

❖ Introduction

The business goal of this conjoint analysis was to support Star Technologies Company (STC) to develop a computer tablet product as their way of breaking into the marketplace with their background in remote controllers for televisions and audio systems. In this analysis, Neverending Marketing Insights along with Star's internal product development manager by focusing on five important features, brand, retail unit price, screen size, processor speed, and RAM. Interaction between price and brand is also a factor, which will be created as a new variable for our analysis in understanding which feature is more important than the other in terms of purchasing decision. Finally, we will evaluate the covariate indicating previous ownership of a STC product, and one without this covariate and see if this is an important predictor or not.

❖ Data Assessment & Preparation

Total of 424 respondents have been reached in this choice-based conjoint (CBC) task. Following five attributes resulted 36 choice sets.

Level Code	Brand	Price	Screen	RAM	Processor
0	STC	\$199	5 inch	8Gb	1.5GHz
1	Somesong	\$299	7 inch	16Gb	2GHz
2	Pear	\$399	10 inch	32Gb	2.5GHz
3	Gaggle				

I used provided `efcode.attmat.f()` to re-code our variables, similar to regression, intercept is the grand mean, and the slopes are the delta from grand mean. Brand and price interaction variable was also created by using `X.BrandByPrice = X.brands*pricevec`. Combining that, now there is a data frame with 14 variables with 108 possibilities.

Now we have prepared the data, we will begin fitting Hierarchical Bayes (HB) Multinomial Logit (MNL) modeling to create models including and not including the prior STC product ownership covariable. With MLE method, maximize the likelihood function to solve for betas. With Bayesian methods, we compute posterior = likelihood function*prior for the betas.

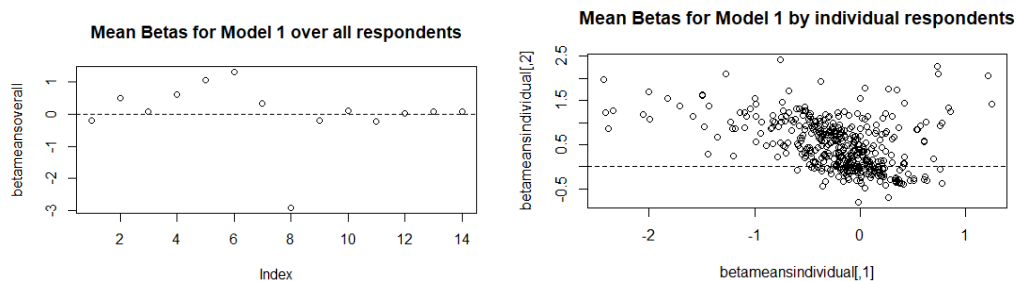
❖ Modeling

For modeling, we will estimate the regression coefficients by using `rhierMnIDP()` function from the R package (`bayesm`) for both scenarios as mentioned above. Models will then be estimated using Markov Chain Monte Carlo (MCMC) simulations.

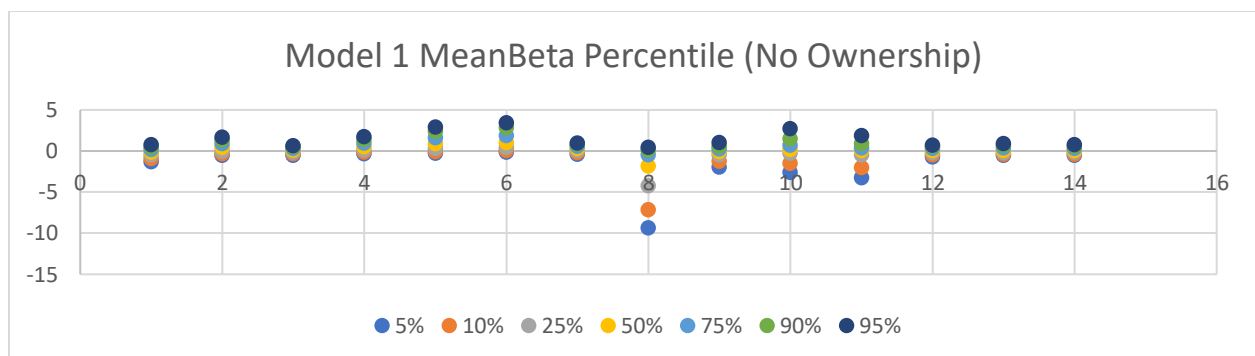
Model 1 Overall mean beta vs Individual mean beta without ownership

