Summary

The dataset for this project was collected from kaggle and originates from Mendeley Data: The Impact of Covid-19 Pandemic on the Global Economy: Emphasis on Poverty Alleviation and Economic Growth. The data I investigate here consists of records on the impact of covid-19 on the global economy including 210 countries.

Main objective of the analysis is to focus on prediction. In this project, we will employ linear regression algorithms to find relationship between common GDP and human development index and total number of death. We will then choose the best candidate algorithm from preliminary results. The goal with this implementation is to construct a model that accurately predicts how the global economy of each country is affected.

Exploratory Data Analysis

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.model_selection import KFold, cross_val_predict
from sklearn.linear_model import LinearRegression, Lasso, Ridge, RidgeCV, LassoCV
from sklearn.pipeline import Pipeline

# Mute the sklearn warning about regularization
import warnings
warnings.filterwarnings('ignore', module='sklearn')

data = pd.read_csv('./raw_data.csv', sep=',')
data = data.rename(columns={'human_development_index':'hdi'})
data.head()
```

Out[1]:

	iso_code	location	date	total_cases	total_deaths	stringency_index	population	gdp_per
0	AFG	Afghanistan	2019-12-31	0.0	0.0	0.0	38928341	1
1	AFG	Afghanistan	2020-01-01	0.0	0.0	0.0	38928341	1
2	AFG	Afghanistan	2020-01-02	0.0	0.0	0.0	38928341	1
3	AFG	Afghanistan	2020-01-03	0.0	0.0	0.0	38928341	1
4	AFG	Afghanistan	2020-01-04	0.0	0.0	0.0	38928341	1

In [2]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50418 entries, 0 to 50417
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   iso_code          50418 non-null  object 
 1   location          50418 non-null  object 
 2   date              50418 non-null  object 
 3   total_cases       47324 non-null  float64
 4   total_deaths      39228 non-null  float64
 5   stringency_index  43292 non-null  float64
 6   population        50418 non-null  int64  
 7   gdp_per_capita    44706 non-null  float64
 8   hdi               44216 non-null  float64
 9   Unnamed: 9        50418 non-null  object 
 10  Unnamed: 10       50418 non-null  object 
 11  Unnamed: 11       50418 non-null  object 
 12  Unnamed: 12       50418 non-null  float64
 13  Unnamed: 13       50418 non-null  object 
dtypes: float64(6), int64(1), object(7)
memory usage: 5.4+ MB
```

In [3]:

```
print('The total number of records: '+str(len(data.index)))
print('Column names: '+str(data.columns.tolist()))
print('Number of countries: '+str(len(data['location'].unique())))
print('Number of missing values: \n' + str(data.isnull().sum()))
```

```
The total number of records: 50418
Column names: ['iso_code', 'location', 'date', 'total_cases', 'total_deaths', 'st
ringency_index', 'population', 'gdp_per_capita', 'hdi', 'Unnamed: 9', 'Unnamed: 1
0', 'Unnamed: 11', 'Unnamed: 12', 'Unnamed: 13']
Number of countries: 210
Number of missing values: 
iso_code                0
location                0
date                    0
total_cases          3094
total_deaths        11190
stringency_index     7126
population              0
gdp_per_capita       5712
hdi                  6202
Unnamed: 9              0
Unnamed: 10             0
Unnamed: 11             0
Unnamed: 12             0
Unnamed: 13             0
dtype: int64
```

Featureset Exploration

iso_code: country code

location: name of the country

date

total_cases: number of COVID19 cases

total_deaths

stringency_index: The Stringency Index provides a computable parameter to evaluate the effectiveness of the nationwide lockdown. It is used by the Oxford COVID-19 Government Response Tracker with a database of 17 indicators of government response such as school and workplace closings, public events, public transport, stay-at-home policies. The Stringency Index is a number from 0 to 100 that reflects these indicators. A higher index score indicates a higher level of stringency.

population

gdp_per_capita: A country's GDP or gross domestic product is calculated by taking into account the monetary worth of a nation's goods and services after a certain period of time, usually one year. It's a measure of economic activity.

hdi: The HDI was created to emphasize that people and their capabilities should be the ultimate criteria for assessing the development of a country, not economic growth alone. The Human Development Index (HDI) is a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and have a decent standard of living. The HDI is the geometric mean of normalized indices for each of the three dimensions.

