ECON 753 Homweork 1

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My script PS1_JL.R generates the following objects that I present in this report.

```
load("Table_10_Replication.Rdata")
load("Table_11_Replication.Rdata")

load("Table_10_A1.Rdata")
load("Table_11_A1.Rdata")

load("Table_10_A2.Rdata")
load("Table_11_A2.Rdata")

load("prev_1.Rdata")
load("prev_2.Rdata")
load("prevGDP.Rdata")

load("A1.Rdata")
load("A1_A1.Rdata")
load("A2_A1.Rdata")
load("A1_F.Rdata")
load("prev_A.Rdata")
```

Problem 1

Part A

In this part I replicate in R tables 10, 11 and A1 from Pollin and Chakraborty. I take the employment data and original weights from the file "India-Input-Output Analysis–Employment Estimates–09132019.xlsx". The Input-Output data comes from the file "IND_NIOT_row_09132019.xlsx" that I took from the official WIOD page.

Below is a replication of Table A1 which summarizes the weighting system used in the original paper. The last two columns present my alternative weighting system.

```
library(knitr)
kable(A1_F)
```

Category	I-O Industry	Weights	My Weights 1	My Weights 2
Bioenergy	Agriculture, Hunting, Forestry and Fishing	50.0	50	50.0
Bioenergy	Coke, Refined Petroleum and Nuclear Fuel	12.5	20	12.5
Bioenergy	Construction	25.0	15	25.0
Bioenergy	Education	12.5	15	12.5
Solar	Basic Metals and Fabricated Metal	17.5	25	17.5
Solar	Electrical and Optical Equipment	35.0	25	35.0

Category	I-O Industry	Weights	My Weights 1	My Weights 2
Solar	Construction	30.0	25	30.0
Solar	Education	17.5	25	17.5
Wind	Rubber and Plastics	12.0	20	12.0
Wind	Basic Metals and Fabricated Metal	12.0	15	12.0
Wind	Electrical and Optical Equipment	43.0	30	43.0
Wind	Construction	26.0	10	26.0
Wind	Education	7.0	25	7.0
Geothermal	Mining and Quarrying	15.0	15	15.0
Geothermal	Electrical and Optical Equipment	10.0	10	10.0
Geothermal	Construction	45.0	45	45.0
Geothermal	Education	30.0	30	30.0
Hydro	Other Non-Metallic Mineral	18.2	35	18.2
Hydro	Electrical and Optical Equipment	21.0	25	21.0
Hydro	Construction	18.2	25	18.2
Hydro	Education	42.9	15	42.9
Weatherization and Building Retrofits	Construction	100.0	100	100.0
Industrial Energy Efficiency	Electrical and Optical Equipment	50.0	70	50.0
Industrial Energy Efficiency	Construction	20.0	20	20.0
Industrial Energy Efficiency	Education	30.0	10	30.0
Grid Upgrades	Electrical and Optical Equipment	75.0	50	75.0
Grid Upgrades	Construction	25.0	50	25.0
Coal	Mining and Quarrying	50.0	75	50.0
Coal	Chemicals and Chemical Products	50.0	25	50.0
Oil and Gas	Mining and Quarrying	50.0	30	50.0
Oil and Gas	Coke, Refined Petroleum and Nuclear Fuel	50.0	70	50.0
Renewable Energy	Bioenergy	20.0	20	40.0
Renewable Energy	Solar	20.0	20	40.0
Renewable Energy	Wind	20.0	20	10.0
Renewable Energy	Geothermal	20.0	20	5.0
Renewable Energy	Hydro	20.0	20	5.0
Energy Efficiency Building Retrofits	Weatherization and 50.0	50	20.0	
Energy Efficiency	Industrial Energy Efficiency	25.0	25	40.0
Energy Efficiency	Grid Upgrades	25.0	25	40.0
Fossil Fuel	Coal	50.0	50	70.0
Fossil Fuel	Oil and Gas	50.0	50	30.0

Each of the 35 I-O industries belongs to at least a sub-sectoral energy category (10 in total) and each of those can be classified in 3 broad energy categories: renewable, efficiency and fossil fuels.

