PCA-on-Financial-Market-in-2020

May 30, 2021

1 Abstract

The project aims for understanding correlation between global stock indices and spread of COVID-19. Is there significant correlation between certain degree of COVID-19 and market fluctuation? While it is certain that March in 2020 should showcase strong correlation, it is still controversial if it is still valid hypothesis in year-round analysis. While the year of 2020 has been one of the most interesting years to measure the impact of one macroeconomic variable on entire market, I intend to understand how market has fluctuated in 2020.

2 Literature Review

The paper `Principal Components as a Measure of Systemic Risk` written by Kritzman et al. (2010) [1] introduces how we could use Principal Component Analysis as a method to measure systemic risk. *Principal Component Analysis (PCA)* is to extract features by applying an orthogonal transformation into simpler dimensional data. It is often used to simplify complexity of high-dimensional data because it preserves almost all information with minimizing the dimensions of data as small as possible. Kritzman et al. (2010) [1] argues that Principal Component Analysis could measure systemic risk.

2.1 Systemic Risk

Systemic Risk defines a ratio of systematic risk to idiosyncratic risk. Because systematic risk describes risk that is shared by entire market, idiosyncratic risk is about specific part of market. In other words, systemic risk measures how fragile the market is. According to the paper of Kritzman et al. (2010):

> “the absorption ratio, which equals the fraction of the total variance of a set of asset returns explained or “absorbed” by a fixed number of eigenvectors. The absorption ratio captures the extent to which markets are unified or tightly coupled. When markets are tightly coupled, they are more fragile in the sense that negative shocks propagate more quickly and broadly than when markets are loosely linked."

However, in my project, I only use Principal Component Analysis up to the use that measures correlaion bewteen economic variables. `Explained variance`, or the `absorption ratio`, essentially measures degree of correlation, and it is reasonable to understand how market fluctuation is correlated with the spread of COVID-19 in 2020.

3 Import Data

3.0.1 Load Packages

In [1]:
```
# Load Packages

import yfinance as yf
import csv
import pandas as pd
import numpy as np
from datetime import date, time, timedelta
import datetime
from countryinfo import CountryInfo
from datetime import datetime, timedelta
from sklearn.decomposition import PCA
from datapackage import Package
from sklearn.cluster import KMeans

today = datetime.today()
yesterday = str(today - timedelta(2))[:10]

# Convert Date
def date_convert(dates):
    dates_return = []

    for date in dates:
        date = date.split("/")
        year = '20' + str(date[2])
        month = str(date[0])
        day = str(date[1])

        if int(month) < 10:
            month = '0' + month

        if int(day) < 10:
            day = '0' + day

        date = year + "-" + month + "-" + day
        dates_return.append(date)

    return dates_return

start = "2020-01-22"
end = "2021-01-01"

# Matplotlib
import matplotlib.pyplot as plt
pd.set_option('max_rows', 500)
```

```
pd.set_option('max_columns', 500)
np.set_printoptions(suppress=True)

%matplotlib inline
plt.rcParams["figure.figsize"] = (16, 12)
plt.style.use('seaborn-pastel')
plt.rcParams['lines.linewidth'] = 1
plt.figure(dpi=300)
plt.rcParams['lines.color'] = 'b'
plt.rcParams['axes.grid'] = True
plt.tight_layout()
```

```
<Figure size 4800x3600 with 0 Axes>
```

