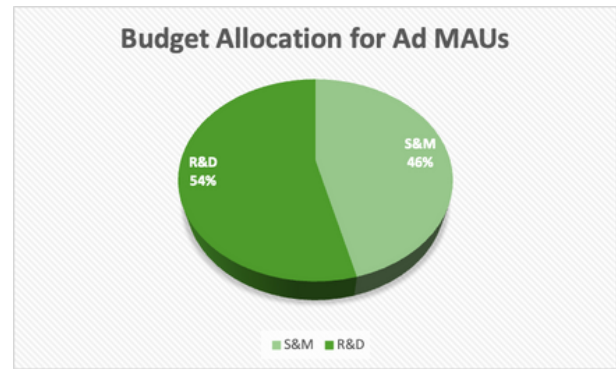
*Graph 4: Original Budget Allocation*



*Graph 5: Investment Trends for S&M, R&D and G&A*



Graph 6: Recommended Budget Allocation:  
Premium MAUs




Graph 7: Recommended Budget Allocation:  
Ad MAUs

## F. Predictive Ability of Model


The predictive ability of a model refers to its capacity to accurately forecast or estimate the outcomes of data based on patterns and relationships identified in the training data. Predictive modelling is a fundamental aspect of statistical analysis and machine learning. The project focused on the predictive analysis of how the total number of customers would grow over the time period for both Premium and Ad-supported categories. The predictive model was trained on 80% of the total observations and used to predict the remaining 20% values. The results for both Premium MAUs and Ad MAUs were plotted for comparison with the actual data. The predicted model was then compared to the actual data in order to understand the overall fit of the models (Appendix, Exhibit I). MAPE stands for Mean Absolute Percentage Error and is used as a metric to evaluate the accuracy of a predictive model. MAPE measures the average percentage difference between predicted and actual values for the two dependent variables. The MAPE value for Premium MAUs is 0.097 suggesting that the mean absolute error in the predictive model is 9.7%. Similarly, the MAPE for Ad MAUs is 0.093, showing the mean absolute error in the predictive model is 9.3%.


## INSIGHTS AND RECOMMENDATIONS

In pursuit of actionable strategies, the two fundamental research questions are reiterated: (1) Assess the comparative profitability between Ad and Premium accounts, and (2) Find the most effective strategy for increasing revenue and gross profit whilst attracting Premium and Ad MAUs.

 The comparative gross profit between free and Premium accounts, as seen in Graph 1, demonstrates a steady growth of both account categories, with more ad-supported users than Premium users. Furthermore, Graph 2 shows that although the ad-supported user base is larger, the majority of Spotify's income is derived from premium subscribers whilst the costs remain similar for both options. Although premium subscriptions led to more revenues, the graphs display a large demand for an ad-supported version. Spotify does have several options of Premium services available at various price points to cater to different users: Premium Individual, Premium Duo, Premium Family and Premium Student (Carbone, 2023). Additionally, as a first-time Premium user, these plans can be tried for one month free and cancelled anytime.



 - Seeing as Premium subscriptions resulted in more revenues, Spotify should focus on ad-supported user conversion and new customer acquisition. To attract existing ad-supported users to purchase premium subscriptions, it is important to address the cost sensitivity for these users. For example, Spotify can offer extended free trial periods and limited offers. Moreover, to expand its customer reach to new users, Spotify can consider partnering with device manufacturers and telecommunications companies, bundling Premium subscriptions with their offerings to attract new users. To incentivise both new and existing Premium users, Spotify can introduce a referral program in which existing Premium users are rewarded for referring friends/family that subscribe to Premium.

 - Based on the chosen mean-centred log-log regression for both Ad and Premium MAUs, the results of the S&M and R&D coefficients are highly significant and positively correlated to the dependent variables. Further, the ratio of elasticities backed up by the adstock predictor variables, S&M had the highest positive carryover effect and R&D showed a positive carryover effect for Premium MAUs which motivates the increase in S&M and R&D in the budget allocation.

