Marketing Strategy for Lucky Lab Coffee Co.

The University of Texas at Austin, McCombs School of Business

MKT/BAX 360: Information and Analysis

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December 4, 2023

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I. Introduction

Lucky Lab Coffee Co. is an Austin coffee chain that has been providing specialty drinks and scratch pastries for the past six years. Their premise is providing delicious coffee and treats for a man's best friend, with a pet-friendly atmosphere and a commitment to raising money for local rescue shelters. Lucky Lab opened their first brick-and-mortar location in Austin's West Campus in 2017, and in 2022, they built 2 new locations on the UT main campus. Despite their success, Starbucks stands as one of Lucky Lab's chief competitors in the area. As a global coffee giant, Starbucks maintains strong visibility and brand awareness on the UT campus, consistently attracting students with its familiar products with frequent lines across locations before and after morning class sessions. In 2023, Lucky Lab has observed around $1.1M in revenue[1] and around 122,000 monthly visits[2]. Starbucks on the other hand made $3.5B in revenue in 2023 alone, with 100 million monthly visits. Although the data for profit per store or revenue per square feet is not publicly available, these figures still showcase the market share captured by Starbucks. As Lucky Lab competes with such a global force within UT Austin, we designed the following research question:

"How can Lucky Lab Coffee Co. optimize pricing, loyalty incentives, order personalization, and promotion strategies to better compete with Starbucks and enhance customer loyalty and satisfaction?"

As UT students ourselves, we noticed the growing presence of Lucky Lab on campus. We <u>predict</u> that one way Lucky Lab can bring in students from Starbucks would be through clever promotion strategies catered to college students's schedules and preferences, as it is most likely the differentiating factor beyond the price point and the coffee itself. Hence, our research

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[1] Zippia editors. *Zippia.com*. https://www.zippia.com/lucky-labs-careers-1403892/revenue/
[2] Crunchbase editors. *Crunchbase.com*. https://www.crunchbase.com/organization/lucky-lab-coffee-co/technology

question aims to identify current customer sentiment, satisfaction, and loyalty, which will allow us to not only determine the product students gravitate towards, but also the things they value about a coffee shop. This question is not merely a speculative inquiry, as it is grounded in the necessity for Lucky Lab to understand and adapt to UT students' brand perceptions. We will focus on the strategies that Lucky Lab can employ with their new on-campus locations by exploring the dynamics of pricing, loyalty programs, and ordering preferences, with the ultimate goal of providing actionable insights that can empower Lucky Lab to better penetrate the UT student market and become the preferred choice in the vibrant coffee culture of UT Austin.

II. Methodology

Designing the Data Analysis Framework

To answer our research question, we decided to perform a conjoint analysis to understand the trade-offs between certain attributes of a coffee shop experience. After speaking to our friends and classmates about their preferences, we decided to include a total of four attributes: Brand, Price, Coffe order, and Promotion (See *Figure 1. Conjoint analysis attributes and levels*). We decided to not include the pet-friendly offering as an attribute, since we are targeting on-campus locations, where students are less likely to bring their pets when purchasing coffee. This design gives us a total of 2 x 3 x 2 x 3 = 36 possible profiles. Utilizing the fractional factorial design, we simplified it down to 12 key profiles, which we then imported and made into a Qualtrics survey (See *Figure 2. Conjoint analysis fractional factorial set of profiles*).

Survey Design and Reducing Bias

We selected Qualtrics as the platform for our survey due to its user-friendly interface and robust survey capabilities. Within the survey, we asked the respondents to rate our 12 key coffee shop profiles in order to collect data for the conjoint analysis. When deciding which response option to employ, we considered the scale and the slider. We decided against the slider, as its starting position might have a default effect and influence the respondents' input. With a simple selection scale, the survey asks respondents to rate each profile on a scale from 1 to 10, based on the likelihood of them visiting the coffee shop described in the profile on any given day (1 indicates "Very unlikely" and 10 indicates "Very likely").

To mitigate potential biases from the ordering of the questions, we randomized the order of profiles on the survey. Furthermore, as we are aware of the ongoing Israeli-Palestinian conflict, we also included a message stating that we do not affiliate with any of the political stances represented by the companies in the profiles and that for the sake of the study, we ask respondents to answer without consideration of the brand's political stances. The complete questionnaire is attached to this report in the Appendix section.

Data Collection

Since the target market of the research is UT students, the survey was sent to our direct peers. To diversify the respondents, we recruited members from distinct student organizations. We collected data from a total of 8 respondents, which falls in the 5-10 range of our goal. Below are the relevant descriptive statistics of the respondents:

Gender		Classification		Housing		Area	
Female	7	Junior	3	On-campus	2	West Campus	8
Male	1	Senior	5	Off-campus	6		

III. Data Analysis and Results

Data Analysis Walkthrough

After we collected data, we cleaned and organized the attribute levels into a binary matrix (excluding one level per attribute to be later used as a baseline) along with the respondents' ratings (See *Figure 3. Excel Conjoint Analysis Data Matrix*). From here, as opposed to running a regression analysis in Excel to obtain part-worths, attribute ranges, and relative importances for every respondent, we decided to create a Python script that has the capability to automate our conjoint analysis with a long term goal in mind: if we wanted to expand our analysis to be much closer to representing our target market based on the number of respondents, our code would significantly reduce the time required to perform the necessary conjoint data analysis, with only minor changes being needed by any given user.

After importing the conjoint analysis data matrix as shown in Figure 3 and making minor changes in Python to correct any discrepancies caused by the import process, our resulting dataframe in Python is shown (See *Figure 4. Python Conjoint Analysis Data Matrix*).

Next, before running a regression for each respondent, we need to define the structure that maps each independent variable to its corresponding attribute along with the the baselines for each attribute. Setting the baselines for each attribute is essential because this allows us to determine the gain in utils for any given customer when one of our profiles has that feature, relative to the baseline. Our code for grouping our independent variables and baselines to their respective attributes are shown (See *Figure 5. Attribute Mapping and Baseline Code in Python*).

Now that our attributes, levels, and baselines are recognized by Python, we turned our attention to running a regression for each respondent and getting the part-worths (the value of a level to a respondent), which are represented by the coefficients for each independent variable and baseline level for each attribute. We used a *for-loop*, where for each respondent, we set our dependent variable to be that respondent's ratings for each profile, our independent variables to be all the remaining data (excluding the other respondents' ratings), fit an ordinary least squares (OLS) linear regression, store the coefficients (part-worths), and initialize/set the baseline part-worths to be 0. This *for-loop* was set to iterate for each customer from Customer 1 to Customer 8. Our code to run a OLS linear regression for each respondent is shown (See *Figure 6: OLS Linear Regression Code in Python*).

