Effectiveness Analysis of Advertising Activities

BAX-401-002 Group D

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Executive Summary

We attempted to explain and assess the effectiveness of the firm's advertising spend on a specific product given data since a product's launch. Using our model from selected variables of interest, our results suggest increased offline advertising activities like catalogs may be negatively impacting sales. Our results were mixed with online activities, though we found effectiveness in key activities such as Search ads. We recommend shifting allocation to effective activities and exploration in online advertising to boost sales, as well as further research into other factors that could be affecting sales of this product.

Introduction

A cosmetics firm launched a product around four years ago and is seeking to understand the effectiveness of its advertising spend on the sales of said product. The firm provided us with the product's monthly unit sales and the breakdown of the related advertising spend over 42 months. Based on the provided data, we want to determine the effectiveness of the mix of marketing activities conducted by the firm and create a preliminary model to guide the firm.

Problem Formulation

The company's marketing activities were divided into offline and online advertising. Offline consists mainly of catalogs sent to different customer subgroups and various non-catalog mailings. Online advertising consists of Banner, Search, Social Media, Newsletter, Retargeting, and Portals, with no customer segmentation. The data shows the expenditure spent on various marketing activities. We see total expenditure on advertisement and separate data for online and offline advertising expenditure.

- Catalogs, classified by existing customers, winback customers (those that have not bought in at least six months), and new customers. We note that most catalog expenditure was spent for catalogs for existing customers, which was also the most persistent catalog expenditure.

- The data for banners and social media are almost all zero which means the firm has not focused spending on these activities, though we note there was spend on banners for four months late into the dataset. While no further information was provided, we believe this may indicate a short-run experiment was conducted.
- Consistent expenditure was made for Search and Newsletter, especially in the last seven months for the former.
- The data for mailing shows no expenditure has been done on mailing for most of the time frame, which may be normal given today's more digital climate.

We aim to explain the effectiveness of these advertising activities on sales, as follows:

$$Y_t = \lambda Y_{t-1} + ß_1 X_{1t} + ß_2 X_{2t} + ... + ß_n X_{nt} + intercept + \varepsilon_t$$

Where Y is Sales and advertising activities are denoted by X, which their months denoted by t. The model shows Y as a function of X variables for up to n advertising activities.

Data Description

Dranove (n.d.) stated that the most important criterion in the selection of a variable for the right hand side of a regression model is theoretical relevance. He noted that kitchen sink regressions, which use all variables, indicate lack of thought on why variables should be included.

We first removed variables which had little to no expenditure: Social Media and Banner. We then considered other variables with multiple months of no expenditure: Catalogs for win back and new customers, as well as mailings had multiple months of no expenditure. We did not include these in the final model due to no further information on the irregular pattern of spend. However, we note that in **Appendix XX**, we did run a model including these variables for testing purposes. We found that Retargeting only began in month 26 though it was consistent after.

We then looked at variables we could combine: At first glance, combining the three Catalog variables seemed an obvious strategy. However, since the patterns of expenditure and the target markets are different, the combination may not be an effective choice. In **Appendix XX,** we see that combining these variables was not as effective as separating them. We chose to keep only the consistent Catalogs (Existing Customers) for our model. Of the other online advertising spends, Portals is a broad bundle of services (Marketing, n.d.) that may coincide with Retargeting efforts. We chose to add Retargeting and Portals into a single variable, allowing the costs of retargeting for the quarter to be included without negatively affecting the outcome of the allocation model. In addition, the combination lowered the AIC compared to just having the variable portal, which suggests a more accurate version of reality.

We end up with the final variables of: Catalogs (Existing Customers), Search, Newsletter, and the combined variable Retargeting+Portal.

Model Development, Estimation, and Results

We use the log transformation of the four variables chosen above, denoted by Z_{nt} to indicate the transformation of variable X: Z_{nt} = log(X). We ran multiple models using these variables, summarized in **Appendix XX**, and selected the following model:

$$Y_t = -0.16Y_{t-1} - 234.07ß_1Z_{1t} + 1498.72ß_2Z_{2t} + 377.54ß_3Z_{3t} + -201.21ß_4Z_{4t} + \varepsilon_t$$

With the following variables assigned: Z_{1t} for Catalogs for Existing Customers, Z_{2t} for Search, Z_{3t} for Newsletter, and Z_{4t} for Retargeting+Portal. We then calculated elasticity, as follows:

	Effectiveness, ß	Carryover Effect, λ	Elasticity, $\eta = ß/[(1-\lambda)\bar{Y}]$
Catalogs for Existing Customers	-234.0699	-0.1555	-0.04212093

Search	1498.7176	-0.1555	0.2696945
Newsletter	377.5382	-0.1555	0.06793808
Retargeting+Portal	-201.2149	-0.1555	-0.03620866

We see two negative coefficients, suggesting that Catalogs for Existing Customers and Retargeting+Portal may not be effective forms of advertising. Though we note the p-value for Retargeting+Portal indicated this was not statistically significant. The negative coefficient may be explained by customer fatigue from overexposure, where repetition can have a negative effect on performance (IAB Europe, 2019). Search and Newsletter appear to be effective forms of advertising, particularly Search to which Sales is more sensitive. This may be due to the nature of Search ads, which occur when a user is already actively searching and may be more inclined to purchase an item as opposed to being in a state where they are simply exposed to the product's advertising with no such inclinations. The presence of both negative and positive coefficients and elasticities suggests that the current advertising spend has not been allocated properly, upon which we make recommendations in the next section.

