Analysis of Marketing Strategy for Furniture B2B

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1. Abstract

This report discusses the challenge and opportunity business faces nowadays as the development of internet has complicated the marketing strategy. This report explains in detail the process of applying statistical model and computational technology to help a business to allocate its resources of marketing in the optimal way. For company Furniture B2B, the methodology in detail and a comprehensive process of computing the optimal marketing resource allocation strategy are discussed in the report. As the calculation proves in this report, the offline order of Furniture B2B will increase, in theory, by 4.7% and online order stay the same, while it does not need to commit additional resources but simply adjust its strategy of allocating marketing resources. The computation for deriving the optimal allocation strategy and forecasting the long-term gain in this report is mostly done with the help of R.

2. Introduction

Traditionally, both the marketing and selling channels of business are offline. Business relied on newspaper and flyer to advertise their product, and sales representative, telephone, or mail to sell the products. The developments of media, TV, internet have provided business practitioner with various techniques to marketing and sell the product. With more channels of marketing and selling, the marketing strategy has become much more complicated. For better understanding customers metric and maximizing the potential of digital marketing, successful retailers need to understand "cross-category demand effects": the effects of prices, promotions, and sales of a certain product category on the sales of another product category (Wilms, Ines, et al.). But without quantitative analysis and evaluation, businesses might not optimize the effectiveness of their campaign strategy.

With the help of modern computational technology, it is now possible to apply statistical and mathematical model to detect the underlying dependency among the sale performance, marketing actions and selling channels. By analyzing the dependency among those variables, a business could reach an optimal marketing resource allocation and even predict the future order sizes. This report aims to introduce the methodology of analyzing the weekly performance data of Furniture B2B, which include marketing tool, discount, visitation to the website, the numbers of inquiry, quotes, and orders from both the online and offline, and provide answer to the following questions:

1. What is optimal marketing resource allocation of flyer, catalogs, AdWords, and emails that could maximize the number of visits to the website of Furniture B2B?
2. How will the potential optimal marketing resource allocation, found in the question above, contributed to the growth of orders?

3. Methodology

3.1 Optimal Marketing Resource Allocation

Using VAR model to isolate the effects of various marketing instruments, Furniture B2B could develop the optimal allocation strategy of marketing budgets and to maximize the visitation to the website of Furniture B2B. The goals of this step is to determine whether Furniture should re-allocate the money spent on the four marketing tools, and there are four steps to follow.

Firstly, before applying the VAR model, it is important to perform unit root tests to ensure that the mean, variance, and autocorrelation of a time series variable stay stable over time. If the unit root tests return that some of variable within the dataset is not stationary, then taking differences of each variable will convert each of them to a stationary one.

Secondly, after ensuring all the variables are stationary, then we could apply VAR model to estimate those variables and interpret the coefficients. The process of generating a VAR model requires various steps, including determining the optimal lag length by looking at the ACF and PACF plot, estimating the model using OLS and minimizing the error, dropping the variable with the smallest t-statistic, and re-estimating the model until the performance of the model could not improve anymore. The built function in R provides an effective way of applying VAR model.

Thirdly, after estimating the dataset using VAR model, implementing the Impulse-Response Function could help to determine that whether one marketing variable has an impact on the visitation, and, if so, the effectiveness of a marketing variable. To do so, the first step is to evaluate the significance of each IRF coefficient. Since the VAR models include the lower bound and upper bound of each variable, we could derive the standard error of each variables from its confidence interval using the functions:

$$Lowerbound_{ci} = \beta - 1.96 * se \quad [3.1.1]$$

$$Upperbound_{ci} = \beta + 1.96 * se \quad [3.1.2)$$

With the standard error value, we could then calculate the t-statistic using the function:

$$t_{statistic} = \beta / se \quad [3.1.3]$$

If the t-statistics of the IRF coefficient is greater than 1 then it is treated as significant; otherwise, it is treated as zero. With the coefficient significance, we could then calculate the long-term elasticity to determine how does the spending on flyer, catalog, AdWords, and emailing affect the visitation to the website in the long run.

