Projectpart3

June 11, 2023

1 PS 88 Project Part 3 - Due 12/14 at 11:59pm

The goal of the final part of the project is to extend the analysis of one of the replication papers, or any other data set we have worked on in any of the labs or class examples. (If you want to work with a different data set that will probably be fine too, but check with the instructors first.)

Regardless of dataset you start with, the goal is to provide new theoretical insights by introducing some new data and running some new analysis.

The parameters here will be much looser; the only concrete requirements are that you (1) do at least one merging of different data frames, and (2) run at least two new regressions and create at least two visualizations (histograms, scatterplots, line plots, etc), some of which involve the "new" variables you merged in.

On the second part, here are some ideas of what doing new analysis might entail, some of which will work better than others depending on what data you start with: - Run the analysis with a different dependent variable - Run the analysis with a different independent variable - Run the analysis on a subset of the data, where we might expect the causal effect to be different - Add a control variable to the regression that might help control for some confounding variable

See the relevant Piazza posts for some pointers to potentially useful data sources and tips for merging them properly.

In terms of formatting, add as many code/mardown cells as you need below. We provide some general guidance about how much writing/coding to do, but you don't necesarily need to worry if yours is a bit shorter or longer. Feel free to check with us if you are unsure!

A final hint: you may want to complete step 1 last, or at least after you have done the main analysis in steps 2 and 3.

1.1 Step 1: Theory

What is the theoretical question or causal relationship you aim to explore with your analysis? What relationships did you expect to see in the data? (5-10 sentences)

The Conscription of Wealth: Mass Warfare and the Demand for Progressive Taxation by Kenneth Scheve and David Stasavage (2010) showed how progressive taxation rose after WW1 and concluded that mass mobilization for warfare caused increasing demands in progressive taxation. Through this analysis, we want to analyze how progressive taxation is influenced during periods of relative peace – when there is no mass mobilizing warfare. What factor – other than mobilization for war – causes fluctuation in high income tax rates over time? In order to answer this question we needed data from more countries. However, the data available to us is regarding inheritance tax rates not progressive tax rates.

Hence, throughout this analysis, the first question we ask ourselves is: Given our data, can we use inheritance tax rates as a proxy for all taxation?

If the answer to the above question is yes, then: Is ideology the reason behind the decline of tax rates post 1950?

We expect the answer to the latter question to be affirmative. Most importantly, in accordance with common conception of political ideologies, we expect our analysis to show us a positive relationship between left executive and high tax rates.

1.2 Step 2: Merging

Load up the data files you plan to use, and merge them together. Explain what you are doing at each step of the process. Do some checks with `.shape` to see that the merge works as expected. Depending on what you are working with, this will probably take around 10 lines of code, and 1-2 sentences explaining each step.

[1]:
```
# Run this cell to import the packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
%matplotlib inline
plt.rcParams['figure.figsize'] = (16,8)
plt.rcParams['figure.dpi'] = 150
sns.set()
pd.set_option('display.max_columns', None)
```

Part 1: Importing Data

We will first import the data from *The Conscription of Wealth: Mass Warfare and the Demand for Progressive Taxation* (Scheve and Stasavage 2010) under the name ss_2010, then data from *Replication Materials for 'Democracy, War, and Wealth Lessons from Two Centuries of Inheritance Taxation* (Scheve, Kenneth, David Stasavage 2012) under the name ss_2012.

[2]:
```
data_string = "data/Scheve_Stasavage_IO_2010_CoWreplicationdata.csv"
ss_2010 = pd.read_csv(data_string)
ss_2010.head()
```

[2]:
```
  country  ccode  year  enfranchised1  enfranchised2  enfrachisement3  \
0     USA      2  1850            NaN      44.200001              NaN
1     USA      2  1851            NaN      44.200001              NaN
2     USA      2  1852            NaN      44.900002              NaN
3     USA      2  1853            NaN      44.900002              NaN
4     USA      2  1854            NaN      44.900002              NaN
```

```
   inctaxshrn  hifatwaryear  wwi_iihighmob2  decadec  munsuff  topratep  \
0         NaN             0               0        8        0       0.0
1         NaN             0               0        8        0       0.0
2         NaN             0               0        8        0       0.0
3         NaN             0               0        8        0       0.0
4         NaN             0               0        8        0       0.0

   himobpopyearp  himobpopyear2p  leftseatshp    gdppcp    ratiop  topratepl1  \
0            0.0             0.0          0.0  1.830661  0.017015         0.0
1            0.0             0.0          0.0  1.867650  0.019820         0.0
2            0.0             0.0          0.0  1.904639  0.017458         0.0
3            0.0             0.0          0.0  1.941628  0.018436         0.0
4            0.0             0.0          0.0  1.978617  0.020414         0.0

   wwihighmobaft  year3  topdum  topratenoint  topratenointl1  _Idecadec_9  \
0              0    NaN     0.0           0.0             0.0            0
1              0    NaN     0.0           0.0             0.0            0
2              0    NaN     0.0           0.0             0.0            0
3              0    NaN     0.0           0.0             0.0            0
4              0    NaN     0.0           0.0             0.0            0

   _Idecadec_10  _Idecadec_11  _Idecadec_12  _Idecadec_13  _Idecadec_14  \
0             0             0             0             0             0
1             0             0             0             0             0
2             0             0             0             0             0
3             0             0             0             0             0
4             0             0             0             0             0

   _Idecadec_15  _Idecadec_16  _Idecadec_17  _Idecadec_18  _Idecadec_19  \
0             0             0             0             0             0
1             0             0             0             0             0
2             0             0             0             0             0
3             0             0             0             0             0
4             0             0             0             0             0

   _Idecadec_20  _Idecadec_21  _Idecadec_22  _Idecadec_23  _Iccode_20  \
0             0             0             0             0           0
1             0             0             0             0           0
2             0             0             0             0           0
3             0             0             0             0           0
4             0             0             0             0           0

   _Iccode_200  _Iccode_210  _Iccode_220  _Iccode_230  _Iccode_380  \
0            0            0            0            0            0
1            0            0            0            0            0
2            0            0            0            0            0
3            0            0            0            0            0
```

```
4           0           0           0           0           0

   _Iccode_740
0            0
1            0
2            0
3            0
4            0
```

[3]:
```python
data_string = "data/Scheve_Stasavage_APSR_2012_inheritannual.csv"
ss_2012 = pd.read_csv(data_string)
ss_2012.head()
```