Recommendations and Managerial Implications

The negative elasticity in catalogs for existing customers shows there is likely too much investment in catalogs, or even offline advertising, that the firm has lost any increase in sales. The firm can reduce spending here and allocate those funds in other forms, particularly in online advertising to increase sales. While catalogs for existing customers could have retention benefits for the current population of the business, there may be an oversaturation point where it becomes harmful to this specific product's performance.

Online advertising could be improved significantly, given the effectiveness of Search. Additionally, Social Media has no spend, yet based on the online activities there is potentially an impact on sales from this type of advertising. The firm would have to be careful, as Retargeting+Portal showed negativity elasticity so a threshold may be necessary to prevent further investment that would not increase sales. Placing more funds in other forms of online advertisement could open an avenue to drive revenue. Given the industry, the firm should consider testing Social Media advertisements for potential impact in sales.

The magnitude of online advertising investments is currently low compared to offline. The firm could look into improving allocation from offline into online given offline's potentially depressing effect on sales, and then reviewing the effects of the shift. If the firm's resources permit, running experiments (potentially like Banner) may be done to improve sales performance for this product. For Retargeting, the firm could also consider a user's browser or operating system given changing user behavior with some users who increasingly value privacy. Making these considerations could allow for improvement in the online advertising arena.

Additionally, the firm could have completely missed certain factors apart from its advertising activities that may be affecting the performance of this product. There may be marketing strategies such as promotions (discounts) or clearance sales. As it's a cosmetic firm's product, there may also be seasonality issues to consider, such as seasonal trends and behavior of consumers, as well as holidays. Economic factors affecting things such as wage may also be considered, depending on whether the product is viewed as a necessity or luxury, though that would require further information.

Conclusion

Based on 42 months of sales and advertising information provided by a cosmetics firm, we attempted to assess the effectiveness of the firm's advertising spend on a specific product. Given our focal model, our results suggest certain offline advertising activities may not be effective and negatively impact sales. We obtained mixed results for online activities, though key activities such as Search ads were found to be effective. We recommend shifting allocation from offline to online to boost sales, as well as further research into other factors that could be affecting the product's performance.

References

Dranove, D. (n.d.). *Model Specification: Choosing the Right Variables for the Right Hand Side.* Kellogg School of Management, MGMT 469, Empirical Methods in Strategy, Lecture Notes. **https://www.kellogg.northwestern.edu/faculty/dranove/htm/dranove/coursepages/Mgmt%20469/choosing%20variables.pdf**

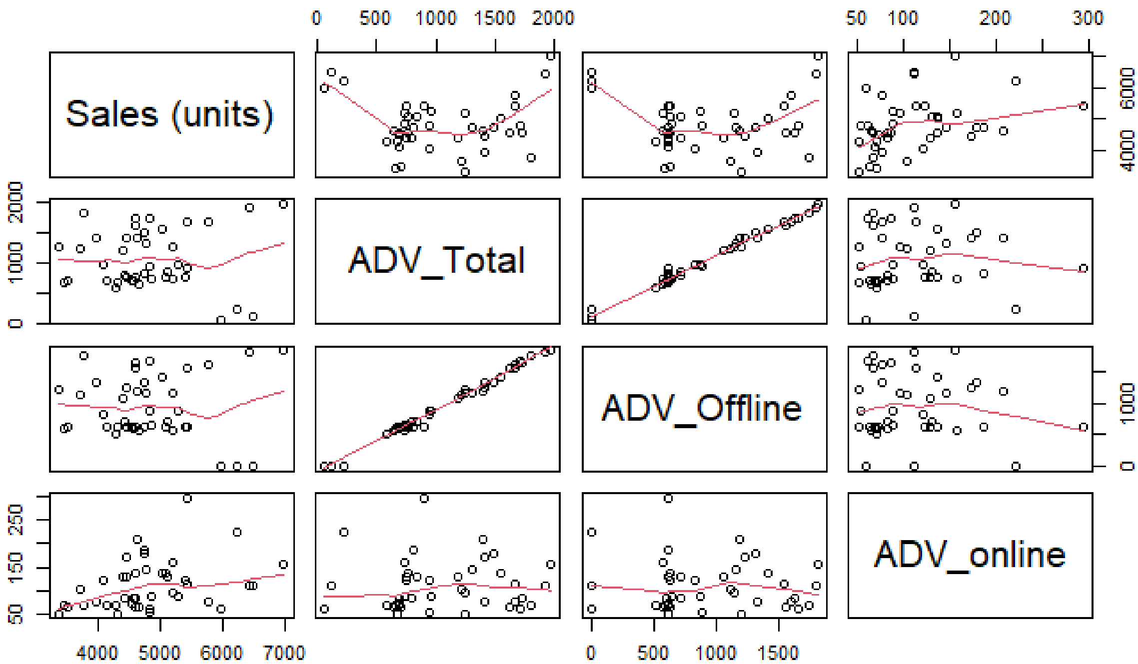
Nichols, W. (2013, March). *Advertising Analytics.* Harvard Business Review. **https://hbr.org/2013/03/advertising-analytics-20**