Lastly, the long-term elasticity could also help to compute the optimal media allocation that could maximize the efficiency of marketing strategy. For example, the optimal spending on flyer could be calculated using function:

$$OptimalAllocation_{Flyer} = \frac{\eta_{Flyer}}{\eta_{Flyer}+\eta_{Catalog}+\eta_{AdWords}+\eta_{Emailing}} \quad [3.1.4]$$

where η is the elasticity of the corresponding marketing tool.

3.2 Potential Contribution to Growth of Orders

The process discussed in section 3.1 computes the optimal allocation of all marketing tools that could maximize the order. However, without quantitative analysis to forecast how large the increase is, the result is not convincing enough. Therefore, in section 3.2, a different model is used to forecast the optimal order if applying the optimal allocation.

For products sold by Furniture B2B, there are both online and offline channels from which the customers take orders. Furniture B2B also provides data of the weekly number of requests for information and offers received via both the online and offline channels before the customers take orders, which could reflect the attitude metric of customer. Therefore, by computing the four important criteria potential, stickiness, responsiveness, and conversion, we could analyze the connection between marketing and financial performance and forecast the new orders given the optimal allocation of marketing tools. Moreover, to get a more precious forecast of order, the online and offline channels are analyzed separately.

The first metric is potential, and the central point of this metric is the diminishing returns: the larger the remaining distance to the maximum level in that metric, the higher the impact potential. For Furniture B2B, the average level of weekly number of leads and quotes received from both online and offline channels are firstly calculated, and the potential is calculated by deducting the average by one.

The second metric is stickiness, which is how long the marketing actions will stay in consumers' minds and hearts. The stickiness of leads and quotes received from both online and offline channels are calculated by running an AR(p) model and summing the coefficients.

The third metric is responsiveness, which is, to what extent, the marketing actions affect consumers mindset. It is the short-term response of customer to a marketing tool. The standard multiplicative response model that produces elasticities as responsiveness metrics is:

$$Y_t = c_{t-1}^{\gamma} X_{1t}^{\beta 1} X_{2t}^{\beta 2} e_t^{u} \quad [3.2.1]$$

where Y is an attitude metric and $X_i (i = 1,2)$ are marketing instruments. An easy way to deal with the model is to take the logarithm of both sides of the equation and estimate the model as a log-linear one. The equation [3.2.1] in log format is:

$$\log(Y_t) = c\grave{} + \gamma \log(Y_{t-1}) + \beta_1 \log(X_{1t}) + \beta_2 \log(X_{2t}) + \grave{e}_t \quad [3.2.2]$$

The responsiveness of each attitude metric could be calculated by fitting equation [3.2.2] into linear regression model.

Fourthly, the last metric is conversion, or whether the marketing actions translate into orders. With intermediate attitude metrics leads (L_t) and quotes (Q_t), a multiplicative funnel model for order (O_t) would be:

$$O_t = cS_{t-1}^{\gamma} L_t^{\beta 1} Q_t^{\beta 2} e_t^{u} \quad [3.2.3]$$

Like equation [3.2.2], it is easier to take the logarithm of both sides of the equation [3.2.3] and estimate the model as a log-linear one.

The four metric discussed above could be used to compute the appeal of each marketing tool using function:

$$Appeal = Poentital * \frac{1}{1-Stickiness} * Responsivenes * Conversion \quad [3.2.4]$$

Finally, with the appeal of each market tools, we could forecast the change of order given the change of marketing allocation strategy. The first step is to compute the short run gain or loss to order after the marketing allocation is changed. Then, with the carry-over parameters from responsiveness models, the short-run gain could be transformed into corresponding long-run gain.