By getting the "Leontieff" inverse matrix and the labor-output ratio, we can also get the direct and indirect labor that goes into the production of one unit of each "good". The following table is a replication of Table 10 of the paper that shows how many jobs would each energy sub-sector generate given a million USD increase in the final demand of the industries that integrate them.

Replication of Table 10

```
library(knitr)
kable(T10)
```

energy_names	Direct Jobs	Indirect Jobs	Direct + Indirect Jobs
Bioenergy	562.58296	61.18570	623.7687
Solar	98.50743	97.50735	196.0148
Wind	75.10361	117.85742	192.9610
Geothermal	145.48118	79.51790	224.9991
Hydro	144.78122	76.14726	220.9285
Weighted Average for Renewables	205.29128	86.44313	291.7344
Weatherization	159.11415	121.08790	280.2021
Industrial Energy Efficiency	105.51909	88.12674	193.6458
Smart Grids	58.69619	115.24087	173.9371
Weighted Average for Efficiency	120.61090	111.38585	231.9967
Coals	49.47604	87.70103	137.1771
Oil and Gas	34.24322	86.81066	121.0539
Weighted Average for Fossil Fuels	41.85963	87.25585	129.1155

Table 11 below is a summary of table 10 as it only includes the weighted averages of each sub-sector classified in the broader sectors of renewable energy, energy efficiency and fossil fuels. The sum of the first two gives the row "Clean Energy Total". Whereas the last row is obtained by the formula $\frac{CleanEnergyTotal-FossilFuels}{FossilFuels}*100\%$ Note: the value of this row is different than in the paper because there they used the weights 67% and 33% to renewables and efficiency, respectively, whereas here I kept the 50-50% of the original table. I keep those final weights for the rest of the analysis

Replication of Table 11

```
library(knitr)
kable(T11_4)
```

Source	Jobs per million USD
Renewable Energy	291.7344
Energy Efficiency	231.9967
Fossil Fuels	129.1155
Clean Energy Total	261.8656
Clean Energy relative to Fossil Fuels	102.8150

The most salient fact is that an investment of 1 USD for both fossil fuels and clean energy would result in more than double (102.82%) more generated in the latter than in the former.

Part B

In this part I conduct the same analysis but changing the weights at the I-O industry level. These new weights are in the column "My Weights 1" in the first table.

Although not making the analysis very formal, in these new weights I tried to punish a little those industries that intuitively are more labor-intensive, such as education or construction, and to increa the weight of capital intensive industries such as mining and construction.

The new results are shown in the below.

```
library(knitr)
kable(A1_T10)
```

energy_names	Direct Jobs	Indirect Jobs	Direct + Indirect Jobs
Bioenergy	551.76192	59.48581	611.2477
Solar	106.00577	89.35041	195.3562
Wind	86.96998	107.14901	194.1190
Geothermal	145.48118	79.51790	224.9991
Hydro	121.19335	100.55646	221.7498
Weighted Average for Renewables	202.28244	87.21192	289.4944
Weatherization	159.11415	121.08790	280.2021
Industrial Energy Efficiency	69.84080	105.94296	175.7838
Smart Grids	92.16884	117.18988	209.3587
Weighted Average for Efficiency	120.05949	116.32716	236.3866
Coals	58.98124	65.30360	124.2848
Oil and Gas	20.54593	104.37245	124.9184
Weighted Average for Fossil Fuels	39.76359	84.83803	124.6016

The summary at the sectoral level is in the next table.

```
library(knitr)
kable(head(A1_T11_4))
```

Source	Jobs per million USD
Renewable Energy	289.4944
Energy Efficiency	236.3866
Fossil Fuels	124.6016
Clean Energy Total	262.9405
Clean Energy relative to Fossil Fuels	111.0250

Maybe not very surprisingly, the new weights didn't alter the basic result: that clean energies would generate more than twice the jobs of fossil fuels (111.02% in this case). I think a large part of this result comes from the fact that I left unchanged the weight of agriculture (that belongs to the bioenergy sub-sector), which is by far the "industry" that generates more jobs in India.