IAB Europe (2019, July 24). *Member Research: Campaign overexposure has negative impact on branding performance.* Interactive Advertising Bureau. **https://iabeurope.eu/blog/member-research-campaign-overexposure-has-negative-impact-on-branding-performance/**

Appendix

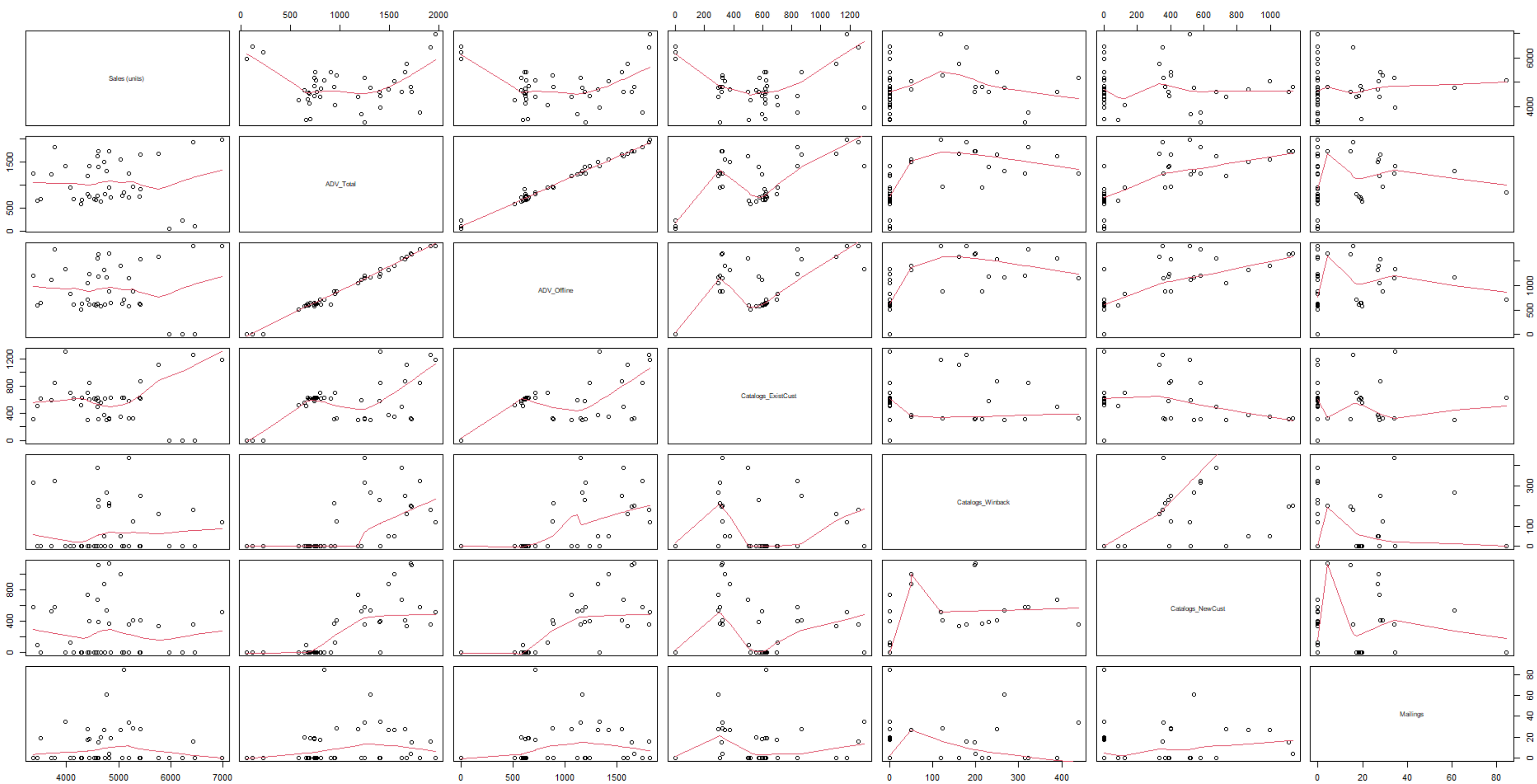
Appendix 01: Variable Assessment

We look at the scatterplots of the aggregate amounts.