Preparing the Data

The following columns contain missing values: total_cases, total_deaths, stringency_index, population, gdp_per_capita, hdi. I decided to drop the rows with missing data as we would still have enough data(31518) to train our models.

In [4]:
```
#drop the irrelevant columns
data = data.drop(['iso_code', 'Unnamed: 9', 'Unnamed: 10', 'Unnamed: 11', 'Unname
```

In [5]:
```
data = data.dropna(axis = 0)
data.isnull().sum()
```

Out[5]:
```
location            0
date                0
total_cases         0
total_deaths        0
stringency_index    0
population          0
gdp_per_capita      0
hdi                 0
dtype: int64
```

In [6]:
```
len(data)
```

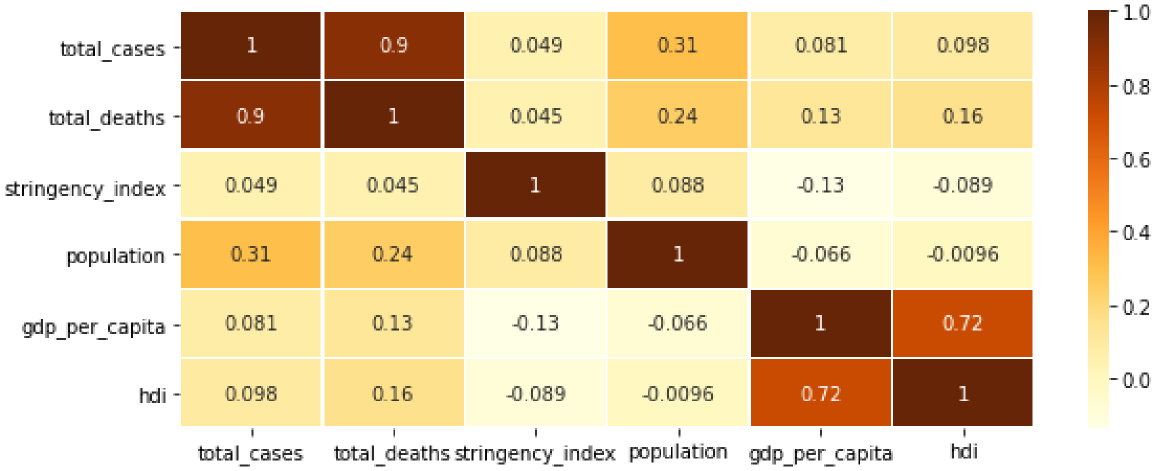
Out[6]:
```
31518
```

Let's look at the correlation coefficient. A coefficient close to 1 means that there’s a very strong positive correlation between the two variables. The diagonal line is the correlation of the variables to themselves, that's why they are 1.

In our case we can quickly see that: The Human Development Index (HDI) is strongly correlated to the GDP per Capita and total number case to deaths. The population also has a strong correlation to the number of total cases and deaths. This is what we expected. A high population will have a higher number of cases and deaths. What we are looking for is the relationship between GDP per capita(or HDI) and total number of cases or deaths.

In [7]:
```
corr = data.corr(method='pearson')
fig = plt.subplots(figsize = (10, 4))
sns.heatmap(corr,
            xticklabels=corr.columns,
            yticklabels=corr.columns,
            cmap='YlOrBr',
            annot=True,
            linewidth=0.5)
```

