The Endowment Effect And Modern Society

Gabriel Varela Kevin Tse

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We will follow the investigation of Coren L. Apicella, Eduardo M. Azevedo, Nicholas A. Christakis and James H. Fowler in *Evolutionary Origins of the Endowment Effect: Evidence from Hunter-Gatherers.*[1]

Introduction

The endowment effect is the phenomenon through which we value objects more simply because we own them. In this project, we will examine how exposure to modern society affects manifestations of the endowment effect by studying camps of a nomadic hunter-gatherer people in Tanzania called the Hadza.

The Hadza live in different camps which have varying contact with modern society. Some have abandoned the nomadic way-of-life and settles next to Mangola, a village in Tanzania that serves as a tourist hub for people who come from afar to see the Hadza. As such, the Hadza near Mangola not only are familiar with modern society but even adapted to suit the tourists by, for example, producing traditional Hadza artefacts for sale. We may therefore compare studies made in camps near to and far from Mangola in order to hypothesise whether modern society is the cause of such a phenomenon.

Studies of the endowment effect consisting of being offered to trade an endowed item were carried out in eight Hadza camps. These studies included experiments concerning both trades between different models of lighters and between different brands of biscuits, in order to control for the possible argument that the endowment effect only holds for items with revolutionary importance, such as food. The investigation was carried out in two conditions; in the first, subjects physically receive the endowed item whilst in the second they are only assigned an endowment but aren't allowed to hold it. This controls for the concern that transaction costs play a role in the endowment effect. Further, in the second condition, a coin flip was used to randomly assign an object to the participant as the randomisation prevents participants from drawing value conclusions from receiving the item, such as inferring merit.

In this exploration, we will compare these studies of the endowment effect with Hadza tribespeople from eight different camps, both with and without contact to Mangola, and try to understand how contact with modern society may affect this phenomenon.

[1] Coren L. Apicella, Eduardo M. Azevedo, Nicholas A. Christakis, and James H. Fowler. "Evolutionary Origins of the Endowment Effect: Evidence from Hunter-Gatherers." *American Economic Review* 104, no. 6 (2014) : 1793 – 1805.

Preliminaries

There are some commands we expect you to know:

```
for (i in n:m) {command}
if (condition) {command 1} else {command 2}
%in%
mean(data, na.rm = TRUE)
ggplot() + geom_point() + geom_bar() + ...
cor(x, y, method = c("pearson", "spearman"))
```

And others that we will introduce along the way. Note also that the ggplot cheatsheet we sent out[2] will come in handy.

You can find out what any command does by searching it in the "Help" tab or by typing a question mark followed by the command into your console, for example:

```
?mean
```

Make sure to keep a .R file with all your commands to send it to us so that we can test your code later.

Background Information

Set your work directory and import the data into a data frame. Here is what some of the columns mean:

- utm36m: UTM geographic coordinates of camp.
- v9: UTM geographic coordinates of camp.
- gpsx: GPS geographic coordinates of camp.
- gpsy: GPS geographic coordinates of camp.
- endowmentcondition: Whether subject was tested according to condition 1 or 2 in the experiment.
- endowmentlighter: Whether subject traded the item in the choice among lighters.
- endowmentbiscuit: Whether subject traded the item in the choice among biscuits.

Cleaning Up Data

You won't need all the columns in the data so, for convenience, begin by deleting the ones you won't need. It's up to you what to delete but keep in mind the objective of our exploration (we won't need GPS co-ordinates).

Look through the data frame. There are two rows that won't be particularly useful to us (why?). Delete them.

Tip: delete row i from data frame df using:

```
df <- df[-c(i),] # What's happening here?
```

Rename columns as you wish.

[2]https://www.rstudio.com/wp-content/uploads/2015/03/ggplot2-cheatsheet.pdf

Data Manipulation

To begin, we want dummies for the trades happening for each object-condition pair. For example, one of these dummies should be a column called (say) lighter_c1 that takes the value of

- 1 if the experiment condition was condition 1 *and* if the lighter was traded
- 0 if the experiment condition was not condition 1 *or* if the lighter was not traded

You should have four such columns.

This may come in handy:

```
if ((condition 1) && (condition 2) && ...) {command}
```

These columns will be very useful later on.

Exposure to Modern Society vs. Endowment Effect

Now we want to begin our analysis of the effect of modern society on the endowment effect. First off, we need to separate the camps that do have connections to Mangola from the ones that don't.

Create a column for the exposure (high or low) of each subject (which will be uniform within each camp). These camps should be labelled as High Exposure (HE): Endadubu, Mayai, Mizeu, Mwashilatu, Onawasi.

What data type do we want this column to have? Think about the second big group session we had.

Before we plot Trades vs. Exposure, we need a new data frame that tells us the trades happening for each value of exposure. We'll use the aggregate function here. A model is given below:

```
aggregate(df[, n:m], by = list("list name" = what_to_list_them_by),
     FUN = f, ...)
```

What aggregate does is, first, aggregate the data we give by some factor and, then, execute a function of our choice on the aggregated data.

In this example, the data it's using is columns n to mm from data frame df. The data we want is the columns we have that tell us how many trades happened (lighter_c1, etc.).