4. Result

4.1 Optimal Marketing Resource Allocation

As the first step is to determine the stationary of the five variables, the cost spent on the four marketing tools and the visitation to the website, the plot of the ACF and PACF graph of the five variables in Appendix 7.1 suggests that the cost spent on

AdWords and Emailing and the visitation to the website are not stationary. The results of running ADF test on the five variables verify the conclusion. For Flyer and Catalog, the p-values are smaller for 0.01. While for AdWords, emailing, visitation, the p-values are 0.2983, 0.2073, 0.2075, respectively. After taking a difference of the three non-stationary variables, the ADF tests verify that those five variables are all stationary.

After ensuring all the variables are stationary, we could use VAR model to discover the relationships between the costs spent on all the marketing channels and the visitation to the website. We take all five variables as endogenous variables since we assume it correlates with other factors in the VAR model. The summary of the VAR model is included in the Appendix 7.2. However, the result of the VAR model itself does not explicitly define the effects of marketing spending on the visitation or the optimal allocation of the marketing strategy to maximize the visitation to the website.

To determine the effects and optimal budget allocation, we could use IRF analysis. The IRF plots of all four marketing variables are included in the Appendix 7.3. From the four IRF plots, it is obvious that flyer, AdWords, and emailing affect the visitations to the website similarly. The increases of spending on flyer, AdWords, and emailing will immediately increase the visitation to the website, while the impact decay fast and get close to zero within five weeks. The spending on Catalog does not impact the visitations as significantly as other three marketing channels. The calculation of long-term elasticity of each spending verifies this conclusion. As Appendix 7.4 shows: An 1% increase in the spending of Catalog increases the visitation by 0.0136% in the long run, but 1% increase in the spending of Flyer increase the visitation by 0.125% in the long run.

Finally, since we already calculated the long-term elasticity for each marketing tools, we could now calculate the optimal allocation of the four marketing tools. By applying function [3.1.4], while the actual allocation is AdWords (42%), Flyer (12%), Catalog (8%) and Emailing (38%), the optimal allocation is AdWords (24%), Flyer (34%), Catalog(4%) and Emailing (38%). On the other word, since the increase of spending on Flyer have a larger impact on the growth of visitation to the website than on AdWords and Catalog, more resource should be allocated to the Flyer.

4.2 Forecast the Growth of Orders

A summary of beginning level, potential stickiness, responsiveness to each marketing tools, conversion for leads, quotes, and orders for both online and offline channels are included in Appendix 7.5. The appeal of each marketing tools onto the lead and quotes for both online and offline channels, calculated using function [3.2.4], are included in Appendix 7.6. With the results summarized from the two tables, we could forecast the long-term gain after applying the optimal resource allocation. As calculated in Section 4.1, the optimal resource allocation of marketing tools is the optimal allocation is AdWords (24%), Flyer (34%), Catalog (4%) and Emailing (38%), while the actual allocation is AdWords (42%), Flyer (12%), Catalog (8%) and Emailing (38%). Therefore, the Furniture B2B should increase the spending on Flyer by 22% and decrease the spending on AdWords and Catalog by 18% and 4%, while keeping the spending on email unchanged. Given the current spending on AdWords, Flyer, Catalog and Emailing are 4790, 854, 1325 and 4320, respectively, the new spending on the four marketing tools is 5844, 820, 1087 and 430, with the total marketing budgets unchanged. Based on the calculation presented in Appendix 7.7 and Appendix 7.8, if the optimal resource allocation of marketing tools is applied, while online order stays nearly unchanged, the offline order increase by 4.7%, which is significant given the total spending on marketing is unchanged.

5. Conclusion

The methodology and process explained above indicate that it is possible to utilize the modern computation model to optimize the resource allocation of marketing tools. The application of VAR model provides the manager of Furniture B2B with a powerful tool to compute the optimal resource allocation. By changing the allocation from AdWords (42%), Flyer (12%), Catalog (8%) and Emailing (38%) to the optimal allocation AdWords (24%), Flyer (34%), Catalog (4%) and Emailing (38%), Furniture B2B could, in theory, optimize the visitation to its website.