Out[7]:
```
<AxesSubplot:>
```

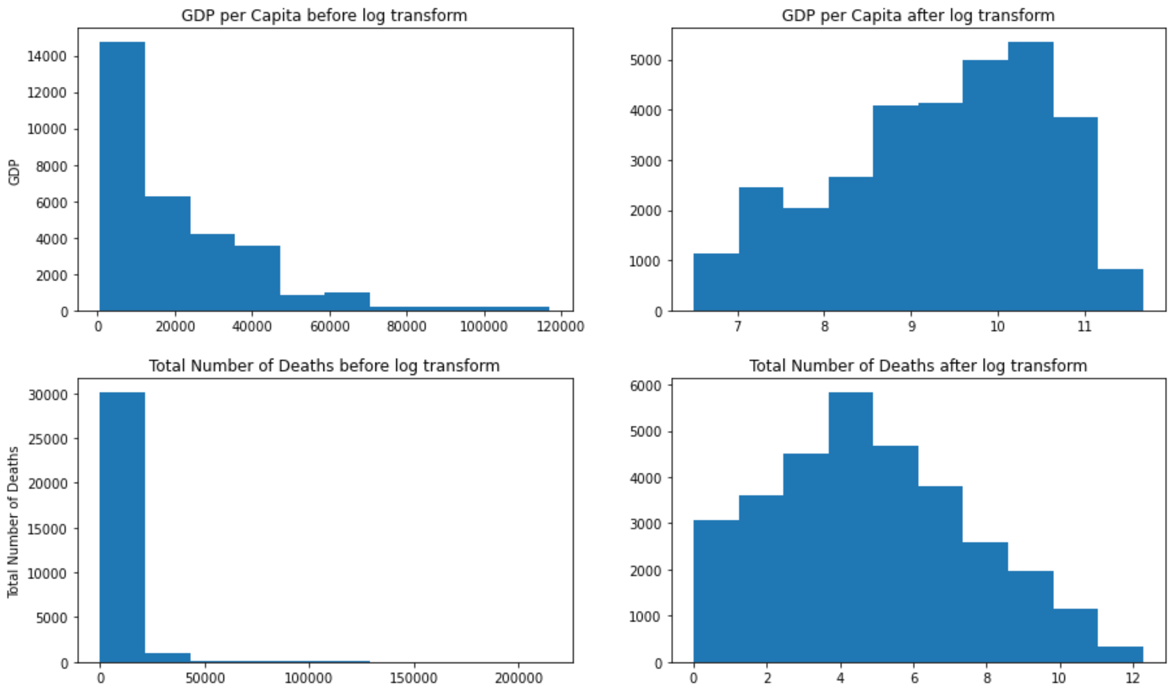


From the heatmap it seems that **GDP** and **HDI** are both more affected by the number of deaths than the number of cases.

In [8]:
```
# Log-transform the skewed features
gdp_transformed = data['gdp_per_capita'].apply(lambda x: np.log(x + 1))
total_deaths_transformed = data['total_deaths'].apply(lambda x: np.log(x + 1))
```

In [9]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (15, 4))

ax1.hist(data['gdp_per_capita'])
ax2.hist(gdp_transformed)
ax1.set_title("GDP per Capita before log transform")
ax2.set_title("GDP per Capita after log transform")
ax1.set_ylabel("GDP")

fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (15, 4))

ax1.hist(data['total_deaths'])
ax2.hist(total_deaths_transformed)
ax1.set_title("Total Number of Deaths before log transform")
ax2.set_title("Total Number of Deaths after log transform")
ax1.set_ylabel("Total Number of Deaths")
```

Out[9]:
```
Text(0, 0.5, 'Total Number of Deaths')
```



In [10]:
```python
data['gdp_per_capita'] = gdp_transformed
data['total_deaths'] = total_deaths_transformed
data.head()
```

Out[10]:

	location	date	total_cases	total_deaths	stringency_index	population	gdp_per_capita	
0	Afghanistan	2019-12-31	0.0	0.0	0.0	38928341	7.498309	0
1	Afghanistan	2020-01-01	0.0	0.0	0.0	38928341	7.498309	0
2	Afghanistan	2020-01-02	0.0	0.0	0.0	38928341	7.498309	0
3	Afghanistan	2020-01-03	0.0	0.0	0.0	38928341	7.498309	0
4	Afghanistan	2020-01-04	0.0	0.0	0.0	38928341	7.498309	0

Apply scaler to normalise data. This ensures that each feature is treated equally when applying supervised learners.

In [11]:
```python
scaler = MinMaxScaler()
numerical = ['total_deaths', 'gdp_per_capita']
features_log_minmax_transform = pd.DataFrame(data = data)
features_log_minmax_transform[numerical] = scaler.fit_transform(data[numerical])
features_log_minmax_transform
```

Out[11]:

	location	date	total_cases	total_deaths	stringency_index	population	gdp_per_capi
0	Afghanistan	2019-12-31	0.0	0.000000	0.00	38928341	0.1938
1	Afghanistan	2020-01-01	0.0	0.000000	0.00	38928341	0.1938

	location	date	total_cases	total_deaths	stringency_index	population	gdp_per_capit
2	Afghanistan	2020-01-02	0.0	0.000000	0.00	38928341	0.1938(
3	Afghanistan	2020-01-03	0.0	0.000000	0.00	38928341	0.1938(
4	Afghanistan	2020-01-04	0.0	0.000000	0.00	38928341	0.1938(
...	...	...	...	...	...	...	
50413	Zimbabwe	2020-10-15	8055.0	0.443642	76.85	14862927	0.2037(
50414	Zimbabwe	2020-10-16	8075.0	0.443642	76.85	14862927	0.2037(
50415	Zimbabwe	2020-10-17	8099.0	0.443642	76.85	14862927	0.2037(
50416	Zimbabwe	2020-10-18	8110.0	0.443642	76.85	14862927	0.2037(
50417	Zimbabwe	2020-10-19	8147.0	0.443642	76.85	14862927	0.2037(

31518 rows × 8 columns

After one-hot encoding the location column I found that the model was overfitting hence I decided to drop that column as it's not necessary for the learning algorithm.

In [12]:

