Introduction to Data Handling and Statistics

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29 November 2018

Preparing your workfile

R is a powerful software for statistical analysis. It is open source and hence FREE software. It is constantly developped and functionality is being improved. The "price" we pay for this is that we have to do a little more set-up work to make it work.

In particular we need packages which are provided for free by researchers/programmers that provide useful functionality.

But we add libraries which enhance its capabilities.

```
library(tidyverse)    # for almost all data handling tasks
```

```
## Warning: package 'tidyverse' was built under R version 3.5.1
```

```
## -- Attaching packages ---------------------------------------------------------------------------
```

```
## v ggplot2 2.2.1     v purrr   0.2.4
## v tibble  1.4.2     v dplyr   0.7.4
## v tidyr   0.8.0     v stringr 1.3.0
## v readr   1.1.1     v forcats 0.3.0
```

```
## -- Conflicts ------------------------------------------------------------------------------------
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(readxl)       # to import Excel data
```

```
## Warning: package 'readxl' was built under R version 3.5.1
```

```
library(ggplot2)      # to produce nice graphiscs
library(stargazer)    # to produce nice results tables
```

```
##
## Please cite as:
```

```
##  Hlavac, Marek (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables.
```

```
##  R package version 5.2.2. https://CRAN.R-project.org/package=stargazer
```

Introduction

Here we use an example which, at the time, made a lot of waves. Carmen Reinhart and Kenneth Rogoff (2010) wrote work that attempted to examine the relationship between Debt to GDP levels and GDP growth. Their general conclusion was that, as long as the debt to GDP ration does not exceed 90% there seems to be no clear relationship between the two. However, countries eunning higher debt to GDP ratios are paying a sizeable growth penalty.

The empirical work of Reinhard and Rogoff was critised on three aspects by Thomas Herndon, Michael Ash and Robert Pollin. This work was published in the Cambridge Journal of Economics in 2014 and previous to that as a working paper. The working paper's website also contains all the relevant data and code.

Importing Data

This is a simplified spreadsheet (based on the work of Herndon et al.)

```
RRData <- read_excel("RRdata.xlsx")
str(RRData)  # prints some basic info on variables
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    1171 obs. of  4 variables:
##  $ Year   : num  1946 1947 1948 1949 1950 ...
##  $ Country: chr  "Australia" "Australia" "Australia" "Australia" ...
##  $ debtgdp: num  190 177 149 126 110 ...
##  $ dRGDP  : num  -3.56 2.46 6.44 6.61 6.92 ...
```

We can see that three variables are numeric (`num`) variables which is as we expect. The fourth variable `Country` is labeled as a character (`chr`) variable, basically text. It will pay off for later toindicate to R that this is a categorical (nominal) variable. This is done as follows:

```
RRData$Country <- as.factor(RRData$Country)
str(RRData)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    1171 obs. of  4 variables:
##  $ Year   : num  1946 1947 1948 1949 1950 ...
##  $ Country: Factor w/ 20 levels "Australia","Austria",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ debtgdp: num  190 177 149 126 110 ...
##  $ dRGDP  : num  -3.56 2.46 6.44 6.61 6.92 ...
```

There are 1171 country-year observations. In the dataset are data from 20 countries:

```
unique(RRData$Country)
```

```
##  [1] Australia   Austria     Belgium     Canada      Denmark
##  [6] Finland     France      Germany     Greece      Ireland
## [11] Italy       Japan       Netherlands New Zealand Norway
## [16] Portugal    Spain       Sweden      UK          US
## 20 Levels: Australia Austria Belgium Canada Denmark Finland ... US
```

And data from 1946 to 2009.

```
summary(RRData$Year)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1946    1964    1980    1979    1995    2009
```

`debtgdp` is the debt to GDP ratio

```
summary(RRData$debtgdp)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   3.279  22.148  40.401  46.283  61.474 247.482
```