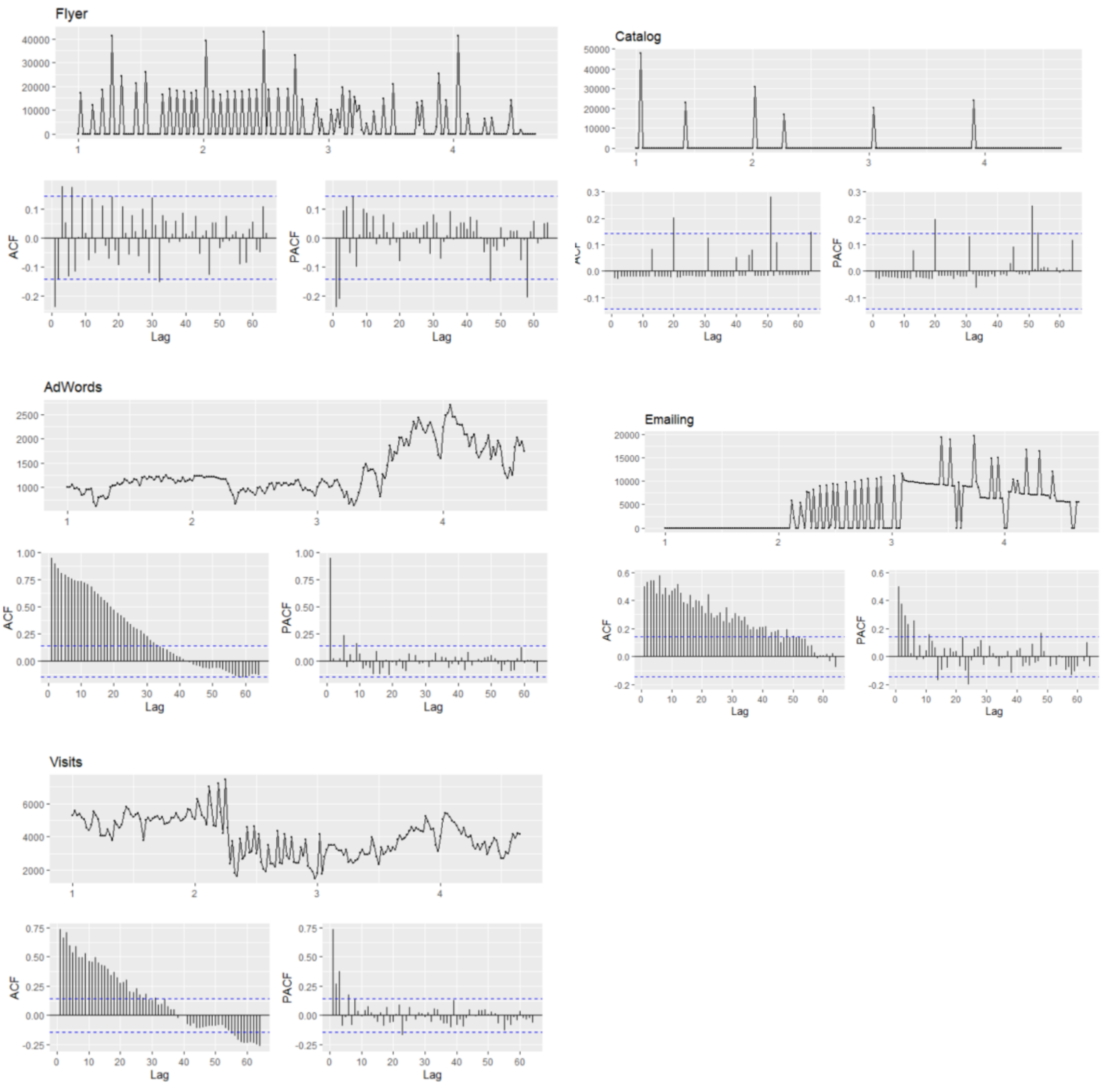
Since Furniture B2B also provides data of weekly number of leads and quotes before the customers take order, we could further analyze the connection between marketing and financial performance by calculating the four important criteria potential, stickiness, responsiveness to each marketing tool, and conversion. By calculating the appeal of each marketing tools on the attitude metric, we could forecast the new orders given the optimal allocation of marketing tools. If Furniture B2B chooses to apply the optimal allocation strategy of marketing tools, then in theory, the offline order will increase by 4.7% in the long run, while the online order stays unchanged.

