# Quantitative Macroeconomics
# Homework 1

Lorenzo De Carolis
(In collaboration with Victor Caballero Cordero and Santiago Albarracin)

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## Question 1:

### (1.1) Compute (and plot) the time series of the monthly employment rate in the U.S. As source of data go to IPUMS and download the latest available CPS monthly data. Detrend and deseasonalize to show the effect of COVID19 in your estimates for year 2020.

First of all, I have downloaded the dataset needed from the webpage provided. Once downloaded it, I have worked with it in order to create a variable that indexed each month with an increasing number (variable name: "yearmonth"). Then I have calculated the unemployment rate by computing the ratio between the total number of unemployed and the labor force. Then I have created the variable employment knowing that the employment rate in 1- the unemployment rate. I have made an estimation of the predicted employment rate in 2020 in the situation without COVID. The process to do so is by calculating the average employment rate between each month in the years 2018 and 2019 (the months I took into account are the ones that have been hit by the COVID shock, so from March 2020 on). Then, I have plotted the predicted employment rate ("pre") and the actual value ("employment") over the period studied. The outcome graph is the one below:

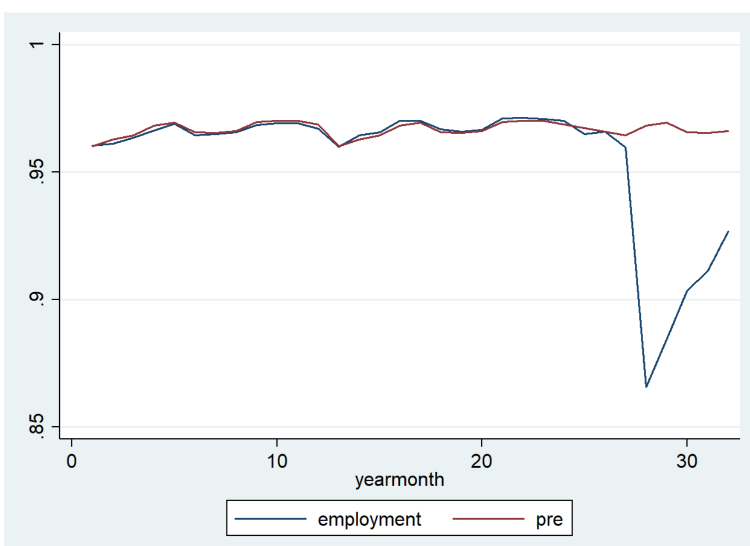


Figure 1:

The analysis shows that there has been a strong impact of COVID over the employment across the US. In particular, by predicting what would have been the trend without COVID (red line in graph), it is clear that the impact is negative.

### (1.2) Redo by education group as ”lower than HS”, ”HS”, ”College” and ”higher than College”.

In order to understand which is the impact of COVID on the employment across different education groups, I divided the dataset in the four categories asked, and calculated the employment rate across each group by month. Then I have plotted the employment rates of each group in the following graph:

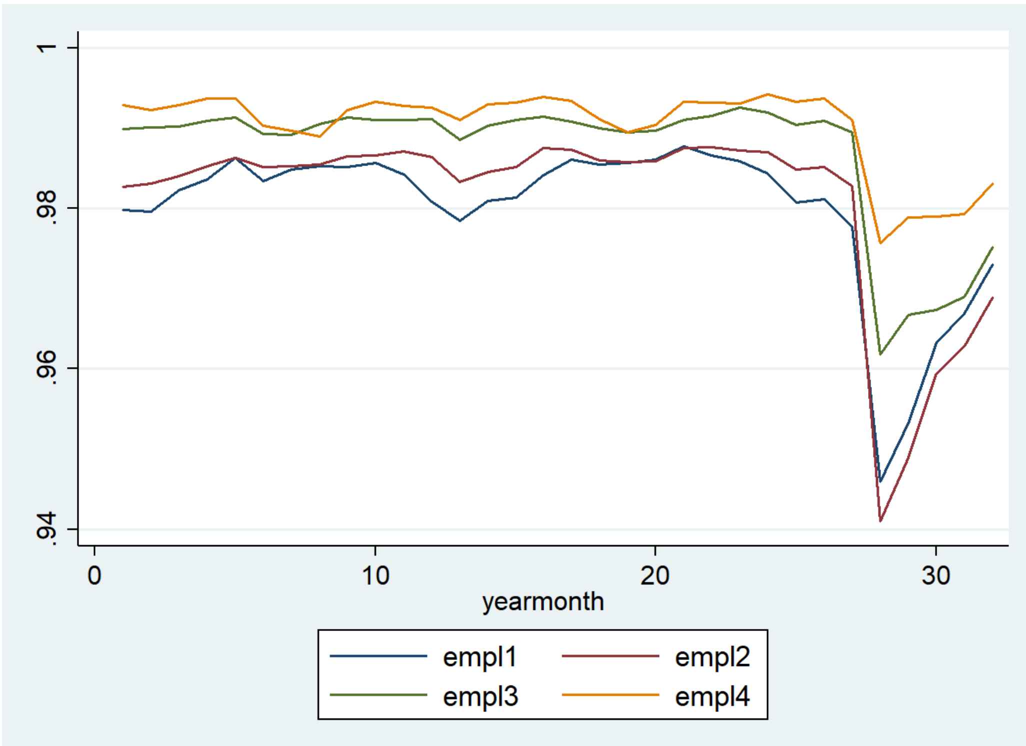


Figure 2:

Each line shows the trend of employment rate for that particular education group across time: empl1 for ”lower than HS”, empl2 for ”HS”, empl3 for ”College” and empl4 for ”higher than College”.
My findings are perfectly in line with what I expected, since the employment rate of higher education groups decreased less than the ones of lower education groups. One possible explanation is that workers having a stronger educational background are harder to substitute, so they have an higher bargaining power against their employers, which are less prone to substitute them.

### (1.3) Redo by industry (for example, create two groups of industries according to their ability to telework).

In order to do so, I have used the variable "ind", which associates a different number to each industry. I decided to divide the whole dataset into two parts: the section "phy" which comprehends all those industries which have a lower ability to telework, and the one "tel" with all the industries with an higher capability of teleworking. In order to do so I used the "Industry Codelist" made by the US Census Bureau (file "census-2012-final-code-list.xls" attached), which explains in details all the different values associated to all industries.

