Università Commerciale "Luigi Bocconi"

Group Project

20595

Business Analytics

Combatting Serial Returners in Online Retail

Investigating Return Blocking to Combat Serial Returners

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5

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Abstract

Serial Returners are a big problem for online retailers. This experiment tests to see whether a blocking policy, blocking people from returning whenever they return an excessive amount, is a policy that reduces the serial returner rate. A survey was run on over 210 correspondents from different walks of life, which showed that the Block Policy would even have an adverse effect to people, returning on average more than when the Block Policy was not introduced. To confirm this we would recommend further experimentation on this subject.

1 Introduction

Returning bought products have a big impact on the bottom line of sellers of online physical products as returned items need to be shipped twice, from the seller to the buyer and from the buyer to the seller. Returning is so much ingrained into our culture that retailers expected about 18% of merchandise during the holiday shopping season to be returned in 2021 (NRF, 2022). Of course you do not want to remove the ability for people to send back items as this is part of the customer experience but because it is so easy for people to buy items without doing research and consequently sending the items back, something has to be done about this. Take for example the situation where a person buys a t-shirt on Amazon from a vendor; however instead of buying only one t-shirt that would fit him, which he can conclude after doing research, he buys three different sizes to fit them at home. Because only one will fit him fine, he will return the other two t-shirts to the vendor, meaning that the vendor has to pay for the return of the items, which can easily cost around $10 in the US (ShipBob, 2023). This is a parasitical relationship between customer and vendor as the vendor often ends up having to pay for all of the downside of this behaviour, whilst for the customer this behaviour does not have any downside. One can see that, besides this having an environmental impact (Khusainova, 2019), it is a risk on the vendor, which should be minimized. This is why we want to investigate the following:

People that buy a lot of items and return most of them, are abusing the refunding system

To test this we want to do an experiment, but before we can do this, it is imperative to first set up a theoretical framework with our beliefs (Camuffo and Pignataro, 2022).

1.1 Theoretical Framework and Initial Beliefs

From research we believe that the following attributes contribute to the reduction of the phenomenon *'serial returning'*:

1. Reasons why products are returned are defined {Yes,No}

2. Price of the product {High, Low}

3. Implementing a block policy that prohibits people from returning products lowers serial returners {Yes,No}

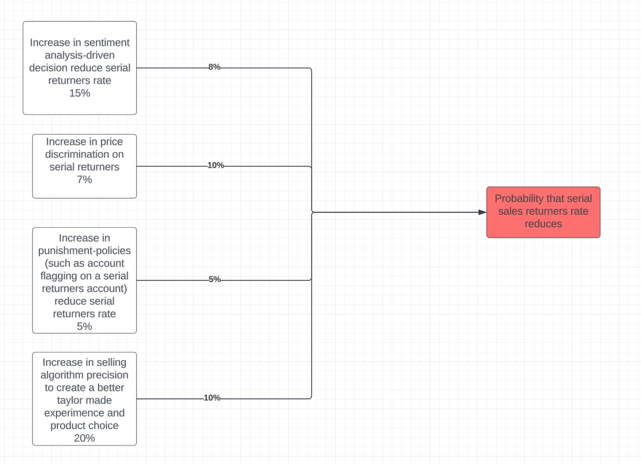
4. Does improving selling algorithm precision increase sales? {Yes, No}

From these attributes we have defined the framework 3a
To found these beliefs, we did a literary research, sentiment analysis on people's reasons to return products and a confirmatory scrape of the product pricing. The outcome and method of these three initial experiments are explained below, but for a more detailed explanation on the latter two, we refer to the Appendix.

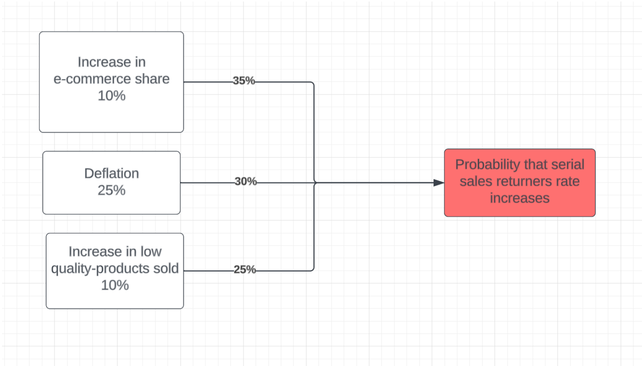
1.1.1 Product Return Reasons

We believe that the reasons as to why products are returned can be found from customer reviews sentiment analysisDuckers, n.d., which we used as our secondary dataset to partially confound our beliefs. This sentiment analysis was done on a tertiary and a quaternary dataset encompassing a Clothes Review Dataset (Feeds, n.d.-a) and an IT Products Reviews Dataset (Feeds, n.d.-b). This gave the following frequency list:

After we did this initial belief experiment (described in Sentiment Analysis) we think that there is a 15% chance that there will be an increase, which will have an impact of 8%.