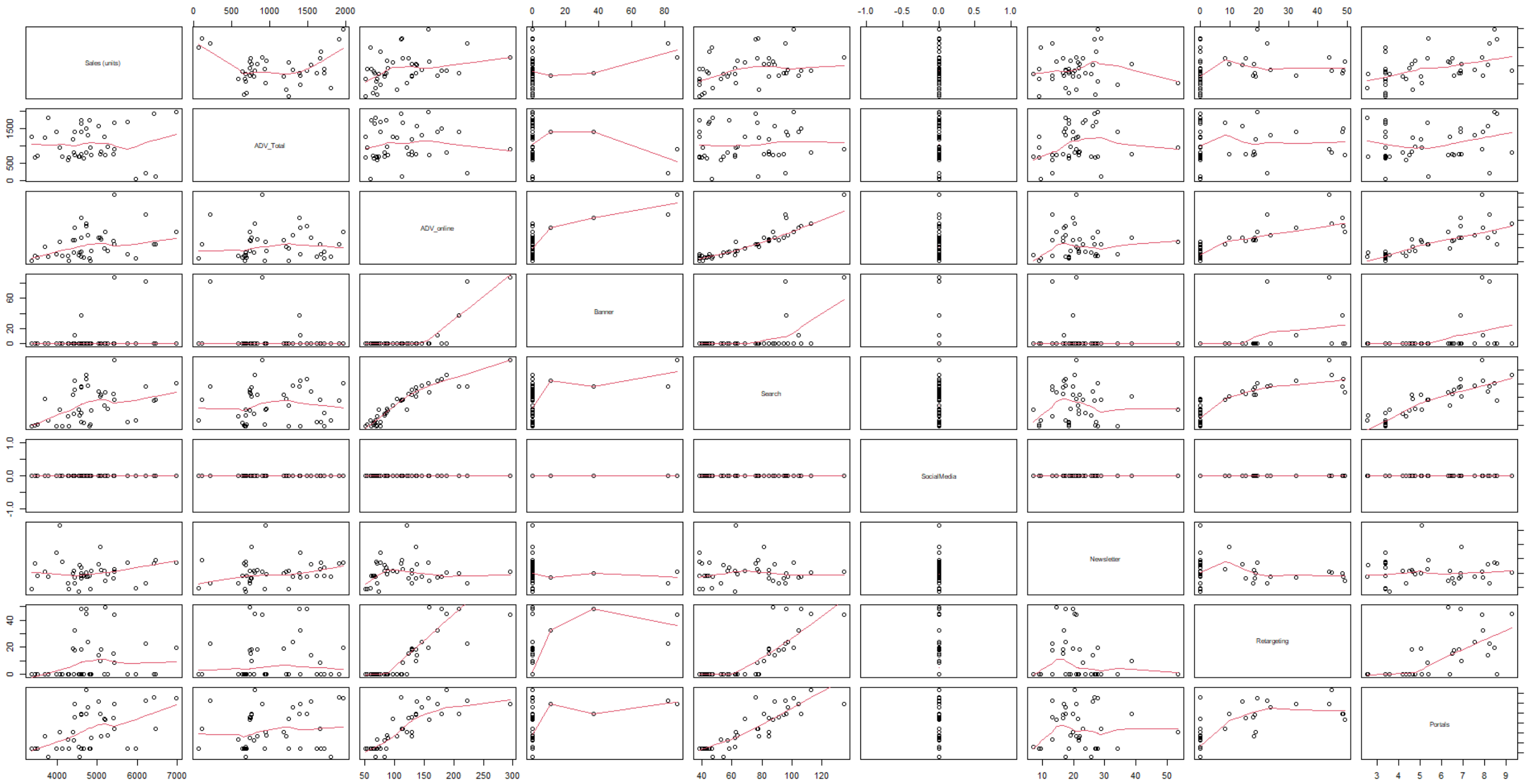


We see that when aggregated, there do not seem to be identifiable linear relationships between sales and each of the advertising activities.

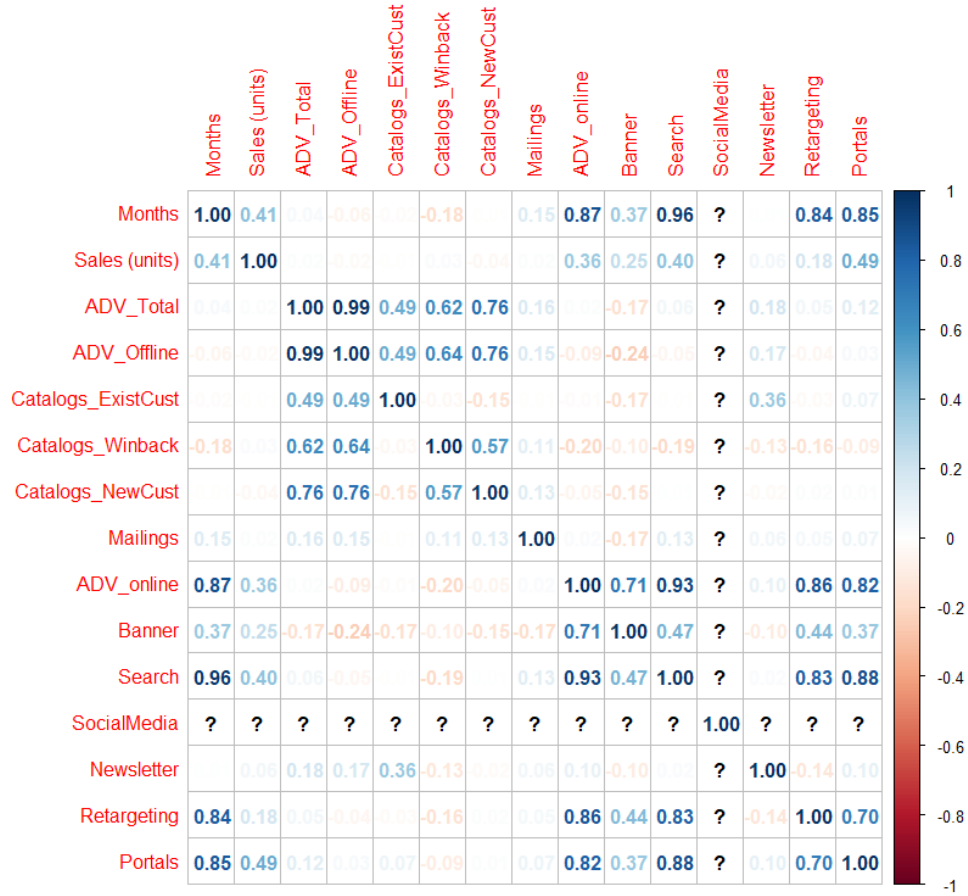
We looked at the scatterplot of Offline Activities and Sales and found no immediately identifiable linear relationships.