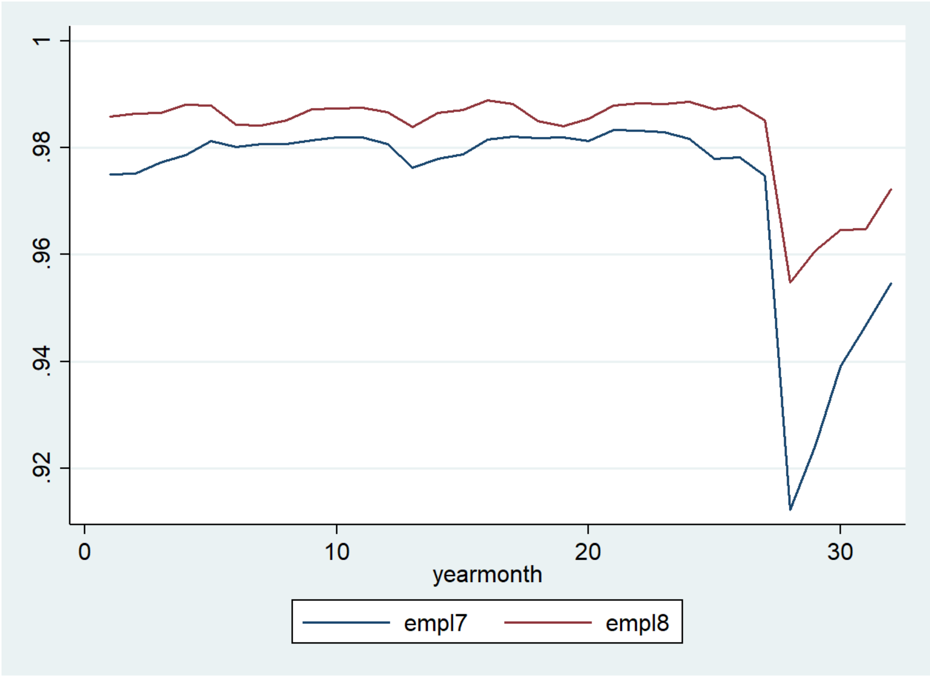


Figure 3:

The line indexed with "empl7" shows the trend of the employment rate of those industries that can not telework, while "empl8" is about the industries which can telework.
The outcome is in line with what expected, since those industries that can telework experience a much smaller negative shock with COVID. The main reson is that when the situation forced the population to confine, those industries that could continue working from remote could keep the business going more than the physical ones, which had to cut jobs.

### (1.4) Redo by occupation. Hint: Find an interesting way to split occupations (2 or 3 groups) that you think is useful to learn the effects of COVID19.

In order to explain the variation of the employment rate across different occupation groups, I used the variable "occupation". The mentioned variable attaches a different numerical value to each occupation. I divided them into three groups: High Officials employment, Public Office employment and Private Sector employment. To do so I consulted the "2010 Census Occupational Classification" (web link: 2010 Census Occupational Classification).
The result is shown in the following graph:

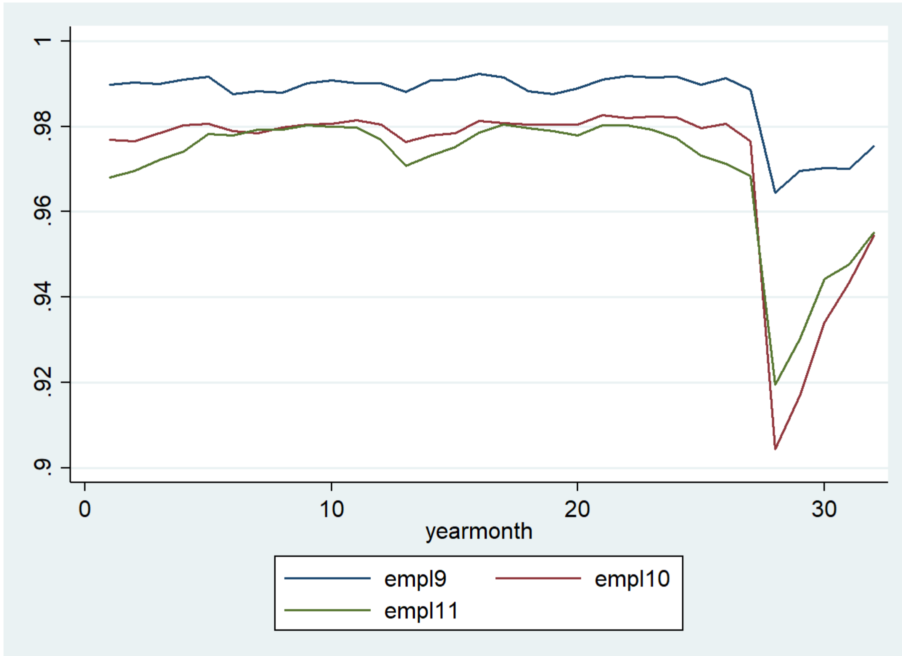


Figure 4:

The line called empl9 shows the employment trade's trend for the occupation classified as "High Officials", the one called empl10 show the "Public Office employment rate" and empl11 "Private sector employment rate".
The outcome is in line with what expected in particular about the "High Officials" trend, which is visibly higher than the other two sections. The explanation is that firstly, occupations of that kind are at an higher hierarchy, thus are those that generally risk less in terms of being fired. Another factor to think about is that usually these kinds of occupations are not physical, thus have an higher probability to be done from remote. Then, there is the skills associated with those occupations, which are usually rare in the labor market, making them more prone to hold the occupation.

