Final Assignment*

June 29, 2023

Contents

*This assignment is prepared solely for Causal Inference at GSERM. Please do NOT circulate.

Instructions

This is the final integrative assignment for Causal Inference. This assignment includes two parts. In the first part of the assignment, you will be working on some quiz questions. In the second part, you are given a dataset for a number of empirical questions. Please download "**CIA.Rdata**" for the second part (short for "causal inference assignment").

For the report format of the assignment, here are some general guidelines:

- *At least 12pt font size with minimum 1.5 lines spacing.*
- *A title page with your name on it.*
- *No more than 15 pages with most relevant information in the body text.*
- *Extra tables and figures as appendices (no page limit for the appendix).*
- *Please also submit your codes, as an appendix of your assignment, for reference.*

In the assignment, you will have three general types of questions: 1) conceptual questions about various concepts or ideas covered in lectures, 2) questions asking you to present and/or interpret the results from data analytics and 2) questions asking you to draw managerial implications from analytical results. Below are the general criteria used in the grading.

For the type-2 questions, the grading is based on:

1. [Clarity]: your writing is clear and professional;
2. [Accuracy]: your analytical results are accurate;
3. [Rigor]: your interpretations reflect the nature of the analytical results;
4. [Relevance]: your interpretations are specific to the marketing contexts.

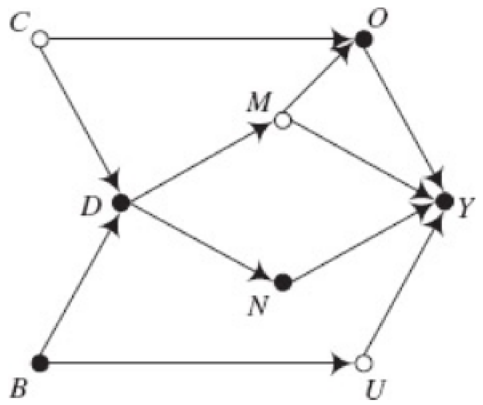
For the type-3 questions, the grading is based on:

1. [Clarity]: you explain your conclusions in a clear and professional way;
2. [Plausibility]: your conclusions are well-grounded in the analytical results;
3. [Coherence]: your conclusions are logically sound and self-consistent;
4. [Relevance]: your conclusions consider the specific marketing contexts.

Part I

Quiz Questions

Question 1.1 DAG (10 points)



Please find all the backdoor and front-door paths that link D and Y in the DAG above.

Question 1.2 Lord's Paradox (10 points)

A large university is interested in investigating the effects on the students of the diet provided in the university dining halls and any sex differences in these effects. Various types of data are gathered. In particular, the weight of each student at the time of his [or her] arrival in September and his [or her] weight the following June are recorded. The data are shown in the table below.

From the table, the average weight for Males was 180 in both September and June. Thus, the average weight gain for Males was zero. The average weight for Females was 130 in both September and June. Thus, the average weight gain for Females was zero.

Question: What is the differential causal effect of the diet on male weights and on female weights?

Two statisticians from the stats department debate about this question.

Statistician 1: Look at gain scores: No effect of diet on weight for either males or females, and no evidence of differential effect of the two sexes, because no group shows any systematic change.

September weight range (in pounds)	% of Men	% of Women	Male average June weight	Female average June weight	Male Weight Gain - Female Weight Gain
< 100	0.2	12.4	114	102	12
100-109	0.5	10.0	120	108	12
110-119	0.7	10.6	122	110	12
120-129	1.7	14.5	134	122	12
130-139	2.5	13.9	146	134	12
140-149	8.0	15.0	152	140	12
150-159	10.0	10.4	158	146	12
160-169	15.4	5.4	166	154	12
170-179	15.0	4.8	176	164	12
180-189	14.8	1.8	184	172	12
190-199	14.0	1.0	191	179	12
> 200	17.2	0.2	204	192	12

Statistician 2: Compare June weight for males and females with the same weight in September: On average, for a given September weight, men weigh more in June than women. Thus, the new diet leads to more weight gain for men.

Please use the potential outcome framework to evaluate the statements of the two statisticians. **First, try to answer the following questions**:

1. What are the treatment units?
2. What are the treatments (or causal states)?
3. What is the assignment mechanism?
4. Is the assignment mechanism unconfounded?
5. Is the causal effect identified under the assignment mechanism?

Based on these aspects, make your final verdict about the statements of the two statisticians.

Question 1.3 Democrat vs. Republican Presidents (10 points)

The US economy has performed better when the president of the United States is a Democrat rather than a Republican[1]. But is this difference due to pure chance? To check this, we may run a permutation test (based on the idea of Fisher's exact test), using the dataset "DR_Gap.csv" (you can find the data in the assignment folder). In the data, there are two columns, and per row stands for one term of presidency (4 years). The columns are:

- Parties: Democrat vs. Republican (D vs. R);
- Presidents: the names of the presidents;

[1] Adapted from: Blinder, Alan S., and Mark W. Watson. 2016. "Presidents and the US Economy: An Econometric Exploration." American Economic Review, 106 (4): 1015-45.