[3]:
```
   ccode         name  year  topitaxrate2  himobpopyear2p  himobpopyearp  \
0    390      denmark  1816          0.00             0.0            0.0
1    225  switzerland  1816          0.00             0.0            0.0
2    200           uk  1816          3.25             0.0            0.0
3    732        korea  1816           NaN             NaN            NaN
4      2          usa  1816          0.00             0.0            0.0

   wwi_iihighmob3  mobpophifatwar  mobpophifatwar2  unisuffrage  democracy  \
0               0             0.0              0.0            0          0
1               0             0.0              0.0            0          0
2               0             0.0              0.0            0          0
3               0             0.0              0.0            0          0
4               0             0.0              0.0            0          1

   directelec  secret  electorate75  electorate50  electorate25  noupper  \
0         0.0     0.0             0             0             0      0.0
1         0.0     0.0             0             0             0      0.0
2         1.0     0.0             0             0             0      0.0
3         NaN     NaN             0             0             0      NaN
4         1.0     0.0             1             1             1      0.0

   leftexec2  gdppc  rgdppc  independence  occupied  Neightopitax2  \
0        0.0    NaN     NaN             1         0        1.00000
1        0.0    NaN     NaN             1         0        0.14375
2        0.0    NaN     NaN             1         0        0.14375
3        0.0    NaN     NaN             1         0        0.00000
4        0.0  132.0     NaN             1         0            NaN

   Rmilexbadjdol  milexbadjdol  hdecadec  decadec
0            NaN           NaN         1      NaN
1            NaN           NaN         1      NaN
2       0.534909      0.088437         1      NaN
3            NaN           NaN         1      NaN
4       0.120703      0.019956         1      NaN
```

Below is information about the new data.

[4]:
```
data_string = "data/Scheve_Stasavage_APSR_2012_Readme.txt"
ss_2012_description = open(data_string).readlines()
for i in ss_2012_description:
    print(i)
```

```
Replication archive for "Democracy, War, and Wealth: Lessons from Two Centuries
of Inheritance Taxation"



Kenneth Scheve and David Stasavage



American Political Science Review, forthcoming (February 2012)



October 12 2011



Included files:



Scheve_Stasavage_APSR_2012_Readme  This file describes contents of replication
archive.

Scheve_Stasavage_APSR_2012_inheritannual.dta This is the 1816-2000 annual
dataset in Stata format needed to replicate the main analyses of the paper.

Scheve_Stasavage_APSR_2012_SSinheritanceRep.do This is the Stata do file that
replicates all the main analyses of the paper including Figures 1 and 2;

Tables 2, 3, and 5; and Appendix Tables A-1, A-2, A-3, A-4, A-5, A-6, A-7, A-8;
and selected further analyses discussed in the text.

Scheve_Stasavage_APSR_2012_SSinheritanceRep.log This is a log file reporting the
output generated by SSinheritanceRep.do

twocenturies_oct11.pdf Final draft of paper with electronic appendix  [[Archive
note: only Appendix is included in archive --
Scheve_Stasavage_APSR_2012_OnlineAppendix.pdf]]
```

Variable definitions and sources:

These are all included in the text and electronic appendix of the paper.

Variable key for inheritannual.dta

ccode Numeric country code

name Country name

year Year

topitaxrate2 Top Rate as defined in paper

himobpopyear2p War Mobilization as defined in paper

himobpopyearp War Mobilization recoded with 5% threshold as discussed in robustness checks

wwi_iihighmob3 War Mobilization coded qualitatively as discussed in robustness checks

mobpophifatwar War Mobilization coding mobilization continuously for high fatality war years as discussed in robustness checks

mobpophifatwar2 War Mobilization coding mobilization continuously for high fatality war years as discussed in robustness checks but with alternative treatment of years for which COW mobilization data is missing

unisuffrage Universal Male Suffrage as defined in paper

democracy Competitive Elections as defined in paper

directelec Direct Elections as defined in paper

secret Secret Ballot as defined in paper

electorate25 Electorate 25 as defined in paper

electorate50 Electorate 50 as defined in paper

```
electorate75 Electorate 75 as defined in paper

noupper No Upper as defined in paper

leftexec2 Left Executive as defined in paper

gdppc Gross domestic product per capita

rgdppc Gross domestic product (real) per capita as defined in paper

independence Dummy variable indicating country was independent

occupied Dummy variable indicating country was occupied

Neightopitax2 Value of topitaxrate2 in neighboring countries

Rmilexbadjdol Military Expenditures as defined in paper

milexbadjdol Military Expenditures in current dollars

hdecadec Indicator variable for half decades

decadec Indicator variable for decades
```

Part 2: Merging the Dataframes

In order to merge the two dataframes together, we need to gather more information about them.

[5]:
```python
[ss_2010["country"].unique(), ss_2012["name"].unique()]
```

[5]:
```
[array(['USA', 'Canada', 'UK', 'Netherlands', 'France', 'Spain', 'Sweden',
        'Japan'], dtype=object),
 array(['denmark', 'switzerland', 'uk', 'korea', 'usa', 'france',
        'netherlands', 'austria', 'japan', 'sweden', 'belgium',
        'new zealand', 'italy', 'canada', 'germany', 'australia', 'norway',
        'finland', 'ireland'], dtype=object)]
```