We looked at the scatterplot of Online Activities and Sales and found no immediately identifiable linear relationships.



We examined the relationships between the variables through correlations, shown below:



We note that there do not seem to be strong correlations between any of the advertising activities and Sales, with the only moderate positive correlations being Search and Sales and Portals and Sales.

Variable	
Months	Time for 42 months.
Sales	The amount of unit sales of the product appears to increase across the months.
ADV_Total	This amount is an aggregate of all advertisement spending. This does not depict an accurate way to determine where advertising should be spent.
ADV_Offline	This includes all values on offline spending, yet the type of advertising impact is missed when including all forms.
Catalogs_ExistCust	These have a few missing values and amount spend varies between 500 to about 1500, though is the most consistent of offline spend.
Catalogs_Winback	Sparse data and several zero values with ranges spent from 49 dollars to higher than 450 dollars per month.
Catalogs_NewCust	Sparse data and several zero values that includes the amount spent from about 87 dollars to over 1000 dollars per month.
Mailings	Multiple months of zero values with amounts spent all less than a hundred.
ADV_Online	This attribute includes all forms of online advertising, yet what is overlooked is the quality of the data for each type.
Banner	Many values are zero here and it appears banner ads were only used for a short period of 4 months.
Search	Is the most invested across online advertisements.
SocialMedia	Social media has no spend in any of the months presented. This variable should be removed.
Newsletter	20 dollars is the average spent. Ranging from 7 to 53 dollars.
Retargeting	The last 16 months of this data, investments

	did increase.
Portals	Portal does not have that much spending compared to other online attributes like Newsletter.

Appendix 02: Model 0 A

For initial testing, we ran the model with no transformed variables. This model was run with intercept, no synergy, and with lag.

AIC: 667.5866

BIC: 679.5817

```
Call:
lm(formula = Sales ~ Stm1 + Med2 + Med8 + Med10 + MedRP)

Residuals:
     Min       1Q   Median       3Q      Max
-1731.36  -382.41   -91.63   443.21  1675.70

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) 2948.48911  863.24276   3.416  0.00163 **
Stm1           0.14490    0.17453   0.830  0.41202
Med2           0.07438    0.46064   0.161  0.87265
Med8          19.97229   10.50993   1.900  0.06565 .
Med10          1.08222   15.74606   0.069  0.94560
MedRP        -16.88975   14.12116  -1.196  0.23971
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 758 on 35 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.2062,    Adjusted R-squared:  0.09277
F-statistic: 1.818 on 5 and 35 DF,  p-value: 0.1348
```

Appendix 03: Model 0 B

We then ran the no-transformation variables in a model with intercept, no synergy, and without lag.

AIC: 682.966

BIC: 693.3919

```
Call:
lm(formula = Sales ~ Med2 + Med8 + Med10 + MedRP)

Residuals:
    Min      1Q  Median      3Q     Max 
-1569.8  -412.6  -118.3   356.9  1631.2 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.379e+03  5.475e+02   6.172 3.67e-07 ***
Med2        -5.649e-03  4.316e-01  -0.013  0.98963    
Med8         2.593e+01  9.407e+00   2.757  0.00901 ** 
Med10       -1.284e+00  1.549e+01  -0.083  0.93435    
MedRP       -2.181e+01  1.363e+01  -1.600  0.11820    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 759.1 on 37 degrees of freedom
Multiple R-squared:  0.2174,	Adjusted R-squared:  0.1328 
F-statistic:  2.57 on 4 and 37 DF,  p-value: 0.05385
```

Our results from Appendix 02 and Appendix 03 indicate that the inclusion of lag would be preferable.

Appendix 04: Model 1

We then ran the transformed model, using square root transformations to account for the diminishing returns effect. This model was run with intercept, without synergy, and with lag.