`dRGDP` is GDP growth rate

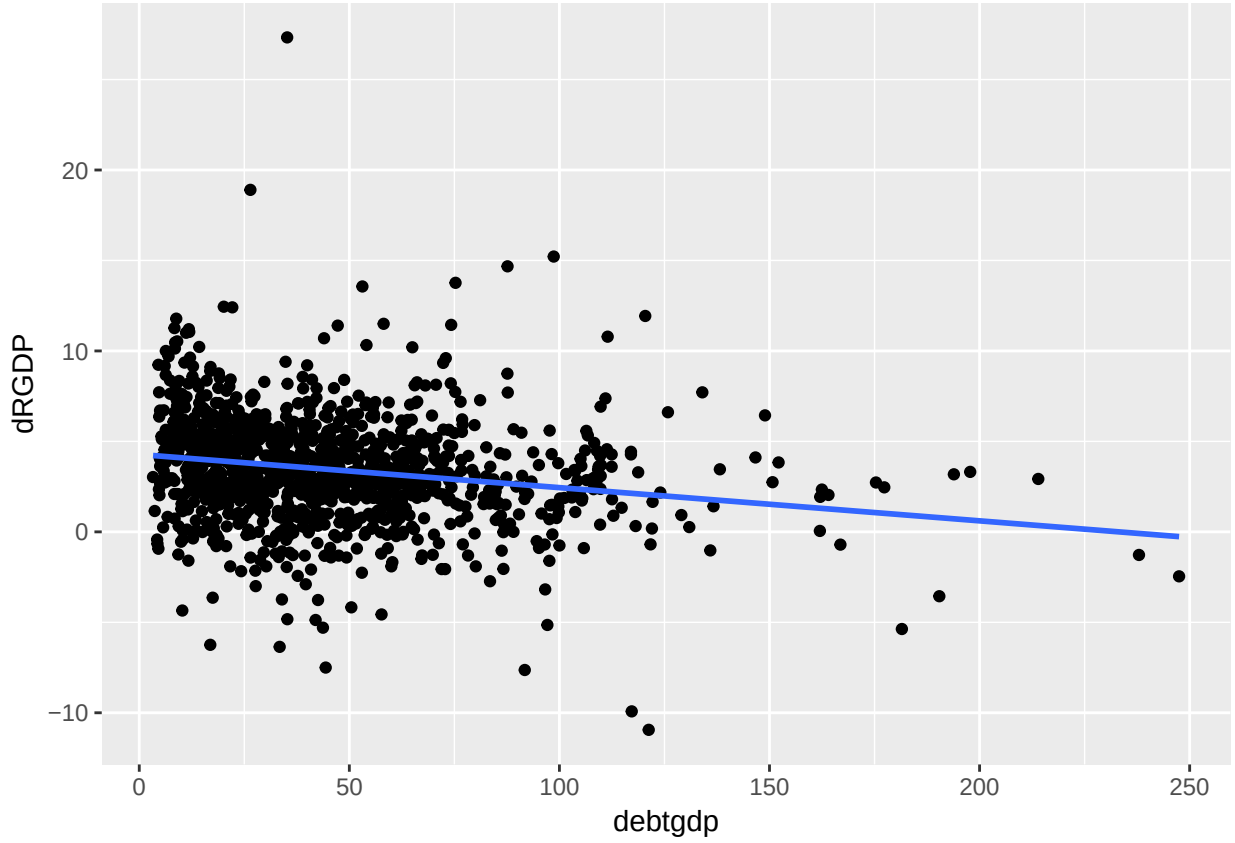
```
summary(RRData$dRGDP)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -10.942   1.911   3.283   3.430   5.100  27.329
```

An initial basic data plots

Let's have a look at some of the data. We will first look at a scatterplot (using the amazing `ggplot` library).

```
p1 <- ggplot(RRData,aes(debtgdp,dRGDP)) +
  geom_point() +     # this produces the scatter plot
  geom_smooth(method = "lm", se = FALSE)  # this adds the linear line of best fit
p1
```



We could actually run this regression

```
mod1 <- lm(dRGDP~debtgdp, data= RRData)
stargazer(mod1,type="text")
```