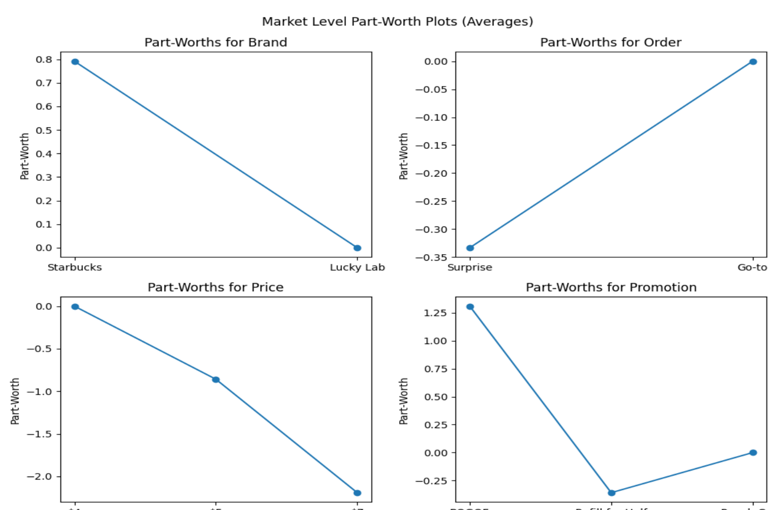
After obtaining the part-worths for each respondent, we then calculated the feature importances to determine which feature is the most important to each respondent and which attribute could change each respondent's total utility - which is the sum of part-worths for each respondent - by the largest amount. Additionally, for each customer, we summed all the range values for future use. Please see *Figures 7, 8 and 9* for the calculations and aggregation of results. The next step is to query the part-worths, attribute ranges, and relative importances for each respondent. *Figure 10* displays the part-worths, attribute ranges, and relative importances for our first respondent, and *Figure 11* displays the respective plots for Customer 1. This process was repeated for all respondents, which can be found in the Appendix.

Based on the results in *Figures 10* and *11*, we found that our first respondent prefers Starbucks, a go-to order, a $4 price, and a BOGOF promotion, and that price is the most important feature to our first respondent with 41% of the total utility variation. We then made these same types of conclusions for the remaining 7 respondents and stated the market-level insights in the next section. Finally, we determined the dollar value of a util for each respondent. This would allow us to answer questions such as "how much is a 'refill for half' promotion worth to our first respondent?" Using the price part-worths, we calculated the price per util by taking the difference of each price level divided by the difference between their respective part-worth, and then averaging those values. We also utilized Python to expedite this process for all respondents, and found the dollar value of a util for our first respondent to be -$1.51 / util. (See *Figure 12: Python Code Calculating Dollar Value of a Util for Respondent 1*).

Market-level Insights

Making the assumption that our sample is representative of the larger student body at UT, we aggregated our calculations for a market-level analysis. At the market level (where we averaged the relative importances for each attribute across all customers), we found the relative importance of each attribute, with price ranked at the top with a 44.15%. Using the average of all the respondents' partworths, we identified the "ideal profile" to be characterized by: a Starbucks brand, a go-to order, a $4 price, and a BOGOF promotion, and the average price per util across all respondents to be -$0.25 / util. Our analysis underscores that pricing strategies and substantial promotions are the key drivers of purchasing decisions within our target audience.

Market Level	Percentage
Price	44.18%
Promotion	27.75%
Brand	17.03%
Order	11.03%



(Left) *Figure 13: Market Level Relative Importance Of Each Attribute*

(Right) *Figure 14: Market Level Part-Worth Plots (Averages)*

Demographic Findings

In addition to our general market-level insights, we also filtered the results based on student classification, and observed a different in the ranking of market-level relative importances by Juniors and Seniors. For Juniors, price is the most important attribute at 48.79%, followed by brand, which is at 29.66%. While Seniors also value price as the most important at 41.41%, they also highly value promotion, which is at 34.12%. This finding suggests a potential opportunity for Lucky Lab to tailor promotional strategies specifically towards Seniors. However, further research needs to be conducted to confirm this finding before we can make any recommendations that effectively resonate with the Senior demographic.

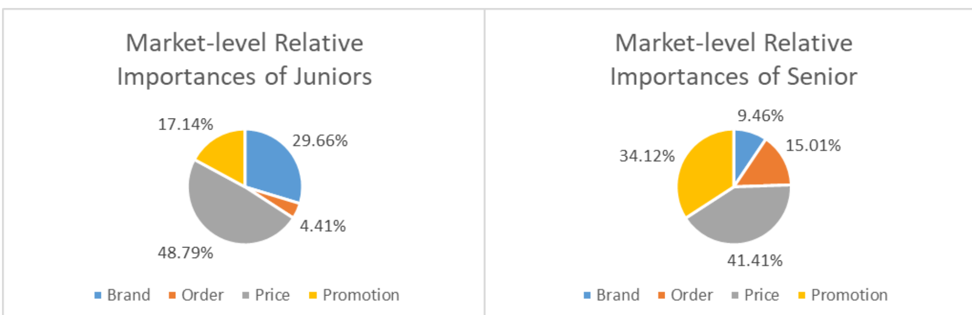


Figure 15: Market Level Relative Importance Of Each Attribute by Juniors and Seniors

Limitations of Results

1. Representativeness of Sample

While we tried our best to recruit UT students with diverse backgrounds, the aggregated descriptive statistics suggest imbalances with an underrepresented male sample, lower classmen, and students who live on-campus. This means that our data is not representative of the entire UT student population, and our results will be skewed. If we had more time to recruit respondents, we would ensure a larger, more demographically representative sample.

2. Social Desirability Effect

Though we asked respondents to rate the profiles without consideration to the brands' political stance, it's possible that our instructions reminded respondents of the current political issue that was taking place at the time the survey was administered, which might influence their perceptions on the brands.

3. Limitations of Conjoint Analysis

The coffee shop profiles presented realistic scenarios, reflecting the actual choices students might face. However, the analysis simplifies the decision-making process compared to real-life situations. Respondents are presented with profiles that vary systematically in terms of specific attributes. In reality, consumers often make decisions in a more holistic manner, considering a multitude of factors simultaneously. For instance, a student might choose a coffee shop not only based on price but also on factors like ambiance, convenience, or social aspects, which a conjoint analysis may not fully capture.