AIC: 665.7669

BIC: 677.7619

```
Call:
lm(formula = Sales ~ Stm1 + SqM2 + SqM8 + SqM10 + SqMRP)

Residuals:
    Min      1Q  Median      3Q     Max 
-1481.8  -405.4  -104.3   388.3  1952.7 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)  
(Intercept) 2501.48458 1221.35572   2.048   0.0481 *
Stm1           0.02198    0.18290   0.120   0.9050  
SqM2         -24.19870   17.54906  -1.379   0.1767  
SqM8         322.23095  194.59673   1.656   0.1067  
SqM10        113.94705  145.71735   0.782   0.4395  
SqMRP       -111.17818  134.87054  -0.824   0.4153  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 741.4 on 35 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.2406,	Adjusted R-squared:  0.1322 
F-statistic: 2.218 on 5 and 35 DF,  p-value: 0.07435
```

Appendix 05: Model 2

We then ran the model with square root transformed variables with intercept, without synergy, and with lag.

AIC: 668.408

BIC: 678.6894

```
Call:
lm(formula = Sales ~ Stm1 + SqM2 + SqM8 + SqM10 + SqMRP - 1)

Residuals:
     Min       1Q   Median       3Q      Max 
-2044.90  -358.77   -24.85   433.70  1644.21 

Coefficients:
       Estimate Std. Error t value Pr(>|t|)   
Stm1     0.1718     0.1749   0.982  0.33256   
SqM2    -9.6293    16.7394  -0.575  0.56870   
SqM8   534.3060   171.9161   3.108  0.00367 **
SqM10  149.3257   150.9737   0.989  0.32922   
SqMRP -247.5505   122.3824  -2.023  0.05057 . 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 773.6 on 36 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.9782,	Adjusted R-squared:  0.9751 
F-statistic: 322.6 on 5 and 36 DF,  p-value: < 2.2e-16
```

Appendix 06: Model 3

We then ran the model with square root transformed variables with intercept, with synergy, and with lag.

AIC: 664.9722

BIC: 682.1079

```
Call:
lm(formula = Sales ~ Stm1 + SqM2 + SqM8 + SqM10 + SqMRP + SqM2 *
    SqM8 + SqM2 * SqM10 + SqM2 * SqMRP)

Residuals:
     Min       1Q   Median       3Q      Max
-1402.97  -393.72   -66.73   378.02  1537.74

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.998e+03  3.132e+03   0.957   0.3457
Stm1        -5.442e-03  1.784e-01  -0.031   0.9759
SqM2        -6.273e+01  1.353e+02  -0.464   0.6460
SqM8         1.121e+03  6.831e+02   1.641   0.1106
SqM10       -9.238e+02  5.105e+02  -1.809   0.0798 .
SqMRP       -9.094e+02  5.168e+02  -1.760   0.0880 .
SqM2:SqM8   -2.965e+01  2.652e+01  -1.118   0.2719
SqM2:SqM10   4.148e+01  1.904e+01   2.179   0.0368 *
SqM2:SqMRP   3.252e+01  2.127e+01   1.529   0.1360
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 713.7 on 32 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.3566,	Adjusted R-squared:  0.1958
F-statistic: 2.217 on 8 and 32 DF,  p-value: 0.0526
```

Appendix 07: Model 4

We then ran the model with square root transformed variables without intercept, with synergy, and with lag.

AIC: 664.1294

BIC: 679.5515

```
Call:
lm(formula = Sales ~ Stm1 + SqM2 + SqM8 + SqM10 + SqMRP + SqM2 *
    SqM8 + SqM2 * SqM10 + SqM2 * SqMRP - 1)

Residuals:
     Min       1Q   Median       3Q      Max
-1455.25  -426.69    -9.79   359.10  1612.57

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
Stm1        1.042e-02  1.774e-01   0.059 0.953497
SqM2        5.853e+01  4.733e+01   1.237 0.224958
SqM8        1.634e+03  4.227e+02   3.866 0.000491 ***
SqM10      -1.020e+03  4.998e+02  -2.041 0.049332 *
SqMRP      -1.222e+03  3.996e+02  -3.060 0.004380 **
SqM2:SqM8  -4.963e+01  1.633e+01  -3.040 0.004609 **
SqM2:SqM10  4.353e+01  1.889e+01   2.304 0.027637 *
SqM2:SqMRP  4.485e+01  1.690e+01   2.655 0.012128 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 712.8 on 33 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.983,	Adjusted R-squared:  0.9789
F-statistic: 238.6 on 8 and 33 DF,  p-value: < 2.2e-16
```

Based on results from the square root transformations, we see that overall models are more statistically significant when intercepts are not included.

Appendix 08: Model 5

From this model onwards, we transformed our independent variables by using logarithmic functions to capture the diminishing returns effect. We first ran the model with the intercept, without taking into account synergy between the variables.

AIC: 658.0336

BIC: 670.0286

```
Call:
lm(formula = Sales ~ Stm1 + LMed2 + LMed8 + LMed10 + LMedRP)

Residuals:
     Min       1Q   Median       3Q      Max 
-1032.81  -438.24    -2.98   327.54  1900.92 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)   
(Intercept) 1325.3459  2391.1818   0.554  0.58292   
Stm1          -0.1551     0.1778  -0.872  0.38892   
LMed2       -243.7919    77.3821  -3.150  0.00333 **
LMed8       1134.5904   761.0439   1.491  0.14496   
LMed10       376.3199   297.6675   1.264  0.21450   
LMedRP       -87.8859   258.5839  -0.340  0.73598   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 674.7 on 35 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.3712,	Adjusted R-squared:  0.2813 
F-statistic: 4.132 on 5 and 35 DF,  p-value: 0.004705
```

We see improvement from using logarithmic transformation over square root transformation. We proceed with analysis on these models.

