Project 2 – Kiwi Bubbles

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1 Introduction

Now we go back to the late 90s. Back then, you were the product and pricing manager of Kiwi, a major soft drink company. You own and sell "Kiwi Regular" and the product currently is doing well in the market. Your main competitor, Mango, produces "Mango Bubbles" that is well-received in the market as well. Your guess is that Mango does well because consumers prefer "Bubbles" over "Kiwi" – but you have the better brand name than Mango, thus your product also does well. Now, a spark comes to your mind: why not launching a new product, "Kiwi Bubbles"? The product combines the best of characteristics "Bubbles" and your brand name "Kiwi", and should be able to do well, right? You launch the product in a test market and collected consumer loyalty card data to aid your global launching and pricing decisions. For the entire project, assume that all 3 products have $0.50 marginal costs.

We have a sub-sample of the dataset, `kiwi_bubbles.csv`. The dataset records the choices of softdrink, of 359 consumers over a course of 3 years. The columns, from left to right, are 1) consumer ID, 2) week code, 3) softdrink-buying trip number of the consumer in the sample period, and 4) prices and 5) purchases, of Kiwi Regular, Kiwi Bubbles and Mango Bubbles. A consumer in a given week only buys one or none of the 3 products. We also have a demographic dataset, `demo.csv`, for *some* of the consumers. With this data structure in mind, let us **A)** try to estimate overall consumer preferences and demand by a logit model [35% out of 10 points]; **B)** set product-line prices for Kiwi Regular and Kiwi Bubbles, and assess cannibalization and competition by calculating the cross-price elasticities [30%]; and **C)** formulate a product launch strategies in the market where consumers' past choices drives their future demand [35%].

Recall that in both Project 2 and 3, we will have a set of bonus questions that add up to 50 points, or 5 percent of the final grade. In this case, the bonus questions are in Part D. I will take the maximum of the two projects to determine your grades in this part, so attempting this part now will increase your chance of obtaining a high grade.

Please hand in a short report documenting your main model, result, interpretation and managerial insights. The project is due in Week 7, on Monday, May 7th at 11:59pm.

2 [A] A logit demand system (35%)

We now understand perfectly that to do pricing (and product-line management), we first want to figure out what demand looks like. In this case, because we have discrete choice data, it is natural to think about discrete choice models. As we walked through in class, let's begin by building a logit model with utility

$$u_{ijt} = \beta_{ij} + \alpha_i \cdot p_{jt} + \varepsilon_{ijt}$$

where $j = 1,2,3$ represent Kiwi Regular (KR), Kiwi Bubbles (KB) and Mango Bubbles (MB). The consumer can also choose to buy none of the three (0), in which case she gets utility

$$u_{i0t} = 0 + \varepsilon_{i0t}.$$

Note that in the above, coefficients β_{ij} and α_i are individual or segment specific. As we walked through in the class, instead of estimating them individual-by-individual, it is more robust and reliable to estimate these coefficients by-segment. Here are some guidelines in terms of which steps to follow, but there is a lot of room to apply your own judgements:

- How do we segment the market? You can consider segmenting by all demographic variables, and choose a clustering algorithm to do so. You can for example follow our exercise in the rating-based conjoint (Week 4) and choice-based conjoint (the last bit of Week 4 material that we did not get to finish in that class). You can also consider doing latent segmentation, which we'll talk about in Week 6.

- If you find segmentation too cumbersome, you can start the analysis using the simplest logit model – the *exact* one covered in Week 5's lecture notes – and later try to build segmentation on that model. Note that the model without segmentation at all might be too simplistic and ignores important insights; but you'll still get most grades for this question if you do not have any segmentation in the analysis.
- Write your logit model code to estimate utility coefficients (note that β's and α are now on the segment-level rather than individual-level). You can program up your own logit code, following what we've done in class. You can also use the package 'mlogit' to do this. However, note that you might still need your own logit functions (and adapt them) when we're dealing with the bonus questions.
- We're not dealing with a huge dataset and you might run into "weird" parameter estimates. If that happens, check whether the sign of your parameters and price elasticities make sense, adjust your starting points and/or number of segments if needed.

3 [B] Segmentation, own- and cross- price elasticities, and pricing (30%)

At the current *average* prices, what are the own- and cross- elasticities among these products? How does the underlying customer segmentation explain this substitution pattern? Which products are closer substitutes and which products are not as close substitutes? Lastly, from the substitution pattern, where (i.e. what price point, targeting to which segment(s)) should Kiwi Bubbles be positioned?

