Solo 2: Conjoint Measurement and Choice Modeling

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STUDY DESIGN

In order to better understand consumer preferences in the computer tablet market before launching their new product, STC conducted a discrete choice experiment (choice-based conjoint task) via an online questionnaire. The study reached 424 people who are currently tablet owners or are likely to buy a tablet in the near future. Each respondent was given 36 choice sets and asked to select one preferred profile out of three options.

Five main attributes that are known to impact tablet preferences were included in the study design: retail unit price, screen size, processor speed, RAM, and brand. The study was also designed to account for a possible interaction effect between brand and price.

METHODOLOGY & RESULTS

Data Preparation

In preparation for the modeling the data using the `rhierMnlDP()` function from the `bayesm` R package, we created two objects in R:

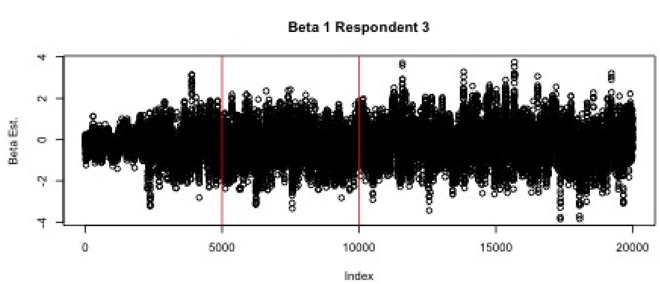
- A list data structure combining the respondent data from stc-cbc-respondents-v3.RData with an effects coded version of the choice task matrix, stb-dc-task-cbc-v3.csv
- A binary covariate vector reflecting which of the respondents previously owned an STC product

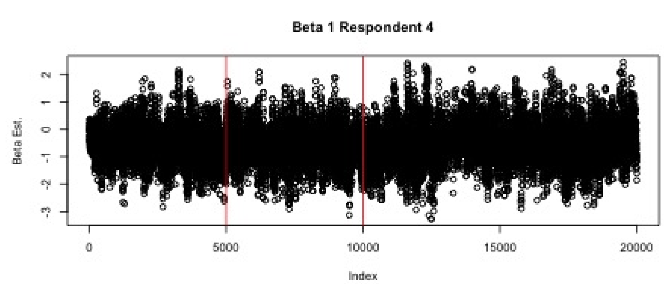
Before combining the response and choice task data, the levels for each attribute in the task matrix were converted to effects coded variables. Originally, attributes in this matrix were coded as 0, 1, or 2 for the four attributes with three levels (screen size, RAM, processor speed, price) and as 0, 1, 2, or 3 for the one attribute with four levels (brand). Using the `efcode.attmat.f()` custom R function that was provided, each of the attributes was re-coded into a set of (k-1) variables, where k is the number of levels for the attribute. Additionally, we added a new set of variables to the task matrix to account for the possible interaction effect between brand and price. The final 14 variable task matrix was then combined with the matrix of 36 choices for each of the respondents.

Model Fitting for Hierarchical Bayes (HB) Multinomial Logit (MNL)

Once the data was prepared, we began the Hierarchical Bayes Multinomial Logit modeling process to create models with and without the prior STC ownership variable included. In both cases, to estimate the regression coefficients we used the `rhierMnlDP()` function from the `bayesm` R package. This package relies on a Markov Chain Monte Carlo (MCMC) algorithm to estimate the model coefficients. We chose to run the model using 100,000 iterations, keeping the output for every 5th sample.

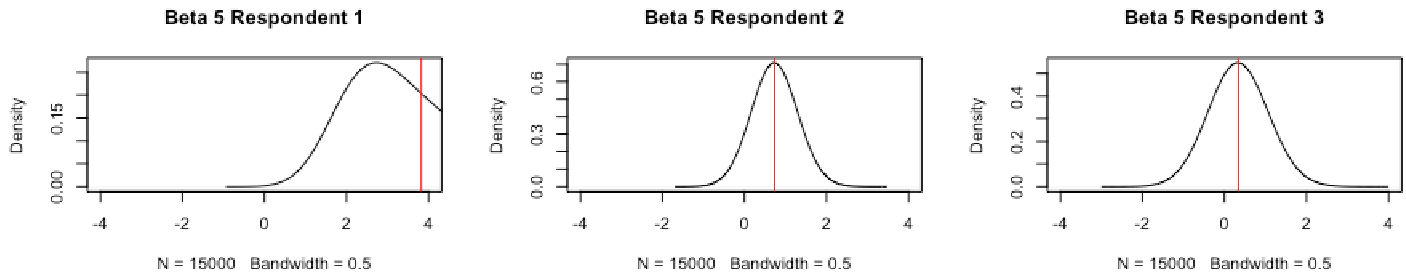
To determine the correct burn-in period for the MCMC algorithm, we created a model without the covariate and examined the beta plots for the first six respondents (see Appendix A for all plots). A visual review of the plots confirmed that removing the first 5,000 samples is sufficient to build a stable model. For example, Respondents 2 and 3 both show early instability in their β_1 values, but stablize before the 5,000 mark.