[6]:
```python
ss_2010.shape
```

[6]:
```
(1248, 45)
```

[7]:
```python
ss_2012.shape
```

[7]:
```
(2929, 27)
```

[8]:
```python
ss_2012.info(), ss_2010.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2929 entries, 0 to 2928
Data columns (total 27 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ccode            2929 non-null   int64
 1   name             2929 non-null   object
 2   year             2929 non-null   int64
 3   topitaxrate2     2808 non-null   float64
 4   himobpopyear2p   2800 non-null   float64
 5   himobpopyearp    2800 non-null   float64
 6   wwi_iihighmob3   2929 non-null   int64
 7   mobpophifatwar   2929 non-null   float64
 8   mobpophifatwar2  2922 non-null   float64
 9   unisuffrage      2929 non-null   int64
 10  democracy        2929 non-null   int64
 11  directelec       2797 non-null   float64
 12  secret           2797 non-null   float64
 13  electorate75     2929 non-null   int64
 14  electorate50     2929 non-null   int64
 15  electorate25     2929 non-null   int64
 16  noupper          2797 non-null   float64
 17  leftexec2        2929 non-null   float64
 18  gdppc            1932 non-null   float64
 19  rgdppc           2591 non-null   float64
 20  independence     2929 non-null   int64
 21  occupied         2929 non-null   int64
 22  Neightopitax2    2714 non-null   float64
 23  Rmilexbadjdol    2331 non-null   float64
 24  milexbadjdol     2331 non-null   float64
 25  hdecadec         2929 non-null   int64
 26  decadec          2879 non-null   float64
dtypes: float64(15), int64(11), object(1)
memory usage: 618.0+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1248 entries, 0 to 1247
Data columns (total 45 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   country          1248 non-null   object
 1   ccode            1248 non-null   int64
 2   year             1248 non-null   int64
 3   enfranchised1    476 non-null    float64
 4   enfranchised2    150 non-null    float64
 5   enfrachisement3  139 non-null    float64
 6   inctaxshrn       248 non-null    float64
 7   hifatwaryear     1248 non-null   int64
 8   wwi_iihighmob2   1248 non-null   int64
```

```
 9   decadec          1248 non-null   int64
 10  munsuff          1248 non-null   int64
 11  topratep         1183 non-null   float64
 12  himobpopyearp    1136 non-null   float64
 13  himobpopyear2p   1136 non-null   float64
 14  leftseatshp      1049 non-null   float64
 15  gdppcp           1126 non-null   float64
 16  ratiop           959 non-null    float64
 17  topratepl1       1188 non-null   float64
 18  wwihighmobaft    1248 non-null   int64
 19  year3            248 non-null    float64
 20  topdum           1183 non-null   float64
 21  topratenoint     1113 non-null   float64
 22  topratenointl1   1118 non-null   float64
 23  _Idecadec_9      1248 non-null   int64
 24  _Idecadec_10     1248 non-null   int64
 25  _Idecadec_11     1248 non-null   int64
 26  _Idecadec_12     1248 non-null   int64
 27  _Idecadec_13     1248 non-null   int64
 28  _Idecadec_14     1248 non-null   int64
 29  _Idecadec_15     1248 non-null   int64
 30  _Idecadec_16     1248 non-null   int64
 31  _Idecadec_17     1248 non-null   int64
 32  _Idecadec_18     1248 non-null   int64
 33  _Idecadec_19     1248 non-null   int64
 34  _Idecadec_20     1248 non-null   int64
 35  _Idecadec_21     1248 non-null   int64
 36  _Idecadec_22     1248 non-null   int64
 37  _Idecadec_23     1248 non-null   int64
 38  _Iccode_20       1248 non-null   int64
 39  _Iccode_200      1248 non-null   int64
 40  _Iccode_210      1248 non-null   int64
 41  _Iccode_220      1248 non-null   int64
 42  _Iccode_230      1248 non-null   int64
 43  _Iccode_380      1248 non-null   int64
 44  _Iccode_740      1248 non-null   int64
dtypes: float64(15), int64(29), object(1)
memory usage: 438.9+ KB
```

[8]:
```
(None, None)
```

The primary key for both dataframes is the country code (ccode) and year. Common features about countries between the two dataframes are country names and war mobilization (himobpopyear2p and himobpopyearp). Hence, we will merge our dataframes on country code, year, country name, himobpopyear2p, himobpopyearp. In order to merge on these features, however, we must first standardize how country names are formatted and the name of the columns.

The country names in the new data are written in all lower case letters. Below, we transform country names in the data from the 2010 paper to all lower case.

[9]:
```
ss_2010["country"] = ss_2010["country"].str.lower()
```

The column names for country names in both dataframes are different. We need to match the column names in order to merge on country names. Below, we rename the column name in the ss_2012 dataframe from name to country.

[10]:
```
ss_2012 = ss_2012.rename(columns = {"name": "country"})
```

Below, we merge the two dataframes. We do an outer join in order to encompass all data.

[11]:
```
merged_table = pd.merge(ss_2010, ss_2012, on = ["ccode", "year", "country",␣
 ↪"himobpopyear2p", "himobpopyearp",
                                                  ],
                        how = "outer")
merged_table
```

[11]:
```
          country  ccode  year  enfranchised1  enfranchised2  enfrachisement3  \
0             usa      2  1850            NaN      44.200001              NaN
1             usa      2  1851            NaN      44.200001              NaN
2             usa      2  1852            NaN      44.900002              NaN
3             usa      2  1853            NaN      44.900002              NaN
4             usa      2  1854            NaN      44.900002              NaN
…             …     …   …            …              …                …
3199        italy    325  2000            NaN            NaN              NaN
3200      finland    375  2000            NaN            NaN              NaN
3201      germany    255  2000            NaN            NaN              NaN
3202  switzerland    225  2000            NaN            NaN              NaN
3203  new zealand    920  2000            NaN            NaN              NaN

      inctaxshrn  hifatwaryear  wwi_iihighmob2  decadec_x  munsuff  topratep  \
0            NaN           0.0             0.0        8.0      0.0       0.0
1            NaN           0.0             0.0        8.0      0.0       0.0
2            NaN           0.0             0.0        8.0      0.0       0.0
3            NaN           0.0             0.0        8.0      0.0       0.0
4            NaN           0.0             0.0        8.0      0.0       0.0
…            …             …              …          …        …
3199         NaN           NaN             NaN        NaN      NaN       NaN
3200         NaN           NaN             NaN        NaN      NaN       NaN
3201         NaN           NaN             NaN        NaN      NaN       NaN
3202         NaN           NaN             NaN        NaN      NaN       NaN
3203         NaN           NaN             NaN        NaN      NaN       NaN

      himobpopyearp  himobpopyear2p  leftseatshp    gdppcp    ratiop  \
0               0.0             0.0          0.0  1.830661  0.017015
1               0.0             0.0          0.0  1.867650  0.019820
2               0.0             0.0          0.0  1.904639  0.017458
```

3	0.0	0.0	0.0	1.941628	0.018436
4	0.0	0.0	0.0	1.978617	0.020414
…	…	…	…	…	…
3199	0.0	0.0	NaN	NaN	NaN
3200	0.0	0.0	NaN	NaN	NaN
3201	0.0	0.0	NaN	NaN	NaN
3202	0.0	0.0	NaN	NaN	NaN
3203	0.0	0.0	NaN	NaN	NaN

	topratepl1	wwihighmobaft	year3	topdum	topratenoint	topratenointl1 \
0	0.0	0.0	NaN	0.0	0.0	0.0
1	0.0	0.0	NaN	0.0	0.0	0.0
2	0.0	0.0	NaN	0.0	0.0	0.0
3	0.0	0.0	NaN	0.0	0.0	0.0
4	0.0	0.0	NaN	0.0	0.0	0.0
…	…	…	…	…	…	…
3199	NaN	NaN	NaN	NaN	NaN	NaN
3200	NaN	NaN	NaN	NaN	NaN	NaN
3201	NaN	NaN	NaN	NaN	NaN	NaN
3202	NaN	NaN	NaN	NaN	NaN	NaN
3203	NaN	NaN	NaN	NaN	NaN	NaN