We see that the overall model is statistically significant, with a p-value of 0.004705. However, looking at the R-squared and the Adjusted R-squared, we see that only about 37.12% or 28.13% (adjusted) of the firm's product sales could be explained by the variables of interest. We also note that only Catalogs (Existing Customers) is significant based on the t-test.

Appendix 09: Model 6 - CHOSEN MODEL

We then ran the log model without the intercept and without taking into account synergy between the variables.

AIC: 656.3919

BIC: 666.6733

```
Call:
lm(formula = Sales ~ Stm1 + LMed2 + LMed8 + LMed10 + LMedRP -
    1)

Residuals:
     Min       1Q   Median       3Q      Max
-1165.50  -403.83   -56.11   274.86  1852.86

Coefficients:
        Estimate Std. Error t value Pr(>|t|)
Stm1     -0.1555     0.1761  -0.883  0.38299
LMed2  -234.0699    74.6392  -3.136  0.00340 **
LMed8  1498.7176   380.4680   3.939  0.00036 ***
LMed10  377.5382   294.7813   1.281  0.20848
LMedRP -201.2149   156.7684  -1.284  0.20751
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 668.2 on 36 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.9837,    Adjusted R-squared:  0.9815
F-statistic: 434.9 on 5 and 36 DF,  p-value: < 2.2e-16
```

The overall model is statistically significant with a p-value of 2.2e-16. We note that this model has a high R-Squared, 0.9837 and an adjusted R-Squared of 0.9815, which may indicate endogeneity as a potential weakness of this model. In this model, we identified two significant variables through the t-test: Catalogs (Existing Customers) with a p-value of 0.00340 and Search with a p-value of 0.00036.

We note that in prior models, the intercept was not statistically significant and could possibly be removed from the model given the chosen variables of interest. This model has the lowest AIC value, hence we decided to proceed with this model.

Appendix 10: Model 7

We then ran the log model with the intercept and without taking into account synergy between the variables.

AIC: 661.1619

BIC: 678.2976

```
Call:
lm(formula = Sales ~ Stm1 + LMed2 + LMed8 + LMed10 + LMedRP +
    LMed2 * LMed8 + LMed2 * LMed10 + LMed2 * LMedRP)

Residuals:
     Min       1Q   Median       3Q      Max
-1044.91  -455.45    26.96   320.79  1679.98

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  -1.802e+04  1.902e+04  -0.948    0.350
Stm1         -1.463e-01  1.813e-01  -0.807    0.426
LMed2         2.741e+03  3.009e+03   0.911    0.369
LMed8         9.587e+03  7.309e+03   1.312    0.199
LMed10       -3.258e+03  2.726e+03  -1.195    0.241
LMedRP       -2.954e+03  2.267e+03  -1.303    0.202
LMed2:LMed8  -1.303e+03  1.132e+03  -1.151    0.258
LMed2:LMed10  5.521e+02  4.067e+02   1.358    0.184
LMed2:LMedRP  4.485e+02  3.553e+02   1.262    0.216

Residual standard error: 681.3 on 32 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.4137,    Adjusted R-squared:  0.2671
F-statistic: 2.823 on 8 and 32 DF,  p-value: 0.01728
```

The overall model is statistically significant with a p-value of 0.0178. However, looking at the R-squared and the Adjusted R-squared, we see that only about 41.37% or 26.71% (adjusted) of the firm's product sales could be explained by the variables of interest. No variables or interactions were significant based on the t-test.

We do not choose this model over the previous one.

Appendix 11: Model 8

We then ran the log model without the intercept and with synergy between the variables.

AIC: 660.2968

BIC: 675.7189

```
Call:
lm(formula = Sales ~ Stm1 + LMed2 + LMed8 + LMed10 + LMedRP +
    LMed2 * LMed8 + LMed2 * LMed10 + LMed2 * LMedRP - 1)

Residuals:
     Min       1Q   Median       3Q      Max
-1041.48  -437.58   -51.37   340.58  1758.67

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
Stm1           -0.1441     0.1810  -0.797   0.4314
LMed2         -85.9585   393.0576  -0.219   0.8282
LMed8        2738.0744  1090.0344   2.512   0.0171 *
LMed10       -949.9922  1223.0563  -0.777   0.4428
LMedRP       -895.5746   648.6894  -1.381   0.1767
LMed2:LMed8  -246.3237   195.3869  -1.261   0.2163
LMed2:LMed10  212.6778   192.3557   1.106   0.2769
LMed2:LMedRP  128.6189   110.7160   1.162   0.2537
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 680.3 on 33 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.9845,    Adjusted R-squared:  0.9808
F-statistic: 262.4 on 8 and 33 DF,  p-value: < 2.2e-16
```

The overall model is statistically significant with a p-value of 2.2e-16. We also note that removing the intercept again raised the R-squared and Adjusted R-squared values to 0.9845 and 0.9808 respectively, which may indicate endogeneity as a potential weakness of this model. This model has only one significant variable identified through the t-test, which is Search with a p-value of 0.0171.