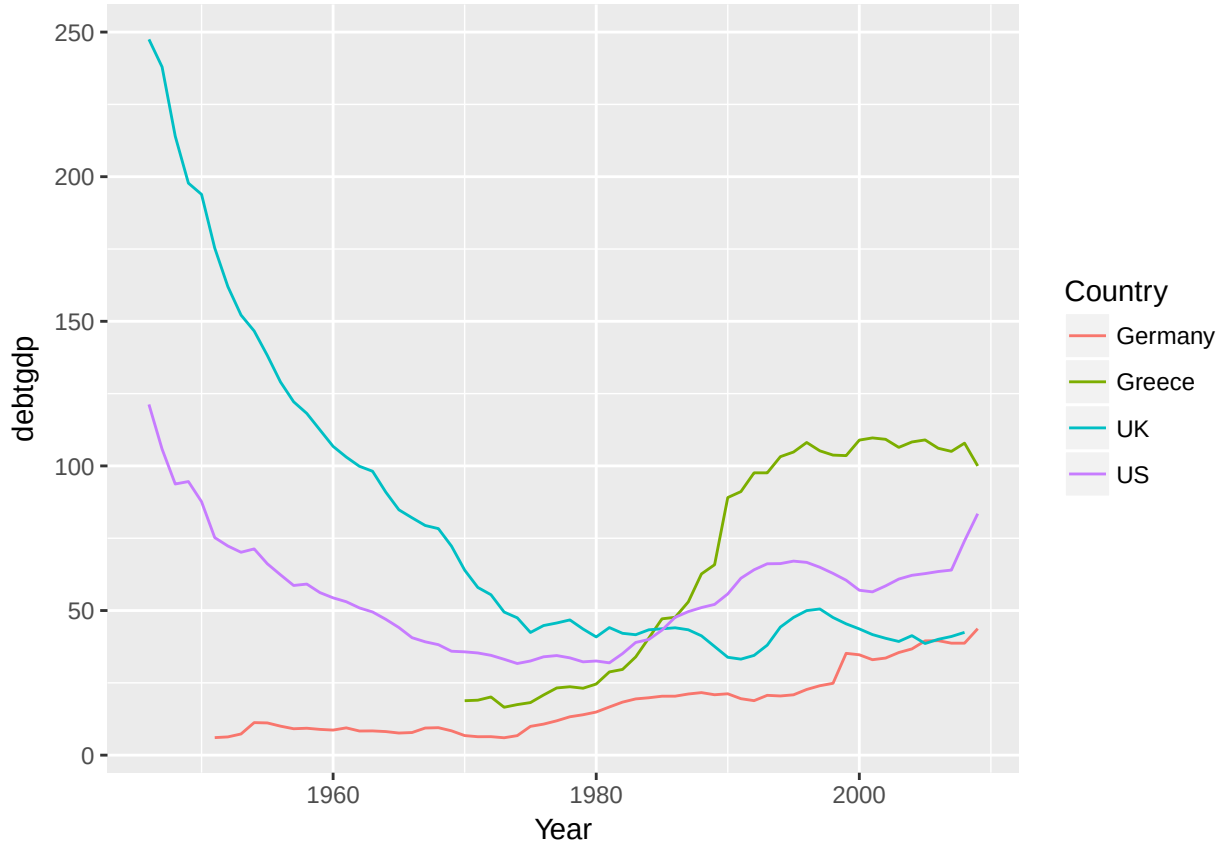
```
##
## ================================================
##                          Dependent variable:
##                      ---------------------------
##                                 dRGDP
## ------------------------------------------------
## debtgdp                        -0.018***
##                                 (0.003)
##
## Constant                       4.279***
##                                 (0.149)
##
## ------------------------------------------------
```

```
## Observations                    1,171
## R2                              0.040
## Adjusted R2                     0.039
## Residual Std. Error       2.922 (df = 1169)
## F Statistic           48.439*** (df = 1; 1169)
## ================================================
## Note:                *p<0.1; **p<0.05; ***p<0.01
```

