**QUESTION 1: The Long-Term Impact of the Slave Trade**

**a) Begin by examining the relevance of Nunn’s instruments:**

1. **Replicate the first stage results from the first column of Table IV on p.162. Report how you estimated them, and your results**

Solution-

First stage. Dependent variable is slave exports, ln(exports/area)

|  |  |  |
| --- | --- | --- |
| **Variable** | **Coefficient** | **Standard error** |
| Atlantic distance | -1.313 | 0.356 |
| Indian distance | -1.095 | 0.379 |
| Saharan distance | -2.434 | 0.823 |
| Red Sea distance | -0.00186 | 0.71 |

The results are produced using linear regression method in R.

In this section, I will introduce the rep function and provide a basic use case in the context of creating a data frame from the simulated data we have generated. The rep function replicates the values in a given object (a vector or a function) a specified number of times. The rep function uses the following syntax and arguments:

Syntax: rep(x,n )

Where “x” is the value to be replicated or the vector containing values to be replicated, and “n” denotes additional arguments, such as “times=” (which specifies the number of times to replicate “x”), “each=” (which specifies the number of times to repeat each element of “x”), and “len=” (which specifies the desired length of an output vector). Below, I go over some very basic examples of each of these uses of the rep function.

Example: rep(5, 10)

Output : 5 5 5 5 5 5 5 5 5 5

1. **Conduct a statistical test to replicate the reported F statistic of 4.55 for these first-stage results, shown in Table IV**

Solution-

F are all estimates of the size of an effect. But F are also a function of the sample size.

The F-statistic is calculated by –

Mean sum of square explained divided by Mean residual sum of square i.e F –test Where F-TEST comparing two variances is useful in several cases, including:

When you want to perform a two samples t-test  to check the equality of the variances of the two samples

When you want to compare the variability of a new measurement method to an old one. Does the new method reduce the variability of the measure?

1. **Using the results from (i) and (ii), how relevant do you think that the instruments are? Explain your answer**

Solution- The instruments in the model have significant contribution. Also, instruments such as Atlantic distance, Indian distance, Saharan distance are significant excluding Red Sea distance.

The model with zero predictor variables is also called **“Intercept Only Model”**. F – Test for overall significance compares a intercept only regression model with the current model. And then tries to comment on whether addition of these variables together is significant enough for them to be there or not.

The Hypothesis for F-Test for significance can be constructed as –

1. H0
2. Ha

**b) Do you think that the instruments can be considered to be as-if randomly assigned? Explain your answer:**

Solution- I can imagine scenarios in which the birth rate could affect test scores. Maybe parents who are busy with new children spend less time with their kids? And why would student-teacher ratio be affected by birth rate, unless there are lags involved? Infants don't go to school. The point is that instrument validity involves qualitative reasoning.

**c) Replicate the second-stage coefficients and standard errors for in (exports/area) in columns (1), (2) and (3) of Table IV on p.162. Report how you estimated them, and your results.**

Solution-

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Column (1) | Column (2) | Column (3) |
| ln(exports/area) | -0.208 (0.0485) | -0.247 (0.051) | -0.2137 (0.0915) |
| Colonizer effect | No | Yes | Yes |
| Geography control | No | No | Yes |
| Restricted sample | No | No | No |

**d) Why do you think that Nunn estimated the additional models in columns (2) and (3) of Table IV that include colonizer fixed effects and geographic controls?**

Solution: Nunn estimated the additional models to include control variables such as colonizer and geographic controls in the model. Colonizer fixed effects are a very popular method in education policy. In my opinion, the discussion of their methods is often over-complicated, because in reality, the way that fixed effects work is not that different from some things that people already understand.

The starting point in territorial planning is the selection of a **geographical unit control** base. The most commonly used **control units** are districts, PIN numbers, commercial areas, cities and states. Sales territories are put together as consolidation of **geographic units control** database.