6. Reference List

Wilms, Ines, et al. Multi-Class Vector AutoRegressive Models for Multi-Store Sales Data. Faculty of Economics and Business, KU Leuven, 11 May 2016, arxiv.org/pdf/1605.03325.pdf.

7. Appendix

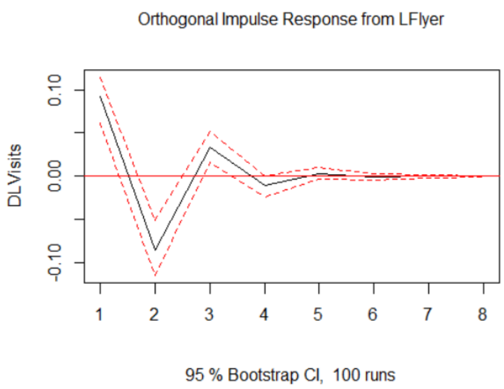
Appendix 7.1: ACF and PACF Plot for the Five Variables

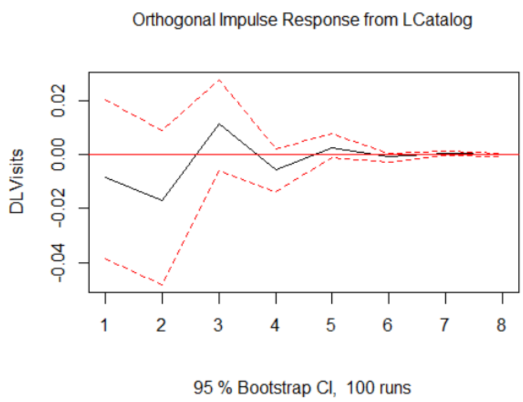


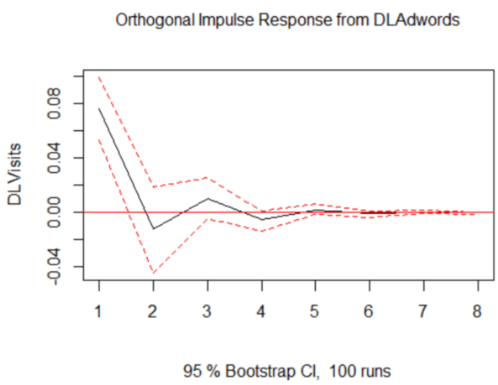
Appndix 7.2: Summary of Var Model

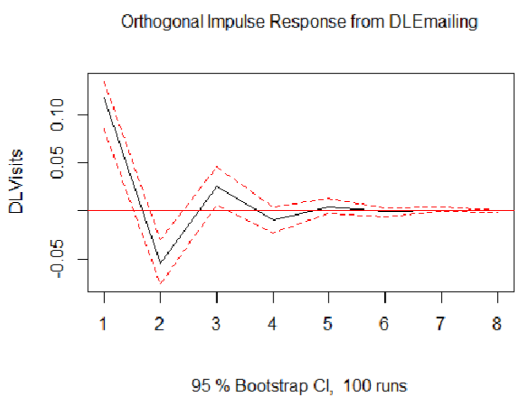
	Dependent variable:				
	LFlyer (1)	LCatalog (2)	DLAdwords (3)	DLEmailing (4)	DLVisits (5)
LFlyer.l1	-0.178** (0.081)	0.028 (0.033)	-0.004* (0.002)	-0.131** (0.065)	-0.013*** (0.004)
LCatalog.l1	-0.134 (0.179)	0.003 (0.073)	-0.004 (0.005)	-0.195 (0.145)	-0.010 (0.009)
DLAdwords.l1	-4.362 (3.354)	-1.080 (1.372)	-0.068 (0.089)	-5.891** (2.719)	-0.031 (0.162)
DLEmailing.l1	-0.061 (0.123)	-0.033 (0.050)	0.003 (0.003)	-0.580*** (0.100)	-0.011* (0.006)
DLVisits.l1	1.403 (2.417)	1.962** (0.989)	0.010 (0.064)	2.900 (1.960)	-0.149 (0.117)
const	3.374*** (0.393)	0.248 (0.161)	0.015 (0.010)	0.533* (0.319)	0.041** (0.019)
Observations	189	189	189	189	189
R2	0.045	0.052	0.033	0.293	0.236
Adjusted R2	0.019	0.026	0.006	0.274	0.215
Residual Std. Error (df = 183)	4.309	1.762	0.115	3.494	0.208
F Statistic (df = 5; 183)	1.737	1.998*	1.230	15.166***	11.318***
Note:					*p<0.1; **p<0.05; ***p<0.01