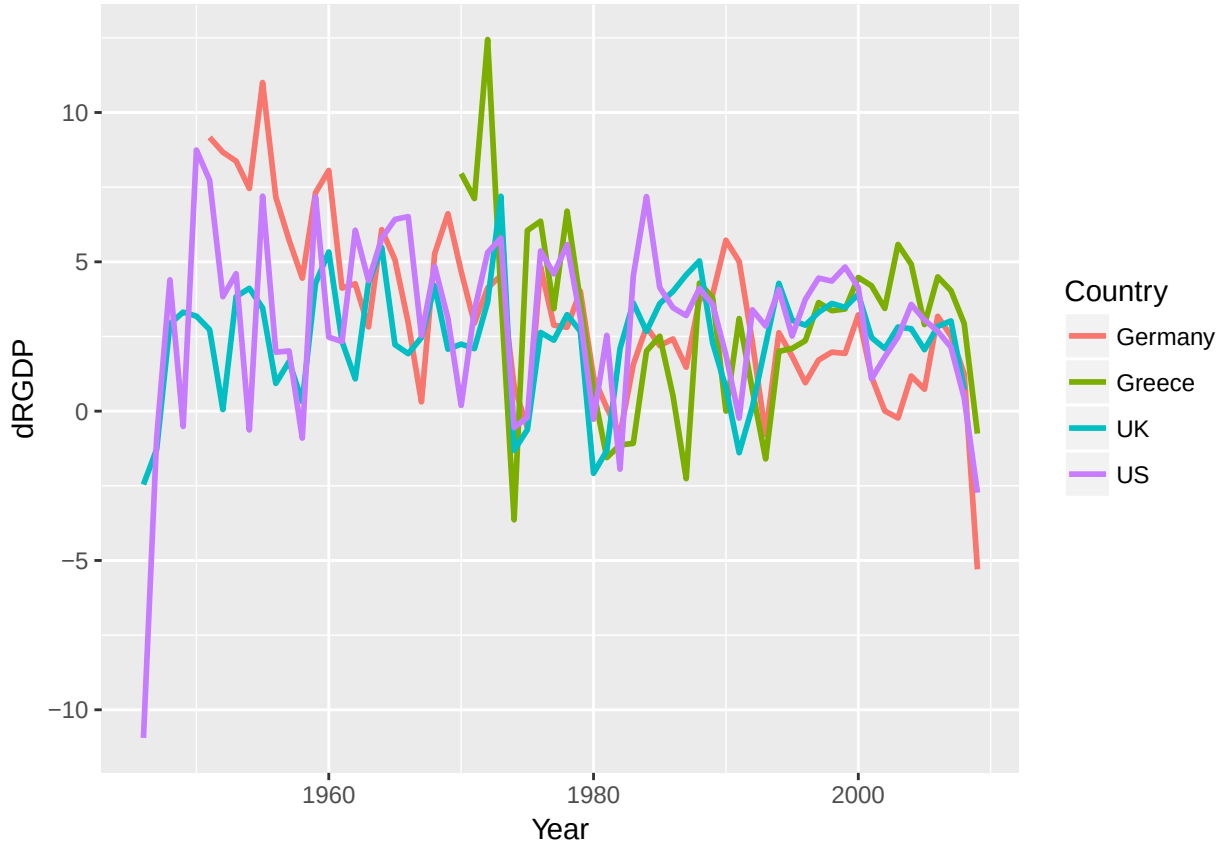
There are issues with running a regression like this. Perhaps most importantly that the observations cannot be argued to be independent. The growth rate and debt to GDP ratios of, say, the UK in 1981 is clearly not independent of the data in 1980. In particular debt to GDP ratios are slow moving data.

To illustrate this point we should look at the data as time series.

```
tempdata <- RRData %>% filter(Country %in% c("Germany","Greece","UK","US"))
ggplot(tempdata,aes(Year,debtgdp,color=Country)) +
  geom_line()      # this produces the scatter plot
```




```
tempdata <- RRData %>% filter(Country %in% c("Germany","Greece","UK","US"))
ggplot(tempdata,aes(Year,dRGDP,color=Country)) +
  geom_line(size=1)      # this produces the scatter plot
```

