# ECOMOMIC DEVELOPMENT AND POLITICAL LIBERALIZATION

## INTRODUCTION

In the past decades, different nations around the world have witnessed instances of economic developments and political liberalizations with most of such studies pegged on economic development. There have emerged questions on whether a country being a democracy results in any form of economic growth or none, with most studies presenting a mix of results (Zhang, 2020). These developments have been attached to growth in trade and liberalization, with more concerns placed on trade openness as being important measures of economic growth. However, the assumption of a positive relation between liberalization and trade has underwent a number of criticisms among different authors. Recently, in examining the joint impacts of economic liberalizations and economic liberalizations, there were conclusions that a number of reforms were quite helpful, especially when countries open up their economies to international trade as causing significant economic growth. Countries that become democracies first before opening up their economies have realized a significant sluggishness in their economic growth measures (Adegboye et.al, 2020). This indicates that countries should undertake liberalizations of their economies before considering political liberalizations.

Economic development measures within countries of the world require sustainment over the years. Most of the developing countries have often underwent challenges from substantial volatility in growth that has a negative effect in economic growth. In this case, policy makers have been advised to consider output volatilities when determining the reform sequences from different global countries (Hummel, 2020). Furthermore, trade openness has also been discussed as aiding economic growth across countries. Nonetheless, it is associated with significant levels of volatility at the macroeconomic levels. Moreover, democratization has also presented ambiguous effects on growth with some positive impacts especially in regards to economic stability from enhanced

cohesion and creation of an enabling business environment for economic growth. Available literature in terms of growth volatility suggests the existence of trade-offs in the liberalization sequences over the years.

## Literature Review

### Economic theory

In economics, economic theory suggests that financial developments have a direct impact on economic growth metrics in the past years. The theory is also linked to political liberalizations since harmonious business environment provided by political stability is essential for business and economic growth (Li & Yao, 2020). These arguments are dated back to Schumpeter in 1912 in which services offered by financial intermediaries were quire helpful in both innovations and relevant developments over the past years. There are five main functions of the financial system across countries that influence economic growth. First, the financial systems enhance mobilization of savings for customers, ensuring that they have appropriate access to their finances across existing commercial banks (Haddad, 2020). The banks across different countries enhance development of the economy through offering savings that customers can use to access credit when in need. Secondly, financial sectors also aid in reducing risks across the economy. This is achieved through the inclusion of insurance corporations, key in terms of offering compensations in the event of any risk. Furthermore, this is also realized through most of customer savings kept within the existing financial systems to assure customers of the funds when needed.

Furthermore, the financial systems across the global economies aid in the facilitation of exchanging goods and services across clients around the world. In this case, governments aid in

creating the good-will through political stable landscapes, to ease exchange of goods and services (Khayitboy & Ilhom, 2020). In this case, the aspect of liberalization plays a critical role especially in ensuring that the individuals realize their specific economic targets, hence improving the economic prospects over the years as witnessed across both developed and developing economies around the world. Most of these provisions are quite helpful in terms of promoting checks and balances, in terms of economic milestones in comparison to the previous years. Appropriate financial systems aids in the realization of underlying functions and roles as stipulated from economic perspectives over the years.

## RESULTS AND DISCUSSION

The goal of this project is to gain a clearer intuition of the relation of distribution of wealth and perception of corruption through visualization. If the Sokoloff-Engerman hypothesis is true, then we would expect to find a correlation (though rigorously testing whether Sokoloff-Engerman hypothesis's explanation for such a correlation existing is correct is beyond the scope of this project).

The Data Used Here¶

This project uses this data set from Transparency International, and this data set from the World Bank. The former is representative of perceptions of corruption in 2017. The latter contains data about inequality observed over the course of 1974 through 2018.

This notebook was executed on kaggle.com, and a version of it will be maintained on github

Kaggle Defaults¶

In [271]:

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load in

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

```
import matplotlib.pyplot as plt
%matplotlib inline



# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory


import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))


# Any results you write to the current directory are saved as output.
/kaggle/input/corruption-index/index.csv
/kaggle/input/corruption-index/history.csv
/kaggle/input/poverty-and-equity-database/povstats-excel-zip-826-kb-/PovStatsEXCEL.xlsx
/kaggle/input/poverty-and-equity-database/povstats-csv-zip-242-kb-/PovStatsCountry.csv
/kaggle/input/poverty-and-equity-database/povstats-csv-zip-242-kb-/PovStatsFootNote.csv
/kaggle/input/poverty-and-equity-database/povstats-csv-zip-242-kb-/PovStatsCountry-Series.csv
/kaggle/input/poverty-and-equity-database/povstats-csv-zip-242-kb-/PovStatsSeries.csv
/kaggle/input/poverty-and-equity-database/povstats-csv-zip-242-kb-/PovStatsData.csv
```

The Transparency International data on corruption¶

This dataset requires very little cleaning. It contains one of the variables of interest (as well as information on measurement error) as well as country codes that can be used for data frame merges. We will do an initial bar-graph visualization of it in order to do an initial intituition check.