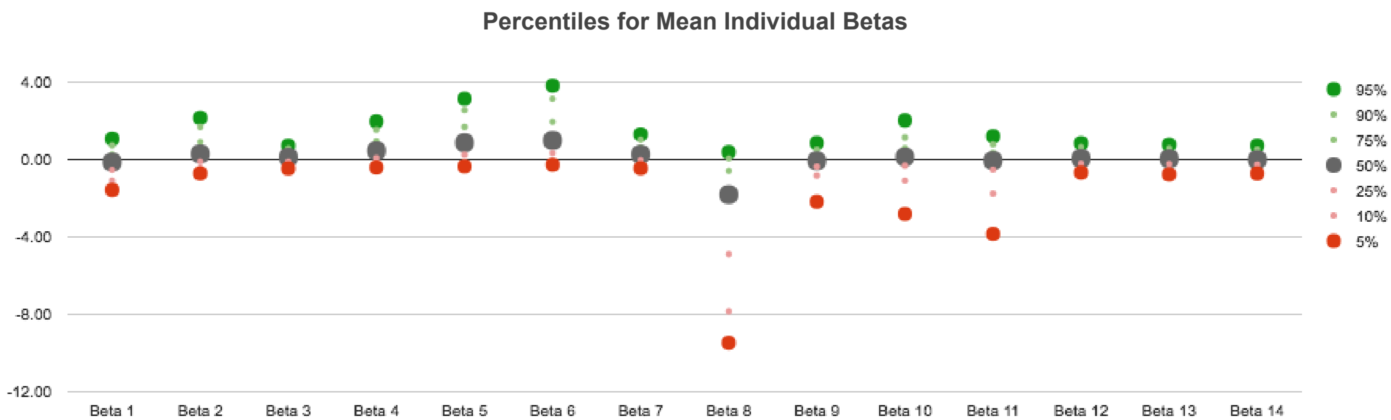


The 15,000 sample iterations that remained after removing the burn-in period were used to examine the patterns and differences amongst the respondents' choices and to make predictions for new task sets.

An review of the individual distribution β_{ij} plots for the retained iterations showed that not all respondents will have the same mean or distribution for a given β_i. For example, respondent 1 has a higher average β_5 than respondents 2 and 3, as shown below (see Appendix B for all plots).



Similarly, by plotting the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles for the individual average β_{ij}, it became clear that some of the model coefficients -- especially β_8 for the $399 price level -- have a wide variability across respondents.



The variability demonstrated in the the individual beta means suggested that using a separate model for each individual would likely perform better than creating a single average model for prediction. To examine this expectation, we built the following four models:

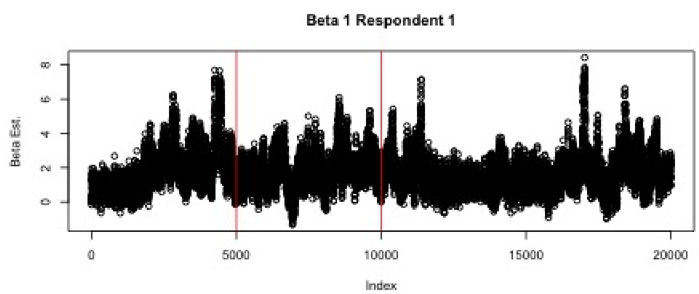
- **Models without Ownership Covariate**
  - **Model 1 - Individual Beta Means**: The β_{ij} for each individual from the first run of the `rhierMnlDP()` function were averaged to create 424 distinct models for each of the respondents.
  - **Model 2 - Pooled Beta Means:** The β_{ij} for all respondents were averaged together to create a single model for all of the respondents.
- **Models with Ownership Covariate**
  - **Model 3 - Individual Beta Means:** The `rhierMnlDP()` function was re-run with the covariate for STC ownership included. The β_{ij} for each individual were averaged to create 424 distinct models for each of the respondents, this time with the covariate included.
  - **Model 4 - Pooled Beta Means:** The β_{ij} with the covariate were averaged together to create a single model for all of the respondents.

Goodness of Fit, Model Validation & Previous Owner Impact

After creating the pooled models and sets of individual models, each model was compared against the actual respondent choices to determine the model's accuracy and to calculate the mean log-likelihood and area under the curve for the ROC plot. The results in the table below show that both of the individual models performed much better than the pooled models according to all three goodness-of-fit metrics. Between the two individual models, we can see that the addition of the STC ownership variable in the model produced only about a 1% improvement in model accuracy.

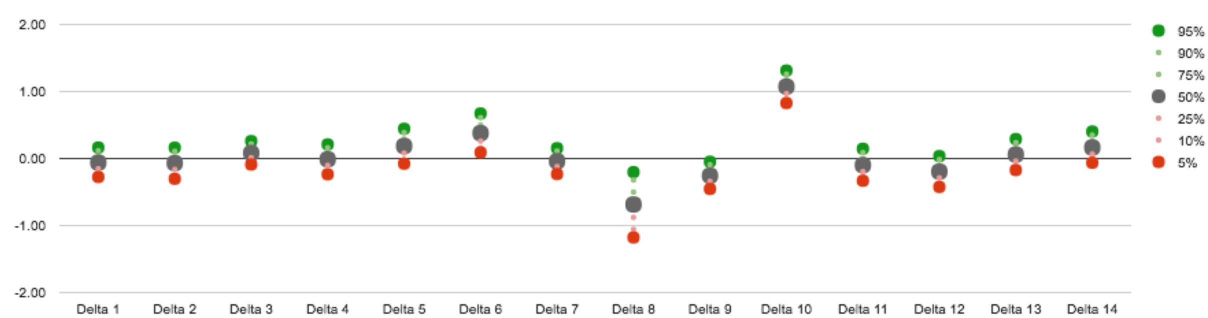
Model	Accuracy	AUC	Mean Log-Likelihood
1. Individual Beta Mean Model without Ownership Covariate	87.39%	0.8546	-5911.976
2. Pooled Beta Mean Model without Ownership Covariate	60.07%	0.6177	--
3. Individual Beta Mean Model with Ownership Covariate	88.42%	0.8679	-5801.683
4. Pooled Beta Mean Model with Ownership Covariate	59.93%	0.6197	--