	_Idecadec_9	_Idecadec_10	_Idecadec_11	_Idecadec_12	_Idecadec_13 \
0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0
…	…	…	…	…	…
3199	NaN	NaN	NaN	NaN	NaN
3200	NaN	NaN	NaN	NaN	NaN
3201	NaN	NaN	NaN	NaN	NaN
3202	NaN	NaN	NaN	NaN	NaN
3203	NaN	NaN	NaN	NaN	NaN

	_Idecadec_14	_Idecadec_15	_Idecadec_16	_Idecadec_17	_Idecadec_18 \
0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0
…	…	…	…	…	…
3199	NaN	NaN	NaN	NaN	NaN
3200	NaN	NaN	NaN	NaN	NaN
3201	NaN	NaN	NaN	NaN	NaN
3202	NaN	NaN	NaN	NaN	NaN
3203	NaN	NaN	NaN	NaN	NaN

	_Idecadec_19	_Idecadec_20	_Idecadec_21	_Idecadec_22	_Idecadec_23	\
0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	
…	…	…	…	…	…	
3199	NaN	NaN	NaN	NaN	NaN	
3200	NaN	NaN	NaN	NaN	NaN	
3201	NaN	NaN	NaN	NaN	NaN	
3202	NaN	NaN	NaN	NaN	NaN	
3203	NaN	NaN	NaN	NaN	NaN	

	_Iccode_20	_Iccode_200	_Iccode_210	_Iccode_220	_Iccode_230	\
0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	
…	…	…	…	…	…	
3199	NaN	NaN	NaN	NaN	NaN	
3200	NaN	NaN	NaN	NaN	NaN	
3201	NaN	NaN	NaN	NaN	NaN	
3202	NaN	NaN	NaN	NaN	NaN	
3203	NaN	NaN	NaN	NaN	NaN	

	_Iccode_380	_Iccode_740	topitaxrate2	wwi_iihighmob3	mobpophifatwar	\
0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	
…	…	…	…	…	…	
3199	NaN	NaN	27.0	0.0	0.0	
3200	NaN	NaN	16.0	0.0	0.0	
3201	NaN	NaN	30.0	0.0	0.0	
3202	NaN	NaN	0.0	0.0	0.0	
3203	NaN	NaN	0.0	0.0	0.0	

	mobpophifatwar2	unisuffrage	democracy	directelec	secret	\
0	0.0	0.0	1.0	1.0	0.0	
1	0.0	0.0	1.0	1.0	0.0	
2	0.0	0.0	1.0	1.0	0.0	
3	0.0	0.0	1.0	1.0	0.0	
4	0.0	0.0	1.0	1.0	0.0	
…	…	…	…	…	…	

```
3199             0.0          1.0        1.0          1.0     1.0
3200             0.0          1.0        1.0          1.0     1.0
3201             0.0          1.0        1.0          1.0     1.0
3202             0.0          1.0        1.0          1.0     1.0
3203             0.0          1.0        1.0          1.0     1.0

      electorate75  electorate50  electorate25  noupper  leftexec2  gdppc  \
0              1.0           1.0           1.0      0.0   0.000000  109.0
1              1.0           1.0           1.0      0.0   0.000000  108.0
2              1.0           1.0           1.0      0.0   0.000000  110.0
3              1.0           1.0           1.0      0.0   0.000000  122.0
4              1.0           1.0           1.0      0.0   0.000000  131.0
…              …           …           …      …        …     …
3199           1.0           1.0           1.0      1.0   1.000000    NaN
3200           1.0           1.0           1.0      1.0   1.000000    NaN
3201           1.0           1.0           1.0      0.0   1.000000    NaN
3202           1.0           1.0           1.0      1.0   0.285714    NaN
3203           1.0           1.0           1.0      1.0   1.000000    NaN

            rgdppc  independence  occupied  Neightopitax2  Rmilexbadjdol  \
0      1805.916382           1.0       0.0            NaN       0.227995
1              NaN           1.0       0.0            NaN       0.192417
2              NaN           1.0       0.0            NaN       0.227754
3              NaN           1.0       0.0            NaN       0.247673
4              NaN           1.0       0.0            NaN       0.284719
…              …           …        …            …            …
3199  18773.570310           1.0       0.0      20.000000       9.801402
3200  19770.363280           1.0       0.0      30.000000       0.746300
3201  18943.515630           1.0       0.0      22.428572      13.358764
3202  22474.859380           1.0       0.0      28.000000       1.398834
3203  16245.660160           1.0       0.0       0.000000       0.384631

      milexbadjdol  hdecadec  decadec_y
0         0.020951       7.0        3.0
1         0.017308       8.0        4.0
2         0.020707       8.0        4.0
3         0.022518       8.0        4.0
4         0.028133       8.0        4.0
…              …       …        …
3199     20.488001      37.0       18.0
3200      1.560000      37.0       18.0
3201     27.924000      37.0       18.0
3202      2.924000      37.0       18.0
3203      0.804000      37.0       18.0

[3204 rows x 67 columns]
```

1.3 Step 3: Analysis

Perform you new analysis. Interpret any graphs or regression output. How do the results change compared to the original paper/lab? This will probably take about 10-15 lines of code, and again provide 1-2 sentences explaining why you are doing what you do and explaining the results.

Part 1

Progressive Tax Rate vs. Inheritance Tax Rate: Can Inheritance Tax Rate be a Proxy to Taxation Policy in General?

Our original paper analyzed the effect of mass mobilization for war on progressive tax rate. However, the new data we imported analyzes inheritance tax. So, firstly we want to analyze how inheretance tax rate and progressive tax rate changed over time on the same plot.

However, data on progressive tax rate only exists for countries from the first paper. Hence, in order to do a true comparison – for this first part – we will limit our dataframe to the countries that are common in both papers.