In [272]:

```
corruption_file = "/kaggle/input/corruption-index/index.csv"
df_corruption_index = pd.read_csv(corruption_file)
```

df_corruption_index = df_corruption_index.iloc[:,:8]

df_corruption_index.head()

Out[272]:

| | CPI Rank | Country | Country Code | Region | Corruption Perceptions Index (CPI) | Standard Error | Lower Confidence Interval | Upper Confidence Interval |
|---|---|---|---|---|---|---|---|---|
| 0 | 1 | New Zealand | NZL | Asia Pacific | 90 | 2.56 | 86 | 94 |
| 1 | 1 | Denmark | DNK | Europe and Central Asia | 90 | 2.46 | 86 | 94 |
| 2 | 3 | Finland | FIN | Europe and Central Asia | 89 | 1.46 | 87 | 92 |
| 3 | 4 | Sweden | SWE | Europe and Central Asia | 88 | 1.33 | 85 | 90 |
| 4 | 5 | Switzerland | CHE | Europe and Central Asia | 86 | 1.57 | 83 | 89 |

In [273]:

# Used documentation from https://stackabuse.com/python-data-visualization-with-matplotlib/ to

#resize the figure so we can see all the countries listed in a large horizontal bar graph

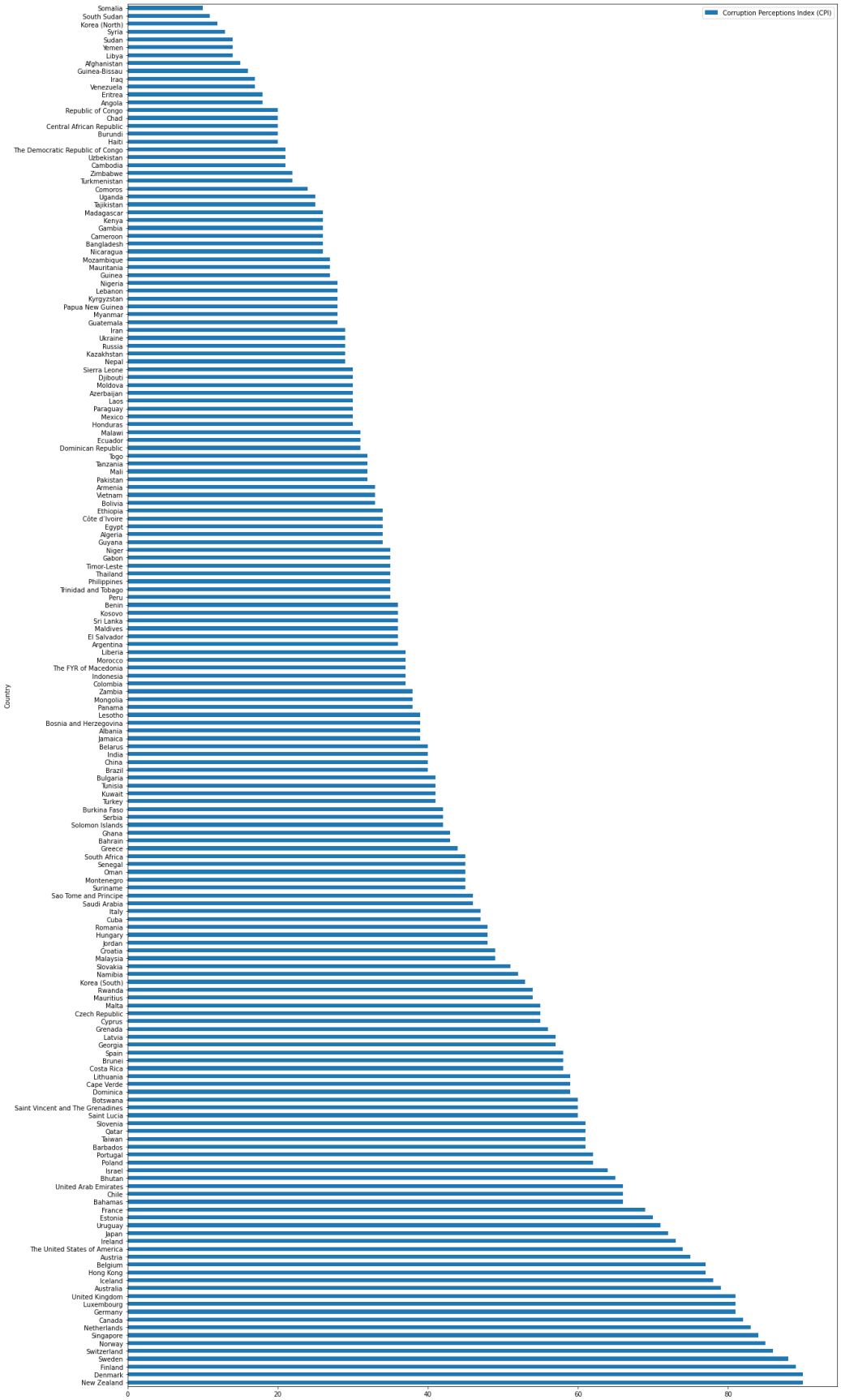
fig_size = plt.rcParams["figure.figsize"]

fig_size[0] = 20

fig_size[1] = 40

plt.rcParams["figure.figsize"] = fig_size

```
#show bar graph

ax_corruption_bar_graph = df_corruption_index.plot(x = "Country", y = "Corruption Perceptions Index (CPI)", kind = 'barh')
```