(a) Theoretical Framework



(b) Alternative Theory Framework

1.1.2 Price of the Product

We believe that the chances for an even bigger increase in price discrimination among packages that are returned and not is highly unlikely. In the secondary dataset (Duckers, n.d.) the price is given for the orders, but we wanted to test if the prices provided by the dataset was correct. For this we did a scrape of the SKU codes on Amazon (see Appendix) and confirmed that the returned to sender (orders that were returned) had the same mean price as was indicated in the dataset. This mean (170) is significantly lower than the average price over all of the orders (648), which is a big price discrimination and as said we do not belief that this will change and therefor we assigned a probability of 7%.

1.1.3 Block Policy

A block policy tries to punish people for returning items concurrently or in large quantities, whilst still allowing for returns by 'honest' customers, by inhibiting access to the return for free option for an extended amount of time after reckless behaviour. We believe that the probability that this functionality can be implemented is 5%.

1.1.4 Selling Algorithm

This node represents "the improve of precision to which a product is suggested to a specific client". The idea behind this is that potential customers who get products recommended that truly fit them, will not return the items because they already get the right size for a t-shirt assigned to them for example. Our initial belief for this attribute is that there is a chance of 20% of our ability to be implemented. If this is implemented, we belief that this will decrease the serial returners rate by 10%

1.2 Alternative Theory

These 4 attributes all connect to the probability that serial sales returners rate reduces. For the alternative theory, we want to test against has the following attributes:

1. E-commerce share trends upwards {Yes,No}
2. Deflation will set in {Yes,No}
3. There will be an increase in low-quality products {Yes,No}

From these attributes we have defined the following theoretical framework in Figure b
We will now go into the attributed beliefs and why these values are assigned

1.2.1 E-commerce Share Trends Upwards

If people will buy more items online and not go to brick and mortar stores, this could increase the amount of return items because people do not go to the physical store to try out the product first. We believe that the ecommerce market share will increase by a probability of 60% and that this will yield a 35% increase in the serial returners rate.

1.2.2 Deflation will set in

If there will be deflation, people will not buy as many products, which could result in people returning more items as they get pickier with what they buy. We believe that this will happen with a probability of 25% and that this will increase the serial returners rate by 30%.

1.2.3 Increase in Low-Quality Products

If there will be an increase in low-quality products, we believe that people will return items more often. We believe that this will happen with a 10% chance and that this will increase serial returners rate by 25%

1.3 Building the Theory

From these aforementioned initial beliefs, we get the following unconditional expected value for the Theory:

$$V = \omega * 0.095 + (\omega - 1)0.1369 \quad where \quad \omega = 0.9$$
$$V = 0.9 * 0.095 + 0.1 * 0.1369 = 0.099 = 9.9\%$$

And the following for the alternative theory:

$$V = \omega * 0.092 + (\omega - 1)0.1875 \quad where \quad \omega = 0.9$$
$$V = 0.9 * 0.092 + 0.1 * 0.1875 = 0.10155 = 10.2\%$$

For the complete calculation we refer to the Appendix.

1.4 Course of Action

For this experiment we want to check whether the blocking policy described in the theoretical framework influences the behaviour of a serial returner. We do this because we want to test the potentially most effective improvement. We want to thus reject or accept the following hypothesis:
Serial Returning will decrease following the implementation of a blocking policy.
If $\theta_{Y,Y}$ is more likely than $\theta_{Y,N}$, we will choose the prior, alternatively we will reject this hypothesis and pursue $\theta_{Y,N}$. This means that we have a threshold of 0 for the following variable: $\Delta\theta = \theta_{YY} - \theta_{YN}$:

$$\text{If } \Delta\theta < 0 \rightarrow \quad \downarrow \omega$$
$$\text{If } \Delta\theta > 0 \rightarrow \quad \uparrow \omega$$

And our prior belief is:

$$\theta_{YY} > \theta_{YN}$$

To test this we will use an A/B testing Survey approach, which is described in the following section.

2 Methods

The Survey tested a Treated and Control group following an A/B testing approach on the blocking policy. An A/B test randomly assigns the Treated and Control group the same scenario with only one difference: the block policy implemented or not. We would like to stress that the assignment of the block policy is completely random and does not depend on any other variables. For this randomization we used the Qualtrics (Survey, 2023) randomization, implemented by Qualtrics.