```
from sklearn.model_selection import train_test_split

X_data =  features_log_minmax_transform[['total_cases','total_deaths','stringency
y_data = features_log_minmax_transform['gdp_per_capita']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_data, y_data, test_size = 0

# Show the results of the split
print("Training set has {} samples.".format(X_train.shape[0]))
print("Testing set has {} samples.".format(X_test.shape[0]))
```

```
Training set has 22062 samples.
Testing set has 9456 samples.
```

Train models

- Train the following models: Vanilla Linear, Ridge, Lasso, RidgeCV, LassoCV, Elastic Net
- Compare accuracy scores
- Compare root-mean square errors
- Plot the results: prediction vs actual

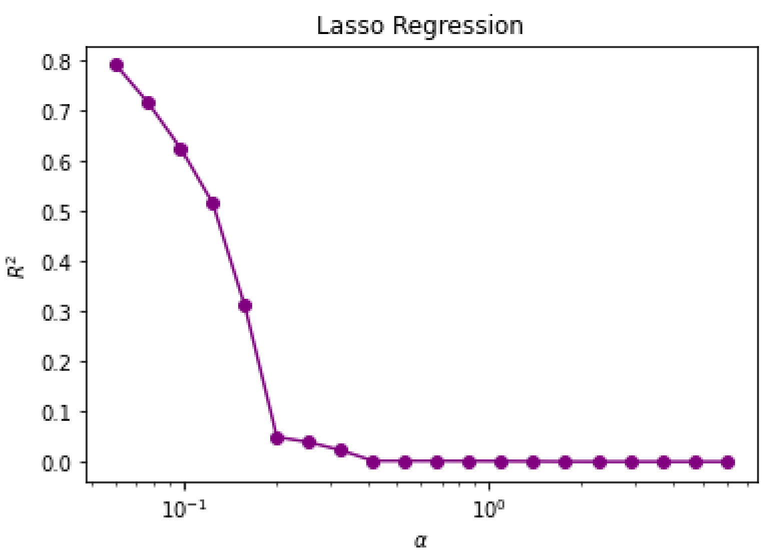
In [13]:

```
kf = KFold(shuffle=True, random_state=72018, n_splits=3)
```

In [14]:
```
# vanilla regression and K-fold cross validation
s = StandardScaler()
lr = LinearRegression()

X_train_s = s.fit_transform(X_train)
lr.fit(X_train_s, y_train)
X_test = s.transform(X_test)
y_pred = lr.predict(X_test)
score = r2_score(y_test.values, y_pred)

# with pipeline
estimator = Pipeline([("scaler", s),("regression", lr)])
predictions_lr = cross_val_predict(estimator, X_train, y_train, cv=kf)
linear_score = r2_score(y_train, predictions_lr)