[12]:
```
common_countries = merged_table[(merged_table["country"]).isin(["usa",␣
↪"netherlands",
                                                   "canada", "uk", "france",␣
↪"sweden", "japan"])]
common_countries.head()
```

[12]:

	country	ccode	year	enfranchised1	enfranchised2	enfrachisement3	\
0	usa	2	1850	NaN	44.200001	NaN	
1	usa	2	1851	NaN	44.200001	NaN	
2	usa	2	1852	NaN	44.900002	NaN	
3	usa	2	1853	NaN	44.900002	NaN	
4	usa	2	1854	NaN	44.900002	NaN	

	inctaxshrn	hifatwaryear	wwi_iihighmob2	decadec_x	munsuff	topratep	\
0	NaN	0.0	0.0	8.0	0.0	0.0	
1	NaN	0.0	0.0	8.0	0.0	0.0	
2	NaN	0.0	0.0	8.0	0.0	0.0	
3	NaN	0.0	0.0	8.0	0.0	0.0	
4	NaN	0.0	0.0	8.0	0.0	0.0	

	himobpopyearp	himobpopyear2p	leftseatshp	gdppcp	ratiop	topratepl1	\
0	0.0	0.0	0.0	1.830661	0.017015	0.0	
1	0.0	0.0	0.0	1.867650	0.019820	0.0	
2	0.0	0.0	0.0	1.904639	0.017458	0.0	
3	0.0	0.0	0.0	1.941628	0.018436	0.0	
4	0.0	0.0	0.0	1.978617	0.020414	0.0	

	wwihighmobaft	year3	topdum	topratenoint	topratenointl1	_Idecadec_9	\
0	0.0	NaN	0.0	0.0	0.0	0.0	
1	0.0	NaN	0.0	0.0	0.0	0.0	
2	0.0	NaN	0.0	0.0	0.0	0.0	

3	0.0	NaN	0.0	0.0	0.0	0.0
4	0.0	NaN	0.0	0.0	0.0	0.0

	_Idecadec_10	_Idecadec_11	_Idecadec_12	_Idecadec_13	_Idecadec_14	\
0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	

	_Idecadec_15	_Idecadec_16	_Idecadec_17	_Idecadec_18	_Idecadec_19	\
0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	

	_Idecadec_20	_Idecadec_21	_Idecadec_22	_Idecadec_23	_Iccode_20	\
0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	

	_Iccode_200	_Iccode_210	_Iccode_220	_Iccode_230	_Iccode_380	\
0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	

	_Iccode_740	topitaxrate2	wwi_iihighmob3	mobpophifatwar	mobpophifatwar2	\
0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	

	unisuffrage	democracy	directelec	secret	electorate75	electorate50	\
0	0.0	1.0	1.0	0.0	1.0	1.0	
1	0.0	1.0	1.0	0.0	1.0	1.0	
2	0.0	1.0	1.0	0.0	1.0	1.0	
3	0.0	1.0	1.0	0.0	1.0	1.0	
4	0.0	1.0	1.0	0.0	1.0	1.0	

	electorate25	noupper	leftexec2	gdppc	rgdppc	independence	\
0	1.0	0.0	0.0	109.0	1805.916382	1.0	

```
1            1.0       0.0         0.0  108.0            NaN            1.0
2            1.0       0.0         0.0  110.0            NaN            1.0
3            1.0       0.0         0.0  122.0            NaN            1.0
4            1.0       0.0         0.0  131.0            NaN            1.0

   occupied  Neightopitax2  Rmilexbadjdol  milexbadjdol  hdecadec  decadec_y
0       0.0            NaN       0.227995      0.020951       7.0        3.0
1       0.0            NaN       0.192417      0.017308       8.0        4.0
2       0.0            NaN       0.227754      0.020707       8.0        4.0
3       0.0            NaN       0.247673      0.022518       8.0        4.0
4       0.0            NaN       0.284719      0.028133       8.0        4.0
```

We will add a column to common_countries that is the difference between Progressive Tax Rate (topratep) and Inheritance Tax Rate (topitaxrate2).

[13]:
```
common_countries["difference_in_tax_rates"] = common_countries["topratep"] -␣
↪common_countries["topitaxrate2"]
```

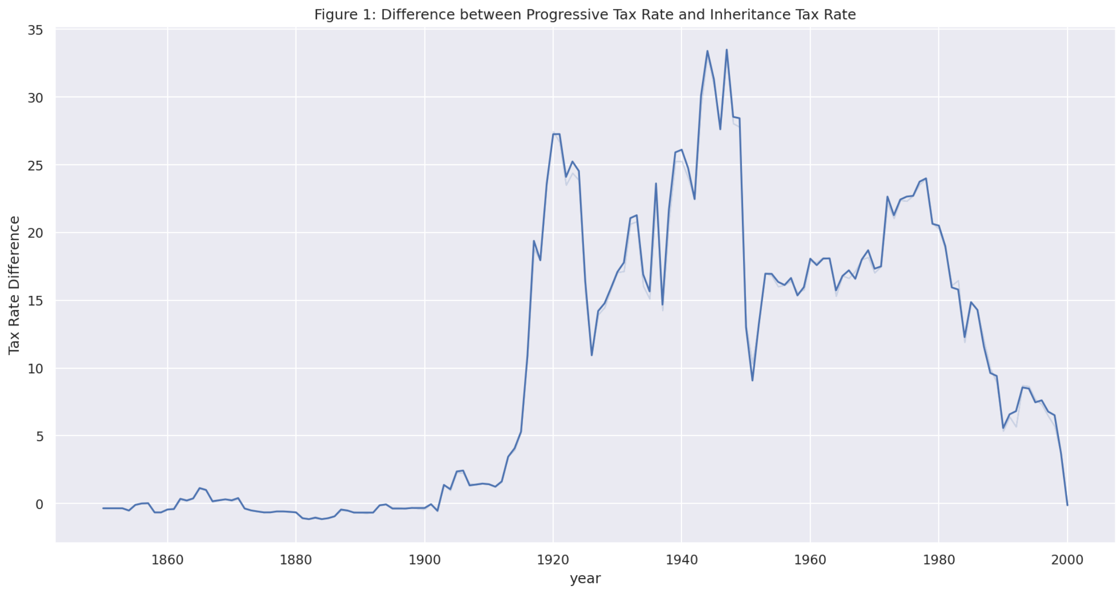
```
/tmp/ipykernel_25/374309041.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  common_countries["difference_in_tax_rates"] = common_countries["topratep"] -
common_countries["topitaxrate2"]
```