2.1 The Blocking Policy

In response to the pervasive issue of serial returns, an innovative solution under consideration is the prospective implementation of a block policy. Unlike current practices, the block policy represents a forward-looking measure aimed at discouraging individuals prone to returning items concurrently or in large quantities. At its core, the block policy endeavors to curb excessive return behavior by imposing restrictions on the return-for-free option for an extended duration. As of now, this strategy has not been incorporated into mainstream retail practices. The fundamental principle guiding the block policy is deterrence. Instead of being a reactive measure already embedded in the system, the block policy functions as a preemptive deterrent against potential serial returners. By effectively communicating a credible threat of restricted return options, the policy aims to dissuade individuals from engaging in thoughtless return practices. While the block policy does not assume guilt across all customers, its design is strategic in neutralizing potential justifications for serial returning. By establishing clear consequences, the policy makes it arduous for individuals to rationalize or justify excessive returns. An insightful study conducted (Dootson et al., 2018) delves into the intricacies of deterring deviant consumer behavior, a concept encompassing actions that deviate from socially accepted norms, ethical standards, or legal regulations within consumer activities. This study draws inspiration from the classical school of criminology and the "rational choice view of human behavior." This perspective posits that individuals assess the costs and benefits of a situation to make rational decisions. Deterrence theory, as outlined by the study, proposes two key approaches. Firstly, it suggests deterring others through the punishment of current offenders, leveraging principles of vicarious learning akin to Bandura's social learning theory. For instance, individuals witnessing the consequences faced by others for a specific action are likely to refrain from engaging in the same behavior to avoid punishment. Secondly, the focus shifts to preventing reoffending. Grounded in the principles of operant conditioning, convicted and punished offenders are expected to refrain from reoffending to avoid future punishments. Understanding the nuanced relationship between deterrence and neutralization, the proposed block policy anticipates a transformative shift in consumer behavior. It aims to foster an environment where "honest" customers face no impediments while simultaneously introducing a robust deterrent for potential serial returners. This multifaceted approach, incorporating theoretical foundations and empirical studies, underscores the comprehensive nature of the proposed block policy in reshaping consumer behavior in the retail landscape.

2.2 Covariates

We controlled for the following variables:

- Gender
- Age
- Culture Background
- Education Status

- Average Monthly Spending

We will briefly go into these covariates down below.

2.2.1 Gender

We believe that people from different genders spend in a different way and therefor want to account for this covariate. For gender we defined the following option set:

$$\{\text{Male}, \text{Female}, \text{Prefer not to specify}, \text{Other}\}$$

2.2.2 Age

Age plays a big role in how people approach online shopping. There are social differences between older and younger people, where for example younger people buy things more easily online, whereas older people will do more research before buying items online. Additionally, age and disposable income are correlated and this covariate, combined with education status is a proxy for online expenditure. We defined the following option set:

$$\{0-23, 24-37, 38-50, >50\}$$

2.2.3 Culture Background

People from different backgrounds, in our case continents, spend money differently. We want to include this as a covariate because of this reason. Additionally, people from different continents have different amounts of money available to spend online. We defined the following option set:

$$\{Europe, Africa, Asia, Oceania, America\}$$

2.2.4 Education Status

Combined with age, we use this as a proxy for online expenditure. Furthermore, people from different education levels have a different spending behaviour. We defined the following option set:

$$\{\text{High School}, \text{Bachelor}, \text{Master}, \text{Higher than Master}\}$$

2.2.5 Average Monthly Spending

People that spend more usually are more keen to return in our belief, which would make it that they care more or less about the policy. We thus want to account for this covariate. We defined a range between 0 and 500 ([0,500]), with 500 meaning 500 or more.

2.3 A/B Testing

We implemented a A/B testing approach, commonly known as split testing, to assess the effectiveness of our policy. A/B testing is a randomized experimentation process wherein different versions of a variable are presented to distinct segments individuals simultaneously. The primary objective is to identify which version yields the most significant impact and drives key business metrics. A/B testing empowers experience optimizers to make well-informed decisions. In this methodology, 'A' signifies the control or the original testing variable, while 'B' represents the treatment or a new version of the original testing variable. To evaluate whether our policy could effectively curb the phenomenon of serial returners, we devised a survey to gather responses from individuals within our sample during the experiment. Our aim was to understand how people would behave when purchasing a product with a characteristic known to contribute to serial return behavior (through the sentiment analysis we performed). Both groups received the same question, but for the treatment group, we introduced the block policy as a potential consequence of serial return behavior. Individuals are being assigned to the control or treatment group randomly, since it is necessary to assume that people have the same characteristics and the only thing that differentiates them is treatment. This approach allows us to discern any variations in the behavior of the two groups based on the survey results. Below the exact questions for the control and the treatment group:

Control Group
Imagine you want to purchase a t-shirt. However, after reading reviews, you discover that many customers have experienced issues with the fit and size. Would you consider buying multiple t-shirts and returning all but the one that fits best?
With the possible answers:

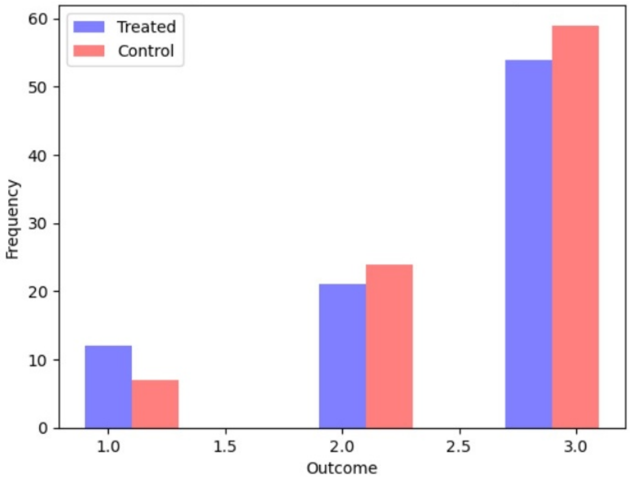
- Yes, I would certainly do as stated
- Yes, I would probably do that
- No, I would not since it is unethical

Treatment Group
Suppose an online retailer has introduced a policy where customers who frequently return multiple items of the same product are prohibited from making any returns fro a duration of six months. Now imagine you want to purchase a t-shirt. However, after reading reviews, you discover that many customers have experienced issues with the fit and size. Would you consider buying multiple t-shirts and returning all but the one that fits best, taking into account the e-commerce platform's enforcement of the aforementioned policy? With the possible answers:

- Yes, I would certainly do as stated
- Yes, I would probably do that
- No, I would not considering the risk of being blocked from any return.
- No, I would not since it is unethical.