IV. Final Recommendations

From our analysis, the ideal profile features Starbucks, with their Go-To order, $4 beverage, and the Buy One Get One Free promotion. Specifically, Starbucks as the chosen brand has a relative importance of 17% at the market level. For Lucky Lab to be competitive against the desirability of this order, they must bring in customer loyalty through classic beverages, continue to attract customers through strategic pricing, and further ensure customer satisfaction through desired promotions.

The ideal profile suggests that students are frequenting on-campus cafes more for the necessity for their daily beverage, and not as an adventurous experience. This is further substantiated in our findings, in which “Go-To" orders take up 11% of the relative importance at the market level. This customer attitude goes against what Lucky Lab currently positions itself as, as their locations frequently display their seasonal menus without properly showcasing their year-long beverage options. This tactic may be pushing students away from preferring Lucky Lab simply because they do not see their classic Lattes, Cappuccinos, etc. on the menu for them to purchase daily. Instead, this emphasis on seasonal flavors could be pushing students to believe the more standard drinks in cafes are not what Lucky Lab has to offer, therefore encouraging them to grab these classics at Starbucks instead. By recreating Lucky Lab's menu to first feature its classic drinks and then its seasonals, students can find their preferred beverage more easily, and begin to see Lucky Lab as a more holistic coffee shop on campus. This recommendation pushes more customers in the door and keeps them frequenting Lucky Lab, as they are encouraged to grab their “go-to” drink on their way to class every day.

With new customers in the door, Lucky Lab then needs to further differentiate itself from Starbucks by marketing its beverages as the more cost-effective option. Lucky Lab should consider reassessing its pricing structure in order to capture more cost-conscious college students. In regards to our findings, the $4 price takes up 44.2% of the relative importance at the market level. Options such as pricing all milk options the same, decreasing price discrepancy for sizes, or even offering a smaller size to match Starbucks’s size options can allow Lucky Lab to price beverages slightly cheaper or at par with Starbucks. By marketing this price difference across campus, students can best understand Lucky Lab’s value proposition on campus and be more open to switching up their daily routine to try out Lucky Lab’s options instead of Starbucks in hopes of saving money.

Finally, Lucky Lab should consider the longevity of newly acquired customers by enhancing customer satisfaction. From the analysis of the Promotion attribute, the “Buy One Get

One Free" has a relative importance of 27.8% at the market level, which suggests that student prefer instantaneous gratification over long-term promotional options when it comes to reward programs. Lucky Lab, unlike Starbucks, does not offer BOGOF sales. Thus, it would be beneficial for Lucky Lab to strategically integrate more frequent BOGOF sales into its daily operations in addition to the punch card that they currently offer. The timing of BOGOF deals can also be strategic: Lucky Lab can align BOGOF offerings during special holidays or peak study times, such as exam periods. These are times when students are more likely to frequent coffee shops, so if Lucky Lab establishes itself as a holistic, cost-effective option for coffee, students will be more likely to keep returning. Lucky Lab can also consider having BOGOF as a reward option for their punch card, where students can earn points with each purchase, leading to a BOGOF reward. Furthermore, Lucky Lab could consider collaborating with student organizations for special events and profit shares, during which students can earn more points for the punch card than usual, leading to more easily achieved BOGOF rewards and creating a win-win scenario.

In conclusion, we aimed to research current customers' satisfaction and loyalty towards Lucky Lab's on-campus locations, and designed a conjoint analysis which surveyed 8 current students. We found competitive pricing and BOGOF promotion to be the key features to integrate into Lucky Lab's current operation, and devised strategic recommendations for Lucky Lab to implement in order to better compete with its competitors, such as Starbucks. By incorporating these strategies for its menu, pricing, and promotions, Lucky Lab will not only be equipped with UT students' desired coffee shop qualities, but also establish itself as the increasingly preferred coffee destination, ensuring maximal market share attainment and long-term business success.

V. Appendix

List of Figures

Figure 1. Conjoint analysis attributes and levels

Attribute	Level
Brand	Starbucks
	Lucky Lab
Price	4
	5
	7
Order	Go-to
	Surprise
Promotions	Punch Card
	Buy One Get On Free
	Refill for Half the Price

Figure 2. Conjoint analysis fractional factorial set of profiles

Profile	Brand	Order	Price	Promotion
	2 Levels	2 Levels	3 Levels	3 Levels
1	Lucky Lab	Go-to	4	Refill for Half the Price
2	Lucky Lab	Surprise	5	Buy One Get One Free
3	Starbucks	Go-to	7	Buy One Get One Free
4	Lucky Lab	Go-to	7	Refill for Half the Price
5	Lucky Lab	Surprise	4	Punch Card
6	Starbucks	Surprise	4	Buy One Get One Free
7	Starbucks	Surprise	7	Refill for Half the Price
8	Starbucks	Go-to	5	Punch Card
9	Starbucks	Go-to	4	Punch Card
10	Lucky Lab	Go-to	5	Buy One Get One Free
11	Lucky Lab	Surprise	7	Punch Card
12	Starbucks	Surprise	5	Refill for Half the Price

Figure 3. Excel Conjoint Analysis Data Matrix

	Brand	Order	Price		Promotion		Customers' Ratings (1-10)							
Profile	Starbucks	Surprise	5 Dollars	7 Dollars	BOGOF	Refill for Half	Customer 1 Rating	Customer 2 Rating	Customer 3 Rating	Customer 4 Rating	Customer 5 Rating	Customer 6 Rating	Customer 7 Rating	Customer 8 Rating
1	0	0	0	0	0	1	5	3	7	4	3	7	6	5
2	0	1	1	0	1	0	6	3	6	3	5	5	7	6
3	1	0	0	1	1	0	5	6	4	9	8	3	6	1
4	0	0	0	1	0	1	2	4	3	3	6	2	4	1
5	0	1	0	0	0	0	5	3	9	3	8	3	4	5
6	1	1	0	0	1	0	6	9	9	8	8	9	5	7
7	1	1	0	1	0	1	3	5	3	3	3	2	3	1
8	1	0	1	0	0	0	6	7	7	3	4	5	7	5
9	1	0	0	0	0	0	8	6	8	5	4	3	8	5
10	0	0	1	0	1	0	7	3	7	7	3	5	7	8
11	0	1	0	1	0	0	2	3	3	3	7	2	4	1
12	1	1	1	0	0	1	4	7	8	4	1	6	4	5