3.0.2 Import 40 Global Stock Indices

This part of code imports **40 Global Indices** as a representation of how global market has worked during 2020 since the outbreak of Coronavirus.

```
In [2]: # Import Market Indices
        SPY = yf.download("SPY", start, end)['Adj Close'].to_frame()
        Singapore = yf.download("^STI", start, end)['Adj Close'].to_frame()
        Dow = yf.download("^DJI", start, end)['Adj Close'].to_frame()
        Nasdaq = yf.download("^IXIC", start, end)['Adj Close'].to_frame()
        FTSE100 = yf.download("^FTSE", start, end)['Adj Close'].to_frame()
        FTSE250 = yf.download("^FTSE", start, end)['Adj Close'].to_frame()
        FTSE350 = yf.download("^FTLC", start, end)['Adj Close'].to_frame()
        FTAI = yf.download("^FTAI", start, end)['Adj Close'].to_frame()
        N225 = yf.download("^N225", start, end)['Adj Close'].to_frame()
        N500 = yf.download("^N500", start, end)['Adj Close'].to_frame()
        N1000 = yf.download("^N1000", start, end)['Adj Close'].to_frame()
        HSI = yf.download("^HSI", start, end)['Adj Close'].to_frame()
        Taiwan = yf.download("^TWII", start, end)['Adj Close'].to_frame()
        SSE = yf.download("000001.SS", start, end)['Adj Close'].to_frame()
        Shenzhen = yf.download("399001.SZ", start, end)['Adj Close'].to_frame()
        DAX = yf.download("^GDAXI", start, end)['Adj Close'].to_frame()
        France = yf.download("^FCHI", start, end)['Adj Close'].to_frame()
        Indonesia = yf.download("^JKSE", start, end)['Adj Close'].to_frame()
        PSEI = yf.download("PSEI.PS", start, end)['Adj Close'].to_frame()
        AORD = yf.download("^AORD", start, end)['Adj Close'].to_frame()
        AXJO = yf.download("^AXJO", start, end)['Adj Close'].to_frame()
        AXKO = yf.download("^AXKO", start, end)['Adj Close'].to_frame()
        kospi = yf.download("^KS11", start, end)['Adj Close'].to_frame()
        India = yf.download("^BSESN", start, end)['Adj Close'].to_frame()
        NZ50 = yf.download("^NZ50", start, end)['Adj Close'].to_frame()
        XAX = yf.download("^XAX", start, end)['Adj Close'].to_frame()
        RUI = yf.download("^RUI", start, end)['Adj Close'].to_frame()
```

```python
RUT = yf.download("^RUT", start, end)['Adj Close'].to_frame()
RUA = yf.download("^RUA", start, end)['Adj Close'].to_frame()
GSPTSE = yf.download("^GSPTSE", start, end)['Adj Close'].to_frame()
N100 = yf.download("^N100", start, end)['Adj Close'].to_frame()
N150 = yf.download("^N150", start, end)['Adj Close'].to_frame()
BFX = yf.download("^BFX", start, end)['Adj Close'].to_frame()
IMOEX = yf.download("IMOEX.ME", start, end)['Adj Close'].to_frame()
MERV = yf.download("^MERV", start, end)['Adj Close'].to_frame()
TA125 = yf.download("^TA125.TA", start, end)['Adj Close'].to_frame()
JNOU = yf.download("^JNOU.JO", start, end)['Adj Close'].to_frame()
AEX = yf.download("^AEX", start, end)['Adj Close'].to_frame()
ATOI = yf.download("^ATOI", start, end)['Adj Close'].to_frame()
BVSP = yf.download("^BVSP", start, end)['Adj Close'].to_frame()
MIB = yf.download("FTSEMIB.MI", start, end)['Adj Close'].to_frame()
ATX = yf.download("^ATX", start, end)['Adj Close'].to_frame()
ISEQ = yf.download("^ISEQ", start, end)['Adj Close'].to_frame()
NSEI = yf.download("^NSEI", start, end)['Adj Close'].to_frame()
MXX = yf.download("^MXX", start, end)['Adj Close'].to_frame()
SSMI = yf.download("^SSMI", start, end)['Adj Close'].to_frame()
STOXX50E = yf.download("^STOXX50E", start, end)['Adj Close'].to_frame()
MDAXI = yf.download("^MDAXI", start, end)['Adj Close'].to_frame()
SDAXI = yf.download("^SDAXI", start, end)['Adj Close'].to_frame()
HSCC = yf.download("^HSCC", start, end)['Adj Close'].to_frame()
HSCE = yf.download("^HSCE", start, end)['Adj Close'].to_frame()
KLSE = yf.download("^KLSE", start, end)['Adj Close'].to_frame()

# Transform into Dataframe
df = pd.concat([
    Dow,
    Nasdaq,
    FTSE100,
    FTSE250,
    FTAI,
    N225,
    SSE,
    Shenzhen,
    DAX,
    France,
    Indonesia,
    PSEI,
    AXKO,
    kospi,
    NZ50,
    RUI,
    RUT,
    RUA,
    GSPTSE,
    N100,
```

```
    N150,
    BFX,
    IMOEX,
    MERV,
    TA125,
    JNOU,
    SPY,
    Singapore,
    AEX,
    ATOI,
    BVSP,
    MIB,
    ATX,
    ISEQ,
    MXX,
    STOXX50E,
    MDAXI,
    SDAXI,
    KLSE
], axis=1)

# Set Columns
df.columns=[
    'US-Dow',
    'US-Nasdaq',
    'GB-FTSE100',
    'GB-FTSE250',
    'GB-FTAI',
    'JP-N225',
    'CN-SSE',
    'CN-Shenzhen',
    'DE-DAX',
    'FR-FCHI',
    'ID-JKSE',
    'PH-PSEI',
    'AU-AXKO',
    'KR-KSII',
    'NZ-NZ50',
    'US-RUI',
    'US-RUT',
    'US-RUA',
    'CA-GSPTSE',
    'FR-N100',
    'FR-N150',
    'BE-BFS',
    'RU-IMOEX',
    'AR-MERV',
    'IL-TA125',
```

```
    'ZA-JNOU',
    'US-SPX',
    'SG-STI',
    'NL-AEX',
    'AU-ATOI',
    'BR-BVSP',
    'IT-MIB',
    'AT-ATX',
    'IE-ISEQ',
    'MX-MXX',
    'DE-Stoxx50E',
    'DE-MDAXI',
    'DE-SDAXI',
    'MY-KLSE'
]

# Eliminate Missing Values
daily_return = df.fillna(method='ffill').fillna(method='bfill')
daily_return1 = daily_return
```