0	1	2	3	4	5	6
Outcome=2	coef	std err	z	P>|z|	[0.025	0.975]
const	1.9012	1.317	1.444	0.149	-0.680	4.482
Q1	-0.4496	0.256	-1.753	0.080	-0.952	0.053
Q2	0.4279	0.585	0.731	0.465	-0.719	1.575
Q3	-0.1820	0.312	-0.583	0.560	-0.794	0.430
Q6	0.1010	0.400	0.252	0.801	-0.683	0.885
Q9_1	-0.0014	0.002	-0.701	0.483	-0.005	0.002
Treatment	-0.6381	0.590	-1.082	0.279	-1.794	0.517
Outcome=3	coef	std err	z	P>|z|	[0.025	0.975]
const	1.8984	1.205	1.576	0.115	-0.463	4.260
Q1	-0.4888	0.228	-2.140	0.032	-0.936	-0.041
Q2	0.7192	0.538	1.337	0.181	-0.335	1.773
Q3	0.1982	0.282	0.702	0.483	-0.355	0.752
Q6	-0.0214	0.359	-0.059	0.953	-0.725	0.683
Q9_1	-0.0013	0.002	-0.748	0.454	-0.005	0.002
Treatment	-0.4861	0.539	-0.902	0.367	-1.542	0.570

(a) Coefficients of Regression



(b) Histogram of Treated and Control

2.4 Data Analysis and Preprocessing

To prepare the data for the regression we had to clean and reorder the variables. We had to create a single column containing all the outcome variables with values in the range [1,3] from two different columns with different range of values (due to a mistake when the survey has been developed), hence, we aggregate two different values together because representing the same outcome variable and we fixed the issue. We had to delete useless rows (the first 3) and columns (all the columns different from the one corresponding to the answers to our survey). We, eventually, decided to get rid, from the resulting dataset, of all the rows with at least one NaN value, being aware that this would have left us with 100 observations. The final data frame on which we worked on had 7 columns and 100 observations. Regarding the data visualization implemented, we looked at the data distribution of each covariates and at their correlation matrix as main tool for understanding the underlining data structure. Eventually we also plot histograms of the Outcome for the treated and control group to visually compare the results of our experiment.

2.5 Regression

When running the regression, the MNlogit function from statsmodel.api was imported in order to run a multinominal logit regression. The model was used to regress the column 'Outcome' versus all other independent variables and the obtained values were discussed in the results section.

3 Results

This experiment yielded the coefficients found in the coefficient matrix displayed in (a), where Q1, Q2, Q3, Q6 and Q9 are the age, the gender, the parents' origins, the highest educational level and the average online monthly spending of the individual respectively, while the variable "Treatment" has value 1 if the individual is treated, 0 otherwise. Of these coefficients only Q1 is statistically significant. The coefficients presented in table (a) represent the estimated multinomial logistic regression coefficients, with the reference group being those who would certainly behave as serial returners (Outcome=1). In the context of multinomial logit interpretation, a unit change in the dependent variable is expected to alter the logit of a particular outcome (Outcome= 2 or 3) relative to the reference group (Outcome=1) by the corresponding coefficient, assuming the other variables are held constant. Upon examining the results, we note that the coefficient for "Treatment" is -0.486 for the subset of individuals who would behave as serial returners. This implies that being in the treatment group is associated with a decrease of -0.486 units in the log of the ratio between the probability of choosing to behave as a serial returner versus the probability of choosing not to. In simpler terms, individuals in the treatment group are less likely to avoid behaving as serial returners compared to those in the control group. This contradicts our initial expectation, as respondents in the scenario where we choose to implement the Block Policy seem more inclined to act as serial returners, which contradicts our intended goal of limiting such behavior. However, as we have previously stated, the results are not significant.

The following correlation matrix was found.

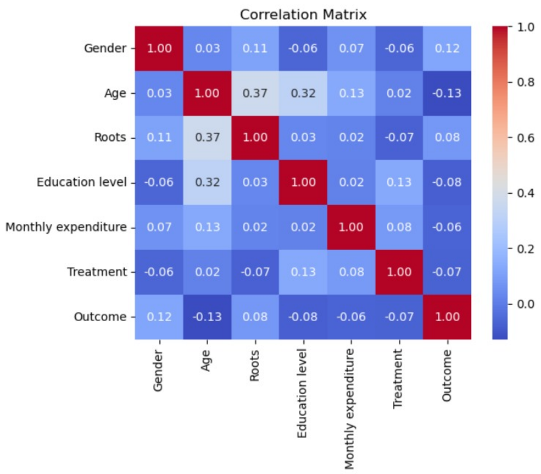


Figure 4: Correlation Matrix of the Covariates and Outcome

As previously stated we assume Age and Education to be a proxy together. These two covariates have a correlation score of 0.32. This is not strongly correlated. For the distributions of the covariates, we refer you to Appendix 5.7.