Now I keep the original weights of each industry but change the weights of each sub-sector. This summarized in the column "My Weights 2" of the first table.

```
library(knitr)
kable(A2_T10)
```

energy_names	Direct Jobs	Indirect Jobs	Direct + Indirect Jobs
Bioenergy	562.58296	61.18570	623.7687
Solar	98.50743	97.50735	196.0148
Wind	75.10361	117.85742	192.9610
Geothermal	145.48118	79.51790	224.9991
Hydro	144.78122	76.14726	220.9285
Weighted Average for Renewables	286.45964	83.04622	369.5059
Weatherization	159.11415	121.08790	280.2021
Industrial Energy Efficiency	105.51909	88.12674	193.6458
Smart Grids	58.69619	115.24087	173.9371
Weighted Average for Efficiency	97.50894	105.56463	203.0736
Coals	49.47604	87.70103	137.1771
Oil and Gas	34.24322	86.81066	121.0539
Weighted Average for Fossil Fuels	44.90619	87.43392	132.3401

The new results are found in the next two tables. Obviously, the amount of indirect and direct jobs generated by each energy subsector are the same as in the original paper, since the weights of industries remained unchanged. The changes come in the weighted averages of each broad sector. But that is better summarized in the table below

```
library(knitr)
kable(A2_T11_4)
```

Source	Jobs per million USD
Renewable Energy	369.5059
Energy Efficiency	203.0736
Fossil Fuels	132.3401
Clean Energy Total	286.2897
Clean Energy relative to Fossil Fuels	116.3288

There we can see that, although with some composition effects, the basic result of the original paper remains, since with this alternative system clean energies generate 116.33% more jobs than fossil fuel energies. This analysis suggests that the results obtained in Pollin and Chakraborty are robust to different weights at different levels.

Poblem 2

1 Replication of figure 2 RR

Below I present a replication of figure 2 in RR paper

```
knitr::include_graphics("F2.png")
```