For this exercise, I am selecting 10,000 iterations and retain every 5th sample. The `post.burndown <- 501:2000` is selected so we can evaluate the beta mean in terms of the model fitness. In order to achieve that we will need to follow few steps below.

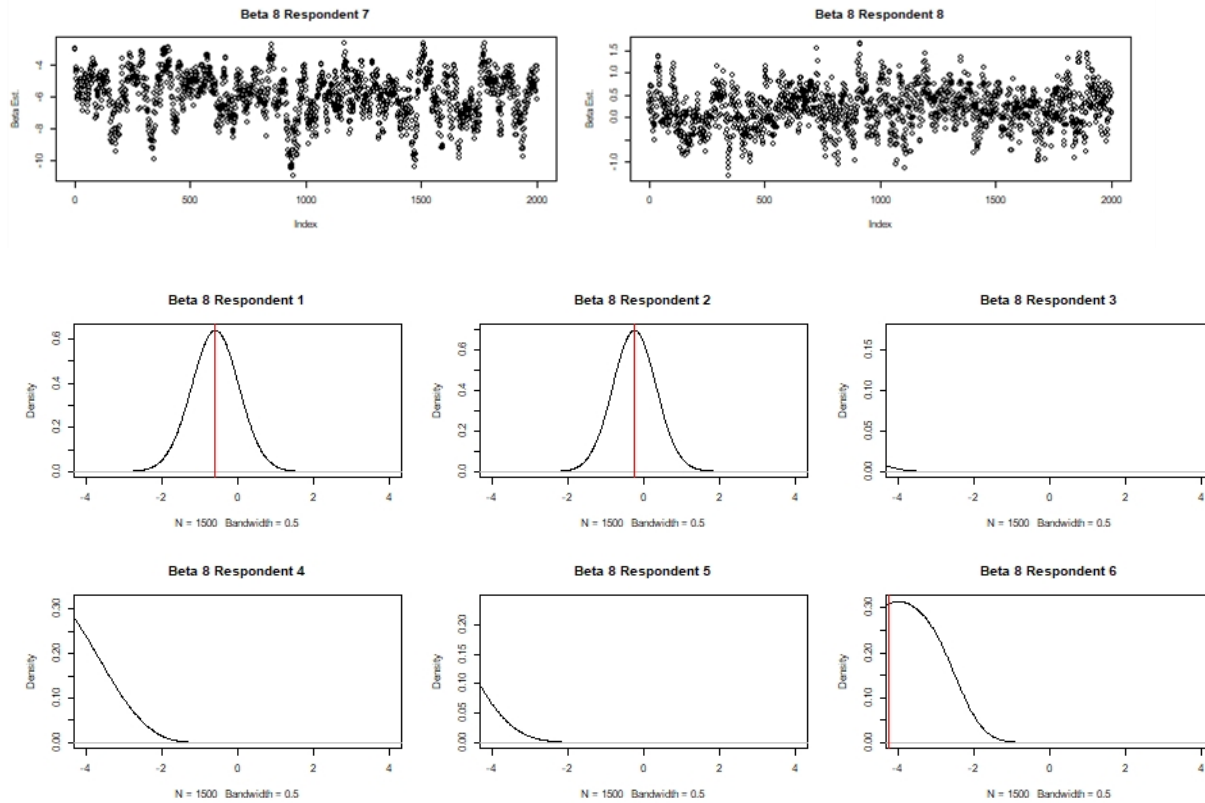
1. Calculate posterior means for each beta of each respondent. This is the key reason and the benefit of using Baysem
2. The matrix would be derived from multiplying the original X-matrix by the posterior means
3. Calculate the exponential that is divided by the row sums of exponentiated betas