4 Conclusion and Discussion

4.1 Conclusion

Comparing the prior expected value of the two theories we have noticed that the main theory has the lower expected probability to happen, hence, we experimented on it, because it's the more uncertain and with, potentially, the highest return. For our research we only experimented on the Block Policy and, we updated our prior beliefs with the coefficient of the treatment variable we derived from the regression run. After the experiment, the expected value of the main theory increases and overcome the expected value of the alternative theory, leading us to choose for the first one. From the regression we saw that none of the coefficients are statistically significant. Still the null hypothesis has not been respected, as the $\Delta\theta$ is lower than 0: $\Delta\theta = 0.48 - 0.51$ hence, we had to change our ω and θ, specifically, we are going to reduce them. Eventually, if we were supposed to choose one theory now, we would pick the alternative theory, because, after experimenting, it yielded the highest expected value. Still, there remains a lot to do, we should experiment all the other attributes too.

4.2 Discussion

Overall the experiment tried to follow as much as possible the best procedure for a randomization experiment, we send the survey to as many people as possible, we have been able to reach people coming from all possible continents (except for Oceania). Most of the responses came from Asia (Turkey first and Kazakhstan second) and Europe (mainly Italy, but also France, Austria, and UK), followed by Africa and America. The survey has been held following the criteria of briefness and concision. Arguably, we could have disposed better the question for monthly online expenditure; thinking widely, the maximum value of 500 could have been replaced with a bigger number. We could have also included questions for other covariates to control for. For example, being able to control people from their country of origin would have given a better understanding of the experiment. Overall, our sample is quite international and balanced in terms of Male-Female (56%-43%) respondent, despite some selection bias are still in place. Furthermore, looking at the data we think we have not been able to deal with heterogeneity, in fact. It seems that lots of the survey respondents behave like defiers (they behave the opposite way on purpose because they have been asked to do something precise). This can be due to a wrong formulation of the question, bad luck in the randomization process or the fact that the survey has not been taken seriously by the respondents. If we were supposed to work again on this project and with bigger budget, we would certainly increase the randomization and distribution of the survey to the population of interest thanks to more powerful (and expensive) tools. We would certainly experiment on all the others attribute too, and more than one time each to reduce the uncertainty on our theory. Additionally, we would consider the possibility of developing an app that automatically retrieve relevant information for us from the internet (web scraping) and automatically update our datasets on which we can run regressions to constantly update our beliefs. Regarding the sentiment analysis tool and the algorithm precision we would certainly invest more money in these technologies to see their marginal impact on the Sales returners phenomenon. Finally, we would also search for new attributes that could affect our final attribute of interest (the Sales returners phenomenon).

5 Appendix

5.1 Sentiment Analysis

Here a concise description of the tool: the Sentiment-Analysis mean is an algorithm that skim through all the reviews given as input, filters for the ones that have rating lower or equal than 1 out of 5, keeps only the most relevant words (especially adjectives) and eventually sort all this words by the number of times they appear in the reviews. Then, the manager decides which of the words, that appear the most in this list, want to use to select, later, the reviews that contain them (the selection of the words in manual, not automatic). Decided the words you want to select on, you create a list of these words and, then, the ml algorithm take it as input and filter the reviews that contain these words, then it exports these reviews in an excel file. Eventually is up to the manager to read all of them and have an overall idea of the reasons of returning the product. Once the manager has a clear idea of the reasons behind the returns, he can proceed on, and elaborate solutions of the problems highlighted by the algorithm. (for a better understanding of the algorithm, see the python code).

5.2 Price Discrimination

Price discrimination for the different orders was done as a verification study. Due to the fact that the data only displayed the SKU (stock-keeping unit) of the items and not the product id or a url, we first needed to find the product behind the SKU. Although an SKU is mainly used by the vendor, it is still part of the metadata of Amazon and therefor can be found by a google search. This is why we ran google searches over all of the SKUs and storing all of the Amazon pages that were found in the search results. After this step was done, we scraped the Amazon product pages and retrieved the price. What we found was that the return rate for certain price buckets is not higher than others, therefore setting our belief to the belief stated in the theoretical framework. For the code, we refer you to the Python Notebook of this project.