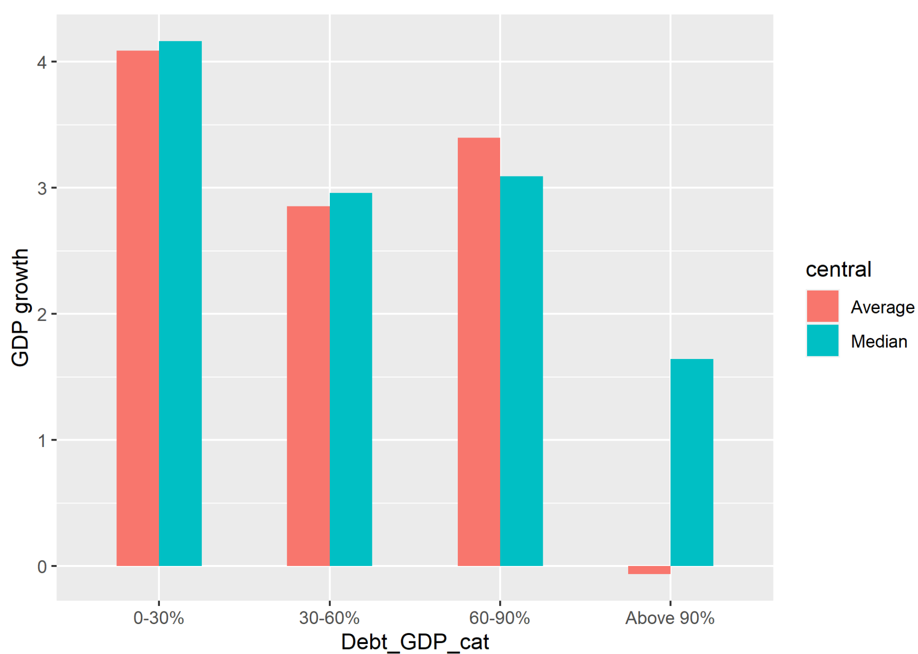

Figure 1: Figure 2 RR

There are two main facts: average and median GDP growth is the highest in the lowest debt/GDP category. But the most important is that once the ratio is above 90%, economic growth is “not viable”. We know that this is largely due to the mistakes of the authors. (Note: in the original figure the first two bars are slightly below 4 and here are above. This was replicated using the code provided by the professor.)

2. Show the prevalence of the four public-debt categories for the sample of countries over time.Show the real GDP growth rate for the sample of countries over time. Discuss any patterns thatyou observe.

First by country and total:

```r
library(knitr)
kable(prev_1)
```

Country	0-30%	30-60%	60-90%	Above 90%
Australia	37	13	9	5
Austria	34	27	1	0
Belgium	0	17	21	25
Canada	3	42	14	5
Denmark	23	16	17	0
Finland	44	16	4	0
France	24	20	10	0
Germany	48	11	0	0
Greece	13	5	3	19
Ireland	10	14	32	7
Italy	26	6	17	10
Japan	22	17	4	11
Netherlands	17	34	2	0
New Zealand	9	33	17	5
Norway	51	12	1	0
Portugal	42	9	7	0
Spain	5	36	1	0
Sweden	18	35	11	0
UK	0	39	6	19
US	0	37	23	4

```r
library(knitr)
kable(prev_2)
```

0-30%	30-60%	60-90%	Above 90%
426	439	200	110

We observe that most countries lied in the first two categories of debt/GDP during the analyzed period. Only a few countries had many episodes of very high debt/GDP, such as Greece, the UK and Japan.

We know observe the prevalence of debt/GDP over time. We observe that the 60s and 70s were periods of low debt/GDP, whereas most episodes of very high debt/GDP are found in the last 20 years as well as in the immediate post-war period.

```r
library(knitr)
kable(prev_A)
```

yearcat	0-30%	30-60%	60-90%	Above 90%
1946-1950	9	18	8	24
1951-1960	81	33	50	11
1961-1970	108	48	21	4
1971-1980	102	71	7	0
1981-1990	57	97	32	14
1991-2000	29	86	55	30
2000-2010	40	86	27	27

Finally, let's observe the prevalence of Real GDP Growth for our sample of countries

```
library(knitr)
kable(prevGDP)
```

Country	1946-1950	1951-1960	1961-1970	1971-1980	1981-1990	1991-2000	2000-2010
Australia	3.7742505	4.057079	5.286783	3.310568	3.246736	3.441959	2.8755253
Austria	19.5468645	6.028140	4.720503	3.644910	2.008400	2.529400	1.4671111
Belgium	7.7478861	2.641468	5.127077	3.573654	2.057382	2.349175	1.2918860
Canada	2.9566400	4.620591	5.079180	4.273472	2.535731	3.710663	1.8610558
Denmark	7.9458545	3.163720	4.499750	1.589972	2.094581	2.605949	0.8501989
Finland	5.6593573	4.975873	4.831884	3.481533	3.034762	2.070023	1.8182061
France	7.4940048	4.578134	5.579828	3.908958	2.535731	3.710663	1.8610558
Germany	NA	7.739168	4.219219	2.756779	2.315392	2.079083	0.4975409
Greece	NA	NA	7.954927	4.674873	0.710200	2.355700	3.5272222
Ireland	3.2026001	1.739933	4.215289	4.736466	2.870000	7.110000	3.1444444
Italy	NA	6.060585	5.815893	3.128034	2.407300	1.592300	0.2064444
Japan	NA	7.906044	9.139496	4.601107	4.643919	1.193078	0.5378570
Netherlands	NA	3.954550	5.085018	2.931332	2.254174	3.067691	1.2723563
New Zealand	7.0369371	3.484836	3.581376	2.239731	1.723000	2.877800	2.4655556
Norway	7.6505874	3.836354	4.197120	4.710583	2.535731	3.710663	1.8610558
Portugal	2.8372935	4.762352	6.382186	4.819081	2.535731	3.710663	1.8610558
Spain	1.6924847	5.737635	NA	NA	2.981895	2.907287	2.3332958
Sweden	6.1217601	3.620328	5.274890	1.967190	2.203565	2.026641	1.6255954
UK	1.1371502	2.670354	2.832633	1.984710	2.733149	2.547979	1.5954352
US	0.1576796	3.547241	4.215048	3.209143	3.266144	3.411775	1.6148628