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```

3.0.3 Import COVID-19 Confirmed

```
In [3]: # COVID-19 Dataset

        states_url = "https://covidtracking.com/api/states/daily"
        us_url = "https://covidtracking.com/api/us/daily"
        case_threshold = 100

        cases = ["confirmed", "deaths", "recovered"]
        sheet = "https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_1
        suffix = "_global.csv"
        df_list = []

        url_confirmed = sheet + "confirmed" + suffix

        df_confirmed = pd.read_csv(url_confirmed, header=0, escapechar="\\")
        df_confirmed1 = df_confirmed.drop(columns=["Lat", "Long"])
        df_confirmed = df_confirmed.drop(columns=["Lat", "Long"])

        df_confirmed = df_confirmed.groupby("Country/Region").agg("sum").T
        df_confirmed1 = df_confirmed1.groupby("Province/State").agg("sum").T
```

```python
# Preprocess Data
dates = df_confirmed.index.tolist()
dates = date_convert(dates)
US = df_confirmed["US"].tolist()
China = df_confirmed["China"].tolist()
Germany = df_confirmed["Germany"].tolist()
Japan = df_confirmed["Japan"].tolist()
UK = df_confirmed["United Kingdom"].tolist()
Korea = df_confirmed["Korea, South"].tolist()
Australia = df_confirmed["Australia"].tolist()
Austria = df_confirmed["Austria"].tolist()
Denmark = df_confirmed["Denmark"].tolist()
Greece = df_confirmed["Greece"].tolist()
Finland = df_confirmed["Finland"].tolist()
Ireland = df_confirmed["Ireland"].tolist()
Italy = df_confirmed["Italy"].tolist()
SouthAfrica = df_confirmed["South Africa"].tolist()
Spain = df_confirmed["Spain"].tolist()
Singapore = df_confirmed["Singapore"].tolist()
Russia = df_confirmed["Russia"].tolist()
NewZealand = df_confirmed["New Zealand"].tolist()
Canada = df_confirmed["Canada"].tolist()
France = df_confirmed["France"].tolist()
Netherlands = df_confirmed["Netherlands"].tolist()
Mexico = df_confirmed["Mexico"].tolist()
Brazil = df_confirmed["Brazil"].tolist()
Philippines = df_confirmed["Philippines"].tolist()
India = df_confirmed["India"].tolist()
Argentina = df_confirmed["Argentina"].tolist()
Indonesia = df_confirmed["Indonesia"].tolist()
Malaysia = df_confirmed["Malaysia"].tolist()
Israel = df_confirmed["Israel"].tolist()
Poland = df_confirmed["Poland"].tolist()
Afghanistan = df_confirmed["Afghanistan"].tolist()

data = [
    US, China, Japan,
    Korea, Australia, Austria,
    Germany, UK, Denmark,
    Greece, Italy, SouthAfrica,
    Spain, Singapore, Russia,
    NewZealand, Canada, France,
    Netherlands, Mexico, Philippines,
    India, Argentina, Indonesia,
    Malaysia, Israel, Poland,
    Brazil, Spain
]
```

```
# Country Codes
country_codes = [
    "US", "CN", "JP",
    "KR", "AU", "AT",
    "DE", "GB", "DK",
    "GR", "IT", "ZA",
    "ES", "SG", "RU",
    "NZ", "CA", "FR",
    "NL", "MX", "PH",
    "IN", "AR", "ID",
    "MY", "IL", "PL",
    "BR", "ES"
]

daily_confirmed = pd.DataFrame(data, index=country_codes, columns=dates).T.diff(1).repl

for code in country_codes:
    population = CountryInfo(code).population()
    daily_confirmed[code] = daily_confirmed[code].div(population, axis=0)

daily_confirmed.index.name = 'Date'
daily_confirmed1 = daily_confirmed
```

3.1 Merge Dataframe (Daily Return + Daily Confirmed)

In [4]:
```
# List of Dates
confirmed = daily_confirmed.index.tolist()
returns = daily_return.index.tolist()

# Build a list to include dates in common
dates_common = []
for date in returns:
    date = (str(date)[:10])
    if date in confirmed:
        dates_common.append(date)

# Only leave dates in common from daily_confirmed
for date in daily_confirmed.index:
    if date not in dates_common:
        daily_confirmed = daily_confirmed.drop(date)

# Only leave dates in common from daily_return
daily_return_index = []
for var in daily_return.index.tolist():
    date = (str(var))[:10]
    if date not in dates_common:
        daily_return = daily_return.drop(var)
```

```
    else:
        daily_return_index.append(str(date))

daily_return.index = daily_return_index
daily_return.index.name = 'Date'

# Now, merge them in same index
df_merged = pd.concat([daily_return, daily_confirmed], axis=1)
```

3.2 Normalize Dataframe

Before diving into dataframe, I need to normalize data as there is too huge difference.

In [5]:
```
# apply the z-score method in Pandas using the .mean() and .std() methods
def z_score(df):
    # copy the dataframe
    df_std = df.copy()
    # apply the z-score method
    for column in df_std.columns:
        df_std[column] = (df_std[column] - df_std[column].mean()) / df_std[column].std

    return df_std

df_merged = z_score(df_merged)
df_merged.head()
```

Out[5]:
```
              US-Dow  US-Nasdaq  GB-FTSE100  GB-FTSE250   GB-FTAI   JP-N225  \
Date
2020-01-22  0.939547  -0.588920    2.638425    2.638425  0.518385  0.593683
2020-01-23  0.929251  -0.576386    2.515415    2.515415  0.475218  0.493928
2020-01-24  0.862253  -0.635046    2.665442    2.665442  0.498276  0.507350
2020-01-27  0.683732  -0.752674    2.332239    2.332239  0.383163  0.302830
2020-01-28  0.757295  -0.665344    2.463681    2.463681  0.385934  0.248790

              CN-SSE  CN-Shenzhen    DE-DAX   FR-FCHI   ID-JKSE   PH-PSEI  \
Date
2020-01-22 -0.265409    -0.852392  1.002068  1.965973  2.073910  1.793167
2020-01-23 -0.622814    -1.128935  0.899557  1.888358  2.104868  2.014524
2020-01-24 -0.622814    -1.128935  1.051121  1.992273  2.094846  2.025110
2020-01-27 -0.622814    -1.128935  0.751703  1.672941  1.876954  1.971458
2020-01-28 -0.622814    -1.128935  0.847444  1.797315  1.833683  1.793122

             AU-AXKO   KR-KSII   NZ-NZ50    US-RUI    US-RUT    US-RUA  \
Date
2020-01-22  1.908808  0.152902  0.388593  0.255018  0.742344  0.295330
2020-01-23  1.830729  0.078752  0.401234  0.265638  0.744795  0.305320
2020-01-24  1.834866  0.078752  0.375466  0.181131  0.643307  0.219231
2020-01-27  1.834866  0.078752  0.297312  0.035360  0.562714  0.078219
```