## Question 2:

### (2.1) Redo the previous item for average weekly hours. Discuss your results.

In order to study the trend of average weekly hours over time, I used the variable ”uhrsworkt”, which provides the value of weekly hours worked by the individual in the according week. Then, I took the mean of the weekly hours across each month. And, in order to calculate the prediction fro 2020 I used the same method as in section 1.1, which takes the average between the value of the same month of the two previous years (2018 and 2019).
The outcome is shown in the following graph:

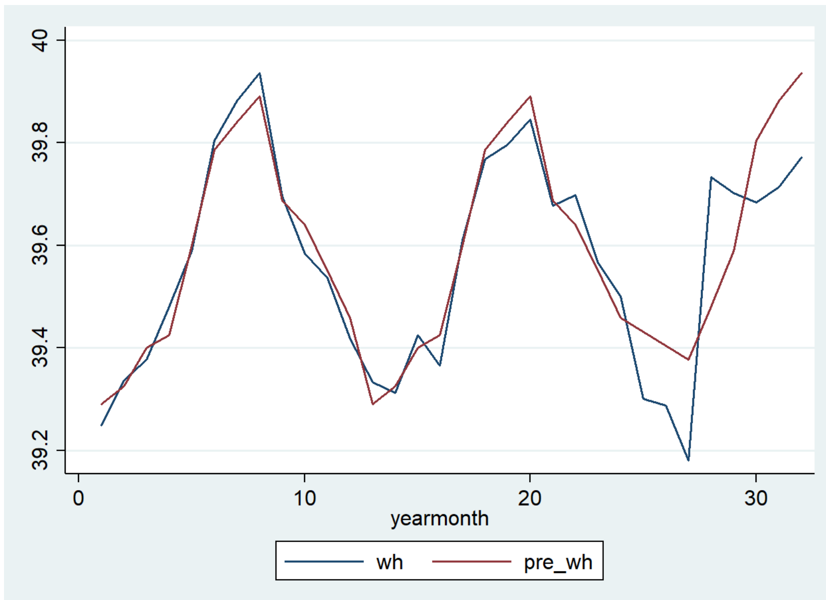


Figure 5:

The line indexed with ”wh” shows the actual trend of weekly hours worked, while the one indexed with ”pre_wh” shows the trend of the predicted values.
The graph is in line with what expected, because in the first months of 2020 the expected value is higher, meaning that COVID had a negative impact on weekly hours worked. The main explanation is that many people are not working because of confinement.

## Question 3:

### (3.1) Is the behavior of aggregate hours driven by employment or by average weekly hours? Decompose using percentage deviations from the predicted value of these items. Discuss your results.

In order to analyze the trend of aggregate weekly hours, I multiplied the number of employed people by the weekly hours variable we saw in section 2.1.
Then, I computed the expected values of it by using the same method as in section 1.1. The outcome is showed by the following graph:

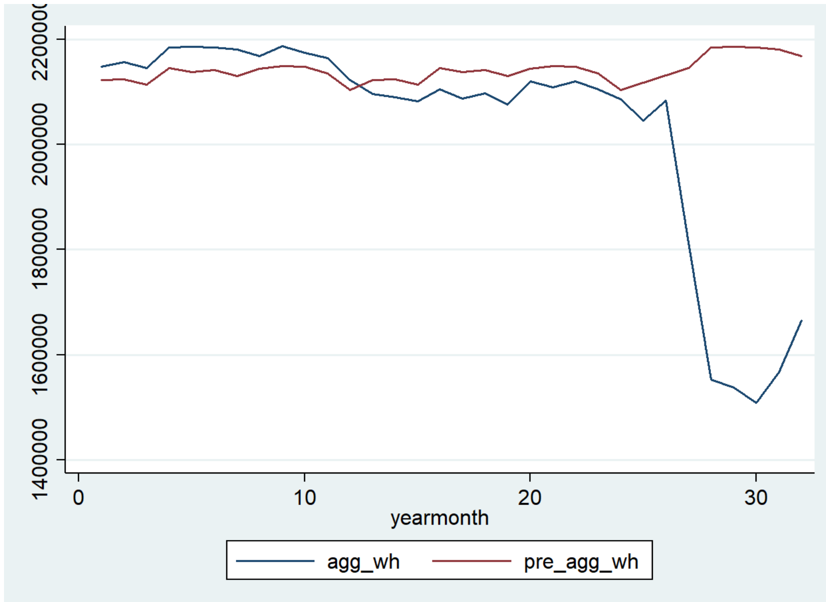


Figure 6:

The outcome we get from studying aggregate weekly hours shows a significant decrease following the COVID crisis. The main factor driving down aggregate weekly hours is employment, because as we can see in section 1.1, employment was strongly hit by the crisis. While, on the other hand average weekly hours had a much smaller slow down due to the crisis (see graph in section 2.1.

## Question 4:

### (4.1) Redo for wages (or earnings).

In order to analyze the trend of wages over time, I used the variable "hourwage", which is a valid way to understand the wage level. It provides the individual's wage per hour of work. In order to have a more effective outcome, I harmonized te wage with the level of inflation. Then, I calculated the predicted wage with the same technique used in section 1.1.
The outcome is showed in the following graph:

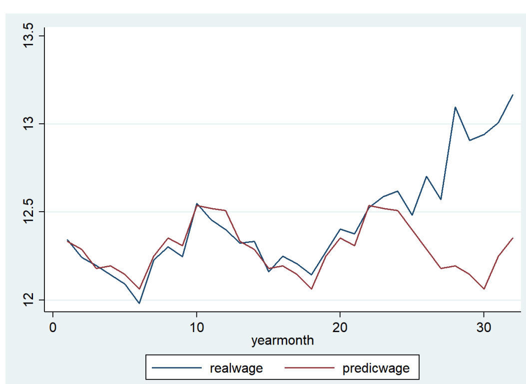


Figure 7: Table_4

The graph displays the actual trend of wages with the variable "realwage", and the prediction with "predicwage".
The graph is not in line with what expected, because since many people passed from being occupied to being unemployed, the bargaining power of employers should have increased, making wages decrease. One possible explanation to the graph above could be that many of those people who lost their job had low-wage incomes, making the average wage increase (among employed people).

## Question 5:

### (5.1) Redo for your own country. Discuss difficulties (if any) in getting the data. Discuss your results.

My country is Italy. There is a national statistical institute that records data about the national population, it's name is ISTAT (Istituto Nazionale di Statistica). I have downloaded macro data from it about the total employment rate from 2013 to 2020. I decided to include such a broad amount of years because Italy does not have monthly data about occupation, but only trimestral data. This means that I collected four values for each year starting in 2013, one value for each 3 months.
I have then computed the predicted value of the employment rate for the first two trimesters of 2020 by using the same method used in section 1.1. Thus, I calculated the average of the values in each trimester across all years from 2013 to 2019. Then I associated the according value to its trimester in 2020. The prediction is showed in the following graph with the red line called "pre_tot":