It is clear that economic growth is highest in the first 3 columns, whereas in the last three GDP growth is mediocre, with just a very few countries growing more than 3%.

3. Replication of figures 1, 2 and 4 of Herndon et al.

```
knitr::include_graphics("Figure_1_Herndon.png")
```

Figure 1 of Herndon et al. shows the very weak relationship between debt/GDP and real GDP growth once the mistakes are corrected. The line connecting the averages would be almost horizontal

```
knitr::include_graphics("Figure_2_Herndon.png")
```

Figure 2 of Herndon et al. (Figure 3 in this report) expands the debt categories by including "above 120%". This figure shows how the average GDP growth in episodes of debt/GDP above 120% is very low. Hence, this illustrates the consequences of choosing different thresholds: they can change substantially the results. For instance, this points to the fact that a debt-GDP ratio only becomes very pervasive to economic growth

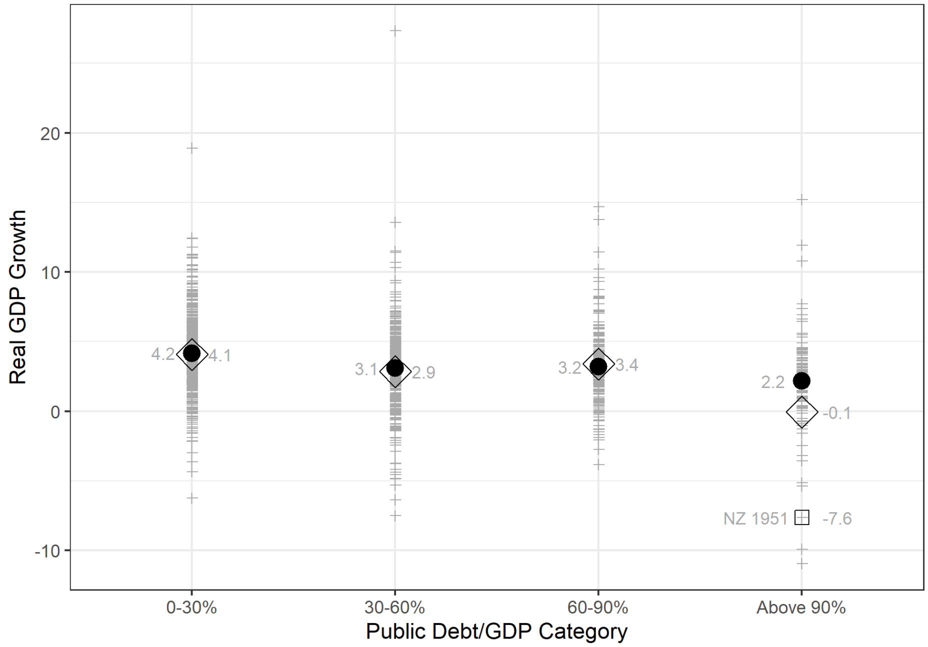

Figure 2: Figure 1 Herndon et al.