- GDP_growth: the GDP growth rate (in %).

Under the actual data, the average GDP growth under the 7 Democrat terms is 4.33 and that under the 9 Republican terms is 2.54, the difference is 1.79. To test if the gap is by pure chance, we may follow the steps in Fisher's exact test. **Please run the permutation test and report the histogram and exact p-value of the test**.

Hints:

- The null hypothesis is no difference in GDP growth between D and R. So whoever runs a term, the GDP growth will be the same for the term.
- The test is about the D-R gap, or average growth under 7 D terms minus that under 9 R terms. So, you may randomly assign 7 terms to D and the remaining to R.
- The p-value refers to % of assignments that produce a gap larger than 1.79.

Question 1.4 Ethereum Effect (10 points)

In recent years, due to the price rise of cryptocurrency, including Bitcoins and Ethers, among others, the cryptocurrency mining activities have been greatly increased. Mining is a validation of transactions, which essentially requires running complex hashing algorithms. Cryptocurrency miners thus require access to computing power. The most cost-effective approach is to use graphics cards (or GPUs). Concurrently around 2017, the prices of GPUs started increasing, and popular favorites of cryptocurrency miners such as Nvidia's GTX 1060 and 1070 graphics cards, as well as AMD's RX 570 and RX 580 GPUs, doubled or tripled in price – or were out of stock. This is known as "Ethereum Effect," or the effect of the prices of cryptocurrency on GPU prices.

To quantify the effect, the European Consumer Centers, gathered a database with the following information:

- CPU, GPU, and RAM prices at SKU-level;
- Prices of 15 main cryptocurrencies.

The data is time-series at daily level, from Jan 1, 2017 to Dec 31, 2018. In addition, we know during the time 2017-2018, only some cryptocurrency could be mined. For example, Bitcoin, DASH, Dogecoin, Ethereum, Litecoin, and Monero are mineable. Cardano, EOS, IOTA, TRON, Tether, NEM, Stellar, and Ripple are non-mineable.

Based on the data, please answer the following two questions:

- Propose a difference-in-difference design to identify the Ethereum Effect. Please be specific about the data you are using, the model(s) and the assumptions you are making (5 points).
- Given the data and the description above, propose a way to assess the main assumption of the DID design (5 points).

Part II

Empirical Questions

Data Description

Background

Augmented Reality (AR) applications have been on the rise with virtual "try-before-you-buy" experiences ranging from previewing furniture and products in your home with everyday brands like IKEA and Home Depot, to virtually trying on luxury fashion such as Louis Vuitton and Gucci. Once a nice-to-have feature, AR has quickly become an essential technology for retailers. And the Covid-19 the pandemic has accelerated the shift to digital shopping by roughly five years. According to a Neilsen global survey from 2019, consumers listed Augmented and Virtual Reality as the top technologies they're seeking to assist them in their daily lives. In fact, just over half (51%) said they were willing to use this technology to assess products.

However, the real value of AR is still in question. First of all, the increasing adoption is mainly due to the "black swan event" of the pandemic, which "forced" many retailers to digitize their businesses, but not the effectiveness of AR applications. For example, some retailers may roll back their AR applications after the pandemic. Second, there are scattered cases of successful AR applications in retailing, but a systematic evaluation is lacking. Third, some retailers have seen some downsides of AR applications. For example, one retailer had seen an increase in product returns after integrating AR functions into their web shops.

In this assignment, we are looking at the possible downsides of AR applications in retailing. Specifically, we are evaluating the effects of AR applications on product return rates. Product return is a main obstacle of retailers migrating their businesses online. According to some estimates, the return rate of online shopping is around 30%-45%, whereas that of offline is around 10%. Consumers oftentimes check carefully online return policies before making purchases, which further leads to lax return policies of online retailers. The product return has becomes a pronounced problem for online retailers. In fact, the concerns over product returns spawn many startups that are specialized in product return management.

Variables

To evaluate the effects of AR applications on product returns, an online retailer has shared data which record all purchases of roughly a month. The unit of analysis is a purchase. The data record the cause variable (whether to use AR during the purchase processes) and the outcome variable (whether to return the product that is purchased). The table below summarizes the variables from the data.

Variables	Coding	Description
id	numeric	The order id's.
AR_usage	binary	The usage of AR (1 - yes and 0 - no).
Country	factor	Country where the order was placed.
Order_size	numeric	Total value of order in euros (standardized).
Payment_method	factor	The method of payment (IDEAL vs. Visa).
New_customers	binary	If the order is from a new customer (1 - yes and 0 - no).
Old_customers_tenure	numeric	If from an old customer, the tenure of the customer (standardized).
Product_return	binary	If the product from the order is returned (1 - yes and 0 - no).
Channel	factor	From which channel the customer direct to the web shop.
Order_day	factor	The date when the order is placed (in total 28 days).
Order_hour	factor	The hour of the order is placed (24 hours).