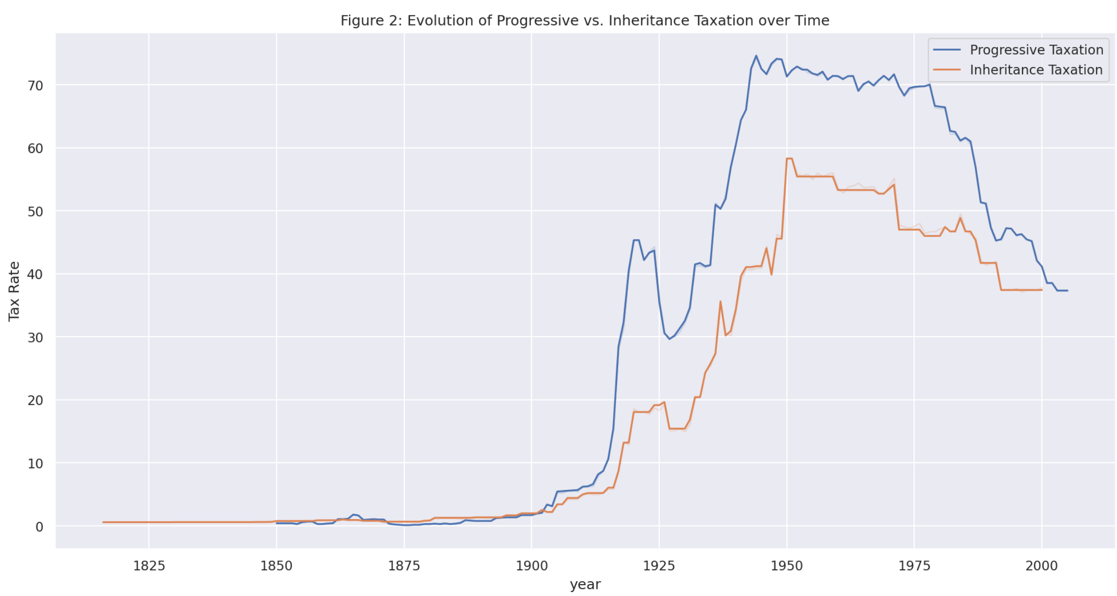
[14]:
```
common_countries["topratep"] - common_countries["topitaxrate2"]
```

[14]:
```
0       0.0
1       0.0
2       0.0
3       0.0
4       0.0
       …
2218    NaN
2499    NaN
2514    NaN
2609    NaN
2618    NaN
Length: 1363, dtype: float64
```

[15]:
```
sns.lineplot(x = "year", y= "difference_in_tax_rates", data = common_countries,␣
↪ci = False)
plt.title("Figure 1: Difference between Progressive Tax Rate and Inheritance␣
↪Tax Rate")
plt.ylabel("Tax Rate Difference");
```



[16]:
```
sns.lineplot(x = "year", y= "topratep", data = common_countries, label =
 ↪"Progressive Taxation", palette = "Set1", ci = False)
sns.lineplot(x = "year", y= "topitaxrate2", data = common_countries, label =
 ↪"Inheritance Taxation", palette = "Set1",ci = False)
plt.title("Figure 2: Evolution of Progressive vs. Inheritance Taxation over
 ↪Time")
plt.ylabel("Tax Rate");
```



The evolution of progressive and inheritance tax rates follows a similar trend. However, figure 1 shows that the difference between tax rates rise post WW1. This indicates that the inheritance tax rate isn't as affected by mass mobilization for warfare during WW1. To test if the causative relationship between mass mobilization for warfare and progressive tax rate exists between mass mobilization for warfare and inheritance tax, we will perform regression.

Below, we replicate a version of the regression we did in part 2 of the project in order to continue the above comparison between progressive tax rate and inheritance tax rate.

The dependent variable is top tax rate and independent variables are mobilization for war, male universal suffrage, proportion of left seats, GDP per capita, revenue to GDP, democracy, direct election, left executive and military expenditure.

[17]:
```
smf.ols('topratep ~ wwihighmobaft + munsuff + leftseatshp + gdppcp + ratiop +␣
↪democracy + directelec + leftexec2 + Rmilexbadjdol',
        data=common_countries).fit().summary()
```

[17]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:               topratep   R-squared:                       0.799
Model:                            OLS   Adj. R-squared:                  0.796
Method:                 Least Squares   F-statistic:                     311.9
Date:                Mon, 20 Dec 2021   Prob (F-statistic):         2.19e-239
Time:                        05:41:04   Log-Likelihood:                -2940.7
No. Observations:                 717   AIC:                             5901.
Df Residuals:                     707   BIC:                             5947.
Df Model:                           9
Covariance Type:            nonrobust
================================================================================
=
                    coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-
Intercept        -9.3850      2.578     -3.640      0.000     -14.447
-4.323
wwihighmobaft    34.3237      1.474     23.286      0.000      31.430
37.218
munsuff          -4.7294      1.547     -3.057      0.002      -7.767
-1.692
leftseatshp       0.1674      0.048      3.477      0.001       0.073
0.262
gdppcp            0.3818      0.189      2.025      0.043       0.012
0.752
ratiop          155.3097      7.013     22.145      0.000     141.540
169.079
```

```
democracy        12.7495      1.976      6.452      0.000      8.870
16.629
directelec       -5.4082      3.033     -1.783      0.075    -11.364
0.547
leftexec2        10.7669      2.309      4.663      0.000      6.233
15.301
Rmilexbadjdol     0.0335      0.016      2.149      0.032      0.003
0.064
==============================================================================
Omnibus:                       12.093   Durbin-Watson:                   0.215
Prob(Omnibus):                  0.002   Jarque-Bera (JB):               19.756
Skew:                          -0.077   Prob(JB):                     5.13e-05
Kurtosis:                       3.798   Cond. No.                         629.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

Below we perform the same regression as above, but we change our dependent variable to inheritance tax rate.

[18]:
```python
smf.ols('topitaxrate2 ~ wwihighmobaft + munsuff + leftseatshp + gdppcp + ratiop␣
 ↪+ democracy + directelec + leftexec2 + Rmilexbadjdol',
        data=common_countries).fit().summary()
```

[18]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:           topitaxrate2   R-squared:                       0.647
Model:                            OLS   Adj. R-squared:                  0.642
Method:                 Least Squares   F-statistic:                     143.9
Date:                Mon, 20 Dec 2021   Prob (F-statistic):          2.66e-153
Time:                        05:41:04   Log-Likelihood:                -3023.1
No. Observations:                 717   AIC:                             6066.
Df Residuals:                     707   BIC:                             6112.
Df Model:                           9
Covariance Type:            nonrobust
================================================================================
=
                    coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-
Intercept        -8.4916      2.892     -2.936      0.003    -14.170
```

```
-2.813
wwihighmobaft    14.0586      1.654      8.502      0.000      10.812
17.305
munsuff          -9.4453      1.736     -5.442      0.000     -12.853
-6.038
leftseatshp       0.3692      0.054      6.834      0.000       0.263
0.475
gdppcp            0.0625      0.212      0.296      0.768      -0.353
0.478
ratiop          116.3816      7.868     14.793      0.000     100.935
131.828
democracy        10.3884      2.217      4.686      0.000       6.036
14.741
directelec       -3.1514      3.403     -0.926      0.355      -9.833
3.530
leftexec2         7.4035      2.590      2.858      0.004       2.318
12.489
Rmilexbadjdol     0.2135      0.018     12.195      0.000       0.179
0.248
==============================================================================
Omnibus:                       21.798   Durbin-Watson:                   0.195
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               23.033
Skew:                           0.415   Prob(JB):                     9.96e-06
Kurtosis:                       3.287   Cond. No.                         629.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

Apart from mass mobilization for warfare, most of the other features have similar coefficients (within each others' standard deviation) for both regressions. Hence, we can assume that for the second half of the 20th century inheritance taxation is a sufficient proxy in understanding the evolution of tax rates.