## **LIMITATIONS**

The report highlights the value of the insights provided for this data set and the research questions, accentuated by the strong fit of the employed models supported by their high adjusted R-squared values (0.95 and 0.92), their strong predictive accuracy (low MAPE of 0.097 and 0.093), and the statistical significance of individual coefficients. Nevertheless, it is imperative to acknowledge certain limitations within this study.

Firstly, the independent variables lack fine granularity wherein the dataset only provided information on active users for Spotify on a quarterly basis, instead of daily or monthly. This may limit the effectiveness of the model and introduce biases such as confounding bias and overfitting. To mitigate such limitations in the future, it is crucial to gather additional data points and perform sensitivity analyses to assess the impact on the confounding variables. More specifically, it is difficult to assess whether the spending on sales is as effective as the spending on marketing since the model only incorporates overall S&M data.

Secondly, due to the lack of specificity of the dataset in relation to time intervals, the model incorporates only 25 sets of input, meaning if it has three predictors it would ideally have 30 observations. Consequently, the fit and predictive accuracy of the model could be negatively affected and could lead to high variability.

Thirdly, the models are subject to omitted variable bias. For instance, the actions of Spotify competitors (e.g., Youtube Music, Apple Music) (Maciejewski, 2019) could have a significant impact on the MAU. A successful marketing campaign by the competition may be enough to make Spotify's users switch to competing products. Thus, the model would be improved if data were collected from competitors and used to identify additional correlations. Other omitted variable biases include seasonality (e.g., trends in the music industry, music festivals, music awards, etc.) as well as changes in hardware sound quality (e.g., updates in headsets)

Lastly, the model is subjected to multicollinearity. Spotify has been adjusting the budget for Sales & Marketing together with that for R&D, resulting in a correlation of nearly one between the two variables.

## REFERENCES

- 2023 Spotify AB. (2023) About Spotify, Spotify. Available at: <https://newsroom.spotify.com/company-info/> (Accessed: 05 October 2023).
- Alonso, T. (2023) How spotify became the standard in convenience and accessibility, Strategy Study. Available at: <https://www.cascade.app/studies/how-spotify-became-the-standard#:~:text=The%20marketing%20strategy%20of%20Spotify,and%20access%20to%20the%20users.> (Accessed: 10 October 2023).
- Carbone, S. (2023) Spotify Free vs premium: Is it worth it?, SoundGuys. Available at: <https://www.soundguys.com/free-spotify-vs-spotify-premium-36632/> (Accessed: 11 October 2023).
- Elasticity (economics) (2023) Wikipedia. Available at: [https://en.wikipedia.org/wiki/Elasticity\\_\(economics\)#:~:text=Elasticity%20can%20be%20quantified%20as,other%20conditions%20remain%20the%20same.](https://en.wikipedia.org/wiki/Elasticity_(economics)#:~:text=Elasticity%20can%20be%20quantified%20as,other%20conditions%20remain%20the%20same.) (Accessed: 10 October 2023).
- Gelman, A. (2008) Scaling regression inputs by dividing by two standard deviations. Available at: <https://onlinelibrary.wiley.com/doi/epdf/10.1002/sim.3107> (Accessed: 09 October 2023).
- Maciejewski, L. (2019) Strategic Audit of Spotify. Available at: <https://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1136&context=honorstheses> (Accessed: 10 October 2023).
- Maurya, S. (2023) Spotify revenue, expenses and its premium users, Kaggle. Available at: <https://www.kaggle.com/datasets/mauryansshivam/spotify-revenue-expenses-and-its-premium-users> (Accessed: 05 October 2023).
- Newsbeat (2018) How spotify came to be worth billions, BBC News. Available at: <https://www.bbc.com/news/newsbeat-43240886> (Accessed: 05 October 2023).
- Wlömert, N. and Papies, D. (2016) ‘On-demand streaming services and music industry revenues — insights from Spotify’s market entry’, *International Journal of Research in Marketing*, 33(2), pp. 314–327. doi:10.1016/j.ijresmar.2015.11.002.