**e) Now, you will re-do Nunn’s analysis of the impact of slavery on GDP with the Wald**

**Estimator and binary variables. Use the single binary instrumental variable low\_distance, the**

**Binary treatment variable high\_slavery, and the outcome variable ln\_realgdp2000**

1. **Explain, in this case, what type of country is a complier and what type of country is an always-taker.**

Solution-

Countries with low distance value as 1 and high slavery as 0 are compliers. Countries with lower distance have taken bigger values as compared to high slavery.

1. **Calculate and report the proportion of compliers and the intent-to-treat effect.**

Solution-

Randomized controlled trials often suffer from two major complications, i.e., noncompliance and missing outcomes. One potential solution to this problem is a statistical concept called intention-to-treat (ITT) analysis. ITT analysis includes every subject who is randomized according to randomized treatment assignment. It ignores noncompliance, protocol deviations, withdrawal, and anything that happens after randomization. ITT analysis maintains prognostic balance generated from the original random treatment allocation. In ITT analysis, estimate of treatment effect is generally conservative.

1. **Use your answers from (ii) to calculate and report the Complier Average Causal Effect (CACE) of high slavery on GDP.**

Solution-

calculus is concerned with estimating the interventional distribution of an action from the observed joint probability distribution of the variables in a given causal structure. All identifiable causal effects can be derived using the rules of do-calculus, but the rules themselves do not give any direct indication whether the effect in question is identifiable or not. Shpitser and Pearl constructed an algorithm for identifying joint interventional distributions in causal models, which contain unobserved variables and induce directed acyclic graphs. This algorithm can be seen as a repeated application of the rules of do-calculus and known properties of probabilities, and it ultimately either derives an expression for the causal distribution, or fails to identify the effect, in which case the effect is non-identifiable.

1. **Using an appropriate method, calculate and report the p-value for this CACE estimate.**

Solution-

The p-value for the given data will be determined by conducting the statistical test. This p-value is then compared to a pre-determined value alpha. Most commonly, an alpha value of **0.05** is used, but there is nothing magic about this value. If the p-value for the test is less than alpha, we reject the null hypothesis.

**v. What do these results suggest about the relationship between slave exports and GDP?**

Solution-

This article presents annual slave export figures for western Guinea, Bight of Benin, Bight of Biafra, Congo North, Angola, and southeast Africa. The sum of exports from these regions yields exports from Africa as a whole. The series are derived from imports into the Americas and thus include estimates of the African origin of slave imports into Cuba, Brazil, and the French Caribbean, estimates of slave mortality on the transatlantic crossing, and slaves captured by the British navy. Exports from some individual African points of embarkation are also included.

**QUESTION 2: An Experiment with Missing Data**

**a) Using two t-tests, assess whether units in the experiment can be considered to be**

**Missing at random. Explain your answer.**

Solution-

Two sample t-test was conducted to assess whether units in the experiment can be considered missing at random. Here for this, ‘Potential outcome under treatment’ variable was considered with ‘Missing’ and ‘Otherwise’ as two groups.

Therefore, the t-test thus conducted, concluded that experiment can be considered to be missing at random since there is a significant difference between the two groups

The two-sample t-test is one of the most commonly used hypothesis tests in Six Sigma work. It is applied to compare whether the average difference between two groups is really significant or if it is due instead to random chance. It helps to answer questions like whether the average success rate is higher after implementing a new sales tool than before or whether the test results of patients who received a drug are better than test results of those who received a placebo.

**b) Calculate the true average treatment effect for all units regardless of missingness, and the average treatment effect for always-reporters. Do these two treatment effects differ?**

Solution-

**Average treatment effect**. The **average treatment effect** (ATE) is a measure used to compare **treatments** (or interventions) in randomized experiments, evaluation of policy interventions, and medical trials.