linear_score, score #almost identical
```

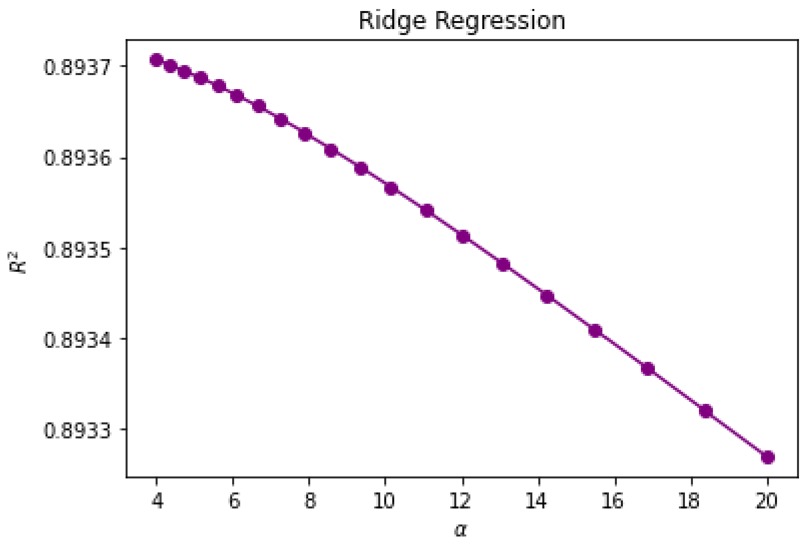
Out[14]:
```
(0.7996927742013763, 0.8002741740995301)
```

In [15]:
```
# lasso regression and K-fold cross validation
s = StandardScaler()
pf = PolynomialFeatures(degree=3)
kf = KFold(shuffle=True, random_state=72018, n_splits=3)
scores = []
alphas = np.geomspace(0.06, 6.0, 20)
predictions_lsr = []
for alpha in alphas:
    las = Lasso(alpha=alpha, max_iter=100000)

    estimator = Pipeline([
        ("scaler", s),
        ("make_higher_degree", pf),
        ("lasso_regression", las)])

    predictions_lsr = cross_val_predict(estimator, X_train, y_train, cv = kf)

    score = r2_score(y_train, predictions_lsr)

    scores.append(score)
plt.semilogx(alphas, scores, '-o', color='purple')
plt.title('Lasso Regression')
plt.xlabel('$\\alpha$')
plt.ylabel('$R^2$');
```



In [16]:
```
best_estimator = Pipeline([
                    ("scaler", s),
                    ("make_higher_degree", PolynomialFeatures(degree=2)),
                    ("lasso_regression", Lasso(alpha=0.03))])

best_estimator.fit(X_train, y_train)
lasso_score = best_estimator.score(X_train, y_train)
```

In [17]:
```
# ridge regression and K-fold cross validation
pf = PolynomialFeatures(degree=2)
alphas = np.geomspace(4, 20, 20)
scores=[]
predictions_rr = []
for alpha in alphas:
    ridge = Ridge(alpha=alpha, max_iter=100000)

    estimator = Pipeline([
        ("scaler", s),
        ("polynomial_features", pf),
        ("ridge_regression", ridge)])

    predictions_rr = cross_val_predict(estimator, X_train, y_train, cv = kf)
    score = r2_score(y_train, predictions_rr)
    scores.append(score)

plt.plot(alphas, scores, '-o', color='purple')
plt.title('Ridge Regression')
plt.xlabel('$\\alpha$')
plt.ylabel('$R^2$');
```



In [18]:
```
best_estimator = Pipeline([
                    ("scaler", s),
                    ("make_higher_degree", PolynomialFeatures(degree=2)),
                    ("ridge_regression", Ridge(alpha=0.03))])

best_estimator.fit(X_train, y_train)
ridge_score = best_estimator.score(X_train, y_train)
```

In [19]:
```
# comparing scores
pd.DataFrame([[linear_score, lasso_score, ridge_score]],columns=['linear', 'lasso
```

Out[19]:

	linear	lasso	ridge
score	0.799693	0.834543	0.893962

Conclusion: Both Lasso and Ridge with proper hyperparameter tuning give better results than plain Linear Regression!

In [20]:

```
def rmse(ytrue, ypredicted):
    return np.sqrt(mean_squared_error(ytrue, ypredicted))

# Fit a basic linear regression model
linearRegression = LinearRegression().fit(X_train, y_train)
linearRegression_rmse = rmse(y_test, linearRegression.predict(X_test))

# Fit a regular (non-cross validated) Ridge model
alphas = [0.005, 0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 80]
ridgeCV = RidgeCV(alphas=alphas, cv=4).fit(X_train, y_train)
ridgeCV_rmse = rmse(y_test, ridgeCV.predict(X_test))