## APPENDIX

### Exhibit A: Linear regression result of Premium and Ad Revenue for Premium and Ad MAUs

Call:  
lm(formula = spotify\_data\$`Ad Revenue` ~ spotify\_data\$`Ad MAUs`,  
data = spotify\_data)

Residuals:  
Min 1Q Median 3Q Max  
-85.679 -21.581 7.638 28.115 90.841

Coefficients:  
Estimate Std. Error t value Pr(>|t|)  
(Intercept) -21.7647 23.1578 -0.94 0.357  
spotify\_data\$`Ad MAUs` 1.3768 0.1243 11.07 1.08e-10 \*\*\*  
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 43.67 on 23 degrees of freedom  
Multiple R-squared: 0.8421, Adjusted R-squared: 0.8352  
F-statistic: 122.6 on 1 and 23 DF, p-value: 1.077e-10

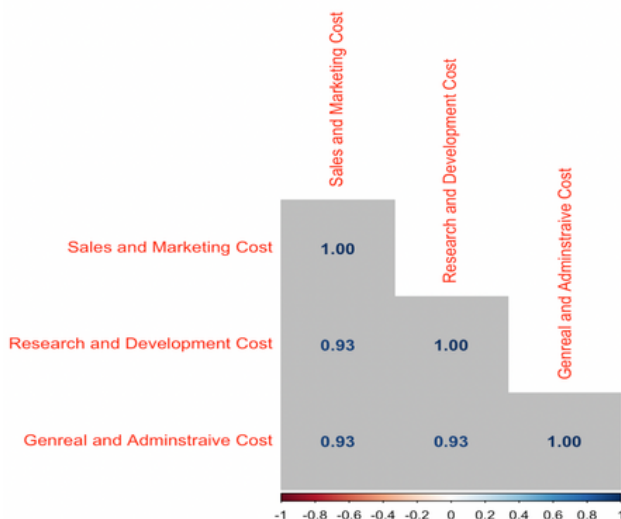
Call:  
lm(formula = spotify\_data\$`Premium Revenue` ~ spotify\_data\$`Premium MAUs`,  
data = spotify\_data)

Residuals:  
Min 1Q Median 3Q Max  
-134.624 -27.811 8.366 38.936 147.476

Coefficients:  
Estimate Std. Error t value Pr(>|t|)  
(Intercept) 154.2611 39.2322 3.932 0.000666 \*\*\*  
spotify\_data\$`Premium MAUs` 12.0475 0.2826 42.625 < 2e-16 \*\*\*  
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 68.45 on 23 degrees of freedom  
Multiple R-squared: 0.9875, Adjusted R-squared: 0.987  
F-statistic: 1817 on 1 and 23 DF, p-value: < 2.2e-16

### Exhibit B: Distance (correlation) matrix



### Exhibit C: Linear regression result of Premium and Ad MAUs vs S&M, R&D and G&A costs

Call:  
lm(formula = spotify\_data\$`Premium MAUs` ~ spotify\_data\$`Sales and Marketing Cost` +  
spotify\_data\$`Research and Development Cost` + spotify\_data\$`Genreal and Adminstraive Cost`,  
data = spotify\_data)

Residuals:  
Min 1Q Median 3Q Max  
-28.313 -12.961 0.336 10.527 31.900

Coefficients:  
Estimate Std. Error t value Pr(>|t|)  
(Intercept) 21.2032 13.9026 1.525 0.14215  
spotify\_data\$`Sales and Marketing Cost` 0.3665 0.1242 2.952 0.00762 \*\*  
spotify\_data\$`Research and Development Cost` 0.1652 0.1122 1.472 0.15585  
spotify\_data\$`Genreal and Adminstraive Cost` -0.1370 0.3323 -0.412 0.68423  
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 18.33 on 21 degrees of freedom  
Multiple R-squared: 0.8797, Adjusted R-squared: 0.8625  
F-statistic: 51.2 on 3 and 21 DF, p-value: 7.844e-10

lm(formula = spotify\_data\$`Ad MAUs` ~ spotify\_data\$`Sales and Marketing Cost` +  
spotify\_data\$`Research and Development Cost` + spotify\_data\$`Genreal and Adminstraive Cost`,  
data = spotify\_data)