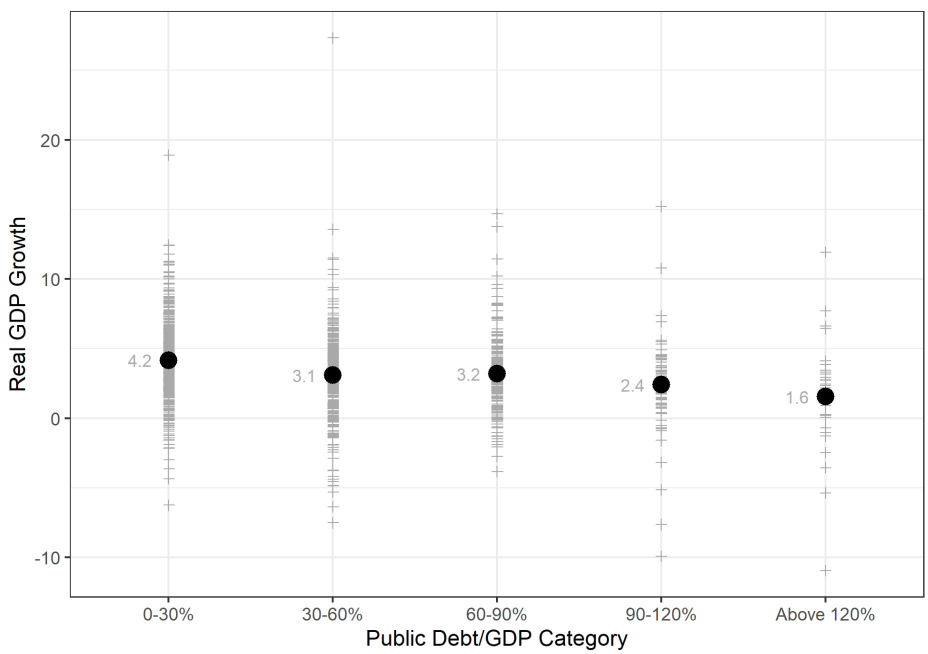

Figure 3: Figure 2 Herndon et al.

once it passes a very high threshold. An interesting direction to expand this research, I think, is to make us of regressions that determine endogenously the thresholds, such as Panel Transition Regression or Panel Smooth Transition Regression models.

```
knitr::include_graphics("Figure_4_Herndon.png")
```

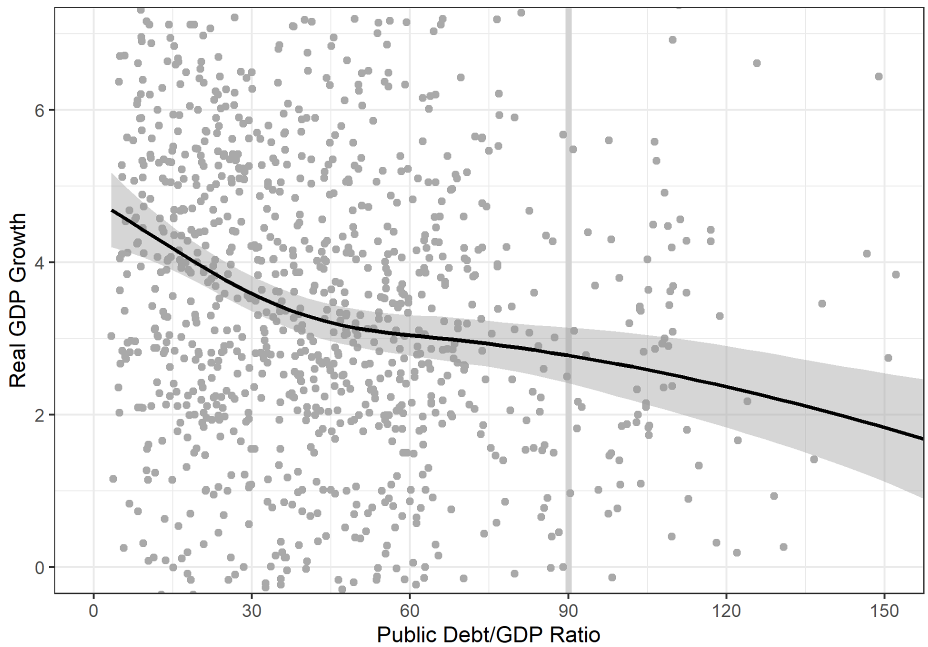

Figure 4: Figure 4 Herndon et al.