Figure 4: Python Conjoint Analysis Data Matrix

	Starbucks	Surprise	5 Dollars	7 Dollars	BOGOF	Refill for Half	Customer 1 Rating	Customer 2 Rating	Customer 3 Rating	Customer 4 Rating	Customer 5 Rating	Customer 6 Rating	Customer 7 Rating	Customer 8 Rating
1	0	0	0	0	0	1	5	3	7	4	3	7	6	5
2	0	1	1	0	1	0	6	3	6	3	5	5	7	6
3	1	0	0	1	1	0	5	6	4	9	8	3	6	1
4	0	0	0	1	0	1	2	4	3	3	6	2	4	1
5	0	1	0	0	0	0	5	3	9	3	8	3	4	5
6	1	1	0	0	1	0	6	9	9	8	8	9	5	7
7	1	1	0	1	0	1	3	5	3	3	3	2	3	1
8	1	0	1	0	0	0	6	7	7	3	4	5	7	5
9	1	0	0	0	0	0	8	6	8	5	4	3	8	5
10	0	0	1	0	1	0	7	3	7	7	3	5	7	8
11	0	1	0	1	0	0	2	3	3	3	7	2	4	1
12	1	1	1	0	0	1	4	7	8	4	1	6	4	5

Figure 5: Attribute Mapping and Baseline Code in Python

```python
# Define a structure that maps each independent variable to its attribute
attribute_mapping = {
    'Brand': ['Starbucks'],
    'Order': ['Surprise'],
    'Price': ['5 Dollars','7 Dollars'],
    'Promotion': ['BOGOF','Refill for Half']
}

# Define the baselines for each attribute
baselines = {
    'Brand': 'Lucky Lab',
    'Order': 'Go-to',
    'Price': '4 Dollars',
    'Promotion': 'Punch card'
}
```

Figure 6: OLS Linear Regression Code in Python

```
# Run regression for each customer and get coefficients
models = {}
part_worths = {}
attribute_ranges = {}
relative_importances = {}

for i in range(1, 9):  # Replace with the actual number of customers
    y = df[f'Customer {i} Rating']
    X = df.drop(columns=[f'Customer {j} Rating' for j in range(1, 9)]) # Replace with the actual number of customers
    X = sm.add_constant(X)

    model = sm.OLS(y, X).fit()
    models[f'Customer_{i}'] = model

    # Store coefficients (part-worths) and initialize baselines to 0
    part_worths[f'Customer_{i}'] = model.params.drop('const').to_dict()
    for baseline in baselines.values():
        # Set baseline part-worths to 0 if not already present
        part_worths[f'Customer_{i}'].setdefault(baseline, 0)
```

Figure 7: Feature Importances Code in Python

```
# Calculate ranges for each attribute and store in attribute_ranges
for customer in part_worths:
    attribute_ranges[customer] = {}
    total_range = 0  # Initialize total range sum for the customer

    for attribute, levels in attribute_mapping.items():
        # Get part-worths for all levels of this attribute, including the baseline
        level_part_worths = [part_worths[customer].get(level, 0) for level in levels]
        level_part_worths.append(0)  # Add the baseline to the level_part_worths
        # Calculate the range
        attribute_range = max(level_part_worths) - min(level_part_worths)
        attribute_ranges[customer][attribute] = attribute_range
        total_range += attribute_range  # Add to total range
```

Figure 8: Relative Importances Code in Python

```
# Calculate relative importance for each attribute
relative_importances[customer] = {attribute: (range_val / total_range) * 100
                                  for attribute, range_val in attribute_ranges[customer].items()}
```

Figure 9: Combined Python code for Attribute/Baseline Mapping, OLS Linear Regression, Feature Importances and Relative Importances

```
# Define a structure that maps each independent variable to its attribute
attribute_mapping = {
    'Brand': ['Starbucks'],
    'Order': ['Surprise'],
    'Price': ['5 Dollars','7 Dollars'],
    'Promotion': ['BOGOF','Refill for Half']
}

# Define the baselines for each attribute
baselines = {
    'Brand': 'Lucky Lab',
    'Order': 'Go-to',
    'Price': '4 Dollars',
    'Promotion': 'Punch card'
}

# Run regression for each customer and get coefficients
models = {}
part_worths = {}
attribute_ranges = {}
relative_importances = {}

for i in range(1, 9): # Replace with the actual number of customers
    y = df[f'Customer {i} Rating']
    X = df.drop(columns=[f'Customer {j} Rating' for j in range(1, 9)]) # Replace with the actual number of customers
    X = sm.add_constant(X)

    model = sm.OLS(y, X).fit()
    models[f'Customer_{i}'] = model

    # Store coefficients (part-worths) and initialize baselines to 0
    part_worths[f'Customer_{i}'] = model.params.drop('const').to_dict()
    for baseline in baselines.values():
        # Set baseline part-worths to 0 if not already present
        part_worths[f'Customer_{i}'].setdefault(baseline, 0)

# Calculate ranges for each attribute and store in attribute_ranges
for customer in part_worths:
    attribute_ranges[customer] = {}
    total_range = 0  # Initialize total range sum for the customer

    for attribute, levels in attribute_mapping.items():
        # Get part-worths for all levels of this attribute, including the baseline
        level_part_worths = [part_worths[customer].get(level, 0) for level in levels]
        level_part_worths.append(0)  # Add the baseline to the level_part_worths
        # Calculate the range
        attribute_range = max(level_part_worths) - min(level_part_worths)
        attribute_ranges[customer][attribute] = attribute_range
        total_range += attribute_range  # Add to total range

    # Calculate relative importance for each attribute
    relative_importances[customer] = {attribute: (range_val / total_range) * 100
                                      for attribute, range_val in attribute_ranges[customer].items()}
```

Figure 10: Part-Worths, Feature Importances, and Relative Importances for Respondent 1

```python
def print_dict_in_table(dictionary, title):
    print(title)
    print("-" * len(title))
    for key, value in dictionary.items():
        print(f"{key:20}: {round(value,2)}")
    print()

# Print outputs for Customer 1
print_dict_in_table(part_worths['Customer_1'], "Part-Worths for Customer 1")
print_dict_in_table(attribute_ranges['Customer_1'], "Attribute Ranges for Customer 1")
print_dict_in_table(relative_importances['Customer_1'], "Relative Importances for Customer 1")
```

```
Part-Worths for Customer 1
--------------------------
Starbucks           : 0.83
Surprise            : -1.17
5 Dollars           : -0.47
7 Dollars           : -2.73
BOGOF               : 0.87
Refill for Half     : -1.07
Lucky Lab           : 0
Go-to               : 0
4 Dollars           : 0
Punch card          : 0

Attribute Ranges for Customer 1
-------------------------------
Brand               : 0.83
Order               : 1.17
Price               : 2.73
Promotion           : 1.93

Relative Importances for Customer 1
-----------------------------------
Brand               : 12.5
Order               : 17.5
Price               : 41.0
Promotion           : 29.0
```