Despite a fairly high accuracy rate for both individual models, the instability of the burn-in plots for some of the respondents' β_i values shows that the model will not always fit well for all respondents. For example, the plot for Respondent 1's β_1 shown below does not stabilize, even after 100,000 iterations. Normally, we would dig deeper into the cases where the individual model does not fit well to determine if there were flaws in the study design or if other factors preventing the model from fitting well.



To determine which of the individual models to select, we examined a plot of the quantiles for the Model 3 individual delta draws as shown below. This plot demonstrates how much of an impact the ownership covariate has on each of the model coefficients compared to a model without the covariate. From the plot below, we made the following observations:

- Prior ownership has a negative impact on the utility $399 price level (Delta 8), meaning that the utility of this price is even lower for previous STC owners.
- Prior ownership has a positive impact on the utility of the Somesong brand (Delta 10), meaning that utility of this brand is higher for previous STC owners.
- Prior ownership has a small positive impact on the utility of the 2.5 GHz processor (Delta 6), meaning that the utility of this processor speed is slightly higher for previous STC owners.
- For all of the other deltas, the impact of prior ownership is negligible.



Despite the plot showing that some additional information is captured when the covariate is added to the model, the increase in model accuracy is insignificant enough that we decided to leave it out of the final prediction model to avoid adding unnecessary complexity to an already sufficient Model 1. The table in Appendix C compares the actual versus Model 1 predicted outcomes for all 36 scenarios with only task set 30 having a different predicted outcome compared to the actual results. This model looks good for us to use for predicting additional scenarios later on.

Parts Worth, Importance, & Price Sensitivity

Using the pooled means for Model 1, we calculated the part-worths, odds ratios, and importance measurements for each of the attributes as follows:

- **Part-worths Utilities:** The part-worths for each attribute level were calculated by taking the pooled means for each β_i coefficient across all respondents. For the baseline attribute levels that do not have a dedicated coefficient in the model, the part-worth utility was calculated by adding all β_i for the attribute level as represented in the model and subtracting this value from zero. In short, the sum of all part-worth utilities for each attribute level should add up to zero.
- **Odds Ratios:** Odds ratios were calculated by exponentiating each of the pooled means (i.e. part-worth utilities).
- **Importance:** The importance measurement is calculated from the part-worth utilities. For each attribute, an attribute utility range was calculated by subtracting the lowest part-worth from the highest. This utility range divided by the sum of the utility ranges for all attributes gives the relative importance percent.

The table to the right provides the importance measurements, odds ratios, and part-worth utilities for each attribute and attribute level.

Price was by far the most influential attribute on stated preferences (48% importance). The wide range in part-worth utilities shows that respondents were very sensitive to price (302 times higher preference at $199 vs. $399 and 10 times higher preference at $199 vs. $299).

The second most important factor was processor speed (30% importance), with both the 2 GHz and 2.5 GHz options having over 30 times higher preference vs. 1.5 GHz.

Attribute	Importance	Beta	Attribute Level	Part-worth Utilities	Odds Ratio
Screen	6.0%		5"	-0.28	0.76
		1	7"	-0.16	0.85
		2	10"	0.44	1.55
RAM	10.7%		8 GB	-0.69	0.50
		3	16 GB	0.11	1.12
		4	32 GB	0.59	1.80
Processor	30.2%		1.5 GHz	-2.34	0.10
		5	2 GHz	1.07	2.91
		6	2.5 GHz	1.27	3.57
Price	47.8%		$199	2.69	14.79
		7	$299	0.32	1.38
		8	$399	-3.02	0.05
Brand	4.3%		STC	0.18	1.19
		9	Somesong	-0.21	0.81
		10	Pear	0.03	1.03
		11	Gaggle	-0.34	0.71
Brand * Price	0.9%		STC * Price	-0.06	0.94
		12	Somesong * Price	0.05	1.05
		13	Pear * Price	0.01	1.01
		14	Gaggle * Price	0.02	1.02

The third most important factor was RAM storage (11% importance), with 32 GB 4 times higher preference over 16 GB, and 2 times higher preference over 8 GB. Screen size had 6 % importance, with the 10" screen size having about 2 times higher preference against the other screen sizes. Brand had only 4% importance in the overall model. Respondents had a slight preference for STC products, but the difference was far less significant than the preference variation for other attributes.

Finally, the brand and price interaction variable had only 1% importance in the model. To interpret whether there is a significant interaction effect, we summed and exponentiated the difference between two brands' part-worths without price included and the difference between two brands' part-worths with price included. We did this for each price level and each brand combination.