5.3 Theory

5.3.1 Prior Beliefs

Attribute 1: Sentiment Analysis

$$\theta = \begin{cases} \theta_{Y,Y} = 0.15 \\ \theta_{Y,N} = 0.85 = 1 - \theta_{Y,Y} \end{cases} \rightarrow \begin{cases} \theta_{N,N} = 0.95 \\ \theta_{N,Y} = 0.05 = 1 - \theta_{N,N} \end{cases}$$

$\theta_Y = 0.5 =$ prob. serial returners decrease($= \theta_N = 1 - \theta_Y =$ prob. serial returners does not decrease)
Step 1.

$$\begin{aligned} H_0: \quad & V(\theta) = 0.85 + 0.5(0.15 - 0.85) = 0.5 \\ & \mu(\theta|\Theta) = 0.15 * 0.85 * 0.5 = 0.06375 \\ H_1: \quad & V(\theta) = 0.05 + 0.5(0.95 - 0.05) = 0.5 \\ & \mu(\theta|\tilde{\Theta}) = 0.95 * 0.05 * 0.5 = 0.02375 \end{aligned}$$

Attribute 2: Price Discrimination

$$\theta = \begin{cases} \theta_{Y,Y} = 0.07 \\ \theta_{Y,N} = 0.93 = 1 - \theta_{Y,Y} \end{cases} \rightarrow \begin{cases} \theta_{N,N} = 0.5 \\ \theta_{N,Y} = 0.5 = 1 - \theta_{N,N} \end{cases}$$

$\theta_Y = 0.5 =$ prob. serial returners decrease($= \theta_N = 1 - \theta_Y =$ prob. serial returners does not decrease)
Step 1.

$$\begin{aligned} H_0: \quad & V(\theta) = 0.93 + 0.5(0.07 - 0.93) = 0.5 \\ & \mu(\theta|\Theta) = 0.07 * 0.93 * 0.5 = 0.03255 \\ H_1: \quad & V(\theta) = 0.5 + 0.5(0.5 - 0.5) = 0.5 \\ & \mu(\theta|\tilde{\Theta}) = 0.5 * 0.5 * 0.5 = 0.125 \end{aligned}$$

Attribute 3: Block Policies

$$\theta = \begin{cases} \theta_{Y,Y} = 0.85 \\ \theta_{Y,N} = 0.15 = 1 - \theta_{Y,Y} \end{cases} \rightarrow \begin{cases} \theta_{N,N} = 0.8 \\ \theta_{N,Y} = 0.2 = 1 - \theta_{N,N} \end{cases}$$

$\theta_Y = 0.5 =$ prob. serial returners decrease($= \theta_N = 1 - \theta_Y =$ prob. serial returners does not decrease)
Step 1.

$$\begin{aligned} H_0: \quad & V(\theta) = 0.15 + 0.5(0.85 - 0.15) = 0.5 \\ & \mu(\theta|\Theta) = 0.05 * 0.95 * 0.5 = 0.02375 \\ H_1: \quad & V(\theta) = 0.2 + 0.5(0.8 - 0.2) = 0.5 \\ & \mu(\theta|\tilde{\Theta}) = 0.8 * 0.2 * 0.5 = 0.08 \end{aligned}$$

Attribute 4: Selling Algorithm Precision

$$\theta = \begin{cases} \theta_{Y,Y} = 0.2 \\ \theta_{Y,N} = 0.8 = 1 - \theta_{Y,Y} \end{cases} \rightarrow \begin{cases} \theta_{N,N} = 0.9 \\ \theta_{N,Y} = 0.1 = 1 - \theta_{N,N} \end{cases}$$

$\theta_Y = 0.5 =$ prob. serial returners decrease($= \theta_N = 1 - \theta_Y =$ prob. serial returners does not decrease)
Step 1.

$$\begin{aligned} H_0: \quad & V(\theta) = 0.8 + 0.5(0.2 - 0.8) = 0.5 \\ & \mu(\theta|\Theta) = 0.2 * 0.8 * 0.5 = 0.08 \\ H_1: \quad & V(\theta) = 0.1 + 0.5(0.9 - 0.1) = 0.5 \\ & \mu(\theta|\tilde{\Theta}) = 0.9 * 0.1 * 0.5 = 0.045 \end{aligned}$$

5.3.2 Conditional Expected Value

$$\begin{aligned} H_0: \quad & E_{H_0}(V(\theta)|\Theta) = V_\Theta = 0.5 * 0.06375 + 0.5 * 0.03255 + 0.3 * 0.02375 + 0.5 * 0.08 = 0.095 \\ H_1: \quad & E_{H_1}(V(\theta)|\tilde{\Theta}) = V_{\tilde{\Theta}} = 0.5 * 0.02375 + 0.5 * 0.125 + 0.5 * 0.08 + 0.5 * 0.045 = 0.1369 \end{aligned}$$

5.4 Unconditional Expected Value

$$V = \omega * 0.095 + (\omega - 1)0.1369 \quad where \quad \omega = 0.9$$
$$V = 0.9 * 0.088 + 0.1 * 0.1369 = 0.099 = 9.9\%$$

5.5 Alternative Theory

5.5.1 Prior Beliefs

Attribute 1: E-Commerce Share

$$\theta = \begin{cases} \theta_{Y,Y} = 0.1 \\ \theta_{Y,N} = 0.9 = 1 - \theta_{Y,Y} \end{cases} \rightarrow \begin{cases} \theta_{N,N} = 0.5 \\ \theta_{N,Y} = 0.5 = 1 - \theta_{N,N} \end{cases}$$