Appendix 7.3: IRF Plots for the Four Marketing Variables









Appendix 7.4： Long-Term Effort of the Four Marketing Tools

	Flyer	Catalog	AdWords	Emailing
Period				
1	0.092	0	0.076	0.117
2	0	0	0	0
3	0.033	0.011	0.01	0.025
4	0	0	0	0
5	0	0.0025	0.0022	0
Cumulative	0.125	0.0136	0.088	0.142

Appendix 7.5: Summary of beginning level, potential stickiness, responsiveness to each marketing tools, conversion for leads, quotes, and orders for both online and offline channels

Item	Online Leads	Online Quotes	Offline Leads	Offline Quotes	Online Orders	Offline Orders
beginning level	0.206	0.048	0.118	0.226		
potential	0.794	0.952	0.882	0.774		
stickiness	0.803	0.937	0.532	0.862		
Responsiveness to Flyer	0.0082	-0.0005	-0.0001	-0.0004	0.0066	0.0125
Responsiveness to Catalog	0.0063	-0.0004	-0.0001	-0.0003	0.005	0.0173
Responsiveness to AdWords	0.0431	-0.0138	-0.0044	0.0167	0.0268	-0.1185
Responsiveness to Emailing	-0.0162	-0.0077	-0.0005	0.0032	-0.0003	-0.0088
Conversion	0.0629	0.004	0.0887	-0.0109		

Appendix 7.6: Summary of Appeal of Each Marketing Tools

	Online Leads	Online Quotes	Offline Leads	Offline Quotes
appeal_Flyer	0.002079	0	0	0
appeal_Catalog	0.001597	0	0	0
appeal_Adwords	0.010927	-0.00083	-0.00074	-0.00102
appeal_Emailing	-0.00411	-0.00047	0	-0.0002

Appendix 7.7 Forecast of Online Order

	Start	New	Gain	LRGain	Conversion
Flyer	4790	5843.8	1053.8	/	/
Catalog	854	819.84	-34.16	/	/
Adwords	1325	1086.5	-238.5	/	/
Emailing	4320	4320	0	/	/
Online_Leads	0.206	0.204526	-0.00715	-0.31655	-0.01991
Online_Quotes	0.048	0.048128	0.002659	0.033197	0.000133
Online_Order	85.69	85.32999	-0.0042	-0.00771	/

Appendix 7.8: Forecast of Offline Order

	Start	New	Gain	LRGain	Conversion
Flyer	4790	5843.8	1053.8	/	/
Catalog	854	819.84	-34.16	/	/
Adwords	1325	1086.5	-238.5	/	/
Emailing	4320	4320	0	/	/
Offline_Leads	0.118	0.118101	0.000858	0.037953	0.003366
Offline_Quotes	0.226	0.225237	-0.00338	-0.04214	0.000459
Offline_Order	85.69	87.88525	0.025619	0.047032	/