2020-01-28	1.713249	-0.164939	0.162360	0.128488	0.625843	0.169232

	CA-GSPTSE	FR-N100	FR-N150	BE-BFS	RU-IMOEX	AR-MERV	\
Date							
2020-01-22	1.214549	1.765530	1.423998	1.889892	1.350814	-0.036628	
2020-01-23	1.230693	1.670931	1.327632	1.779004	1.207118	-0.143357	
2020-01-24	1.189044	1.790602	1.342677	1.851744	1.228616	-0.294686	
2020-01-27	1.098522	1.486264	1.140706	1.557287	0.966164	-0.333466	
2020-01-28	1.141572	1.601194	1.214468	1.713230	1.086298	-0.181798	

	IL-TA125	ZA-JNOU	US-SPX	SG-STI	NL-AEX	AU-ATOI	\
Date							
2020-01-22	2.281831	1.494917	0.213724	2.563842	1.190420	1.982149	
2020-01-23	2.255830	1.293148	0.224871	2.477405	1.061627	1.902600	
2020-01-24	2.255830	1.345032	0.138341	2.501770	1.248528	1.908937	
2020-01-27	1.869836	1.012109	-0.016237	2.501770	0.911369	1.908937	
2020-01-28	1.910983	0.995726	0.083198	2.239514	1.003953	1.789394	

	BR-BVSP	IT-MIB	AT-ATX	IE-ISEQ	MX-MXX	DE-Stoxx50E	\
Date							
2020-01-22	1.543137	1.707168	2.344428	1.163883	2.083301	1.717660	
2020-01-23	1.628281	1.707612	2.246994	1.096735	2.044253	1.610125	
2020-01-24	1.542014	1.823824	2.316883	1.177827	1.942126	1.748249	
2020-01-27	1.250413	1.578536	2.176897	1.009560	1.634891	1.417481	
2020-01-28	1.399957	1.849994	2.239818	1.039594	1.812891	1.552569	

	DE-MDAXI	DE-SDAXI	MY-KLSE	US	CN	JP	\
Date							
2020-01-22	0.880938	0.445955	0.749134	-0.931591	-0.240411	-0.770413	
2020-01-23	0.781045	0.363458	0.710835	-0.931591	-0.160476	-0.770413	
2020-01-24	0.898508	0.459396	0.693202	-0.931575	-0.007338	-0.770413	
2020-01-27	0.654479	0.275284	0.693202	-0.931591	0.434408	-0.770413	
2020-01-28	0.735153	0.337657	0.464169	-0.931591	1.974205	-0.766998	

	KR	AU	AT	DE	GB	DK	\
Date							
2020-01-22	-0.678543	-0.608785	-0.569349	-0.617341	-0.698235	-0.593634	
2020-01-23	-0.678543	-0.608785	-0.569349	-0.617341	-0.698235	-0.593634	
2020-01-24	-0.674811	-0.608785	-0.569349	-0.617341	-0.698235	-0.593634	
2020-01-27	-0.674811	-0.601236	-0.569349	-0.617234	-0.698235	-0.593634	
2020-01-28	-0.678543	-0.608785	-0.569349	-0.617019	-0.698235	-0.593634	

	GR	IT	ZA	ES	SG	RU	\
Date							
2020-01-22	-0.579911	-0.622729	-0.781292	-0.776747	-0.669622	-1.062938	
2020-01-23	-0.579911	-0.622729	-0.781292	-0.776747	-0.665700	-1.062938	
2020-01-24	-0.579911	-0.622729	-0.781292	-0.776747	-0.661777	-1.062938	
2020-01-27	-0.579911	-0.622729	-0.781292	-0.776747	-0.665700	-1.062938	

```
2020-01-28 -0.579911 -0.622729 -0.781292 -0.776747 -0.661777 -1.062938

                  NZ        CA        FR        NL        MX        PH  \
Date
2020-01-22 -0.418028 -0.822006 -0.546408 -0.700558 -1.146176 -0.977223
2020-01-23 -0.418028 -0.822006 -0.546408 -0.700558 -1.146176 -0.977223
2020-01-24 -0.418028 -0.822006 -0.546266 -0.700558 -1.146176 -0.977223
2020-01-27 -0.418028 -0.822006 -0.546408 -0.700558 -1.146176 -0.977223
2020-01-28 -0.418028 -0.821540 -0.546337 -0.700558 -1.146176 -0.977223

                  IN        AR        ID        MY       IL        PL  \
Date
2020-01-22 -1.000833 -0.974345 -1.010972 -0.606623 -0.77309 -0.549867
2020-01-23 -1.000833 -0.974345 -1.010972 -0.606623 -0.77309 -0.549867
2020-01-24 -1.000833 -0.974345 -1.010972 -0.606623 -0.77309 -0.549867
2020-01-27 -1.000833 -0.974345 -1.010972 -0.606623 -0.77309 -0.549867
2020-01-28 -1.000833 -0.974345 -1.010972 -0.606623 -0.77309 -0.549867

                  BR        ES
Date
2020-01-22 -1.188057 -0.776747
2020-01-23 -1.188057 -0.776747
2020-01-24 -1.188057 -0.776747
2020-01-27 -1.188057 -0.776747
2020-01-28 -1.188057 -0.776747
```

4 Principal Component Analysis

For this, I take five principal components.