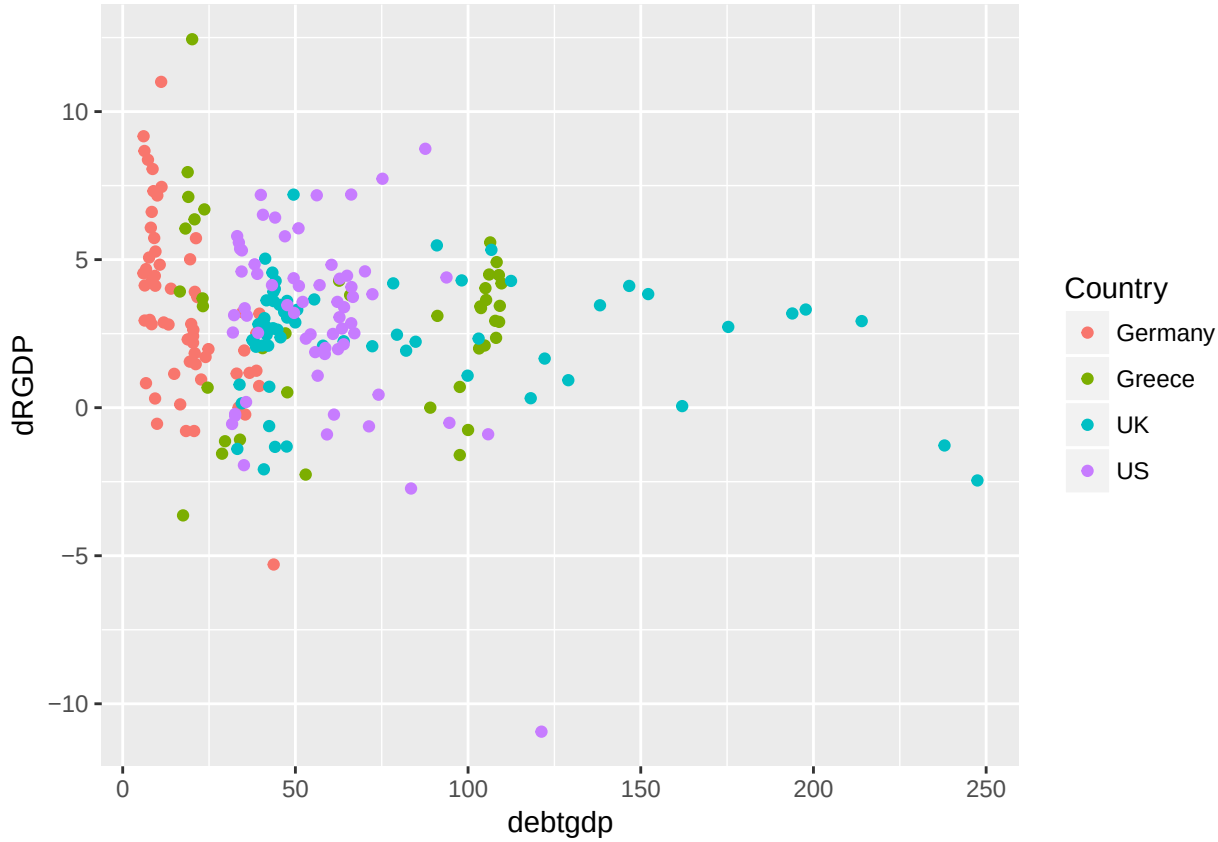


You can clearly see that the `debtgdp` data, from year to year, are dependent. Also, the `dRGDP` plot reveals that there is a fair bit of correlation between the growth rates in economies.

Some data cuts

Let's look at the data for a few countries

```
tempdata <- RRData %>% filter(Country %in% c("Germany","Greece","UK","US"))
ggplot(tempdata,aes(debtgdp,dRGDP,color=Country)) +
  geom_point()      # this produces the scatter plot
```



From here you can see that different countries appear to have quite different patterns.

Let's calculate average and median growth rates and debt to gdp ratios for these countries. To achieve this we will first group the data by Country `group_by(Country)` and then summarise the variables `dRGDP` and `debtgdp` (`summarise_at(c("dRGDP", "debtgdp"), ...)`) in the resulting groups by applying the mean and median function (`funs(mean, median, sd)`).

```
tempdata %>% group_by(Country) %>%
            summarise_at(c("dRGDP", "debtgdp"), funs(mean, median,sd)) %>%
            print()
```

```
## # A tibble: 4 x 7
##   Country dRGDP_mean debtgdp_mean dRGDP_median debtgdp_median dRGDP_sd
##   <fct>        <dbl>        <dbl>        <dbl>          <dbl>    <dbl>
## 1 Germany       3.31         17.8         2.88           14.9     2.91
## 2 Greece        2.93         67.7         3.39           77.5     3.11
## 3 UK            2.41         78.7         2.68           47.6     1.90
## 4 US            3.00         56.0         3.38           56.3     3.04
## # ... with 1 more variable: debtgdp_sd <dbl>
```