Figure 11: Part-Worth Plots for Respondent 1

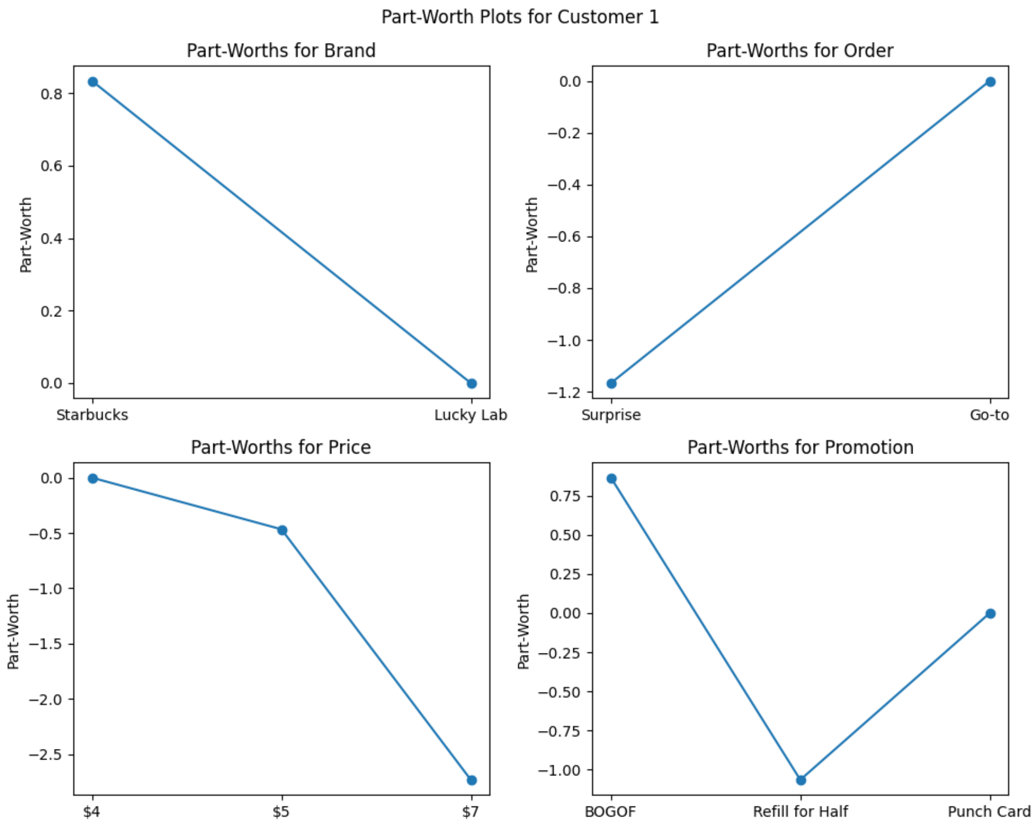


Figure 12: Python Code Calculating Dollar Value of a Util for Respondent 1

```
avg_price_per_util = 0

# Price per util for Customer 1

# $7 - $5 = 2
five_to_seven = 2/(part_worths['Customer_1'].get("7 Dollars") - part_worths['Customer_1'].get("5 Dollars"))
# $5 - $4 = 1
four_to_five = 1/(part_worths['Customer_1'].get("5 Dollars") - part_worths['Customer_1'].get("4 Dollars"))

price_per_util = (five_to_seven + four_to_five)/2
avg_price_per_util += round(price_per_util, 2)
print(round(price_per_util, 2))
```

```
-1.51
```

Survey Questions

Link to Qualtrics: https://utexas.qualtrics.com/jfe/form/SV_0MtSUWrsgC2fmWa

Hello, this survey is being conducted for a marketing class at McCombs to gain insights into student demographics and attitudes in regards to coffee shops around the UT area. Your responses are anonymized and greatly appreciated.

There are 12 coffee shop profiles.

Please rank the following coffee shop profiles on a scale from 1-10, with 1 meaning it would be very unlikely for you to visit the coffee shop on any given day, and 10 meaning you would very likely visit the coffee shop on any given day.

Brand - This is the brand of the coffee shop. There are two brands: Starbucks and Lucky Lab. *Please note that for the sake of these analyses, these brands were chosen as the 2 options available on UT Campus. We do not affiliate with any of the political stances currently represented by these companies. Please provide your ratings without consideration of the brands' political stances.

Order - This represents the type of drink order you would be making. There are two types of orders: your "go-to" drink or trying something new, a "surprise" drink.

Price - This is the price of the drink you plan on purchasing. There are three values: $4, $5, and $7.

Promotion - This is the offerings for making a purchase at the coffee shop. There are 3 types of promotions: a punch card (which allows you to get a free drink upon completion of the card), buy one get one free, or a refill for half the price.