It's aggregating this data by a some list we place after "by = ". In the example, we are creating a list called "list name" that lists what_to_list_them_by. We want our data aggregated by exposure so we need to create a list called "Exposure" and the list needs to list the exposure of each subject (so use the exposure column of our data frame).

It then applies the function f. We want the mean number of trade by exposure. Why the mean, not the total?

We can also give aggregate more commands. In this case we want to tell it "na.rm = TRUE". This is important. See what happens if we don't add this.

Try to figure out how to do this by yourself. If you can't, here's our code to help (you'll have another opportunity to use aggregate later on):

```
Mangola <- aggregate(Hadza[10:13], by = list(Exposure = Hadza$Exposure),
     FUN = mean, na.rm = TRUE)
View(Mangola)
```

This new data frame should have one column for exposure (1 or 0) and four others aggregating the means of lighter_c1, lighter_c2, etc. by exposure.

Just to make it prettier, replace exposure == 1 with "HE" and exposure == 0 with "LE".

Hint: Assign it a new value to it with some condition (%in% will come in handy).

What we want isn't trades by object-condition pair but total trades. So make a new column for this? How should we create this new column?

Hint: It should be the mean of the trades in all object-condition pais. These may come in handy:

```
?rowMeans
for (i in n:m) {command}
```

We want row i in the "total" column to be the mean of the rows i of all the object-condition pair columns.

Finally, plot trades with exposure using ggplot. Try to make a plot exactly like the one we sent you. This is so that you practice using different ggplot functions. The cheat sheet will help here.

Save your plot as an object for easier access:

```
plot1 <- ggplot() + ...
```

Distance from Mangola vs. Endowment Effect

Now we want to explore the effect of the actual distance from Mangola village (the only contact between the Hadza and modern society) and how much the endowment effect manifests itself. So we will need a column with the distance from Mangola to each subject (which, again, will be uniform within camps).

We will use UTM co-ordinates for this. Mangola's UTM co-ordinates are: utm36m = 765668 and v9 = 9611785.

Each unit in UTM corresponds to about a metre in distance and each value (utm39m and v9) can be thought of as the x and y positions of the place it points to. So you should be able to use Pythagoras' Theorem to find the distance of each camp from Mangola in metres and then just change this to kilometres.

Now we want a new data frame with the data for our second plot: distance, trades and camp size (point size is proportional to camp size in the plot).

Hint: Use aggregate to create a data frame like the one for exposure but with distance instead of exposure and then add a camp size column. The distance from Mangola for camp i will be equal to the mean distance of each subject in camp i from Mangola. And the size of a camp is the sum of that camp's appearances in the original data frame.

Now plot a graph just like the one we sent you. This one's tricky but you should be able to use the cheat sheet to do it.

These should also help:

```
+ annotate("text", label = "label_you_want", x = x_pos, y = y_pos, size = 4)
     # Don't change the first argument.
+ scale_size_area(max_size = 12)
     # This isn't necessary but without it the points would be very small.
```

Again, save your plot as an object.

Correlation and Regression

Now we want to find out the numerical relationship between exposure, distance and trades. Start off by correlating trades with distance by camp (it is important to do it by camp! Can you think of why?).

To do the same with trades and exposure, we first need a numerical variable for exposure. Create one. What type of variable is this? There's a specific method of correlation coefficient we need to us for this kind of variable. Carry out the correlation.

Look at your correlation coefficients. Do they seem reasonable?

There is a problem with these values. The problem is that since distance and exposure are themselves related, each one also influences the coefficient for the other (i.e. in measuring the effect of distance, for example, we are also implicitly measuring the effect of exposure and vice-versa). So a simple comparison of these coefficients tells us nothing about their relative effect on the endowment effect.

So we need to control for one variable in order to examine the correlation of trade with the other. How do we do this?

Our end goal with this exercise to compare the importance of exposure and distance on trade. One way to do this is to model trades as a function of both:

$$trades = \alpha \times exposure + \beta \times distance$$

and compare the magnitudes of the coefficients α and β. This is called making a linear regression.

Usually we cannot make linear regressions with independent variables and that have covariance. But there are functions that correct for covariance. For example, the function:

```
lm(dep_var ~ indep_var1 + indep_var2)
```

creates an equation of the form

$$dep\_var = \alpha \times indep\_var1 + \beta \times indep\_var2$$

with a correction for the covariance of $indep\_var1$ and $indep\_var2$.

Make a linear regression of trade as a function of exposure and distance.

There's one more problem, however. The range of exposure values is *far* smaller than the range of distances. Why is this a problem?

To correct this problem, create a new column for distance that has the same range as exposure (i.e. 1). You can assign to the farthest camp a value of 1 for this column. This may help:

```
max()
```

Now, do the regression again using this new variable instead of distance.

Hint: if you save your regression as an object, you can access the result more easily and with more information:

```
reg <- lm()
reg
summary(reg)
```

Look at your regression. Does it seem reasonable? Compare the coefficients for distance and for exposure. What conclusion can we draw from this?

Conclusion

By now you should have three objects corresponding to your linear regression and your two plots. Pull them up and compare them.

According to the linear regression, which factor (exposure or distance) most significantly affects the endowment effect? Do your graphs agree with this?

We hope you enjoyed this project and we hope you enjoyed working with R. There's more to come next quarter!