Let's say Mango Bubbles is priced at $1.43 and does not react to Kiwi's pricing. Before you launch Kiwi Bubbles, how should you price Kiwi Regular? After you launch Kiwi Bubbles, how should you price Kiwi Regular and Kiwi Bubbles? Compare the prices of Kiwi Regular, before and after Kiwi Bubble's launch: how does KR's price change and what is the intuition behind it?

4 [C] Testing for consumer behavior and insights for pricing strategies [35%]

4.1 Brand loyalty or variety seeking? [25%]

Your supervisor hinted that your demand model might be too simplistic and you might miss out some important insights and pricing opportunities. In particular, after your meeting with her, you decided to estimate how much tendency the consumer has in buying what she bought previously – i.e. how "inertial" the consumer demand is. Specifically, in the utility function we had above (and in class note), add a term, y_{it-1}, that determines the product the consumer *previously purchased*, i.e.

$$y_{it-1} = \begin{cases} y_{it-2} & \text{if consumer does not purchase anything in week } t-1 \\ j & \text{if consumer buys } j \text{ in } t-1 \end{cases}$$

Note that y_{it-1} can be directly constructed from the data. With this added term, you estimate

$$u_{ijt} = \beta_{ij} + \alpha_i \cdot p_{jt} + \gamma_i \cdot 1\left(y_{it-1} = j\right) + \varepsilon_{ijt}$$

here: $1\left(y_{it-1} = j\right)$ indicates whether the product is the same as the one the consumer last purchased, and γ_i is also segment-specific. Before we estimate this: does a positive γ_i tell you that consumers are brand loyal – i.e. they tend to purchase the product they bought last time – or variety seeking – i.e. they tend to switch product and buy something they did not take last time?

Re-estimate the entire model with this added term. How different are β_{ij} and α_i compared to before? What is the sign and magnitude of γ_i and what kind of consumer behavior does it represent?

4.2 Insights [10%]

From your insights above, what pricing strategies can you come up with? Specifically, let's think about pricing over time (i.e. dynamic pricing). If you increase your prices, how does your demand change from this consumer in her next trip? Likewise, if you decrease your prices, how does the consumer demand change in her next trip? Let us roll with the thought: if you try to maximize profit across multiple weeks –during which a consumer repeatedly come to the chain to buy soft drinks– how should you set prices over time to account for that prices in one trip might affect consumer demand in the subsequent trips? Do you think you will price higher or lower, compared to when consumers do not display this type of purchasing patterns?

5 [D] Competition and policy [extra 50%]

5.1 Price competition [30%]

For simplicity, in Part D, you do not need to consider the history-dependent behavior you analyze in Part C.

You now consider strategic actions from your competitor, Mango. You realize that Mango might be as smart as you are in that they might also realize their $1.43 price might not be optimal. In this case, how would Mango set prices, given that you set an optimal price assuming that they price at $1.43? Is it higher or lower than $1.43?

Now, it is your turn: if Mango set prices at the level you predict, would you stick to the pricing strategy you derive from Part B? If not, how would you set prices then, and do you think Mango will stick to the prices they just arrived at?

Take this argument iteratively: what would be the stable set of prices you and Mango charge, such that neither you or Mango is willing to change the price(s). If you are familiar with game theory, these prices are referred to as the Nash Equilibrium in the setting we analyze. How different are they compared to the ones where Mango commits to \$1.43?

5.2 Collusion and anti-trust policy [15%]

Your boss looks at the number and says: “why don’t we call up Mango and set a ’truce’?” Of course, communicating with the competitor and engage in joint price-setting is referred to as “collusion” and is strictly illegal. Your boss quickly realizes that and backs off from that thought. However, for curiousity, you are interested in knowing how much more profit you can make if you collude. For now, pretend that Kiwi and Mango is a combined firm and will jointly set prices. How should you set prices and how much profit you will gain? Do you think you should try to propose a merger with Mango?

5.3 Sensitivity of the analysis [5%]

Typically, anti-trust authorities and legal consulting firms will run these analysis and try to understand the outcome of a merger proposal. But before calling it a day, you need to run some sensitivity analysis and make sure that your reports are based on stable and solid analysis. Run some sensitivitiy analysis on the way you set up segmentation: does it matter to your results how many clusters you have, which demographic variables you choose, etc.? To be clear, I am *not* looking for an exhaustive list of possible sensitivity analysis; it suffices to have one or two tweaks of your model and see how much the results change.