Part 2

Political Ideology and Taxation

We want to analyze if a decrease in leftist ideology in the second part of the 20th century (fueled by Cold War) can be associated with the stagnation and decrease in high income and inheritance tax rates.

Reminder: we are using inheritance tax rates as a proxy to all high income tax rates.

Below, we create a new dataframe called post_1950 that includes data on all countries in the merged_table for years after 1950 (1950 included).

[19]:
```
post_1950 = merged_table[merged_table["year"]>1949]
post_1950.head()
```

[19]:
```
    country  ccode  year  enfranchised1  enfranchised2  enfrachisement3  \
100     usa      2  1950            NaN      97.599998              NaN
101     usa      2  1951            NaN      97.599998              NaN
102     usa      2  1952            NaN      98.000000              NaN
103     usa      2  1953            NaN      98.000000              NaN
104     usa      2  1954            NaN      98.000000              NaN

     inctaxshrn  hifatwaryear  wwi_iihighmob2  decadec_x  munsuff  topratep  \
100         NaN           1.0             0.0       18.0      0.0      91.0
101         NaN           1.0             0.0       18.0      0.0      91.0
102         NaN           1.0             0.0       18.0      0.0      92.0
103         NaN           1.0             0.0       18.0      0.0      92.0
104         NaN           0.0             0.0       18.0      0.0      91.0

     himobpopyearp  himobpopyear2p  leftseatshp     gdppcp    ratiop  \
100            0.0             0.0          0.0   9.561348  0.142005
101            0.0             1.0          0.0  10.116246  0.160138
102            0.0             1.0          0.0  10.315545  0.193433
103            0.0             1.0          0.0  10.612608  0.192398
104            0.0             0.0          0.0  10.359108  0.192295

     topratepl1  wwihighmobaft  year3  topdum  topratenoint  topratenointl1  \
100   82.129997            1.0    NaN     1.0          91.0       82.129997
101   91.000000            1.0    NaN     1.0          91.0       91.000000
102   91.000000            1.0    NaN     1.0          92.0       91.000000
103   92.000000            1.0    NaN     1.0          92.0       92.000000
104   92.000000            1.0    NaN     1.0          91.0       92.000000

     _Idecadec_9  _Idecadec_10  _Idecadec_11  _Idecadec_12  _Idecadec_13  \
100          0.0           0.0           0.0           0.0           0.0
101          0.0           0.0           0.0           0.0           0.0
102          0.0           0.0           0.0           0.0           0.0
103          0.0           0.0           0.0           0.0           0.0
104          0.0           0.0           0.0           0.0           0.0

     _Idecadec_14  _Idecadec_15  _Idecadec_16  _Idecadec_17  _Idecadec_18  \
100           0.0           0.0           0.0           0.0           1.0
101           0.0           0.0           0.0           0.0           1.0
102           0.0           0.0           0.0           0.0           1.0
103           0.0           0.0           0.0           0.0           1.0
104           0.0           0.0           0.0           0.0           1.0

     _Idecadec_19  _Idecadec_20  _Idecadec_21  _Idecadec_22  _Idecadec_23  \
100           0.0           0.0           0.0           0.0           0.0
```

101	0.0	0.0	0.0	0.0	0.0
102	0.0	0.0	0.0	0.0	0.0
103	0.0	0.0	0.0	0.0	0.0
104	0.0	0.0	0.0	0.0	0.0

	_Iccode_20	_Iccode_200	_Iccode_210	_Iccode_220	_Iccode_230 \
100	0.0	0.0	0.0	0.0	0.0
101	0.0	0.0	0.0	0.0	0.0
102	0.0	0.0	0.0	0.0	0.0
103	0.0	0.0	0.0	0.0	0.0
104	0.0	0.0	0.0	0.0	0.0

	_Iccode_380	_Iccode_740	topitaxrate2	wwi_iihighmob3	mobpophifatwar \
100	0.0	0.0	77.0	0.0	0.009588
101	0.0	0.0	77.0	0.0	0.020978
102	0.0	0.0	77.0	0.0	0.023078
103	0.0	0.0	77.0	0.0	0.022193
104	0.0	0.0	77.0	0.0	0.000000

	mobpophifatwar2	unisuffrage	democracy	directelec	secret \
100	0.009588	0.0	1.0	1.0	1.0
101	0.020978	0.0	1.0	1.0	1.0
102	0.023078	0.0	1.0	1.0	1.0
103	0.022193	0.0	1.0	1.0	1.0
104	0.000000	0.0	1.0	1.0	1.0

	electorate75	electorate50	electorate25	noupper	leftexec2	gdppc \
100	1.0	1.0	1.0	1.0	0.0	1929.0
101	1.0	1.0	1.0	1.0	0.0	2190.0
102	1.0	1.0	1.0	1.0	0.0	2274.0
103	1.0	1.0	1.0	1.0	0.0	2368.0
104	1.0	1.0	1.0	1.0	0.0	2333.0

	rgdppc	independence	occupied	Neightopitax2	Rmilexbadjdol \
100	9561.347656	1.0	0.0	54.0	49.807739
101	10116.246090	1.0	0.0	54.0	105.901741
102	10315.544920	1.0	0.0	54.0	148.476364
103	10612.608400	1.0	0.0	54.0	152.814163
104	10359.108400	1.0	0.0	54.0	131.127624

	milexbadjdol	hdecadec	decadec_y
100	14.559000	27.0	13.0
101	33.397999	28.0	14.0
102	47.852001	28.0	14.0
103	49.621010	28.0	14.0
104	42.785999	28.0	14.0

The below code is to analyze the different values for leftexec2.