Brand: Lucky Lab

Order: Go-To

Price: $4

Promotion: Refill for Half the Price

Brand: Starbucks

Order: Go-To

Price: $4

Promotion: Punch Card

Brand: Starbucks

Order: Surprise

Price: $4

Promotion: Buy One Get One Free

Brand: Starbucks

Order: Go-To

Price: $7

Promotion: Buy One Get One Free

Brand: Starbucks

Order: Surprise

Price: $7

Promotion: Refill for Half the Price

Brand: Starbucks

Order: Go-To

Price: $5

Promotion: Punch Card

Brand: Lucky Lab

Order: Surprise

Price: $5

Promotion: Buy One Get One Free

Brand: Lucky Lab

Order: Go-To

Price: $5

Promotion: Buy One Get One Free

Brand: Lucky Lab

Order: Surprise

Price: $7

Promotion: Punch Card

Brand: Lucky Lab

Order: Go-To

Price: $7

Promotion: Refill for Half the Price

Brand: Starbucks

Order: Surprise

Price: $5

Promotion: Refill for Half the Price

Brand: Lucky Lab

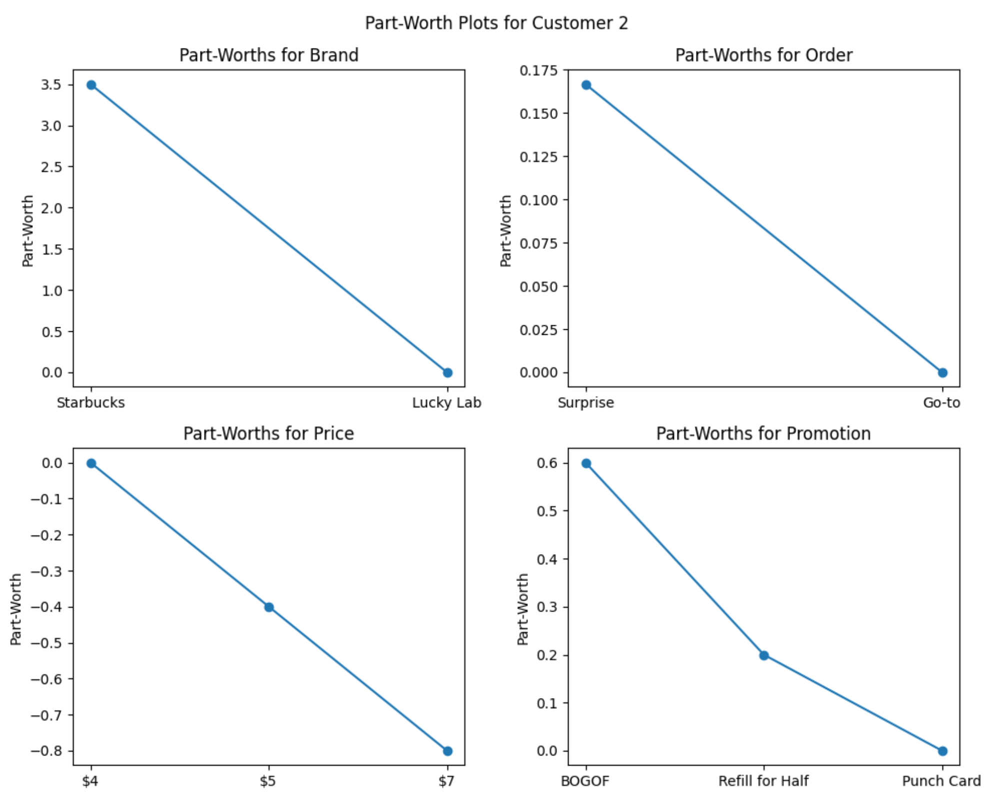
Order: Surprise

Price: $4

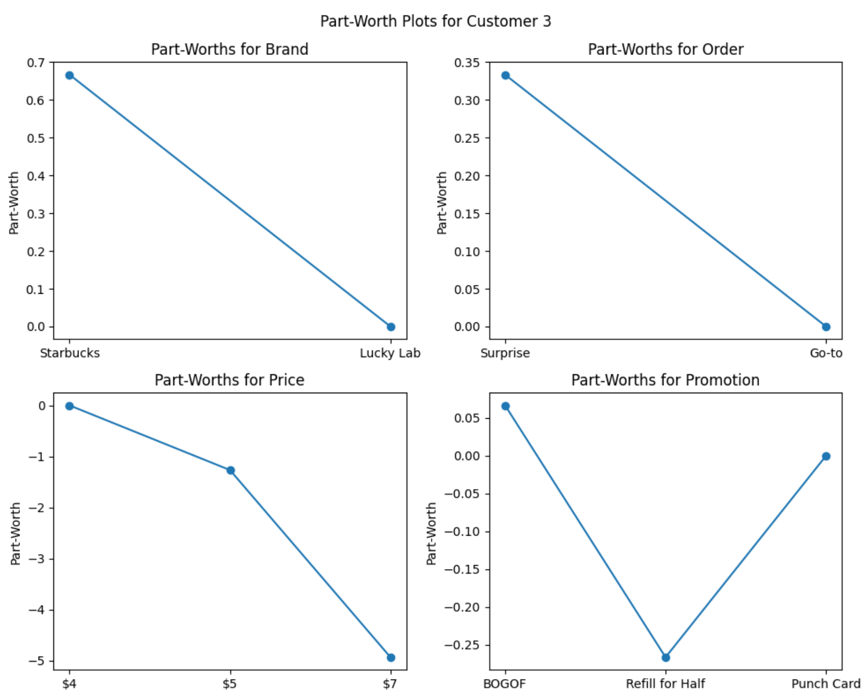
Promotion: Punch Card

Partworths and Plots of Each Attribute for Respondents 2-8

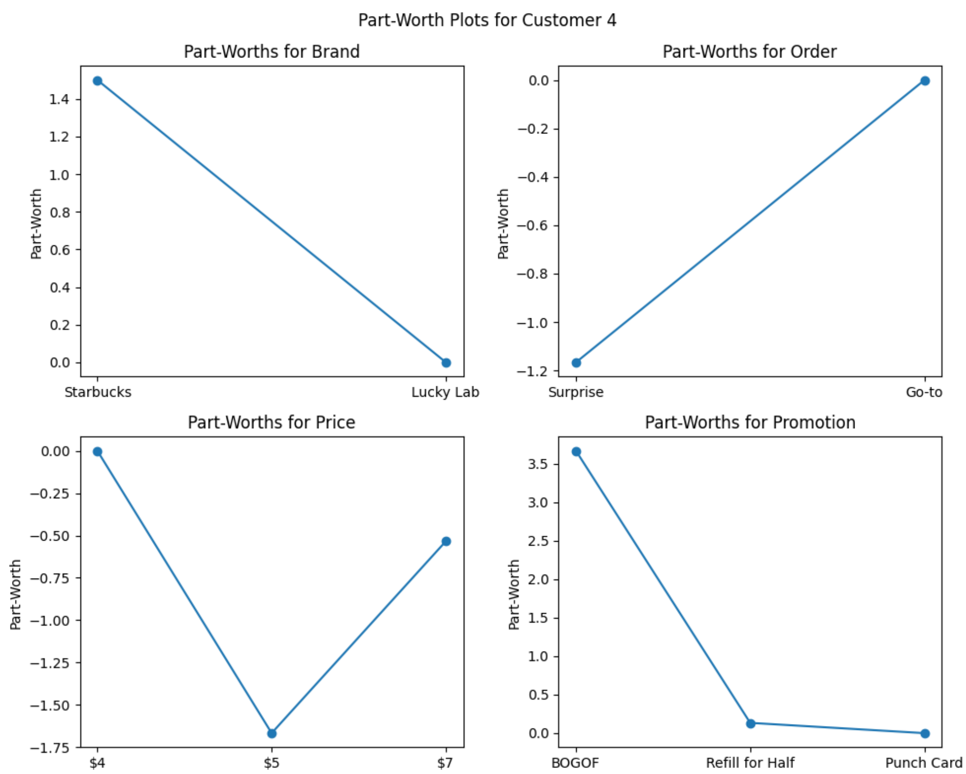
```
Part-Worths for Customer 2
--------------------------
Starbucks            : 3.5
Surprise             : 0.17
5 Dollars            : -0.4
7 Dollars            : -0.8
BOGOF                : 0.6
Refill for Half      : 0.2
Lucky Lab            : 0
Go-to                : 0
4 Dollars            : 0
Punch card           : 0

Attribute Ranges for Customer 2
-------------------------------
Brand                : 3.5
Order                : 0.17
Price                : 0.8
Promotion            : 0.6

Relative Importances for Customer 2
-----------------------------------
Brand                : 69.08
Order                : 3.29
Price                : 15.79
Promotion            : 11.84
```