The results in the table to the below show that there is no interaction effect for price -- STC is always preferred over other brands, regardless of price (though it is even more preferred at lower prices, suggesting STC is seen as a cost competitor).

	$199	$299	$399
STC vs. Somesong Preference	1.63	1.47	1.32
STC vs. Pear Preference	1.24	1.15	1.07
STC vs. Gaggle Preference	1.80	1.67	1.55
Somesong vs. Pear Preference	0.76	0.79	0.82
Somesong vs. Gaggle Preference	1.11	1.14	1.17
Pear vs. Gaggle Preference	1.45	1.45	1.44

Prediction for Additional Scenarios & Product Recommendations

Using Model 1 -- the individual beta means model without the covariate -- we estimated outcomes for six additional task scenarios. The two additional task scenarios that Obee wanted predictions for are shown at the top of the table on the right along with four other prediction scenarios that we selected. The winning choice for each scenario is shown in bold.

Screen	RAM	Processor	Price	Brand	Prob. of Choice
10 inch	8 GB	2 GHz	$199	Gaggle	9%
10 inch	**32 GB**	**2 GHz**	**$199**	**STC**	**60%**
10 inch	16 GB	2 GHz	$199	Pear	31%
5 inch	8 GB	1.5 GHz	$199	STC	36%
5 inch	**16 GB**	**1.5 GHz**	**$199**	**Gaggle**	**52%**
7 inch	16 GB	1.5 GHz	$399	Pear	12%
10 inch	**16 GB**	**2.5 GHz**	**$199**	**STC**	**54%**
10 inch	16 GB	2.5 GHz	$199	Somesong	35%
10 inch	16 GB	2.5 GHz	$399	Pear	10%
10 inch	16 GB	2.5 GHz	$299	STC	22%
10 inch	**16 GB**	**2.5 GHz**	**$199**	**Somesong**	**67%**
10 inch	16 GB	2.5 GHz	$399	Pear	11%
10 inch	16 GB	2.5 GHz	$399	STC	16%
10 inch	**16 GB**	**2.5 GHz**	**$199**	**Somesong**	**74%**
10 inch	16 GB	2.5 GHz	$399	Pear	10%
10 inch	**32 GB**	**2 GHz**	**$199**	**STC**	**53%**
10 inch	16 GB	2.5 GHz	$199	STC	18%
7 inch	32 GB	2.5 GHz	$199	STC	29%

For Obee's first new scenario, STC tablet with a 10" screen, 32 GB of RAM, and a 2 GHz processor at a price of $199 was preferred over the Pear and Gaggle alternatives that varied only on brand and RAM. If affordable to produce, this combination actually seems like a good product to bring to the market in order to compete with the other leading brands.

For Obee's second new scenario, the Gaggle tablet with a 5" screen, 16 GB of RAM, and a 1.5 GHz processor at $199 was preferred over STC's lower RAM alternative and Pear's larger, pricier alternative.

The third through fifth scenarios in the table at the right were run in order to develop a price elasticity estimation for STC tablets. This helps us consider the impact of price when all other variables are held equal and demonstrates the exponential change increase in preference for STC tablets as price decreases.

Estimated Price Elasticity for STC Brand

The final scenario in the table demonstrates how trade-offs between screen size, RAM, and processor speed play out when price is held steady for the STC brand. From the example scenario, it's clear that the 10" screen, 32 GB RAM, and 2 GHz processor will have a higher preference than making trade-offs to get more processing speed by giving up screen size or RAM.

In the end, the best case scenario for STC would be if they could produce the following tablet:

Screen Size: 10", **RAM:** 32 GB, **Processor:** 2.5 GHz, **Price:** $199

In reality, however, having the "best" of each of these features may not be profitable for STC. Still, with preference share increasing more quickly with price for STC tablets than other brands, they should position themselves as a cost competitor if they can. If the above tablet cannot be produced at a price of $199, the first trade-off to make would be to reduce the processing speed to 2 GHz. This has a minimal impact on preference since both top speeds show similar utility for users. The next possible trade-off would be to reduce the screen size to seven inches instead of 10 inches (rather than reducing the processing speed more or reducing the RAM).

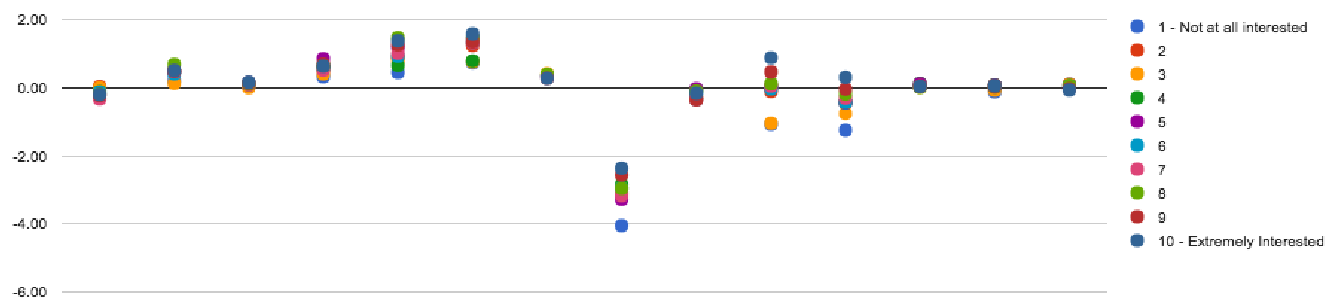
Study Limitations

The major missing piece of this analysis is the inclusion of data to estimate how feature selection impacts potential revenue or profit. It could be that a 2.5 GHz processor is significantly more costly to manufacture into the tablet than a 2 GHz processor or that it is much more expensive to buy the glass for a 10" tablet than a 7" one. Without the cost information for the screen, RAM, and processor attributes, it is difficult to determine which trade-offs would actually be affordable to make to keep the STC tablet at the low $199 price.