Residuals:  
Min 1Q Median 3Q Max  
-33.158 -15.583 -2.414 11.116 48.778

Coefficients:  
Estimate Std. Error t value Pr(>|t|)  
(Intercept) 24.0297 16.9674 1.416 0.1714  
spotify\_data\$`Sales and Marketing Cost` 0.4209 0.1516 2.777 0.0113 \*  
spotify\_data\$`Research and Development Cost` 0.4166 0.1370 3.042 0.0062 \*\*  
spotify\_data\$`Genreal and Adminstraive Cost` -0.3783 0.4056 -0.933 0.3616  
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 22.37 on 21 degrees of freedom  
Multiple R-squared: 0.9148, Adjusted R-squared: 0.9027  
F-statistic: 75.2 on 3 and 21 DF, p-value: 2.127e-11

## Exhibit D: Log-log regression result of Premium and Ad MAUs and S&M, R&D and G&A costs

```

Residuals:
    Min       1Q   Median       3Q      Max
-0.242875 -0.031283  0.006862  0.044408  0.136847

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                    -9.6794    4.8390  -2.000   0.0608 .
log(spotify_data$Sales and Marketing Cost')  0.3695    2.5039   0.148   0.8843
log(spotify_data$Research and Development Cost') 6.6211    2.6087   2.538   0.0206 *
log(spotify_data$Genreal and Adminstraive Cost') -2.6467    2.8304  -0.935   0.3621
log(spotify_data$Sales and Marketing Cost'):log(spotify_data$Research and Development Cost') -0.6823    0.3863  -1.766   0.0943 .
log(spotify_data$Sales and Marketing Cost'):log(spotify_data$Genreal and Adminstraive Cost') 0.8296    0.6595   1.258   0.2245
log(spotify_data$Research and Development Cost'):log(spotify_data$Genreal and Adminstraive Cost') -0.4673    0.4778  -0.978   0.3411
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.09767 on 18 degrees of freedom
Multiple R-squared:  0.9599,    Adjusted R-squared:  0.9465
F-statistic: 71.78 on 6 and 18 DF,  p-value: 1.376e-11

Residuals:
    Min       1Q   Median       3Q      Max
-0.227722 -0.083783 -0.009231  0.067922  0.206470

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                    -1.6569    5.9971  -0.276   0.785
log(spotify_data$Sales and Marketing Cost') -1.1412    3.1032  -0.368   0.717
log(spotify_data$Research and Development Cost') 3.6545    3.2331   1.130   0.273
log(spotify_data$Genreal and Adminstraive Cost') -0.9055    3.5078  -0.258   0.799
log(spotify_data$Sales and Marketing Cost'):log(spotify_data$Research and Development Cost') -0.1287    0.4788  -0.269   0.791
log(spotify_data$Sales and Marketing Cost'):log(spotify_data$Genreal and Adminstraive Cost') 0.5332    0.8174   0.652   0.522
log(spotify_data$Research and Development Cost'):log(spotify_data$Genreal and Adminstraive Cost') -0.4843    0.5922  -0.818   0.424
---
Residual standard error: 0.1211 on 18 degrees of freedom
Multiple R-squared:  0.9396,    Adjusted R-squared:  0.9195
F-statistic: 46.71 on 6 and 18 DF,  p-value: 5.226e-10

```

## Exhibit E: Log-log regression result of Premium MAUs using mean-centred predictor variables

```

Residuals:
    Min       1Q   Median       3Q      Max
-0.242875 -0.031283  0.006862  0.044408  0.136847

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    4.87557    0.02864 170.239 < 2e-16 ***
SM_centered    0.61183    0.17920   3.414 0.003092 **
RD_centered    0.78424    0.18360   4.271 0.000459 ***
GA_cenetred   -0.57767    0.23034  -2.508 0.021942 *
SM_centered:RD_centered -0.68231    0.38632  -1.766 0.094320 .
SM_centered:GA_cenetred 0.82959    0.65952   1.258 0.224516
RD_centered:GA_cenetred -0.46726    0.47780  -0.978 0.341062
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.09767 on 18 degrees of freedom
Multiple R-squared:  0.9599,    Adjusted R-squared:  0.9465
F-statistic: 71.78 on 6 and 18 DF,  p-value: 1.376e-11