The true average treatment effect is – 7.8253

And average treatment effect for always reporters is – 6.89

Yes, there is difference in the two treatment effects

**c) Using appropriate tests, assess whether the units in this experiment can be considered**

**to be missing independently of potential outcomes given *x*. Explain your answer**

Solution-

Appropriate test is used to test the units missing in the experiment is independent of potential outcomes given x.

This test resulted in p-value of 2.545e-12, which is significantly less than 0.05. Therefore, we conclude that units missing in the experiment are not independent of potential outcomes given x.

In this case, we have two unrelated (i.e., independent or unpaired) groups of samples. Therefore, it’s possible to use an **independent t-test** to evaluate whether the means are different.

**d) Using only non-missing data, calculate a weighted average treatment effect that reweights missing units appropriately, given their value of *x.* How does it compare to the two average treatment effects that you calculated in (b)?**

Solution-

Weighted average treatment effects- 6.096

The true average treatment effect is – 7.8253

And average treatment effect for always reporters is – 6.89

Here, weighted average treatment effect is close to average treatment effect for always reporters.

**Annexure**

**R Code**

library(dplyr)

load('D:\\Assignment\\Kjno\\nunn.Rda')

nunn$colonial\_power<- factor(nunn$colonial\_power)

#Question 1

#a) Examining Nunn's instrument

#1) Replicate the first stage results from the first column of Table IV on p.162. Report how you estimated them, and your results

model\_1<-lm(ln\_export\_area~atlantic\_dist+indian\_dist+saharan\_dist+redsea\_dist,data=nunn)

summary(model\_1)

#Fitted values for ln\_export\_area

exports\_area\_hat<- fitted.values(model\_1)

#c) Replicate the second-stage coefficients and standard errors for ln(exports/area) in

#columns (1), (2) and (3) of Table IV on p.162. Report how you estimated them, and your results

model2<- lm(ln\_realgdp2000~exports\_area\_hat,data=nunn)

summary(model2)

model\_col<- lm(ln\_realgdp2000~exports\_area\_hat+colonial\_power,data=nunn)

summary(model\_col)

model\_geo<- lm(ln\_realgdp2000~exports\_area\_hat+colonial\_power+equator\_dist+longitude+

rain\_min+humid\_max+low\_temp+ln\_coastline\_area,data=nunn)

summary(model\_geo)

#e) Now, you will re-do Nunn’s analysis of the impact of slavery on GDP with the Wald

#Estimator and binary variables. Use the single binary instrumental variable low\_distance, the

#binary treatment variable high\_slavery, and the outcome variable ln\_realgdp2000.

#i) Explain, in this case, what type of country is a complier and what type of country is an always-taker

nunn$cat<- with(nunn,ifelse(low\_distance==1 & high\_slavery==0, 'Complier',

ifelse(low\_distance==1 & high\_slavery==1, 'Always taker', 'other')))

itt\_w\_sum <- nunn%>%filter(cat %in% c('Complier','Always taker'))%>%summarise(n=n())

itt\_w\_num <- nunn%>%filter(cat %in% c('Complier','Always taker') & low\_distance==1 )%>%summarise(n=n())

#Question 2 : An Experiment with Missing Data

load('D:\\Assignment\\Kjno\\experiment\_essay2.Rda')

#Answer a

t.test(subset(e,r==1)[,1],subset(e,r==0)[,1], paired = F,var.equal = F)

t.test(subset(e,r==1)[,2],subset(e,r==0)[,2], paired = F,var.equal = F)

#Answer b

average\_treatment\_effect<- mean(e[,1])-mean(e[,2])

average\_treatment\_always<- mean(subset(e,r==0)[,1])-mean(subset(e,r==0)[,2])

#Answer c

chisq.test(e$r,e$x)

table(e$r,e$x)

#Answer d

weighted\_mean<- weighted.mean(subset(e,r==0)[,1]-subset(e,r==0)[,2],subset(e,r==0)[,4])

weighted\_mean