Corruption Perceptions Index (CPI)
Country
Somalia
South Sudan
Korea (North)
Syria
Sudan
Yemen
Libya
Afghanistan
Guinea-Bissau
Iraq
Venezuela
Eritrea
Angola
Republic of Congo
Chad
Central African Republic
Burundi
Haiti
The Democratic Republic of Congo
Uzbekistan
Cambodia
Zimbabwe
Turkmenistan
Comoros
Uganda
Tajikistan
Madagascar
Kenya
Gambia
Cameroon
Bangladesh
Nicaragua
Mozambique
Mauritania
Guinea
Nigeria
Lebanon
Kyrgyzstan
Papua New Guinea
Myanmar
Guatemala
Iran
Ukraine
Russia
Kazakhstan
Nepal
Sierra Leone
Djibouti
Moldova
Azerbaijan
Laos
Paraguay
Mexico
Honduras
Malawi
Ecuador
Dominican Republic
Togo
Tanzania
Mali
Pakistan
Armenia
Vietnam
Bolivia
Ethiopia
Côte d'Ivoire
Egypt
Algeria
Guyana
Niger
Gabon
Timor-Leste
Thailand
Philippines
Trinidad and Tobago
Peru
Benin
Kosovo
Sri Lanka
Maldives
El Salvador
Argentina
Liberia
Morocco
The FYR of Macedonia
Indonesia
Colombia
Zambia
Mongolia
Panama
Lesotho
Bosnia and Herzegovina
Albania
Jamaica
Belarus
India
China
Brazil
Bulgaria
Tunisia
Kuwait
Turkey
Burkina Faso
Serbia
Solomon Islands
Ghana
Bahrain
Greece
South Africa
Senegal
Oman
Montenegro
Suriname
Sao Tome and Principe
Saudi Arabia
Italy
Cuba
Romania
Hungary
Jordan
Croatia
Malaysia
Slovakia
Namibia
Korea (South)
Rwanda
Mauritius
Malta
Czech Republic
Cyprus
Grenada
Latvia
Georgia
Spain
Brunei
Costa Rica
Lithuania
Cape Verde
Dominica
Botswana
Saint Vincent and The Grenadines
Saint Lucia
Slovenia
Qatar
Taiwan
Barbados
Portugal
Poland
Israel
Bhutan
United Arab Emirates
Chile
Bahamas
France
Estonia
Uruguay
Japan
Ireland
The United States of America
Austria
Belgium
Hong Kong
Iceland
Australia
United Kingdom
Luxembourg
Germany
Canada
Netherlands
Singapore
Norway
Switzerland
Sweden
Finland
Denmark
New Zealand
0
20
40
60
80

Gut check¶

The data does not look surprising. Countries that have a reputation as developing countries score poorly, whereas countries that have a reputation as wealthy, developed liberal democracies score highly.

This bar graph helps us get an intuitive feel for what CPI as a variable looks like. It varies from 0 to 100, 0 representing being perceived as most corrupt, 100 being least corrupt (that is, it runs on the "high score = good" intuition). It also serves as a guide, as the CPI varies numerically, which countries that numerical variation actually corresponds to.

In [274]:

```
# Return the figure size to something more managable for future plotting

fig_size = plt.rcParams["figure.figsize"]

fig_size[0] = 12

fig_size[1] = 10

plt.rcParams["figure.figsize"] = fig_size
```

The World Bank's data set¶

The World Bank's dataset records various economic indicators for multiple regions and countries, with observations recorded by year. However, an observation does not exist for every indicator for every country. Furthermore, we are not necessarily interested in all the indicators in this data set. Because we are interested in seeing the relationship between corruption and inequality, we are most interested in their estimates of countries' Gini index, which is the standard measure of economic inequality. We shall therefore need to slice and clean the data frame.

In [275]:

```
poverty_stats_series_file = "/kaggle/input/poverty-and-equity-database/povstats-csv-zip-242-kb-/PovStatsSeries.csv"

poverty_stats_country_file = "/kaggle/input/poverty-and-equity-database/povstats-csv-zip-242-kb-/PovStatsCountry.csv"

poverty_stats_country_series_file = "/kaggle/input/poverty-and-equity-database/povstats-csv-zip-242-kb-/PovStatsCountry-Series.csv"


poverty_stats_data_file = "/kaggle/input/poverty-and-equity-database/povstats-csv-zip-242-kb-/PovStatsData.csv"
```

df = pd.read_csv(poverty_stats_data_file)

df.head()

Out[275]:

| | Country Name | Country Code | Indicator Name | Indicator Code | 1974 | 1975 | 1976 | 1977 | 1978 | 1979 | ... | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Unnamed: 49 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | East Asia & Pacific | EAS | Annualized growth in per capita real survey me... | SI.SPR.PC40.ZG | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 1 | East Asia & Pacific | EAS | Annualized growth in per capita real survey me... | SI.SPR.PT10.ZG | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 2 | East Asia & Pacific | EAS | Annualized growth in per capita real survey me... | SI.SPR.PT60.ZG | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 3 | East Asia & Pacific | EAS | Annualized growth in per capita real | SI.SPR.PCAP.ZG | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

| | Country Name | Country Code | Indicator Name | Indicator Code | 1974 | 1975 | 1976 | 1977 | 1978 | 1979 | ... | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Unnamed: 49 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | survey me... | | | | | | | | | | | | | | | | | | |
| 4 | East Asia & Pacific | EAS | GINI index (World Bank estimate) | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