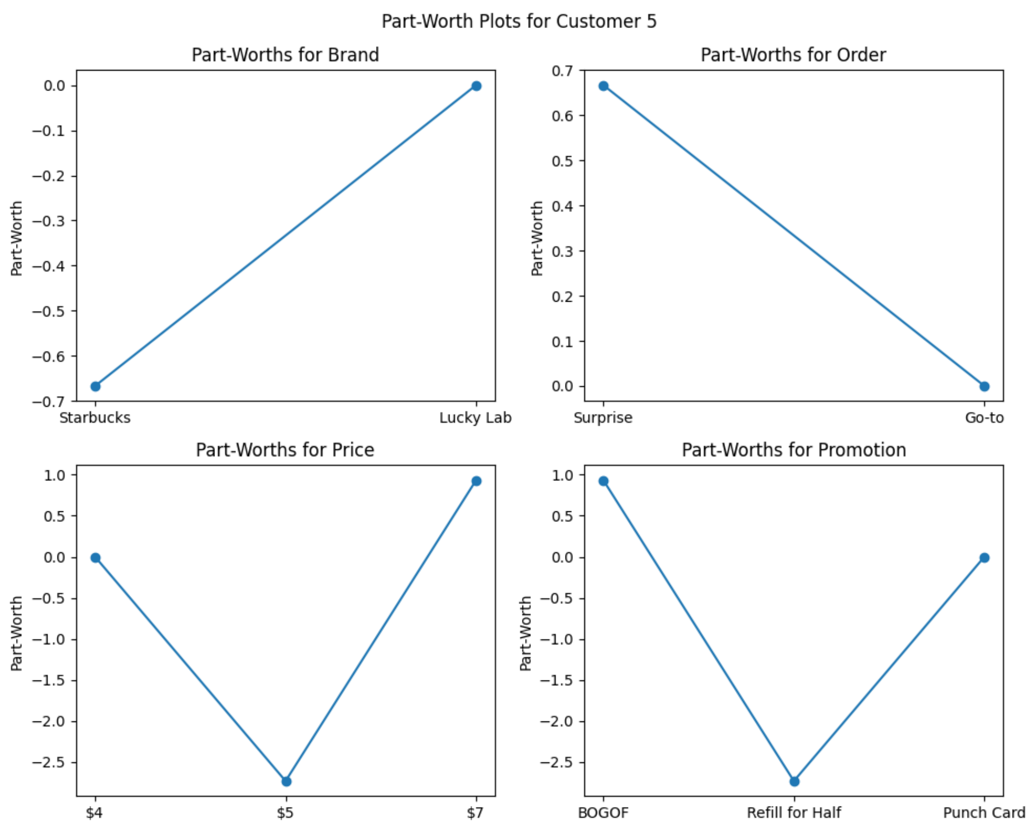
```
Part-Worths for Customer 3
--------------------------
Starbucks           : 0.67
Surprise            : 0.33
5 Dollars           : -1.27
7 Dollars           : -4.93
BOGOF               : 0.07
Refill for Half     : -0.27
Lucky Lab           : 0
Go-to               : 0
4 Dollars           : 0
Punch card          : 0

Attribute Ranges for Customer 3
-------------------------------
Brand               : 0.67
Order               : 0.33
Price               : 4.93
Promotion           : 0.33

Relative Importances for Customer 3
-----------------------------------
Brand               : 10.64
Order               : 5.32
Price               : 78.72
Promotion           : 5.32
```



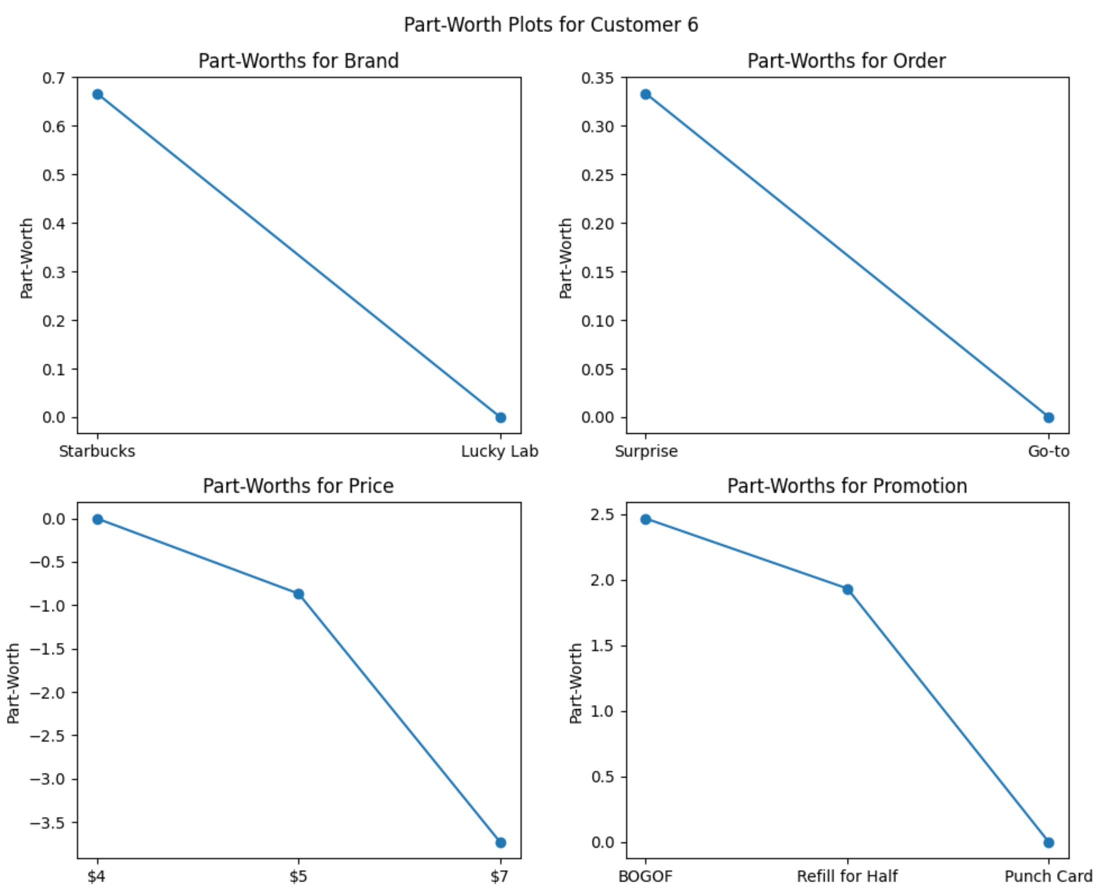
```
Part-Worths for Customer 4
--------------------------
Starbucks           : 1.5
Surprise            : -1.17
5 Dollars           : -1.67
7 Dollars           : -0.53
BOGOF               : 3.67
Refill for Half     : 0.13
Lucky Lab           : 0
Go-to               : 0
4 Dollars           : 0
Punch card          : 0

Attribute Ranges for Customer 4
-------------------------------
Brand               : 1.5
Order               : 1.17
Price               : 1.67
Promotion           : 3.67

Relative Importances for Customer 4
-----------------------------------
Brand               : 18.75
Order               : 14.58
Price               : 20.83
Promotion           : 45.83
```