[20]:
```
pd.crosstab(post_1950["country"], post_1950["leftexec2"])
```

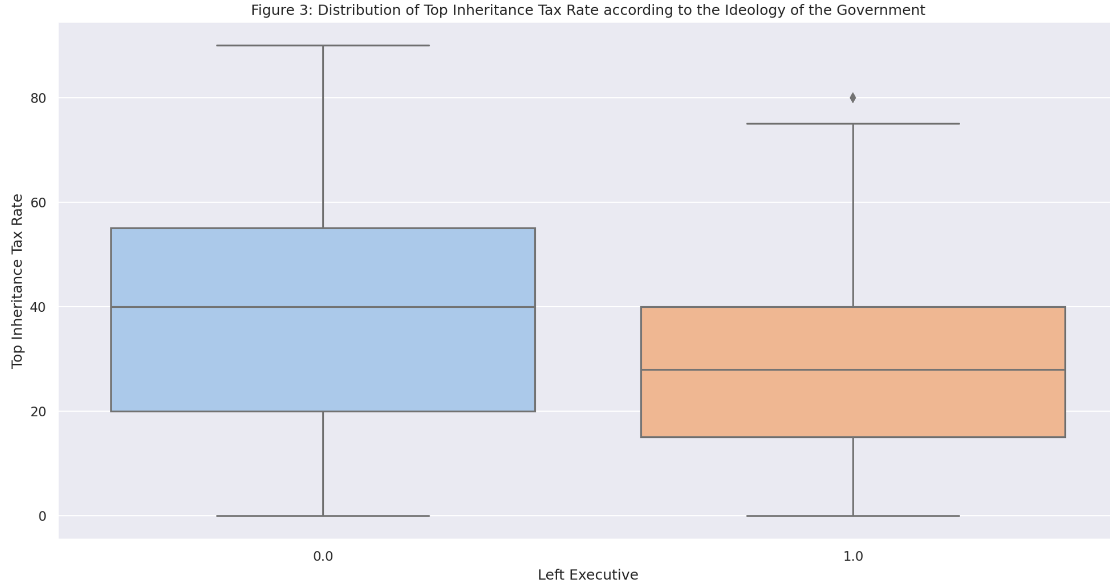
[20]:

leftexec2	0.000000	0.142857	0.285714	1.000000
country				
australia	33	0	0	18
austria	20	0	0	31
belgium	44	0	0	7
canada	51	0	0	0
denmark	15	0	0	36
finland	21	0	0	30
france	32	0	0	19
germany	34	0	0	17
ireland	51	0	0	0
italy	41	0	0	10
japan	48	0	0	3
korea	51	0	0	0
netherlands	30	0	0	21
new zealand	34	0	0	17
norway	11	0	0	40
sweden	7	0	0	44
switzerland	6	4	41	0
uk	32	0	0	19
usa	51	0	0	0

Switzerland is the only country with nonbinary values attached to leftexec2. In order to avoid any errors that might have happened during data entry and in order to make the figure below easier to read, we will remove Switzerland from our analysis.

[21]:
```
sns.boxplot(x = "leftexec2", y = "topitaxrate2", data =␣
 ↪post_1950[post_1950["country"]!="switzerland"],
            palette = "pastel")
plt.xlabel("Left Executive")
plt.ylabel("Top Inheritance Tax Rate")
plt.title("Figure 3: Distribution of Top Inheritance Tax Rate according to the␣
 ↪Ideology of the Government");
```

Figure 3: Distribution of Top Inheritance Tax Rate according to the Ideology of the Government



The box plots show that the median tax rate is 10 points lower for left-wing governments compared to right wing governments. They illustrate that in general right executives are associated with high tax rates. This finding contradicts common belief. We will further analyze it with the regression below.

In the regression below, top inheritance tax rate is our dependent variable and left executive is our main independent variable. We use war mobilization, GDP per Capita and military expenditure as control variables.

[22]:
```
smf.ols('topitaxrate2 ~ leftexec2 + himobpopyear2p + himobpopyearp + gdppc +␣
↪Rmilexbadjdol',
        data=post_1950).fit().summary()
```

[22]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:           topitaxrate2   R-squared:                       0.168
Model:                            OLS   Adj. R-squared:                  0.164
Method:                 Least Squares   F-statistic:                     40.54
Date:                Mon, 20 Dec 2021   Prob (F-statistic):           5.85e-31
Time:                        05:41:05   Log-Likelihood:                -3565.0
No. Observations:                 806   AIC:                             7140.
Df Residuals:                     801   BIC:                             7163.
Df Model:                           4
Covariance Type:            nonrobust
================================================================================
==
```

```
                     coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
--
Intercept         38.7046      0.978     39.559      0.000      36.784
40.625
leftexec2         -7.7443      1.532     -5.056      0.000     -10.751
-4.738
himobpopyear2p    14.4378      7.238      1.995      0.046       0.230
28.646
himobpopyearp   1.966e-14   8.84e-15      2.223      0.027     2.3e-15
3.7e-14
gdppc          -4.673e-08   1.96e-07     -0.239      0.811   -4.31e-07
3.37e-07
Rmilexbadjdol      0.1976      0.020     10.012      0.000       0.159
0.236
==============================================================================
Omnibus:                       55.031   Durbin-Watson:                   0.771
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               34.975
Skew:                           0.381   Prob(JB):                     2.54e-08
Kurtosis:                       2.322   Cond. No.                     8.46e+23
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.58e-32. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
"""
```

The above regression also illustrates a clear negative association between left executive and top tax rates for the period after 1950.

1.4 Step 4: Conclusion

What did you learn form this exercise? How would you extend or modify your analysis if you had more time/data available? (5-10 sentences)

When we first embarked on this analysis, we believed that the decline in high income and inheritance tax rates in the second half of 20th century would be strongly associated with the decline of leftist ideology. However, our analysis showed that, contrary to common belief, left executives were associated with lower high income tax rates.

However, we believe that our data is insufficient to actually conclude that there is a negative causation between left leaning governments and high income taxation. There is simply too many confounding variables and the dataset is limited to the same kind of countries.

As of know, our analysis doesn't contradict any of the findings in the original paper. On the contrary, it reinforces them.

However, we want to truly understand how taxation is influenced in times of no mass mobilization. Hence, if we had more time and resources we would extend our analysis to all countries. We would gather data on progressive tax rates, type of regime, ideology of government, gdp per capita, military expenditure, tax revenue per capita on all countries around the world starting from 1950 to 2020. We understand that the cold war and the existence of communist regimes might make it impossible to find this data. However, we should expand our dataset.

Finally, this exercise showed us the importance of performing qualitative research alongside quantitative research. During this post WW2 period, it would be interesting to more deeply analyze the particular moments that led to policy decisions in certain countries to cut down high income taxation. Was it due to lobbying groups? Domestic pressure? Change in political party? All of these questions can be answered substantively thorough qualitative research on certain case studies.

[ ]:

```

```