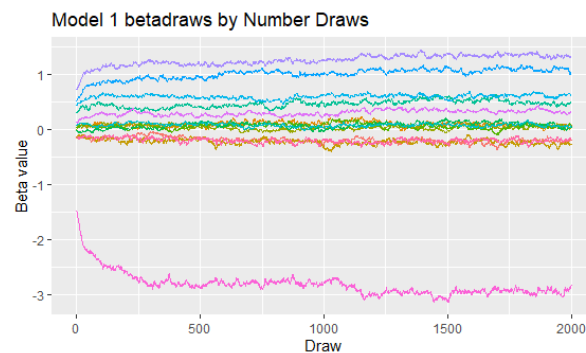
Based on the graph above, variable 8 which is the price point of \$399 highly not preferred by respondents based on the aggregated view from our Model 1. Variable 6 which is 2.5Ghz Processor is more preferred across the respondents. Percentile also sheds a light on the breakdown based on beta by the variable.



Take a closer look at the beta 8, and the individual respondent density and distribution also showed the variety of the response at the individual level. This suggests while mean beta at the overall level gives us a generalized direction of the preference, individualized coefficients can give the researcher much richer insights.



MCMC simulation for Model 1 over 14 beta draws recorded below shows the number of draws starting to stabilize at n=1500 level, so it seems increasing iterations would not be needed for the dataset we have.



Part-worth Beta mean calculation and interpretation

As a part of the pre-processing of our data, we used effect coding, so the model would not directly estimate beta mean values for the reference level of each attribute. Therefore, based on the example table below for screen size. In order to estimate beta mean for 5-inch screen, we need to calculate the 0 level by use V1 of $-0.213*(-1) + V2$ of $0.482*(-1)$. This is also a general step to calculate the part-worth utilities.

The sum of all part-worth utilities for each attribute level should add up to zero.

Screen	X1	X2
0	-1	-1
1	1	0
2	0	1

This gives us the beta mean of -0.269 for the 5-inch screen. And looking at the screen choice sets, we can conclude the respondents prefer 10-inch screen the most. Preference of 10-inch screen is 1.6 times greater than no preference.

MODEL 1	Attribute	BetaMean log (OR)	EXP(BetaMean) Odds Ratio
Screen	5 inch Screen	-0.269	0.764
	7 inch Screen	-0.213	0.808
	10 inch Screen	0.482	1.619
RAM	8Gb RAM	-0.666	0.514
	16Gb RAM	0.071	1.074
	32Gb RAM	0.595	1.813
Processor	1.5 GHz Processor	-2.339	0.096
	2GHz Processor	1.049	2.855
	2.5Ghz Processor	1.29	3.633
Price	\$199	2.582	13.224
	\$299	0.311	1.365
	\$399	-2.893	0.055
Brand	STC Brand	0.356	1.428
	Somesong Brand	-0.215	0.807
	Pear Brand	0.101	1.106
	Gaggle Brand	-0.242	0.785
Brand*Price	STC Brand by Price	-0.174	0.840
	Somesong Brand by Price	0.022	1.022
	Pear Brand by Price	0.066	1.068
	Gaggle Brand by Price	0.086	1.090

In addition, RAM of 32Gb, Processor 2.5Ghz, Price at \$199, and STC brand are considered top preference for the respondents. It is worth to call out price at \$199 is 13.2 times greater than no preference, which is a highest odds ratio over all attributes to the respondents. \$299 price point is 1.365 times greater than no preference. \$399 is only 0.05 times greater than no preference.

Generally, this tells us the respondents would like the biggest screen, fastest speed and biggest storage but at a lowest price. This certainly is not surprising. STC is also in a good position since the brand is well perceived among other more established brands who currently already in the marketplace with the tablets. STC brand is 1.428 times greater than no preference, and following as second brand choice is Pear, which is 1.1 times greater than no preference.