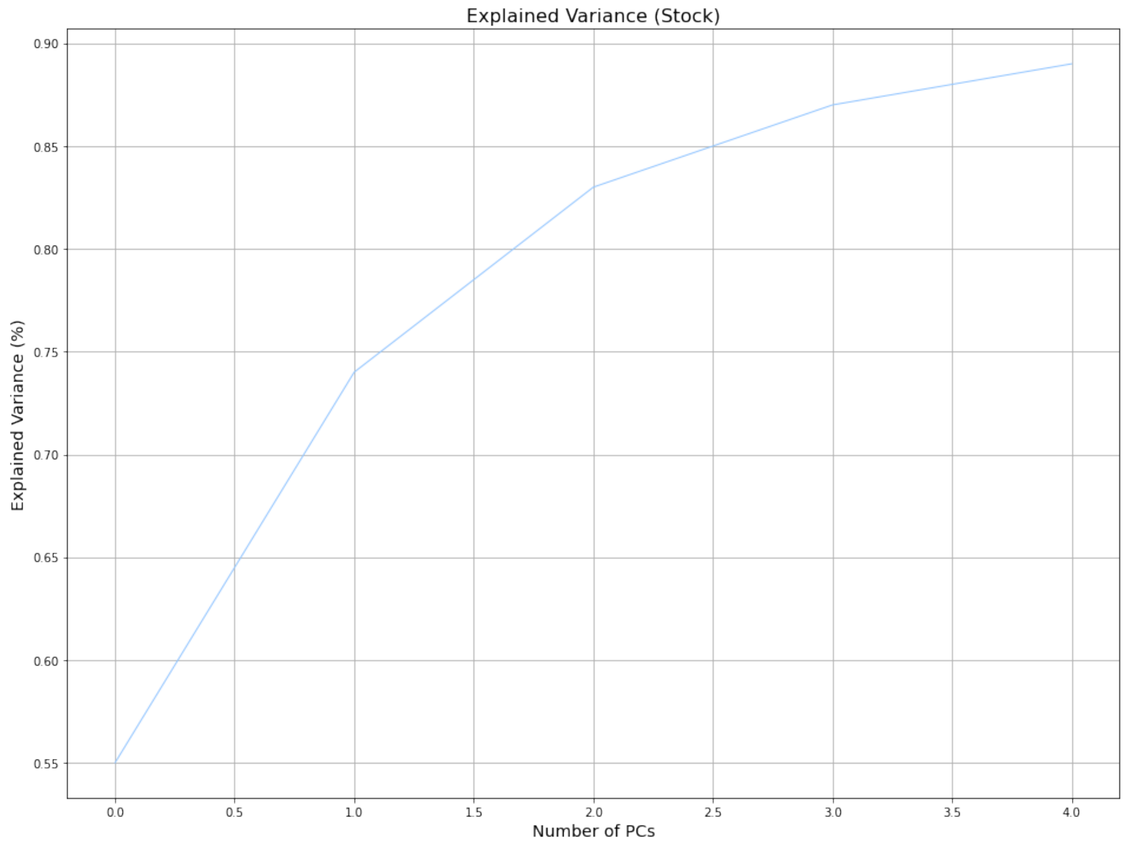
4.1 Verifying Correlation

4.1.1 Explained Variance

In [6]:
```
pca = PCA(5).fit(df_merged)
daily_return_factors = pd.Series(index=df_merged.columns, data=pca.components_[0])
print("Principal Components", pca.explained_variance_ratio_.round(2))

variance_stock = PCA(5).fit(df_merged).explained_variance_ratio_.cumsum().round(2)
plt.plot(variance_stock)
plt.title('Explained Variance (Stock)', fontsize = 16)
plt.xlabel('Number of PCs', fontsize = 14)
plt.ylabel('Explained Variance (%)', fontsize = 14)
plt.show()
```

```
Principal Components [0.55 0.19 0.08 0.04 0.02]
```



Principal Components seem to indicate approximately 55% is explained by the first principal component, whereas two principal components combinedly explain 70% of all variance. If we extend the degree of variance into five, almost 90% is explained.

4.1.2 Insights

While the major intention in this experiment is to verify how correlated market price fluctuation and global COVID confirmed rate are, it appears that it is correlated to the certain extent. However, it still appears that it does not explain reasonable amount of variance.

4.2 PCA Loadings

4.2.1 Meaning of Eigenvectors

Intuitively speaking, Principal Component Analysis is a technique to reduce dimensionality. Smaller dimension of features can be achieved by a linear combination of columns, which explain the maximum variation explained. This concept is what we used to understand `correlation` and `systemic risk` in the previous section of analysis. Each Principal Component Loading is an example of `unit vector`.

$$u := \min\left(\frac{1}{n}\sum_{i}^{n}(x_i^T x_i - (u_1^T x_i)^2)\right)$$

Principal Component Analysis aims for minimizing total distance of a unit vector whose perpendicular distance is minimized as a result. And it is the eigenvector of the covariance matrix of X.