Create categorical debt to GDP ratios

In order to replicate some of the analysis in Reinhard and Rogoff and the subsequent critique in Herndon et al. we will want to create categorical variables for the Debt to GDP ratio. In other words we want to

```
RRData <- RRData %>% mutate(dgcat = cut(RRData$debtgdp, breaks=c(0,30,60,90,Inf)))

RRData %>% group_by(dgcat) %>%
            summarise_at("dRGDP", funs(mean, median)) %>%
            print()
```

```
## # A tibble: 4 x 3
##   dgcat     mean median
##   <fct>    <dbl>  <dbl>
## 1 (0,30]    4.17   4.15
## 2 (30,60]   3.12   3.11
## 3 (60,90]   3.22   2.9
## 4 (90,Inf]  2.17   2.34
```

Hypothesis Testing - means and differences in mean

Hypothesis testing is at the core of much empirical analysis. Here we will show how to perform hyothesis tests. We are using the `t.test` function. Often hypothesis tests will be testing hypotheses about the mean of a random variable. We also learn how to perform hypothesis on regression coefficients (often these are nothing else but ways to estimate means!).

Let's start by testing a hypothesis on the sample mean of the GDP growth rate (`dRGDP`) Let's say we want to test the hypothesis that the mean growth rate is 3.3% (note that 3.3% in the dat aiis represented as 3.3). Let's get one calculated and then diiscuss what we really did:

```
t.test(RRData$dRGDP, mu=3.3)
```

```
##
##  One Sample t-test
##
## data:  RRData$dRGDP
## t = 1.4896, df = 1170, p-value = 0.1366
## alternative hypothesis: true mean is not equal to 3.3
## 95 percent confidence interval:
##  3.258847 3.600675
## sample estimates:
## mean of x
##  3.429761
```

You may remember that, in order to perform a hypothesis test you, the applied economist, has to set the null (H_0) and alternative (H_A) hypothesis. Here you set the null hypothesis that the mean (`mu`) is equal to 3 (H_0:`mu=3.3`). You also need to specify an alternative hypothesis. We didn't specify any so R (or better `t.test`) used it's default option, two sided alternative ($H_A : mu \neq 3.3$).

The judgemment here is that it is possible that the true, yet unknown population mean is equal to 3.3. The test statistic is 1.4896 and the p-value is 0.1366. Only if the p-value is smaller than our chosen level of significance (often 0.01, 0.05 or 0.1) would we reject the null hypothesis H_0.

Make sure you use the help function (type `?t.test` into the command window) or search for help (type "R t.test" into your favourite search engine) to understand more details of the function.

Let's calculate a one sided test with the alternative that ($H_A : mu > 3.3$):

```
t.test(RRData$dRGDP, mu=3.3, alternative="greater")
```

```
##
```

```
##  One Sample t-test
##
## data:  RRData$dRGDP
## t = 1.4896, df = 1170, p-value = 0.0683
## alternative hypothesis: true mean is greater than 3.3
## 95 percent confidence interval:
##  3.28636     Inf
## sample estimates:
## mean of x
##  3.429761
```

Changing the alternative does not change the t-test but change the p-value. Now the p-value is 0.0683 and whether we reject or do not reject H_0 depends on our chosen significance level.

At this stage a we need to mention a huge caveat to the above tests. Our standard tests are based on the assumption that the data are identically and independently distributed. In some sense we have already seen that the this assumption cannot be defended with the data at hand. We saw the time-series plot above which showed that observations are correlated between years and ountries, so they are not independent observations. But let's, for the sake of this introduction, ignore this complication, but note that we need to interpret results with caution.

Above we sliced the data into different subsets. Let's use the debt level categories and compare means of growth between the subsets.

```
temp_high <- RRData %>% filter(dgcat == "(90,Inf]")
temp_middle <- RRData %>% filter(dgcat == "(60,90]")

t.test(temp_high$dRGDP,temp_middle$dRGDP)
```

```
##
##  Welch Two Sample t-test
##
## data:  temp_high$dRGDP and temp_middle$dRGDP
## t = -2.7221, df = 184.28, p-value = 0.007109
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.817628 -0.290037
## sample estimates:
## mean of x mean of y
##  2.167972  3.221804
```

At the bottom of the output you can see the respective sample means (which replicates the sample means we printed earlier in a table). The hyothesis tested is $H_0 : mu_{high} = mu_{middle}$ with the alternative that the respective population means are different ($H_a : mu_{high} \neq mu_{middle}$). As above we could have elected to test an alternative of $>$ or $<$ as well.