Interaction/price sensitivity

Interaction of the brand and price can tell us the price sensitivity among brand switch and tradeoffs respondents that are willing to make. Let's review the top 2 preferred brands for the interaction evaluation. STC and Pear brands.

Price Effect	Brand Switch	(Brand*Price)*Price Effect	Sum	Odds Ratio
-1	0.255	0.24	0.495	1.64049824
0	0.255	0	0.255	1.29046162
1	0.255	-0.24	0.015	1.01511306

At \$199, STC brand is 1.64 times more preferred than Pear.

At \$299, STC brand is 1.29 times more preferred than Pear.

At \$399, STC brand is 0.02 times more preferred than Pear.

This indicates, STC is always more preferred than Pear especially at the price of \$199. But when it's at \$399, the odds are close to zero, so there maybe potential brand switch among individual respondent level.

While there does not seem to be a big variation in mean betas for our brand by price interaction and each value is close to zero. However, the consumer is highly sensitive to price since it's the most important feature among all attributes.

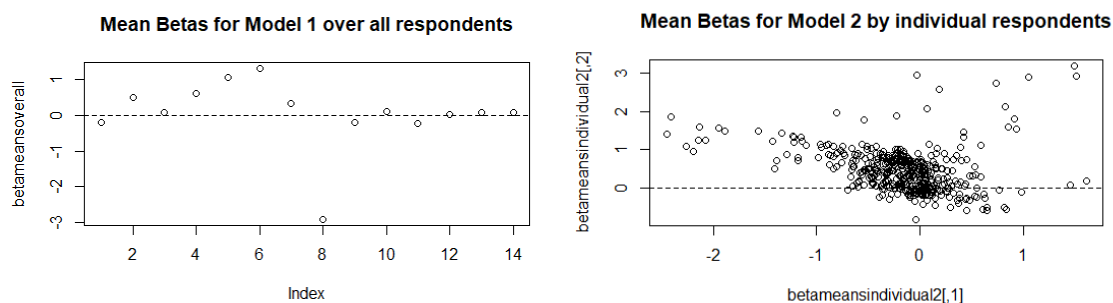
Choice Prediction

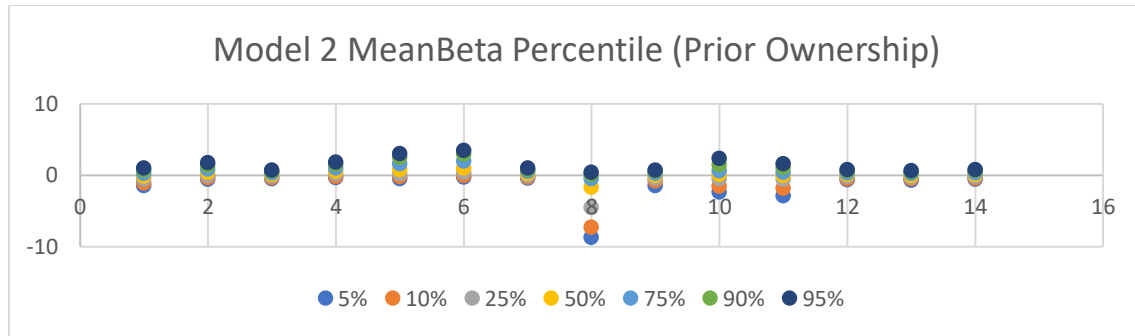
Model 1 choice prediction listed below. Since we have 424 observations with 36 choice sets, so total is 15,264. Prediction accuracy can be calculated as $3636+3688+6030=13,354/15,264=87.48\%$

custchoice	1	2	3
1	3636	468	218
2	246	3688	223
3	322	433	6030

Model 2 Overall mean beta vs Individual mean beta with ownership

Using the same selection as Model 1, 10,000 iterations and retain every 5th sample. In the Model 2 we are including prior ownership of STC and the goal is to understand if the covariate a significant predictor for the model. Visually it seems the beta mean values are very similar to the Model 1, except at the individual respondent level, Model 2 shows the beta mean are more clustered around 0.