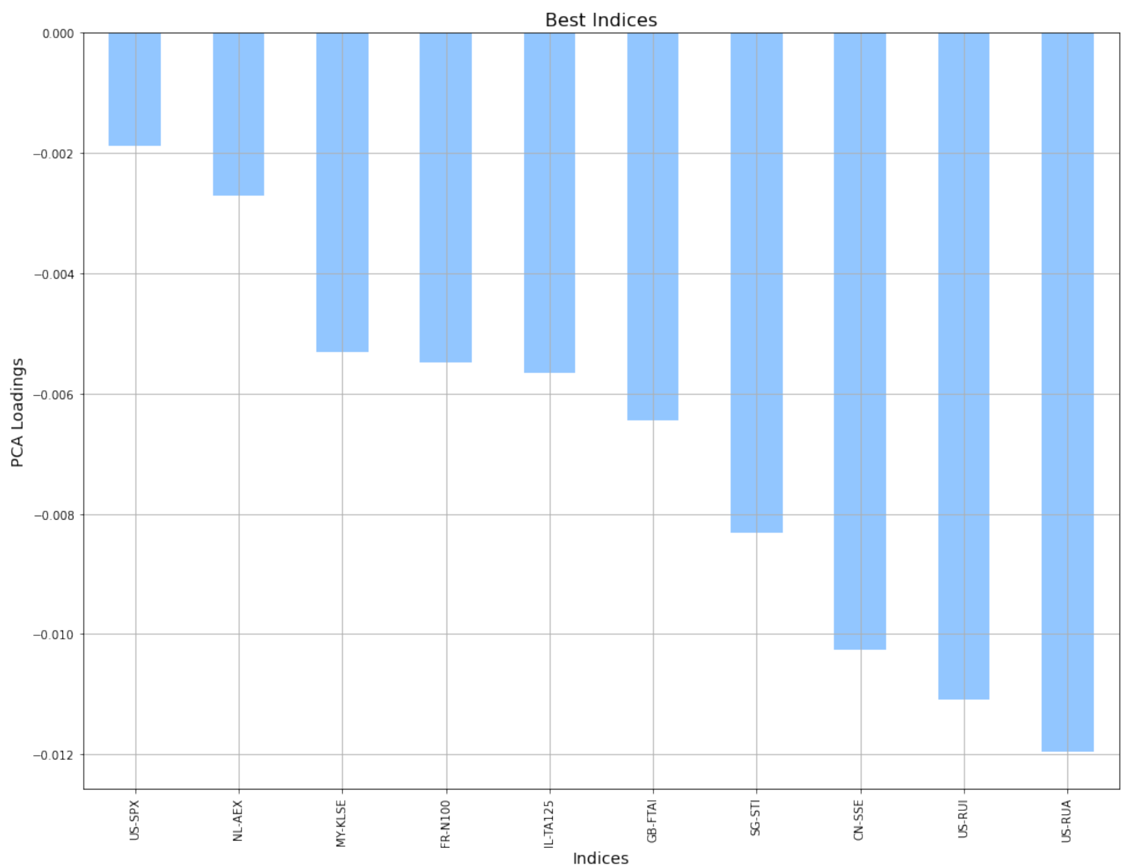
$$Av = \lambda v$$

4.2.2 PCA Loadings as "Degree of Impact"

While it is about 'degree of impact', we may verify how large each extent is.

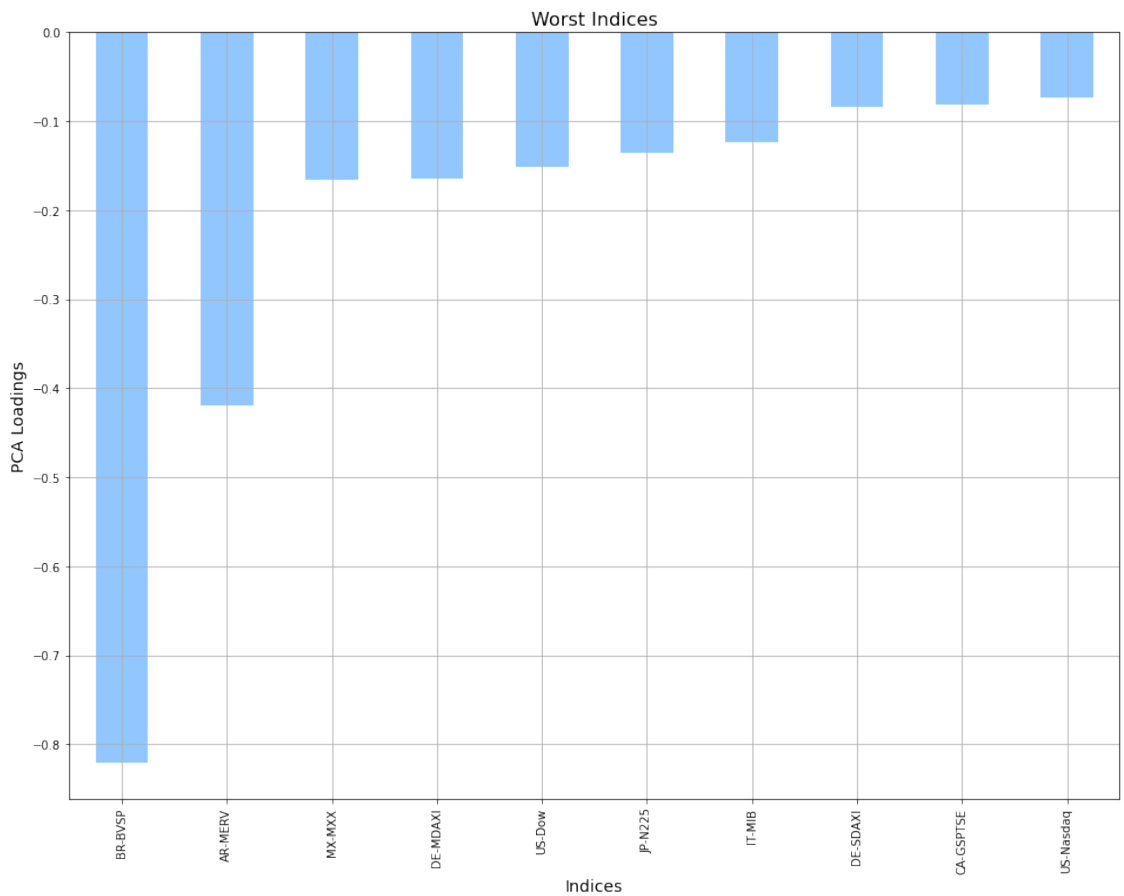
```
In [7]: pca_dr = PCA(1).fit(daily_return1)
        daily_return_factors = pd.Series(index=daily_return1.columns, data=pca_dr.components_[0

        daily_return_factors.nlargest(10).plot.bar()
        plt.title('Best Indices', fontsize=16)
        plt.xlabel('Indices', fontsize=14)
        plt.ylabel('PCA Loadings', fontsize = 14)
        plt.savefig('Best Indices.png', dpi=300)
```




```
In [8]: pca_dr = PCA(1).fit(daily_return1)
        daily_return_factors = pd.Series(index=daily_return1.columns, data=pca_dr.components_[0
```

```
daily_return_factors.nsmallest(10).plot.bar()
plt.title('Worst Indices', fontsize=16)
plt.xlabel('Indices', fontsize=14)
plt.ylabel('PCA Loadings', fontsize = 14)
plt.savefig('Best Indices.png', dpi=300)
```