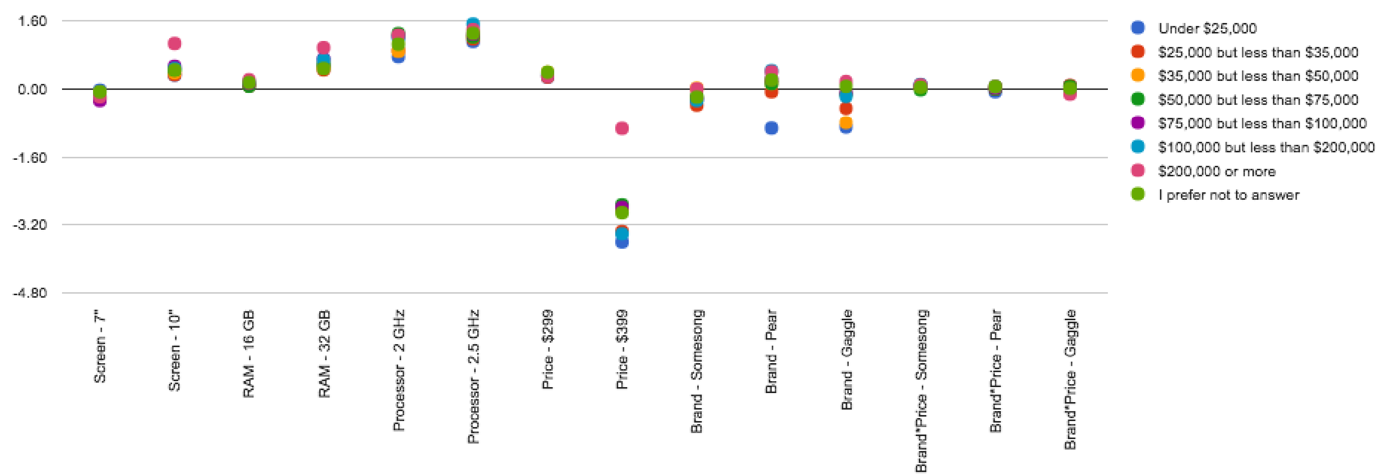
In addition, this study has only scratched the surface of the potential insights to be gained from the model, particularly when it comes to segmenting users. Some users buck the trends shown in the overall model. For example, if we examine the mean betas in the plots below, we can see that users who report a 1 on likelihood to purchase a tablet within the next 12 months have a more negative utility for this price. STC may want to think differently about how tablet owners versus first-time tablet buyers view the marketplace and create segmented models according.

Additionally, users who report a 9 or 10 on likelihood to purchase a tablet within 12 months have a higher average utility for the Pear and Gaggle brands versus other groups. This suggests more brand consciousness for respondents who are closer to a purchase decision.