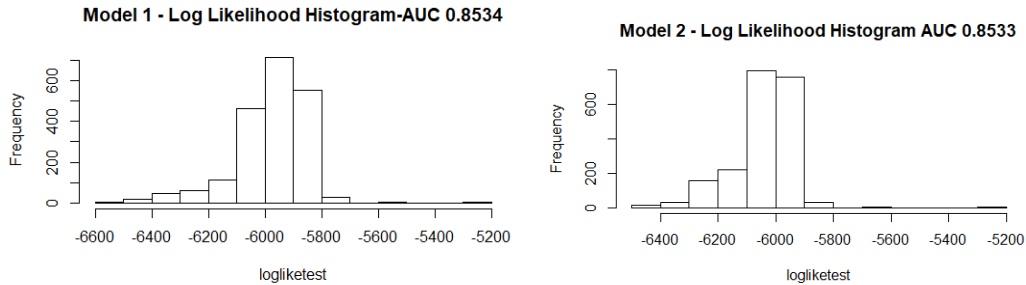


Next, we will compare the beta means at the overall level and evaluate Model 2 as well as reviewing the delta against Model 1.

Table below shows the slight changes across all the beta means and key interpretation remain constant in terms of respondent preference against all the attributes.

MODEL 2	Attribute	BetaMean log (OR)	EXP(BetaMean) Odds Ratio	Model 1 comparison	
				Delta BetaMean	Delta Odds Ratio
Screen	5 inch Screen	-0.289	0.749	-0.02	-0.015
	7 inch Screen	-0.174	0.840	0.039	0.032
	10 inch Screen	0.463	1.589	-0.019	-0.030
RAM	8Gb RAM	-0.707	0.493	-0.041	-0.021
	16Gb RAM	0.09	1.094	0.019	0.021
	32Gb RAM	0.617	1.853	0.022	0.040
Processor	1.5 GHz Processor	-2.231	0.107	0.108	0.011
	2GHz Processor	0.968	2.633	-0.081	-0.222
	2.5Ghz Processor	1.263	3.536	-0.027	-0.097
Price	\$199	2.486	12.013	-0.096	-1.210
	\$299	0.257	1.293	-0.054	-0.072
	\$399	-2.743	0.064	0.15	0.009
Brand	STC Brand	0.324	1.383	-0.032	-0.045
	Somesong Brand	-0.236	0.790	-0.021	-0.017
	Pear Brand	0.098	1.103	-0.003	-0.003
	Gaggle Brand	-0.186	0.830	0.056	0.045
Brand*Price	STC Brand by Price	-0.147	0.863	0.027	0.023
	Somesong Brand by Price	0.075	1.078	0.053	0.056
	Pear Brand by Price	-0.018	0.982	-0.084	-0.086
	Gaggle Brand by Price	0.09	1.094	0.004	0.004

Log Likelihood histogram as well as the AUC scores do not show significant model improvement. Therefore, Model 1 can provide the necessary recommendations instead of incorporation ownership as an attribute which does not bare significant attribute importance.



Model 3 Predict Extra Scenario

Using the HB model results, we proceed to predict choices from Obee's extra scenarios. I converted the choice sets back into the attributes for ease of interpretation.

choice.set	Product	screen	RAM	processor	price	brand
1	1	10-inch	8Gb	2Ghz	\$199	Gaggle
	2	10-inch	32Gb	2Ghz	\$199	STC
	3	10-inch	16Gb	2Ghz	\$199	Pear
2	1	5-inch	8Gb	1.5Ghz	\$199	STC
	2	5-inch	16Gb	1.5Ghz	\$199	Gaggle
	3	7-inch	16Gb	1.5Ghz	\$299	Pear

Preference choice for the 2 choice sets are shown below. This recommends Obee that STC brand tablet with 10-inch screen, 32Gb RAM, 2Ghz processor and priced at \$199 has 67.51% preference share among respondents. The number two choice set, STC brand tablet with 5-inch screen, 8Gb RAM, 1.5Ghz processor and priced at \$199 has 52.85% preference share as the #1 ranked product offering.