5 rows × 50 columns

In [276]:

df_indexed = df.set_index(["Country Code", "Indicator Code"])

df_indexed

Out[276]:

| | | Country Name | Indicator Name | 1974 | 1975 | 1976 | 1977 | 1978 | 1979 | 1980 | 1981 | ... | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Unnamed: 49 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country Code | Indicator Code | | | | | | | | | | | | | | | | | | | | | |
| EAS | SI.SPR.PC40.ZG | East Asia & Pacific | Annualized growth in per capita real survey me... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | SI.SPR.PT10.ZG | East Asia & | Annualized growth in per capita | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

| | | Country Name | Indicator Name | 1974 | 1975 | 1976 | 1977 | 1978 | 1979 | 1980 | 1981 | ... | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Unnamed: 49 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country Code | Indicator Code | | | | | | | | | | | | | | | | | | | | | |
| | | Pacific | real survey me... | | | | | | | | | | | | | | | | | | | |
| | SI.SPR.PT60.ZG | East Asia & Pacific | Annualized growth in per capita real survey me... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | SI.SPR.PCAP.ZG | East Asia & Pacific | Annualized growth in per capita real survey me... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | SI.POV.GINI | East Asia & Pacific | GINI index (World Bank estimate) | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| ZWE | SI.SPR.PCAP | Zimbabwe | Survey mean consum | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

| | | Country Name | Indicator Name | 1974 | 1975 | 1976 | 1977 | 1978 | 1979 | 1980 | 1981 | ... | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Unnamed: 49 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country Code | Indicator Code | | | | | | | | | | | | | | | | | | | | | |
| | | | ption or income per capita, ... | | | | | | | | | | | | | | | | | | | |
| | SI.POV.URGP | Zimbabwe | Urban poverty gap at national poverty lines (%) | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | SI.POV.URGP.NC | Zimbabwe | Urban poverty gap at national poverty lines (%... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | SI.POV.URHC | Zimbabwe | Urban poverty headcount ratio at national pove... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | SI.POV.URHC.NC | Zimbabwe | Urban poverty headcount ratio at | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

| | | Country Name | Indicator Name | 1974 | 1975 | 1976 | 1977 | 1978 | 1979 | 1980 | 1981 | ... | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Unnamed: 49 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country Code | Indicator Code | | | | | | | | | | | | | | | | | | | | | |
| | | | national pove... | | | | | | | | | | | | | | | | | | | |

8140 rows × 48 columns

In [277]:

```
df_grouped = df.groupby("Indicator Code")

df_grouped = df_grouped.get_group("SI.POV.GINI")

df_grouped = df_grouped.set_index(["Country Code"])

df_grouped
```

Out[277]:

| | Country Name | Indicator Name | Indicator Code | 1974 | 1975 | 1976 | 1977 | 1978 | 1979 | 1980 | ... | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Unnamed: 49 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country Code | | | | | | | | | | | | | | | | | | | | | |
| EAS | East Asia & Pacific | GINI index (World Bank estimate) | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| ECS | Europe & Central Asia | GINI index (World Bank | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

| | Country Name | Indicator Name | Indicator Code | 1974 | 1975 | 1976 | 1977 | 1978 | 1979 | 1980 | ... | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Unnamed: 49 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country Code | | | | | | | | | | | | | | | | | | | | | |
| | | estimate) | | | | | | | | | | | | | | | | | | | |
| FCS | Fragile and conflict affected situations | GINI index (World Bank estimate) | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| HIC | High income | GINI index (World Bank estimate) | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| DFS | IDA countries classified as fragile situations | GINI index (World Bank estimate) | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| VNM | Vietnam | GINI index (World Bank | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | 39.3 | NaN | 35.6 | NaN | 34.8 | NaN | 35.3 | NaN | NaN | NaN |

| | Country Name | Indicator Name | Indicator Code | 1974 | 1975 | 1976 | 1977 | 1978 | 1979 | 1980 | .. | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Unnamed: 49 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country Code | | | | | | | | | | | | | | | | | | | | | |
| | | estimate) | | | | | | | | | | | | | | | | | | | |
| PSE | West Bank and Gaza | GINI index (World Bank estimate) | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | NaN | .. | 35.3 | 34.4 | NaN | NaN | NaN | NaN | 33.7 | NaN | NaN | NaN |
| YEM | Yemen, Rep. | GINI index (World Bank estimate) | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | NaN | .. | NaN | NaN | NaN | NaN | 36.7 | NaN | NaN | NaN | NaN | NaN |
| ZMB | Zambia | GINI index (World Bank estimate) | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | NaN | .. | 55.6 | NaN | NaN | NaN | NaN | 57.1 | NaN | NaN | NaN | NaN |
| ZWE | Zimbabwe | GINI index (World Bank estimate) | SI.POV.GINI | NaN | NaN | NaN | NaN | NaN | NaN | NaN | .. | NaN | 43.2 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

185 rows × 49 columns

Which number is "the" Gini index for our purposes?¶

A glance at the above data frame shows us that, as much as we would have liked to have a Gini index number for every country in the world at every year, the numbers we actually have correspond to irregular observations over the course of 1974 through to 2018. Further, as time marches on, economic, social, and political forces will be acting to change the level of inequality in any given country. The irregularity of the observations may disguise interesting trends within a country, to take one example, or patterns that represent causal forces acting on many countries at once, to take another example.