5 Measuring Impact with Regressions

5.1 K-means Clustering

It is my intention to extract new insights and sources of new question. I thus implemented another machine learning algorithm, `K-means Clustering`, to cluster a range of countries. Simply put, K-Means Clustering is an algorithm to cluster data points by making `smallest distances` between data points. As a result, we are able to see how each data shares **similarity** with others. Because the experiment is based on the country-based comparison, it is a great tool to visualize and simplify our intuition.

```
In [9]: pca_covid = PCA(2).fit(daily_confirmed1)
        daily_confirmed1 = daily_confirmed1.diff(1)[1:]
```

```
daily_confirmed_factors = pd.Series(index=daily_confirmed1.columns, data=pca_covid.comp

df1 = pd.DataFrame(daily_return_factors)
df2 = pd.DataFrame(daily_confirmed_factors)

df_list = []

df1_temp = df1.T
df2_temp = df2.T

for index in df1_temp:
    nation = index.split("-")[0]
    indice = index.split("-")[1]
    factor_return = df1_temp[index]
    try:
        factor_input = df2_temp[nation]
    except:
        factor_input = df2_temp['FR'] + df2_temp['DE'] / 2

    df_list.append(
        [nation,
         indice,
         index,
         factor_input.values[0],
         factor_return.values[0]
        ]
    )

df = pd.DataFrame(
    df_list,
    columns=["Country", "Index", "Full-Name", "Confirmed", "Return"]
)

index = df.iloc[:,1].values.tolist()
df_default = df
df = df[['Confirmed', 'Return']]
df.index = index

kmeans_kwargs = {
    "init": "random",
    "n_init": 10,
    "max_iter": 300,
    "random_state": 42
}

sse = []

kmeans = KMeans(
```

```
             init="random",
             n_clusters=3,
             n_init=100,
             max_iter=300,
             random_state=42
         )

         kmeans.fit(df)

         print("The lowest SSE:", kmeans.inertia_)
         print("Final Centroids:", kmeans.cluster_centers_)
         print("Number of Iterations Required:", kmeans.n_iter_)

         a = df[kmeans.labels_== 0]
         b = df[kmeans.labels_== 1]
         c = df[kmeans.labels_== 2]

         a = a.index.values.tolist()
         b = b.index.values.tolist()
         c = c.index.values.tolist()

         groups = pd.DataFrame([a, b, c], index=['Group A', 'Group B', 'Group C'])
         groups = groups.T
```

```
The lowest SSE: 0.43867003721274683
Final Centroids: [[-0.05606432 -0.05434758]
 [-0.35523704 -0.03186833]
 [-0.14895533 -0.61949229]]
Number of Iterations Required: 3
```