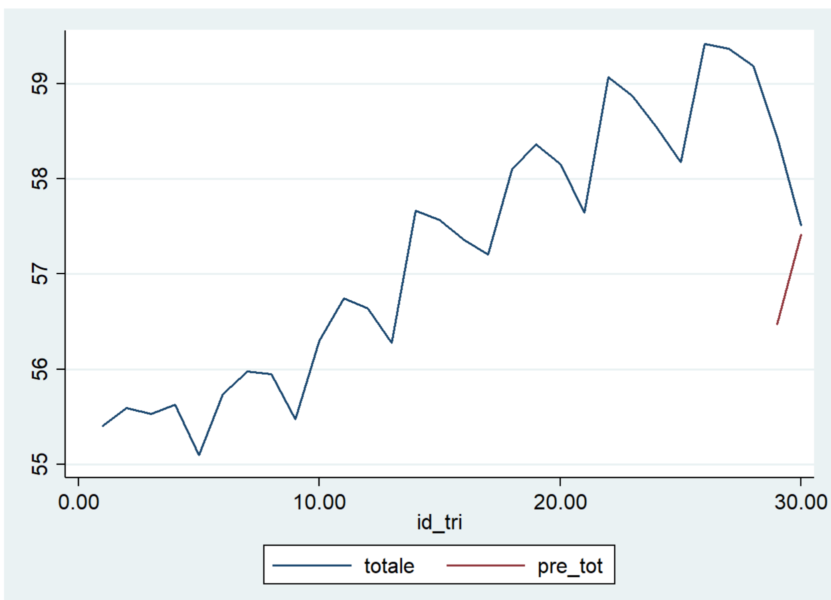


Figure 8:

The other line is instead the actual value of the employment rate.
The output shows that the predicted value for the employment rate is lower than the actual one. It could be inferred that COVID had a positive impact on the employment rate in Italy, but we will discuss this matter in the following paragraph.

I have also decided to study the trend of the employment rate for the different education groups, in order to understand if the outcome seen before is confirmed.
To do so I collected the employment rate associated with people having the same education background. I divided the dataset into 4 categories: Elementary school (”elementari”), Middle school (”media”), High school (”diploma”) and University or higher (”laurea”).
I have then plotted the four trends on the following graph:

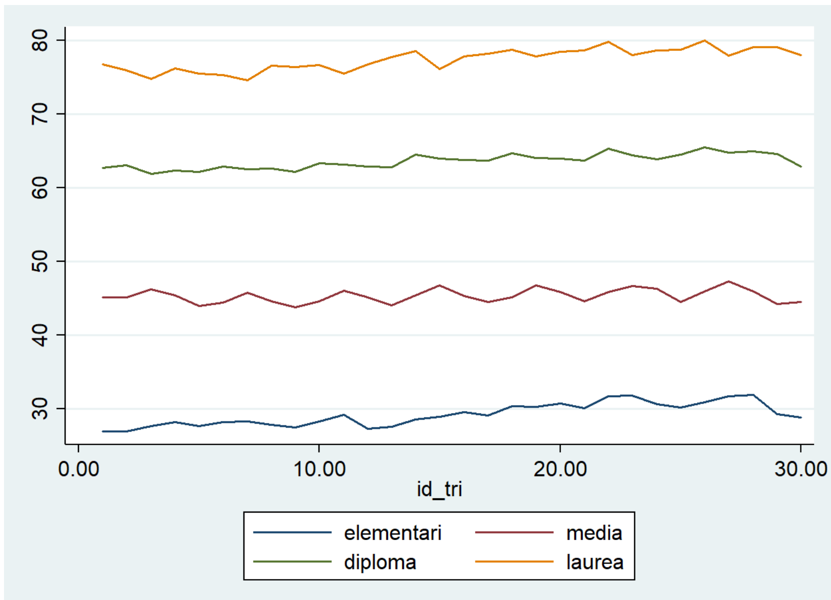


Figure 9:

It is clear that there was not an interesting shock on none of the four categories, even if they maintain their differences due to their structural characteristics.
The latter outcome confirms what the first Italian graph shows, that employment rate did not vary consistently due to the COVID chrisis. The reason for such a particular finding has to be searched at the political level. Indeed, the Italian Government pursued heavy exceptional policies in order to protect employees from being fired all together, causing a massive number of unemployment all at once.
In order to do so, they decided to pay employees of firms that were at risk by a fiscal instrument called ”cassa integrazione”. The adoption of such a policy created the situation that we are analyzing, making the employment rate not respond to the crisis as in other countries such as the US, where the labor market is less regulated and left more free of following its ”natural” path.