```

## Exhibit F: Log-log regression result of Ads MAUs using mean-centred predictor variables

```

Residuals:
    Min       1Q   Median       3Q      Max
-0.227722 -0.083783 -0.009231  0.067922  0.206470

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    5.09637    0.03549 143.584 < 2e-16 ***
SM_centered    0.62614    0.22208   2.819 0.01135 *
RD_centered    0.74264    0.22755   3.264 0.00431 **
GA_cenetred   -0.53300    0.28546  -1.867 0.07826 .
SM_centered:RD_centered -0.12872    0.47878  -0.269 0.79110
SM_centered:GA_cenetred 0.53316    0.81737   0.652 0.52246
RD_centered:GA_cenetred -0.48430    0.59216  -0.818 0.42413
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1211 on 18 degrees of freedom
Multiple R-squared:  0.9396,    Adjusted R-squared:  0.9195
F-statistic: 46.71 on 6 and 18 DF,  p-value: 5.226e-10

```

## Exhibit G: Log-log regression result of Premium and Ad MAUs using adstock variables with lambda = 0.8

```
Call:
lm(formula = log(spotify_data$`Premium MAUs`) ~ log(`Sales and Marketing Cost Adstock`) +
  log(`Research and Development Cost Adstock`) + log(`Genreal and Adminstraive Cost Adstock`),
  data = spotify_data)

Residuals:
    Min       1Q   Median       3Q      Max
-0.12938 -0.04359  0.00986  0.04913  0.11053

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)      1.2385     0.2952   4.196 0.000407 ***
log(`Sales and Marketing Cost Adstock`)  1.1775     0.4475   2.631 0.015610 *
log(`Research and Development Cost Adstock`)  1.1255     0.3199   3.518 0.002043 **
log(`Genreal and Adminstraive Cost Adstock`) -1.9716     0.3496  -5.640 1.35e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07222 on 21 degrees of freedom
Multiple R-squared:  0.9744,    Adjusted R-squared:  0.9708
F-statistic: 266.5 on 3 and 21 DF,  p-value: < 2.2e-16

lm(formula = log(spotify_data$`Ad MAUs`) ~ log(`Sales and Marketing Cost Adstock`) +
  log(`Research and Development Cost Adstock`) + log(`Genreal and Adminstraive Cost Adstock`),
  data = spotify_data)

Residuals:
    Min       1Q   Median       3Q      Max
-0.23972 -0.06942  0.00640  0.07467  0.17611

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)      2.0338     0.4053   5.017 5.75e-05 ***
log(`Sales and Marketing Cost Adstock`)  1.2893     0.6146   2.098 0.04820 *
log(`Research and Development Cost Adstock`)  1.8128     0.4393   4.127 0.00048 ***
log(`Genreal and Adminstraive Cost Adstock`) -2.9417     0.4801  -6.128 4.43e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.09918 on 21 degrees of freedom
Multiple R-squared:  0.9527,    Adjusted R-squared:  0.946
F-statistic: 141.1 on 3 and 21 DF,  p-value: 4.478e-14
```

## Exhibit H: New elasticity using mean-centred variables

ratio of elasticity for Premium MAUs: SM cost=0.61/(0.61+0.78)=0.44  
RD cost=0.78/(0.61+0.78)=0.56

ratio of elasticity for AD MAUs: SM cost=0.63/(0.63+0.74)=0.46  
RD cost=0.74/(0.63+0.74)=0.54

## Exhibit I: Predictive Ability of Model (MAPE)

	$\lambda = 0$	$\lambda = 0.3$	$\lambda = 0.5$	$\lambda = 0.8$
Premium MAUs	0.90	0.94	0.94	0.97
Ad MAUs	0.92	0.93	0.92	0.95