Mean Betas by Interest in Purchasing a Tablet within the Next 12 Months



Mean Betas by Income Level



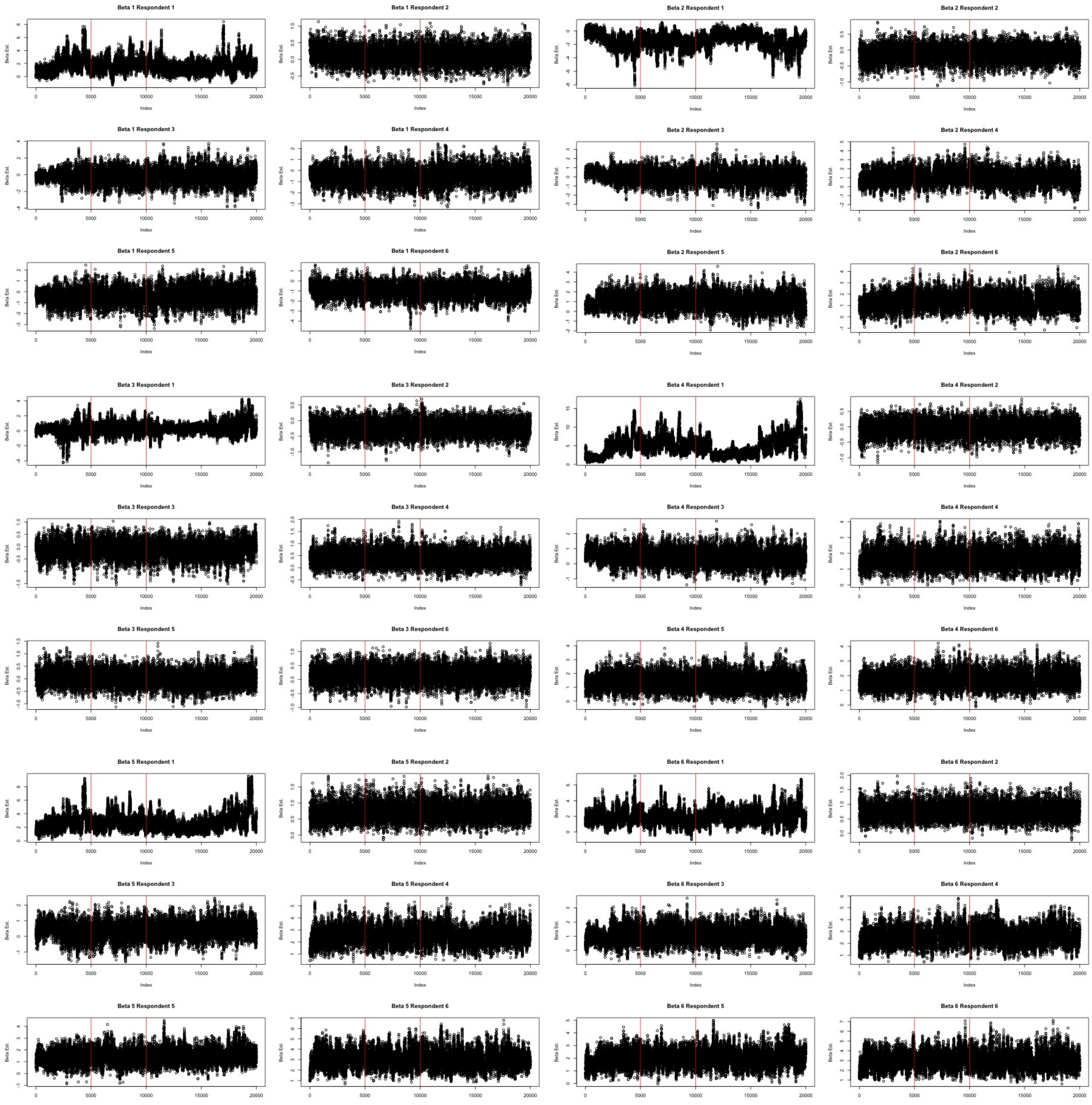
Similarly, looking at the mean betas by income level in the plot above reveals that respondents reporting incomes of $200K+ have a much lower sensitivity to price than other respondents. If STC is interested in competing for a share of these high-income customers' spend, they may need to consider developing a separate model to account for the differing trade-offs that this segment will make.

Finally, from a statistical standpoint, the approach we took did make several assumptions that normally should be checked when creating a market simulation using HB MNL.

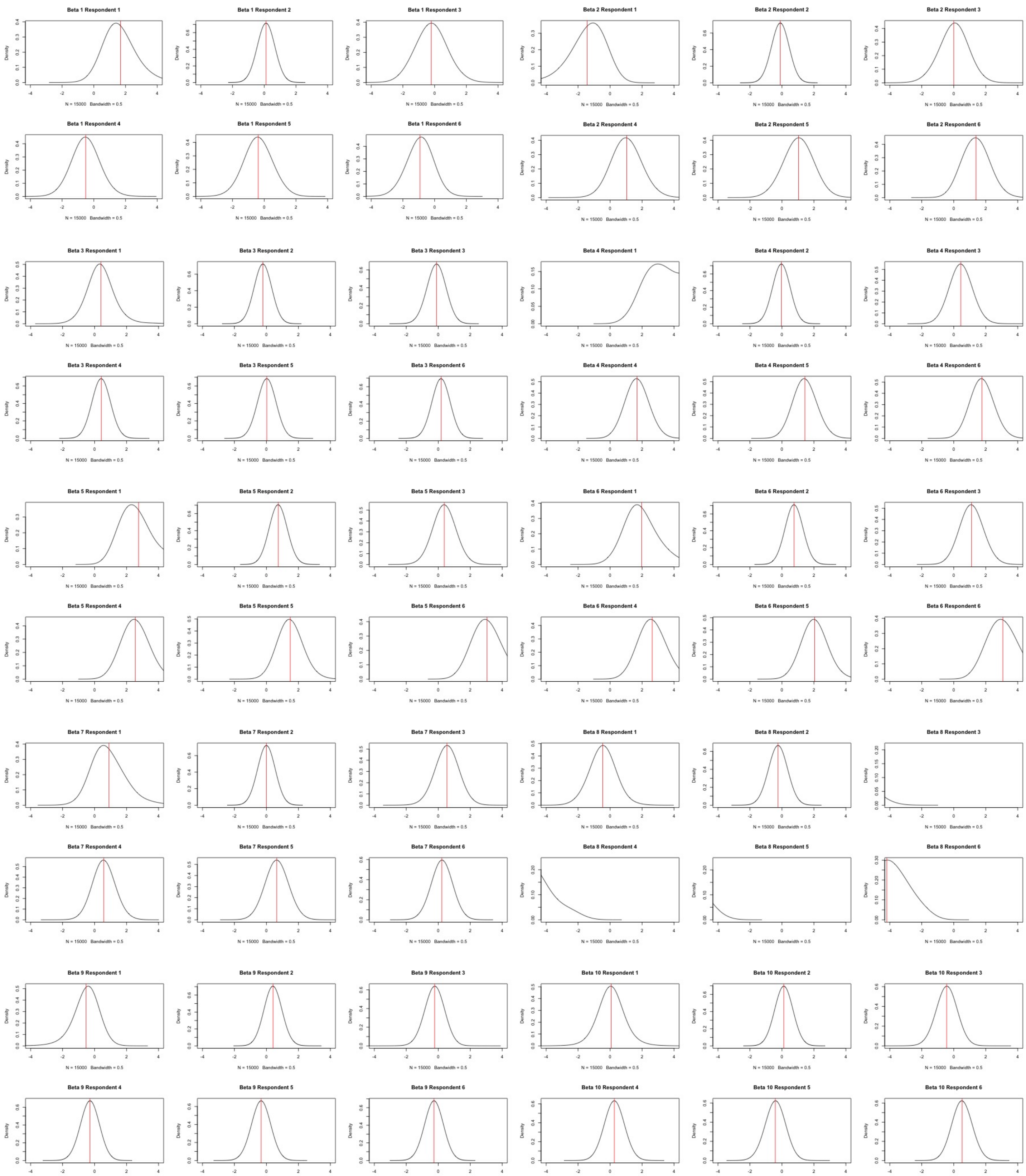
- We assumed that the posterior probabilities match the default Dirichlet Prior distributions set by the `rhierMnlDP()` function. The priors may follow another distribution.
- We assumed that the mean would be sufficient for estimating all model coefficients, despite some of the coefficients not following a normal distribution. We did not check whether using the median would produce better performance.
- We assumed that the internal data validation for the models was sufficient to select a model. In reality, it would be far better to validate the models against a holdout sample of data.
- We did not account for the uncertainty in the beta means for the overall models, which could have an impact on the predictions.