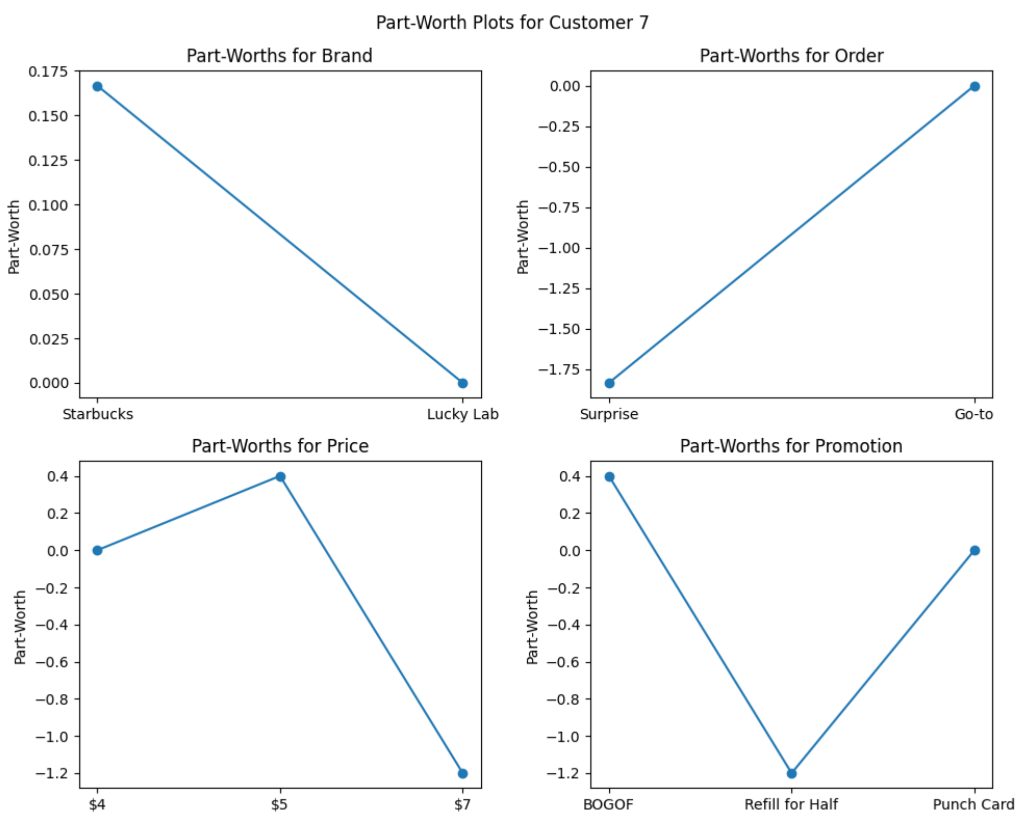
```
Part-Worths for Customer 5
--------------------------
Starbucks            : -0.67
Surprise             : 0.67
5 Dollars            : -2.73
7 Dollars            : 0.93
BOGOF                : 0.93
Refill for Half      : -2.73
Lucky Lab            : 0
Go-to                : 0
4 Dollars            : 0
Punch card           : 0

Attribute Ranges for Customer 5
-------------------------------
Brand                : 0.67
Order                : 0.67
Price                : 3.67
Promotion            : 3.67

Relative Importances for Customer 5
-----------------------------------
Brand                : 7.69
Order                : 7.69
Price                : 42.31
Promotion            : 42.31
```



```
Part-Worths for Customer 6
--------------------------
Starbucks           : 0.67
Surprise            : 0.33
5 Dollars           : -0.87
7 Dollars           : -3.73
BOGOF               : 2.47
Refill for Half     : 1.93
Lucky Lab           : 0
Go-to               : 0
4 Dollars           : 0
Punch card          : 0

Attribute Ranges for Customer 6
-------------------------------
Brand               : 0.67
Order               : 0.33
Price               : 3.73
Promotion           : 2.47

Relative Importances for Customer 6
-----------------------------------
Brand               : 9.26
Order               : 4.63
Price               : 51.85
Promotion           : 34.26
```



```
Part-Worths for Customer 7
--------------------------
Starbucks           : 0.17
Surprise            : -1.83
5 Dollars           : 0.4
7 Dollars           : -1.2
BOGOF               : 0.4
Refill for Half     : -1.2
Lucky Lab           : 0
Go-to               : 0
4 Dollars           : 0
Punch card          : 0

Attribute Ranges for Customer 7
-------------------------------
Brand               : 0.17
Order               : 1.83
Price               : 1.6
Promotion           : 1.6

Relative Importances for Customer 7
-----------------------------------
Brand               : 3.21
Order               : 35.26
Price               : 30.77
Promotion           : 30.77
```



```
Part-Worths for Customer 8
--------------------------
Starbucks           : -0.33
Surprise            : -0.0
5 Dollars           : 0.13
7 Dollars           : -4.53
BOGOF               : 1.47
Refill for Half     : 0.13
Lucky Lab           : 0
Go-to               : 0
4 Dollars           : 0
Punch card          : 0

Attribute Ranges for Customer 8
-------------------------------
Brand               : 0.33
Order               : 0.0
Price               : 4.67
Promotion           : 1.47

Relative Importances for Customer 8
-----------------------------------
Brand               : 5.15
Order               : 0.0
Price               : 72.16
Promotion           : 22.68
```