5.1.1 Scatterplot

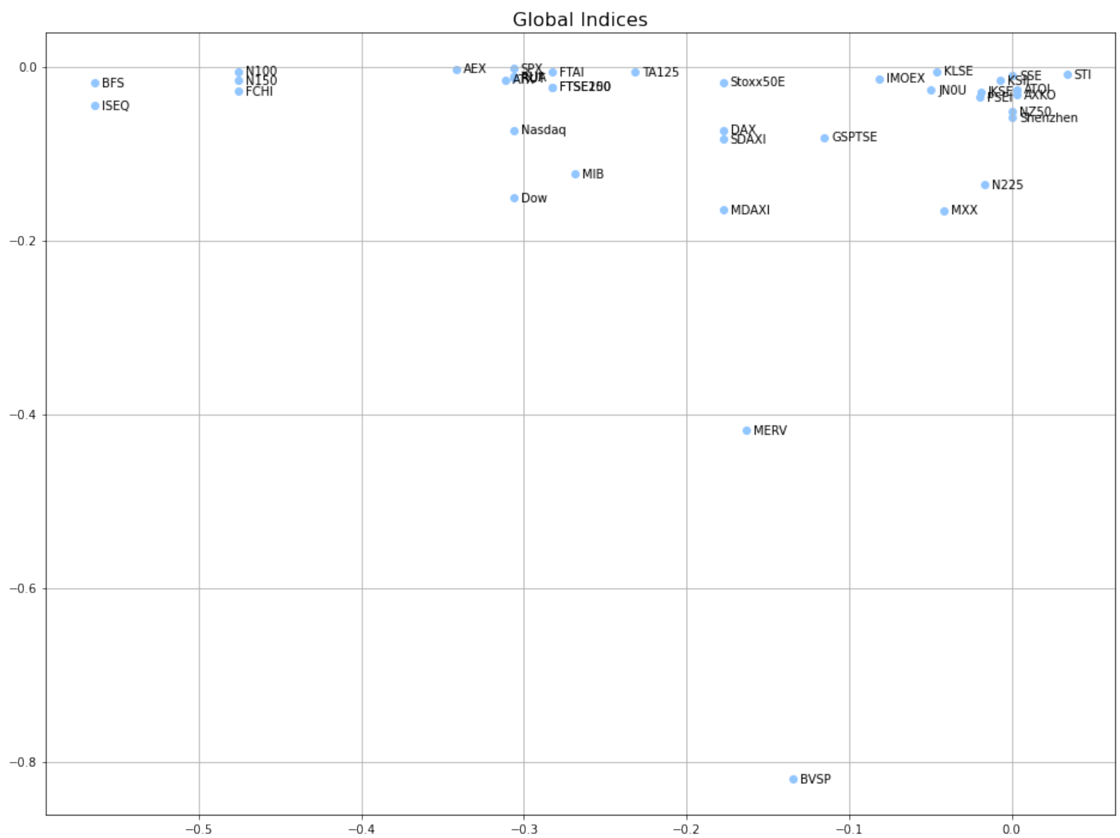
Another way to gain intuitive understanding is using scatterplot. I here visualize to complement K-means cluster technique performed above.

```
In [10]: fig = plt.scatter(df[['Confirmed']].values, df[['Return']].values)

          labels = df.index.tolist()

          for x_pos, y_pos, label in zip(df[['Confirmed']].values, df[['Return']].values, labels
              plt.annotate(label,
                           xy = (x_pos, y_pos),
                           xytext=(6,0),
                           textcoords='offset points',
                           ha='left',
                           va='center'
                          )
```

```python
plt.title("Global Indices", fontsize = 16)
plt.savefig('Scatterplot.png', dpi=300)
```



5.1.2 Three Groups

In [11]: groups

Out[11]:

	Group A	Group B	Group C
0	N225	Dow	MERV
1	SSE	Nasdaq	BVSP
2	Shenzhen	FTSE100	None
3	DAX	FTSE250	None
4	JKSE	FTAI	None
5	PSEI	FCHI	None
6	AXKO	RUI	None
7	KSII	RUT	None
8	NZ50	RUA	None
9	GSPTSE	N100	None
10	IMOEX	N150	None
11	JNOU	BFS	None

```
12        STI    TA125    None
13       ATOI      SPX    None
14        MXX      AEX    None
15   Stoxx50E      MIB    None
16      MDAXI      ATX    None
17      SDAXI     ISEQ    None
18       KLSE     None    None
```

5.2 Generalized Linear Model

Finally, I use generalized linear model, which is to have statistical regression to confirm correlation between spread of Coronavirus and trend of performance of market indices.

In [13]:
```python
import statsmodels.formula.api as smf

GLSAR = smf.glm(
    data=df,
    formula='Return~Confirmed'
    ).fit()

GLSAR.summary()
```

Out[13]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                 Return   No. Observations:                   39
Model:                            GLM   Df Residuals:                       37
Model Family:                Gaussian   Df Model:                            1
Link Function:               identity   Scale:                        0.021119
Method:                          IRLS   Log-Likelihood:                 20.911
Date:                Sun, 30 May 2021   Deviance:                      0.78139
Time:                        10:30:26   Pearson chi2:                    0.781
No. Iterations:                     3
Covariance Type:            nonrobust
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept     -0.0928      0.036     -2.580      0.010      -0.163      -0.022
Confirmed     -0.0996      0.138     -0.723      0.470      -0.370       0.170
================================================================================
"""
```

6 Conclusion

To sum up, it appears that machine learning algorithms prove that Coronavirus-19 is not the appropriate factor to generalize the fluctuation in the stock market. There are a number of factors that provide some insights; **(1) strong monetary policy and fiscal policy globally done in 2020,**

(2) the gap between real variables and nominal variables in macroeconomy, and (3) sudden euphoria arose from sudden increase in asset price from massive money supply.

7 Bibliography

[1] Kritzman, Mark and Li, Yuanzhen and Page, Sebastien and Rigobon, Roberto, Principal Components as a Measure of Systemic Risk (June 30, 2010). MIT Sloan Research Paper No. 4785-10, https://doi.org/10.3905/jpm.2011.37.4.112, Available at SSRN: https://ssrn.com/abstract=1633027 or http://dx.doi.org/10.2139/ssrn.1633027