We need some way to summarize these numbers. For the sake of argument, we will assume that there is no systematic biases effecting when a country could be observed for the sake of this data set, meaning the mean of our observations should be a good estimator of the actual mean Gini index for each country over this period.

While of less intrinsic interest, we also will look at minimum observed Gini indexes and maximum observed Gini indexes. Visualizing these alongside the mean Gini indexes should give a (rough!) intuition of variance.

In [278]:

```
year_range = range(1974,2019,1)

country_codes = df_grouped.index

minimum_gini_series = pd.Series(index=country_codes, name="Minimum observed GINI index")

maximum_gini_series = pd.Series(index=country_codes, name="Maximum observed GINI index")

mean_gini_series = pd.Series(index=country_codes, name="Mean observed GINI index")

num_observations_series = pd.Series(index=country_codes, name="Number of estimations of GINI index")


for country in country_codes:


    #will be used to compute mean observed gini

    successful_gini_observations = 0

    total_gini = 0


    #conceptually, the Gini index ranges from 0 to 100, these are therefore conceptual extremes of minimum/maximum
```

```
    minimum_gini = 100
    maximum_gini = 0
    mean_gini = 0



    country_series = df_grouped.loc[country]
    for year in year_range:
        gini_this_year = country_series.loc[str(year)]
        if pd.notna(gini_this_year):
            successful_gini_observations = successful_gini_observations + 1
            total_gini = total_gini + gini_this_year
            if gini_this_year < minimum_gini:
                minimum_gini = gini_this_year
                #print(minimum_gini)
            if gini_this_year > maximum_gini:
                maximum_gini = gini_this_year
                #print(maximum_gini)

    if successful_gini_observations > 0:
        mean_gini = total_gini / successful_gini_observations

    minimum_gini_series.loc[country] = minimum_gini
    maximum_gini_series.loc[country] = maximum_gini
    mean_gini_series.loc[country] = mean_gini
    num_observations_series.loc[country] = int(successful_gini_observations)
In [279]:
#simplify the data frame now that we have summary statistics
df_grouped = df_grouped.iloc[:,:3]
```

df_grouped["Mean GINI"] = mean_gini_series

df_grouped["Min GINI"] = minimum_gini_series

df_grouped["Max GINI"] = maximum_gini_series

df_grouped["Number of observations"] = num_observations_series

df_grouped

Out[279]:

| | Country Name | Indicator Name | Indicator Code | Mean GINI | Min GINI | Max GINI | Number of observations |
|---|---|---|---|---|---|---|---|
| Country Code | | | | | | | |
| EAS | East Asia & Pacific | GINI index (World Bank estimate) | SI.POV.GINI | 0.000000 | 100.0 | 0.0 | 0.0 |
| ECS | Europe & Central Asia | GINI index (World Bank estimate) | SI.POV.GINI | 0.000000 | 100.0 | 0.0 | 0.0 |
| FCS | Fragile and conflict affected situations | GINI index (World Bank estimate) | SI.POV.GINI | 0.000000 | 100.0 | 0.0 | 0.0 |
| HIC | High income | GINI index (World Bank estimate) | SI.POV.GINI | 0.000000 | 100.0 | 0.0 | 0.0 |
| DFS | IDA countries classified as fragile situations | GINI index (World Bank estimate) | SI.POV.GINI | 0.000000 | 100.0 | 0.0 | 0.0 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| VNM | Vietnam | GINI index (World Bank estimate) | SI.POV.GINI | 36.130000 | 34.8 | 39.3 | 10.0 |
| PSE | West Bank and Gaza | GINI index (World Bank estimate) | SI.POV.GINI | 34.525000 | 33.7 | 35.6 | 8.0 |

| | Country Name | Indicator Name | Indicator Code | Mean GINI | Min GINI | Max GINI | Number of observations |
|---|---|---|---|---|---|---|---|
| Country Code | | | | | | | |
| YEM | Yemen, Rep. | GINI index (World Bank estimate) | SI.POV.GINI | 35.466667 | 34.7 | 36.7 | 3.0 |
| ZMB | Zambia | GINI index (World Bank estimate) | SI.POV.GINI | 52.688889 | 42.1 | 60.5 | 9.0 |
| ZWE | Zimbabwe | GINI index (World Bank estimate) | SI.POV.GINI | 43.200000 | 43.2 | 43.2 | 1.0 |

185 rows × 7 columns

Some further data cleaning¶

Some observed countries simply do not have an observed Gini index at any point. These are no good to us for our purposes. We remove these from the data frame.