Figure 4 shows the relationship between these two variables and better illustrates the finding of last figure, as after 90% of the GDP ratio the relationship between the two variables becomes very negative, but that is not the case in the previous categories.

Reorganization in a meaningful way

In this part I focus on different year categories. I create a dummy variable that takes value 1 if year is greater than 1979 and 0 otherwise. Then I plot the relationship between debt/GDP and real GDP growth and add two linear regressions.

```
knitr::include_graphics("gn.png")
```

Just as we expected, the relationship is more negative for the blue points (after 1979), since those were the years of the highest debt/GDP (just after the immediate postwar).

In figure 6 I plot the relationship between the two variables for the different decades

```
knitr::include_graphics("gycat.png")
```

Very interestingly, the slope of the regression line is the greatest in absolute value for the first 15 years of the period analyzed. Then it becomes almost flat and then big again for the period 2000-2010.

Finally, I look at the evolution of these two variables over time for the US and Japan.

```
knitr::include_graphics("myplot.png")
```

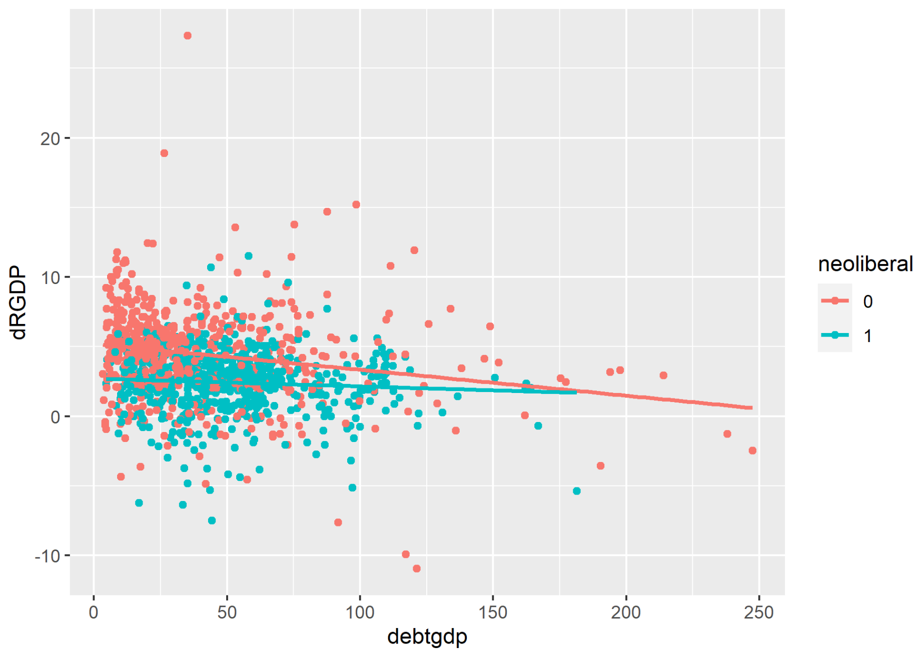

Figure 5: Before and After 1979

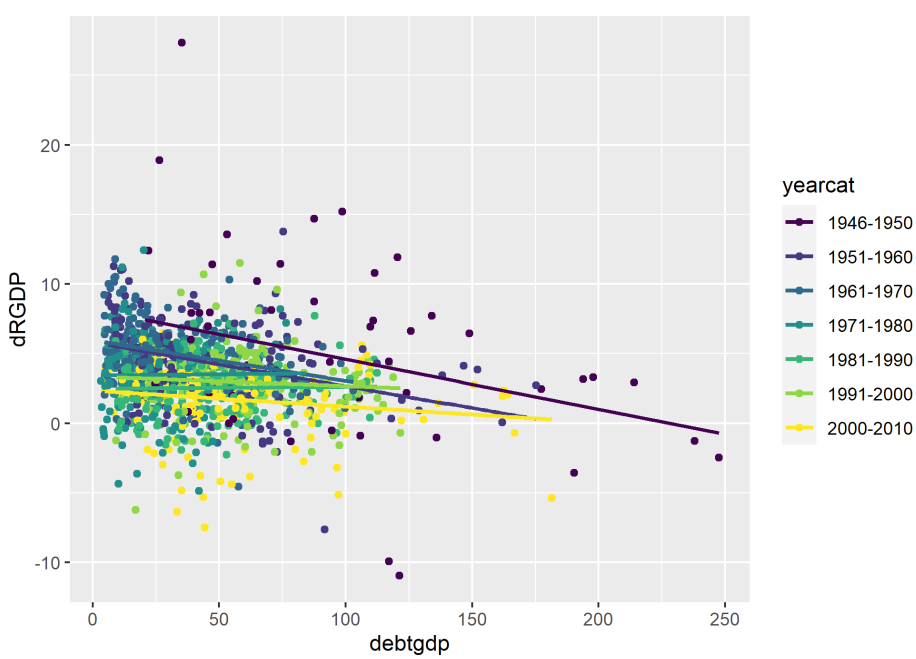

Figure 6: By year categories

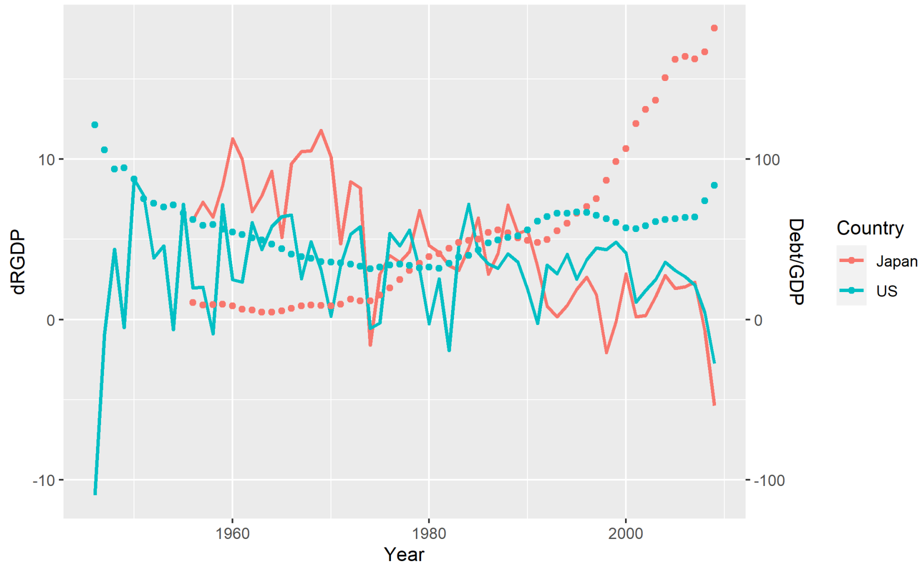

Figure 7: Real GDP Growth vs Debt/GDP for US and Japan

This is shown in Figure 7. The dots represent the Debt-GDP ratio and the line the rate of GDP growth. We can see that, around 1985, the two lines start to diverge: the tendency is towards a greater public debt and lower GDP growth. In my opinion, All these results point to the already discussed complex relationship between public debt and GDP growth, where the direction of causality is not easy to determine (assuming, in the very first place, that it exists).