Table 1: Data Description

More about the channel variables; the company categorize the channels into different types:

1. Affiliate - Small partners, such as web blogs;
2. Campaigning - Communicating via direct channels, such as email;
3. Direct access - Customer directly inserts website into internet browser.
4. Display - Banners and videos online, and TV-commercials;
5. Member-get-member - Customers receive a promotion code to attract new customers;
6. Organic search - Retailer visible on Google, non-advertised;
7. Paid search branded - Advertised visibility on Google when customer browses on retailer;
8. Paid search non-branded - Advertised visibility on Google when customer browses on e.g. 'buying glasses';
9. Paid social - Paid visibility on social media, such as Facebook and Instagram.

Management problems

The company that shares the data would like to explore more about the applications of AR in their web shops. In particular, they raise the following questions:

- Using the data, how to evaluate the effects of the application of AR in their web shop on product returns?
- Does the application of AR in their web shop increase the product return rates?
- For which customer groups or under what situations, the application of AR increases the (relative) product return rates?

Using the data, you are tasked with evaluating the effects of AR usage on product returns. In particular, the company expects you to use AR usage as the cause variable, the product return as the outcome variable, and the remaining variables as "control variables" for your analysis.

Question 2.1 Propensity Scores (15 points)

The data exhibit a flat structure with less observations (orders), relative to the number of variables, especially so given some variables are discrete. It is thus difficult to directly apply classic matching methods based on stratification and data trimming. To adopt the conditioning strategy, it is reasonable to first calculate and examine the propensity scores.

1. Run a logistic regression with the treatment state (AR usage) as dependent variable, and all the control variables as features. Report only the significant features (coefficients and standard errors). (10 points)
   - [Hint: only the main variables; no need to add interactions]
2. Given the propensity scores from Question 2.1.1, propose and run a test to examine if the propensity scores are similarly distributed between the treatment and control group. (5 points)
   - [Hint: be specific about the test you propose, the test results and the conclusion]

Question 2.2 Weighting Estimators (15 points)

With the propensity scores estimated in Question 2.1, estimate the average treatment effects with a weighting approach. Describe how you weight the outcomes (product returns) for the treatment and control group, and report the estimated ATE and its standard errors.

- [Hint: as the outcome variable - product returns, is a binary variable, you cannot apply a linear regression. Instead, try logistic regression with weights, a.k.a. a weighted maximum likelihood approach]

Question 2.3 Heterogeneous Treatment Effects (20 points)

An important managerial problem is to look for the heterogeneous treatment effects for different consumers or purchase situations. For example, if we find somehow in the morning hours, the usage of AR tends to increase the product return rates, the company may find a way to discourage the usage of AR in the morning. In this question, you are expected to help the company to find possible heterogeneous treatment effects by applying the causal random forest method.

1. Use the generalized random forest package (`https://grf-labs.github.io/grf/`), train a causal forest and estimate the average treatment effect. Report the personalized treatment effects predictions (a histogram with the median), estimated ATE and its 95% confidence interval. (10 points)

- You may find the main function of applying the method here: `https://grf-labs.github.io/grf/reference/causal_forest.html`.
- Please use the default setting of the function and set the seeds to 123456789.
- Note that you need to transform the factors into binary matrices, as the "grf" package does not support factors as of now.
- Use "predict(·).predictions" to obtain the personalized treatment effects predictions and "average_treatment_effect(·)" to get the estimated ATE.

2. With the personalized treatment effects predictions, you may test the treatment effects heterogeneity in regard to a feature X. For a simple discrete variable, this may be straightforward. For example, we may compare the personalized treatment effects predictions across different levels and examine if they differ significantly with standard tests such as a two-sample t-test. However, it is not clear how to test heterogeneity for a continuous variable. Propose a way of testing treatment effects heterogeneity for continuous variables. Please be specific about your testing procedure, as well as the test statistics. (5 points)
3. Apply the testing approach that you propose in Question 4.2 and test if there is significant heterogeneity in regard to "*Order_size*" and "*Old_customers_tenure*". Please report the test results and your conclusions. (5 points)

Question 2.4 Auditing the Identification Strategy (10 points)

The identification strategy cited here is the "conditioning strategy". However, there is always a concern of omitted variable bias. That is, there is always a possibility that an omitted variable exists and biases the estimation. Therefore, you need to audit the identification strategy and add credibility to your analysis. Propose and describe a procedure to examine the concerns over the omitted variable bias.

- [Hint: focus on how your procedure can help examine the concerns over the omitted variable bias; it is fine to assume that you may ask for more data from the company, but be specific about what data you intend to have].