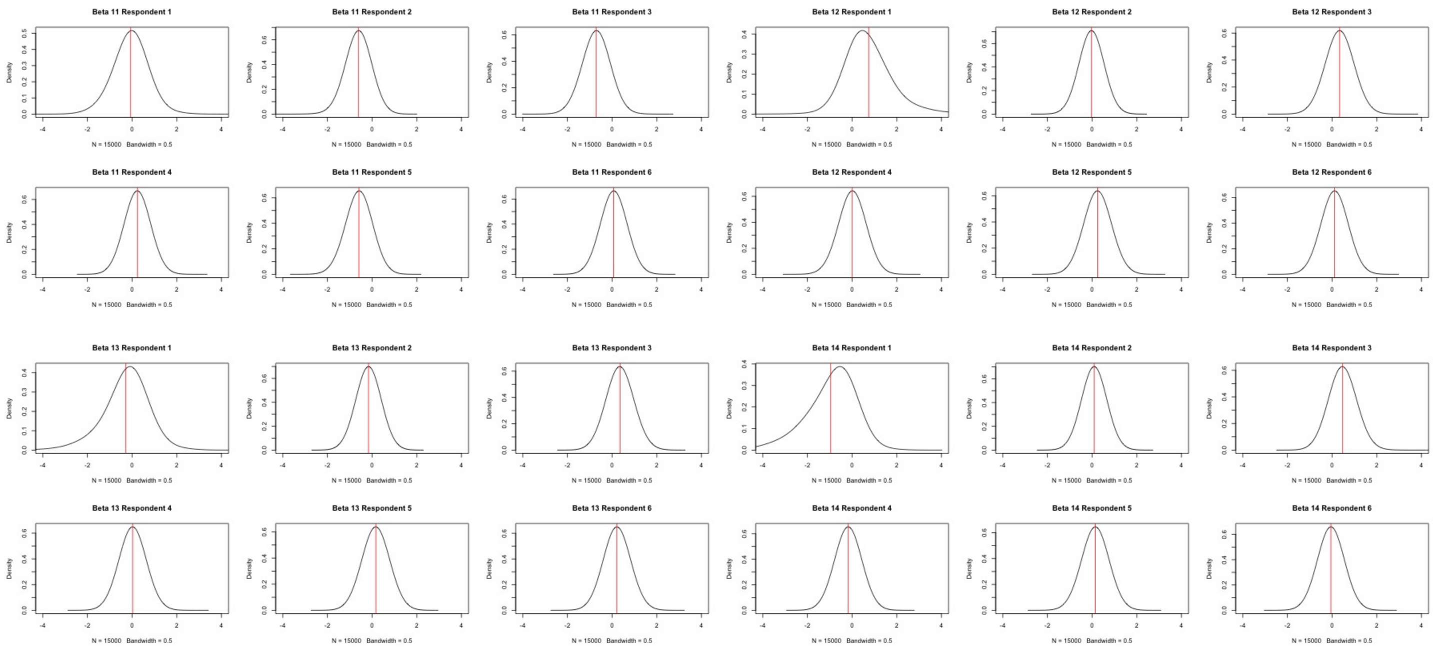
APPENDIX

A. Beta Plots for Determining Burn-In Period



B. Beta Distributions for Respondents 1 through 6



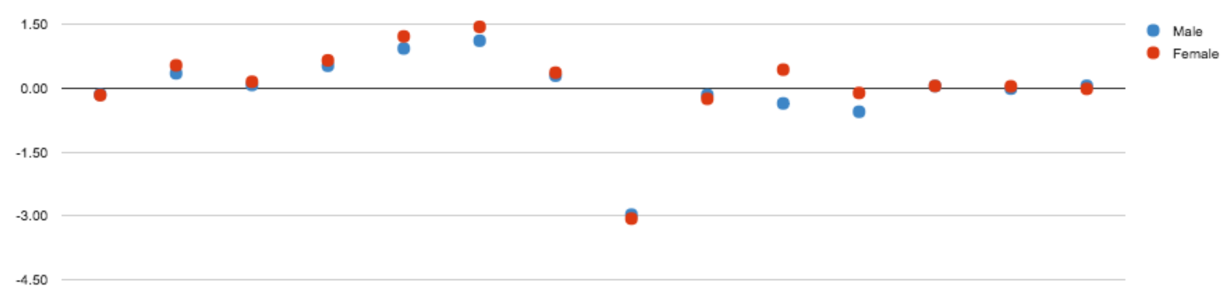

Beta 11 Respondent 1
Beta 11 Respondent 2
Beta 11 Respondent 3
Beta 12 Respondent 1
Beta 12 Respondent 2
Beta 12 Respondent 3
Beta 11 Respondent 4
Beta 11 Respondent 5
Beta 11 Respondent 6
Beta 12 Respondent 4
Beta 12 Respondent 5
Beta 12 Respondent 6
Beta 13 Respondent 1
Beta 13 Respondent 2
Beta 13 Respondent 3
Beta 14 Respondent 1
Beta 14 Respondent 2
Beta 14 Respondent 3
Beta 13 Respondent 4
Beta 13 Respondent 5
Beta 13 Respondent 6
Beta 14 Respondent 4
Beta 14 Respondent 5
Beta 14 Respondent 6

C. Actual vs. Predicted Preferences

	Actual Preference Share			Predicted Preference Share Individual Betas (Model 1)			Predicted Preference Share Pooled Betas (Model 2)		
	1	2	3	1	2	3	1	2	3
DCM1_1	22%	57%	21%	20%	60%	20%	2%	96%	1%
DCM1_2	75%	11%	15%	82%	7%	12%	100%	0%	0%
DCM1_3	51%	42%	6%	57%	39%	4%	77%	23%	0%
DCM1_4	29%	7%	64%	25%	3%	71%	9%	0%	91%
DCM1_5	37%	31%	32%	44%	25%	30%	70%	16%	14%
DCM1_6	17%	20%	64%	16%	12%	72%	1%	6%	94%
DCM1_7	19%	43%	38%	18%	45%	37%	20%	41%	39%
DCM1_8	15%	20%	65%	14%	16%	70%	0%	4%	96%
DCM1_9	24%	5%	71%	25%	2%	73%	5%	0%	95%
DCM1_10	6%	72%	22%	7%	72%	21%	0%	99%	0%
DCM1_11	64%	27%	9%	72%	21%	6%	97%	3%	0%
DCM1_12	45%	51%	4%	46%	51%	3%	36%	64%	0%
DCM1_13	18%	18%	64%	13%	16%	71%	6%	1%	93%
DCM1_14	36%	35%	29%	41%	30%	29%	42%	47%	12%
DCM1_15	4%	33%	63%	4%	28%	69%	0%	17%	83%
DCM1_16	15%	49%	36%	11%	52%	37%	9%	70%	22%
DCM1_17	5%	31%	64%	4%	27%	69%	0%	10%	89%
DCM1_18	15%	16%	69%	13%	15%	73%	4%	0%	96%
DCM1_19	10%	65%	25%	9%	67%	24%	1%	97%	2%
DCM1_20	71%	10%	19%	78%	6%	16%	99%	1%	0%
DCM1_21	53%	35%	12%	62%	26%	12%	63%	37%	0%
DCM1_22	27%	6%	67%	25%	3%	72%	3%	0%	96%
DCM1_23	43%	21%	36%	50%	13%	38%	50%	22%	28%
DCM1_24	9%	21%	71%	7%	18%	75%	0%	4%	96%
DCM1_25	17%	42%	42%	11%	45%	44%	11%	38%	51%
DCM1_26	8%	24%	68%	8%	19%	73%	0%	3%	97%
DCM1_27	26%	4%	70%	22%	2%	76%	2%	0%	98%
DCM1_28	8%	73%	19%	8%	74%	18%	1%	99%	1%
DCM1_29	74%	16%	11%	78%	12%	10%	98%	2%	0%
DCM1_30	45%	49%	6%	54%	41%	5%	47%	53%	0%
DCM1_31	21%	10%	69%	18%	7%	76%	5%	1%	94%
DCM1_32	39%	29%	33%	43%	23%	34%	46%	37%	17%
DCM1_33	6%	27%	67%	5%	21%	74%	0%	10%	89%
DCM1_34	10%	49%	41%	7%	53%	41%	9%	59%	31%
DCM1_35	8%	27%	64%	6%	23%	71%	0%	6%	93%
DCM1_36	20%	8%	71%	15%	6%	79%	3%	0%	97%

D. Beta Means by Segment

Average Utility (Beta Means) by Gender



Average Utility (Beta Means) by Interest in Buying a Phone within the next 12 Months