# Fit a Lasso model using cross validation and determine the optimum value for α
alphas2 = np.array([1e-5, 5e-5, 0.0001, 0.0005])
lassoCV = LassoCV(alphas=alphas2,
                  max_iter=5e4,
                  cv=3).fit(X_train, y_train)
lassoCV_rmse = rmse(y_test, lassoCV.predict(X_test))

# Fit elastic net with the same set of alphas as lasso
l1_ratios = np.linspace(0.1, 0.9, 9)
elasticNetCV = ElasticNetCV(alphas=alphas2,
                            l1_ratio=l1_ratios,
                            max_iter=1e4).fit(X_train, y_train)
elasticNetCV_rmse = rmse(y_test, elasticNetCV.predict(X_test))


rmse_vals = [linearRegression_rmse, ridgeCV_rmse, lassoCV_rmse, elasticNetCV_rmse

labels = ['Linear', 'Lasso', 'Ridge' 'ElasticNet']

rmse_df = pd.DataFrame([[linearRegression_rmse, ridgeCV_rmse, lassoCV_rmse, elast
rmse_df
```

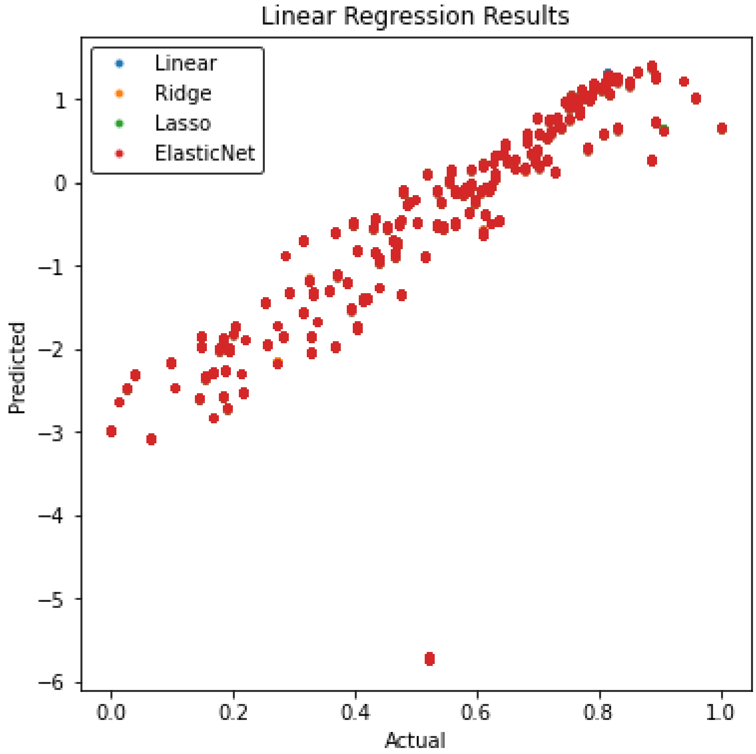
Out[20]:

	Linear	Lasso	Ridge	ElasticNet
rmse	1.397796	1.397007	1.397331	1.397227

In [21]:

```
f = plt.figure(figsize=(6,6))
ax = plt.axes()

labels, models = ['Linear', 'Ridge', 'Lasso', 'ElasticNet'], [linearRegression, r

for mod, label in zip(models, labels):
    ax.plot(y_test, mod.predict(X_test), marker='o', ls='', ms=3.0, label=label,

leg = plt.legend(frameon=True)
leg.get_frame().set_edgecolor('black')
leg.get_frame().set_linewidth(1.0)

ax.set(xlabel='Actual', ylabel='Predicted', title='Linear Regression Results')
```

```
Out[21]: [Text(0.5, 0, 'Actual'),
          Text(0, 0.5, 'Predicted'),
          Text(0.5, 1.0, 'Linear Regression Results')]
```



Conclusion 2: Lasso gives the smallest Root-mean-square error however, the difference in scores and errors are not significant and almost identical. The best candidate based on Root-mean-square error and score results is Lasso Regression, therefore we recommend LassoCV as a final model that best fits the data in terms of accuracy.

Next Steps

We could further try optimize Lasso using GridSearchCV.

To predict the effect on GDP for an individual country, we could one-hot encode the location or iso_code columns and use that for training our models. Perhaps collecting more frequent records on specific countries would help achieve more accurate results.