In [280]:

#For some countries, we simply lack any helpful data about inequality. We can pick these out because Mean GINI is still 0.

```
for country in country_codes:
    row = df_grouped.loc[country]
    if row.loc["Number of observations"] == 0:
        df_grouped = df_grouped.drop([country])
df_grouped
```

Out[280]:

| | Country Name | Indicator Name | Indicator Code | Mean GINI | Min GINI | Max GINI | Number of observations |
|---|---|---|---|---|---|---|---|
| Country Code | | | | | | | |
| ALB | Albania | GINI index (World Bank estimate) | SI.POV.GINI | 29.660000 | 27.0 | 31.7 | 5.0 |
| DZA | Algeria | GINI index (World Bank estimate) | SI.POV.GINI | 34.366667 | 27.6 | 40.2 | 3.0 |
| AGO | Angola | GINI index (World Bank estimate) | SI.POV.GINI | 47.350000 | 42.7 | 52.0 | 2.0 |
| ARG | Argentina | GINI index (World Bank estimate) | SI.POV.GINI | 46.141379 | 40.6 | 53.8 | 29.0 |
| ARM | Armenia | GINI index (World Bank estimate) | SI.POV.GINI | 32.255556 | 28.0 | 37.5 | 18.0 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| VNM | Vietnam | GINI index (World Bank estimate) | SI.POV.GINI | 36.130000 | 34.8 | 39.3 | 10.0 |
| PSE | West Bank and Gaza | GINI index (World Bank estimate) | SI.POV.GINI | 34.525000 | 33.7 | 35.6 | 8.0 |
| YEM | Yemen, Rep. | GINI index (World Bank estimate) | SI.POV.GINI | 35.466667 | 34.7 | 36.7 | 3.0 |
| ZMB | Zambia | GINI index (World Bank estimate) | SI.POV.GINI | 52.688889 | 42.1 | 60.5 | 9.0 |
| ZWE | Zimbabwe | GINI index (World Bank estimate) | SI.POV.GINI | 43.200000 | 43.2 | 43.2 | 1.0 |

164 rows × 7 columns

Merging the data sets¶

'Country Code' is common to both data sets, allowing us to easily perform a merge. We do an inner merge here because that automatically excludes countries (or regions) that are only in one data set or the other. The merged data frame still contains a majority of the countries in the world.

In [281]:

```
df_merged = df_grouped.merge(right=df_corruption_index,how='inner',on='Country Code')
```

```
df_merged
```

Out[281]:

| | Country Code | Country Name | Indicator Name | Indicator Code | Mean GINI | Min GINI | Max GINI | Number of observations | CPI Rank | Country | Region | Corruption Perceptions Index (CPI) | Standard Error | Lower Confidence Interval | Upper Confidence Interval |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | ALB | Albania | GINI index (World Bank estimate) | SI.POV.GINI | 29.660000 | 27.0 | 31.7 | 5.0 | 83 | Albania | Europe and Central Asia | 39 | 1.99 | 36 | 42 |
| 1 | DZA | Algeria | GINI index (World Bank estimate) | SI.POV.GINI | 34.366667 | 27.6 | 40.2 | 3.0 | 108 | Algeria | Middle East and North Africa | 34 | 2.94 | 29 | 39 |
| 2 | AGO | Angola | GINI index (World Bank estimate) | SI.POV.GINI | 47.350000 | 42.7 | 52.0 | 2.0 | 164 | Angola | Sub-Saharan Africa | 18 | 1.68 | 15 | 21 |

| | Country Code | Country Name | Indicator Name | Indicator Code | Mean GINI | Min GINI | Max GINI | Number of observations | CPI Rank | Country | Region | Corruption Perceptions Index (CPI) | Standard Error | Lower Confidence Interval | Upper Confidence Interval |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | ARG | Argentina | GINI index (World Bank estimate) | SI.POV.GINI | 46.141379 | 40.6 | 53.8 | 29.0 | 95 | Argentina | Americas | 36 | 1.76 | 33 | 39 |
| 4 | ARM | Armenia | GINI index (World Bank estimate) | SI.POV.GINI | 32.255556 | 28.0 | 37.5 | 18.0 | 113 | Armenia | Europe and Central Asia | 33 | 4.01 | 26 | 40 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 144 | VEN | Venezuela, RB | GINI index (World Bank estimate) | SI.POV.GINI | 49.307692 | 42.5 | 55.6 | 13.0 | 166 | Venezuela | Americas | 17 | 1.41 | 15 | 20 |
| 145 | VNM | Vietnam | GINI index (World Bank estimate) | SI.POV.GINI | 36.130000 | 34.8 | 39.3 | 10.0 | 113 | Vietnam | Asia Pacific | 33 | 2.46 | 29 | 38 |
| 146 | YEM | Yemen, Rep. | GINI index (World | SI.POV.GINI | 35.466667 | 34.7 | 36.7 | 3.0 | 170 | Yemen | Middle East and | 14 | 3.05 | 9 | 19 |

| | Country Code | Country Name | Indicator Name | Indicator Code | Mean GINI | Min GINI | Max GINI | Number of observations | CPI Rank | Country | Region | Corruption Perceptions Index (CPI) | Standard Error | Lower Confidence Interval | Upper Confidence Interval |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Bank estimate) | | | | | | | | North Africa | | | | |
| 147 | ZMB | Zambia | GINI index (World Bank estimate) | SI.POV.GINI | 52.688889 | 42.1 | 60.5 | 9.0 | 87 | Zambia | Sub-Saharan Africa | 38 | 2.91 | 34 | 43 |
| 148 | ZWE | Zimbabwe | GINI index (World Bank estimate) | SI.POV.GINI | 43.200000 | 43.2 | 43.2 | 1.0 | 154 | Zimbabwe | Sub-Saharan Africa | 22 | 2.59 | 18 | 26 |