Choice Set	Product 1	Product 2	Product 3
1	8.12%	67.51%	24.36%
2	52.85%	46.81%	0.33%

❖ Conclusion/Recommendation

I fit two Hierarchical Bayes (HB) Multinomial Logit (MNL) models in order to measure the price sensitivity of respondent choices which are brand specific and to also examine the possible effects of prior STC product ownership and how it may impact respondent's preferences. Based on our modeling, respondents are very sensitive to price, and 12 to 13 times more likely to choose \$199 as the price point for the tablet than no preference. Prior STC product ownership did not significantly impact product preference, and STC brand has a very high preference share among respondents across all 3 models.

Since we have all part-worth utilities, we can also calculate the attribute importance. I am using Model 1 for my attribute importance calculation.

Step 1: Calculate Attribute Utility Range

Utility Range = Highest Utility Value of an attribute - Lowest Utility Value of an attribute

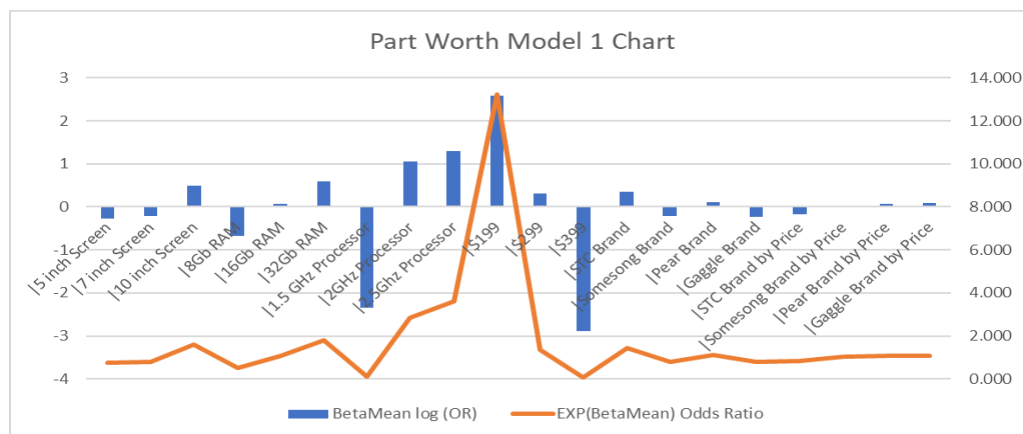
Step 2: Calculate Total Attribute Utility Range

Total Utility Range = Sum of all individual Utility Ranges

Step 3: Calculating Relative Importance of attributes

Relative Importance of attribute = (Attribute Utility Range/Total Attribute Utility Range)*100

Attribute	Utility Range	Total Utility Range	Relative Importance	Importance Rank
Screen	0.751	11.974	6%	4
RAM	1.261	11.974	11%	3
Processor	3.629	11.974	30%	2
Price	5.475	11.974	46%	1
Brand	0.598	11.974	5%	5
Brand*Price	0.26	11.974	2%	6



Based on the analysis, I would recommend STC to evaluate additional cost related information which is missing here. Below 2 options are attractive to the consumers, but profitability should also be an important metrics to understand. If cost for both product offering is the same, then number 1 should be the product launch to ensure maximum success due to the preference share. If cost is significantly unbalanced, then STC should consider product launch with the smaller screen, with the competitor Gaggle in mind since they are closely ranked as second based on the preference share.

Option 1: 10-inch screen, 32Gb RAM, 2Ghz processor at \$199

Option 2: 5-inch screen, 8Gb RAM, 1.5Ghz processor at \$199

In addition, gender, age group, income level, and if the respondent is ready to purchase can be useful supplementary data. These data points can provide needed insights for a more targeted product launch. This information can help with customer segmentation work as well, and combined with individual respondent beta mean, they are rich data set to understand individual preference share at the lowest level when conducting market simulation which is the key benefit of the Hierarchical Bayes (HB) Multinomial Logit (MNL) model.