We do not choose this model over Model 6 in Appendix 09.

Appendix 12: Model 9

We then ran the log model chosen (Model 6) without the intercept and without taking into account synergy between the variables, but with added variables for testing. In this model, we tried to examine the effect of including all customer segmentations and added all three catalog variables separately.

$$Y = \lambda Y_{t-1} + ß_1 Z_1 + ß_2 Z_2 + ß_3 Z_3 + ß_4 Z_4 + ß_5 (Z_1 {*} Z_2) + ß_6 (Z_1 {*} Z_3) + ß_7 (Z_1 {*} Z_4) + ß_0 + \varepsilon_t$$

Where: Y = sales, Z_1 = log(X_1) = Catalogs (Existing Customers), Z_2 = log(X_2) = Catalogs (Winback), Z_3 = log(X_3) = Catalogs (New Customers), Z_4 = log(X_4) = Combined variable (Retargeting + Portal), Z_5 = log(X_5) = Search, Z5 = log(X_6) = Newsletter.

AIC: 648.4113

BIC: 662.1199

```
Call:
lm(formula = Sales ~ Stm1 + LMed2 + LMed3 + LMed4 + LMedRP +
    LMed8 + LMed10 - 1)

Residuals:
    Min      1Q  Median      3Q     Max
-922.60 -350.41  -89.52  346.65 1668.00

Coefficients:
        Estimate Std. Error t value Pr(>|t|)
Stm1      0.1396     0.1792   0.779  0.44139
LMed2  -181.7143    69.0306  -2.632  0.01266 *
LMed3   247.8358    73.3407   3.379  0.00184 **
LMed4  -158.2750    58.3832  -2.711  0.01044 *
LMedRP  -33.6175   147.9381  -0.227  0.82160
LMed8   918.9198   379.3328   2.422  0.02089 *
LMed10  475.3919   264.2525   1.799  0.08090 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 594.1 on 34 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.9878,    Adjusted R-squared:  0.9853
F-statistic: 394.6 on 7 and 34 DF,  p-value: < 2.2e-16
```

While we found a lower AIC and similar R-squared and Adjusted R-Squared values, we decided not to proceed with this model as we have limited information and cannot explain the irregular spend of the company on the two additional offline advertising types included, as seen in the numerous zeroes in the data for those variables. What this tells us, however, is that it may be worthwhile for the firm to try and look at customer segmentation for its advertising activities to determine effectiveness of each segment.

Appendix 13: Summary of Models and Assessments

Model	**Variable Transformation**	**Intercept, Synergy, Lag**	**AIC, BIC**	**Significance**
Model 1	Square Root	With intercept, without synergy	**AIC:** 665.7669 **BIC:** 677.7619	Overall model: 0.07435
Model 2	Square Root	Without intercept, without synergy	**AIC:** 668.408 **BIC:** 678.6894	Overall model: 2.2e-16
Model 3	Square Root	With intercept, with synergy	**AIC:** 664.9722 **BIC:** 682.1079	Overall model: 0.1958
Model 4	Square Root	Without intercept, with synergy	**AIC:** 664.1294 **BIC:** 679.5515	Overall model: 2.2e-16
Model 5	Logarithmic Function	With intercept, without synergy, with lag	**AIC:** 658.0336 **BIC:** 670.0286	Overall model: 0.004705
Model 6	Logarithmic	Without	**AIC:** 656.3919	Overall model:

	Function	intercept, without synergy, with lag	**BIC:** 666.6733	2.2e-16
Model 7	Logarithmic Function	With intercept, with synergy, with lag	**AIC:** 661.1619 **BIC:** 678.2976	Overall model: 0.01728
Model 8	Logarithmic Function	Without intercept, with synergy, with lag	**AIC:** 660.2968 **BIC:** 675.7189	Overall model: 2.2e-16

We see that running the models with the logarithmic transformation yielded more statistically significant models than those with square root and generally lower AICs. The models that removed the intercept also had lower p-values for the overall model and AICs than those that included the intercept.

Appendix 14: Elasticity

We calculate the elasticity of each variable, precisely the change in sales in response to the change in each variable, ceteris paribus or holding all other determining variables constant.

	Effectiveness, ß	Carryover Effect, λ	Elasticity, $\eta = ß/[(1-\lambda)\bar{Y}]$
Catalogs for Existing Customers	-234.0699	-0.1555	-0.04212093
Search	1498.7176	-0.1555	0.2696945

Newsletter	377.5382	-0.1555	0.06793808
Retargeting+Portal	-201.2149	-0.1555	-0.03620866

Appendix 15: Kitchen Sink Regressions

For illustrative purposes, we also ran kitchen sink regressions in initial assessments of the variables and building the model. The following were the AIC values:

AIC Table	**No transformation**	**Square Root**	**Log**
With intercept, without synergy	671.2056	660.4503	647.8362
Without intercept, without synergy	680.5933	667.192	647.6094

We noted that while AIC improved with kitchen sink particularly for log transformation, these may not be the most theoretically sound models.