149 rows × 15 columns

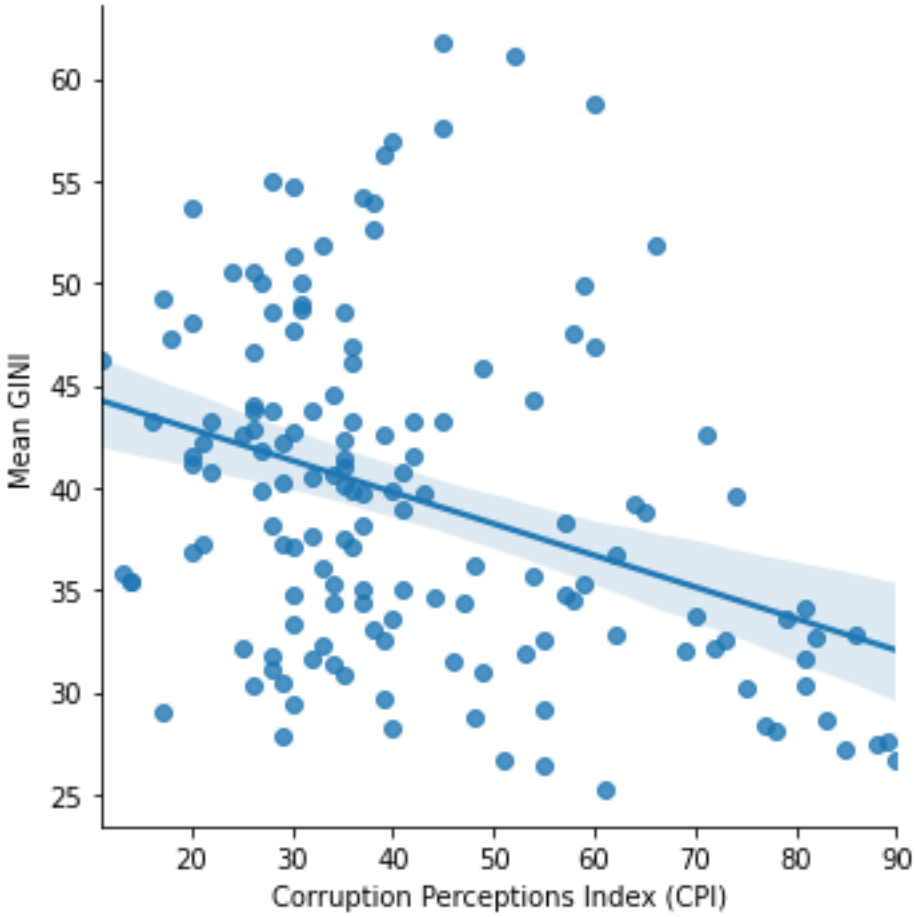
Linear Regressions and Visualizations¶

In [282]:

```
import seaborn as sns
from sklearn import linear_model

linear_regressor = LinearRegression()

x_corruption = df_merged["Corruption Perceptions Index (CPI)"]
y_gini = df_merged["Mean GINI"]

sns.lmplot(data = df_merged, x = "Corruption Perceptions Index (CPI)", y = "Mean GINI")
```

Out[282]:

<seaborn.axisgrid.FacetGrid at 0x7f671308eac8>

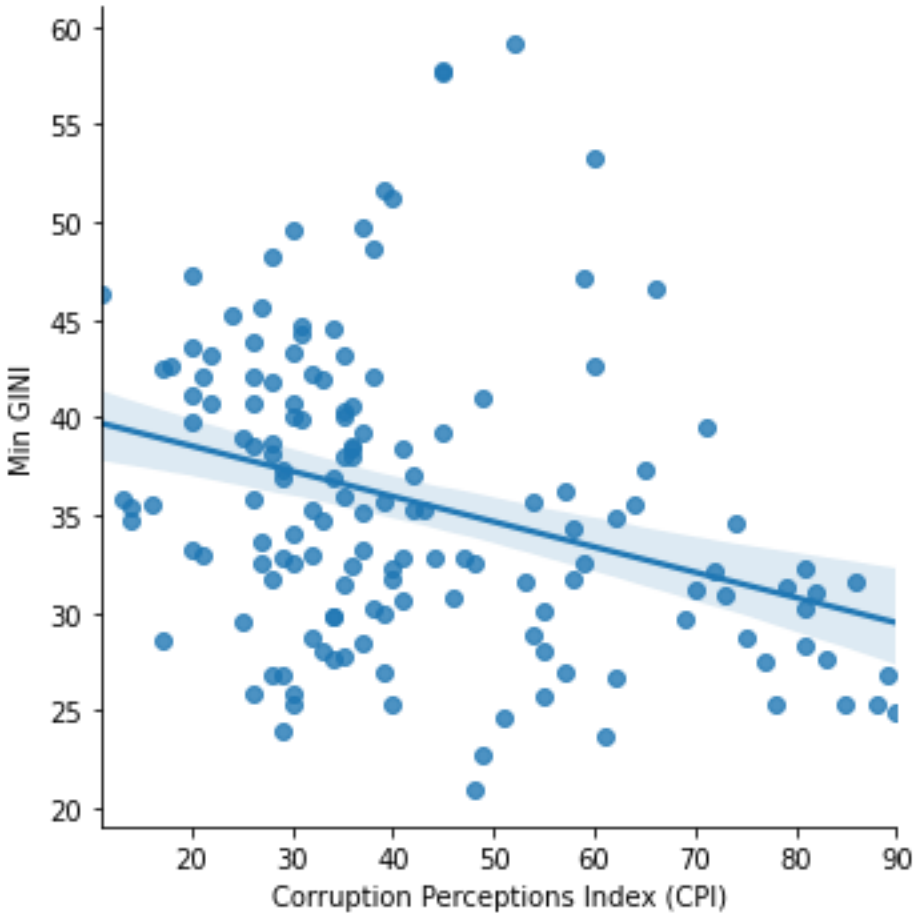



In [283]:

sns.lmplot(data = df_merged, x = "Corruption Perceptions Index (CPI)", y = "Min GINI")

Out[283]:

<seaborn.axisgrid.FacetGrid at 0x7f671304d908>

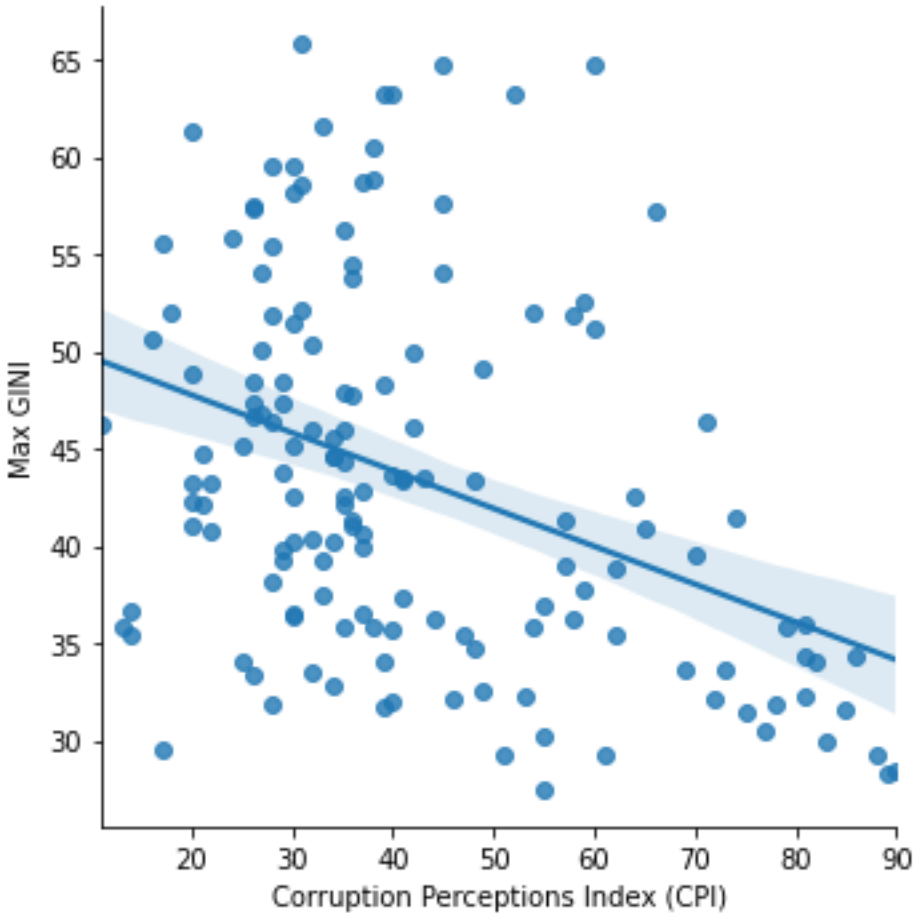



In [284]:

```
sns.lmplot(data = df_merged, x = "Corruption Perceptions Index (CPI)", y = "Max GINI")
```

Out[284]:

<seaborn.axisgrid.FacetGrid at 0x7f6712f73ef0>




What do these graphs mean?¶

CONCLUSION

The Gini index is often described as ranging from a score of 0, which represents a perfectly egalitarian economy with the income or wealth of every person in the economy is exactly equal, to a score of 100, which represents an economy where all the income or wealth goes to a single person and none goes to anyone else. Thus, a lower score is indicative of a more egalitarian economy, and a higher score is indicative of a less egalitarian. The Corruption Perception Index, however, works on the "high score is good" intuition. Low scorers are perceived as corrupt, high scorers are perceived as not corrupt.

Therefore, given the empirical theories mentioned in the introduction about corruption and rent seeking causing inequality, we would predict there to be a negative relationship - which is exactly what our linear regression says we do predict. The slope (though not the intercept, obviously) is even roughly the same regardless of which representative Gini index number we use.

This is of minimum value for confirming the causal hypotheses discussed at the beginning of this report, but it is consistent with those hypotheses in such a way so as to suggest to us they are on the right track.