$\theta_Y = 0.5 =$ prob. serial returners increase($= \theta_N = 1 - \theta_Y =$ prob. serial returners does not increase)
Step 1.

$$\begin{aligned} H_0 : \quad & V(\theta) = 0.9 + 0.5(0.1 - 0.9) = 0.5 \\ & \mu(\theta|\Theta) = 0.1 * 0.9 * 0.5 = 0.045 \\ H_1 : \quad & V(\theta) = 0.1 + 0.5(0.9 - 0.1) = 0.5 \\ & \mu(\theta|\tilde{\Theta}) = 0.9 * 0.1 * 0.5 = 0.125 \end{aligned}$$

Attribute 2: Deflation

$$\theta = \begin{cases} \theta_{Y,Y} = 0.25 \\ \theta_{Y,N} = 0.75 = 1 - \theta_{Y,Y} \end{cases} \rightarrow \begin{cases} \theta_{N,N} = 0.5 \\ \theta_{N,Y} = 0.5 = 1 - \theta_{N,N} \end{cases}$$

$\theta_Y = 0.5 =$ prob. serial returners increase($= \theta_N = 1 - \theta_Y =$ prob. serial returners does not increase)
Step 1.

$$\begin{aligned} H_0 : \quad & V(\theta) = 0.75 + 0.5(0.25 - 0.75) = 0.5 \\ & \mu(\theta|\Theta) = 0.25 * 0.75 * 0.5 = 0.094 \\ H_1 : \quad & V(\theta) = 0.5 + 0.5(0.5 - 0.5) = 0.5 \\ & \mu(\theta|\tilde{\Theta}) = 0.5 * 0.5 * 0.5 = 0.125 \end{aligned}$$

Attribute 3: Percentage of low quality products increases

$$\theta = \begin{cases} \theta_{Y,Y} = 0.1 \\ \theta_{Y,N} = 0.9 = 1 - \theta_{Y,Y} \end{cases} \rightarrow \begin{cases} \theta_{N,N} = 0.5 \\ \theta_{N,Y} = 0.5 = 1 - \theta_{N,N} \end{cases}$$

$\theta_Y = 0.5 =$ prob. serial returners increase($= \theta_N = 1 - \theta_Y =$ prob. serial returners does not increase)
Step 1.

$$\begin{aligned} H_0 : \quad & V(\theta) = 0.9 + 0.5(-.1 - 0.9) = 0.5 \\ & \mu(\theta|\Theta) = 0.1 * 0.9 * 0.5 = 0.045 \\ H_1 : \quad & V(\theta) = 0.5 + 0.5(0.5 - 0.5) = 0.5 \\ & \mu(\theta|\tilde{\Theta}) = 0.5 * 0.5 * 0.5 = 0.125 \end{aligned}$$

5.5.2 Conditional Expected Value

$$\begin{aligned} H_0 : \quad & E_{H_0}(V(\theta)|\Theta) = V_\Theta = 0.5 * 0.045 + 0.5 * 0.094 + 0.5 * 0.045 = 0.092 \\ H_1 : \quad & E_{H_1}(V(\theta)|\tilde{\Theta}) = V_{\tilde{\Theta}} = 0.5 * 0.125 + 0.5 * 0.125 + 0.5 * 0.125 = 0.1875 \end{aligned}$$

5.5.3 Unconditional Expected Value

$$V = \omega * 0.092 + (\omega - 1)0.1875 \quad where \quad \omega = 0.9$$
$$V = 0.9 * 0.092 + 0.1 * 0.1875 = 0.10155 = 10.2\%$$

Hence we experiment the main theory.

5.6 Updating Beliefs

5.6.1 Attribute 3: Block Policy

$$\theta = \begin{cases} \theta_{Y,Y} = |-0.4861| \\ \theta_{Y,N} = 0.5139 = 1 - \theta_{Y,Y} \end{cases} \rightarrow \begin{cases} \theta_{N,N} = 0.8 \\ \theta_{N,Y} = 0.2 = 1 - \theta_{N,N} \end{cases}$$

$$\begin{aligned} H_0: \quad & V(\theta) = 0.51 + 0.5(0.49 - 0.51) = 0.5 \\ & \mu(\theta|\Theta) = 0.49 * 0.51 * 0.5 = 0.12495 \\ H_1: \quad & V(\theta) = 0.5 \\ & \mu(\theta|\tilde{\Theta}) = 0.08 \end{aligned}$$

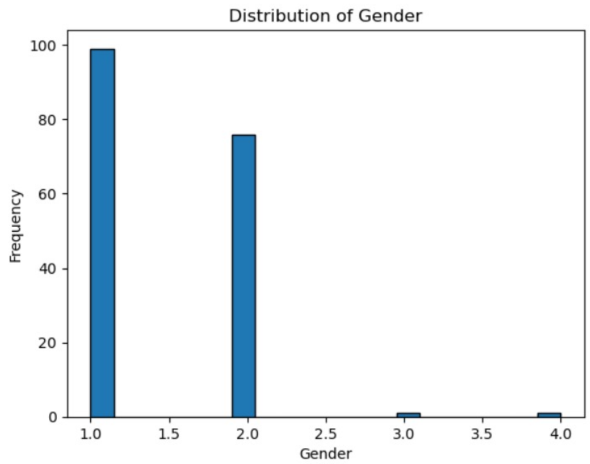
5.6.2 Conditional Expected Value

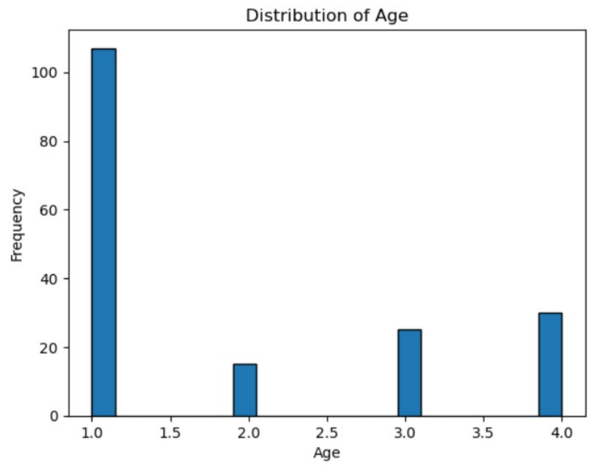
$$\begin{aligned} H_0: \quad & E_{H_0}(V(\theta)|\Theta) = V_\Theta = 0.5 * 0.06375 + 0.5 * 0.03255 + 0.5 * 0.012485 + 0.5 * 0.08 = 0.058 \\ H_1: \quad & E_{H_1}(V(\theta)|\tilde{\Theta}) = V_{\tilde{\Theta}} = 0.5 * 0.02375 + 0.5 * 0.125 + 0.5 * 0.08 + 0.5 * 0.045 = 0.1369 \end{aligned}$$

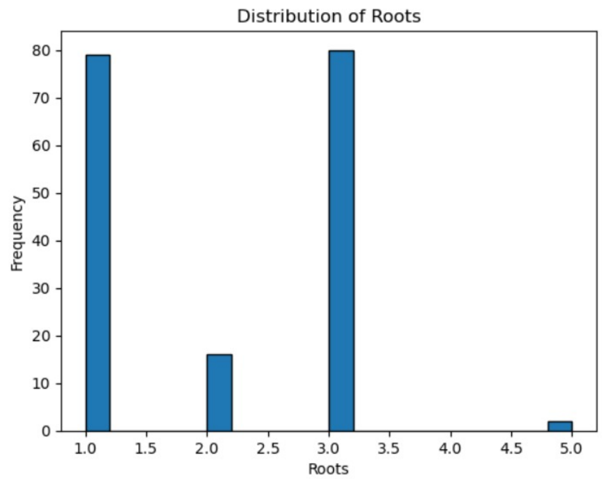
5.6.3 Unconditional Expected Value

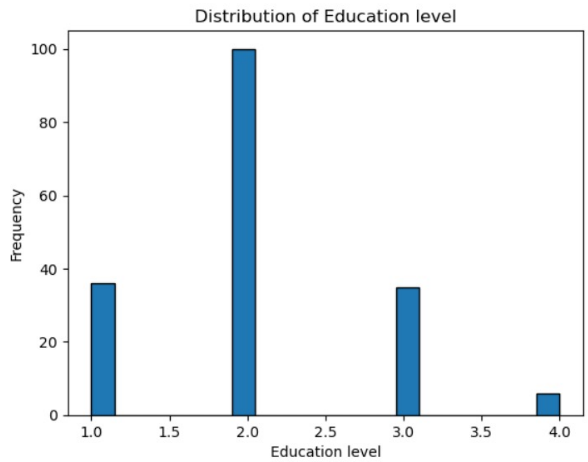
$$\begin{aligned} V &= \omega * 0.058 + (\omega - 1)0.1369 \quad where \quad \omega = 0.5 \\ V &= 0.5 * 0.058 + 0.5 * 0.1369 = 0.097 = 9.7\% \end{aligned}$$

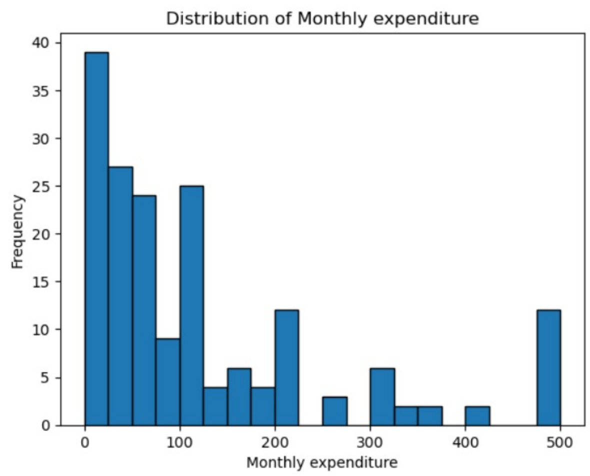
5.7 Data Visualizations











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