PCA-on-Financial-Market-in-2020

May 30, 2021

1 Motivation

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 Principal Component Analysis

3.1 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>
```

3.2 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()
```

```
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',
```

```python
    '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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```

3.3 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
```

3.4 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)
```

3.5 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
```

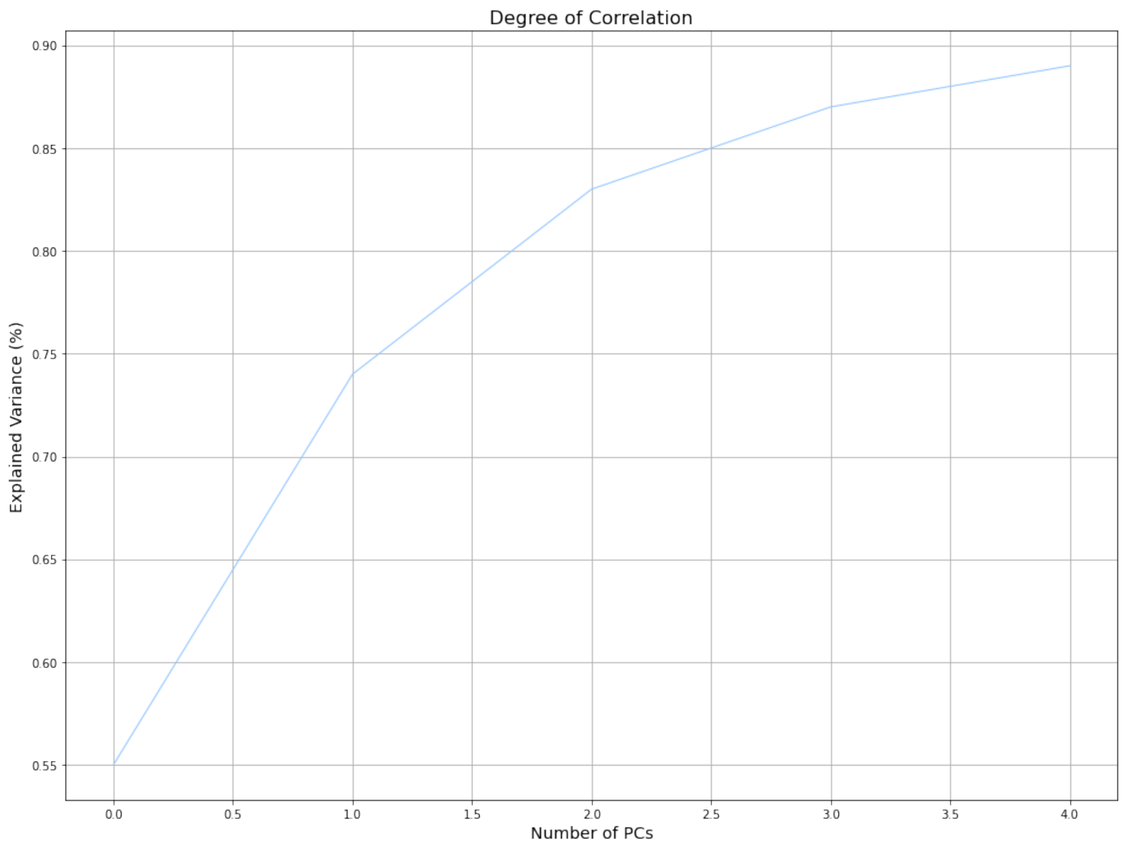
3.6 Extraction of Five Principal Components

```
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))
```

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

3.7 Visualization of Explanatory Power for Each Principal Component

```
In [7]: variance_stock = PCA(5).fit(df_merged).explained_variance_ratio_.cumsum().round(2)
        plt.plot(variance_stock)
        plt.title('Degree of Correlation', fontsize = 16)
        plt.xlabel('Number of PCs', fontsize = 14)
        plt.ylabel('Explained Variance (%)', fontsize = 14)
        plt.show()
```



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 Analysis on Eigenvectors

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.

4.1 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.

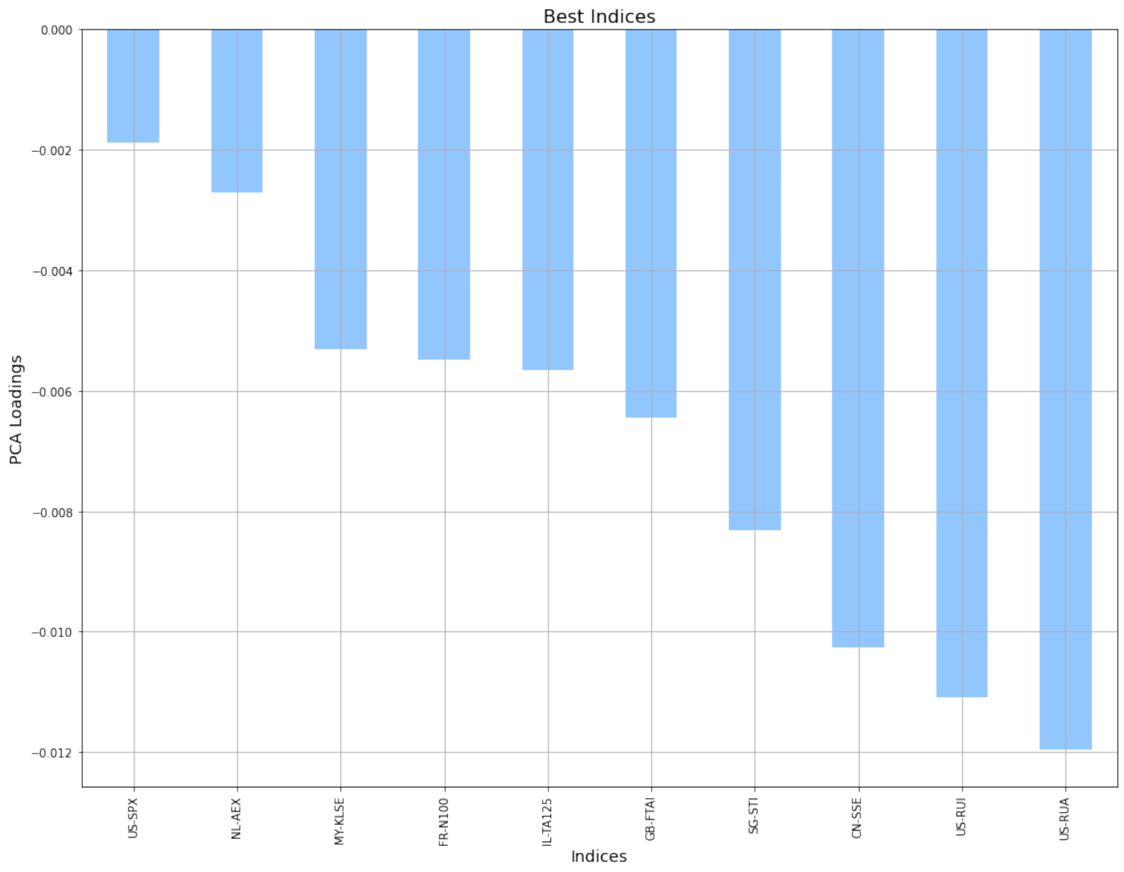
$$Av = \lambda v$$

4.2 PCA Loadings as "Degree of Impact"

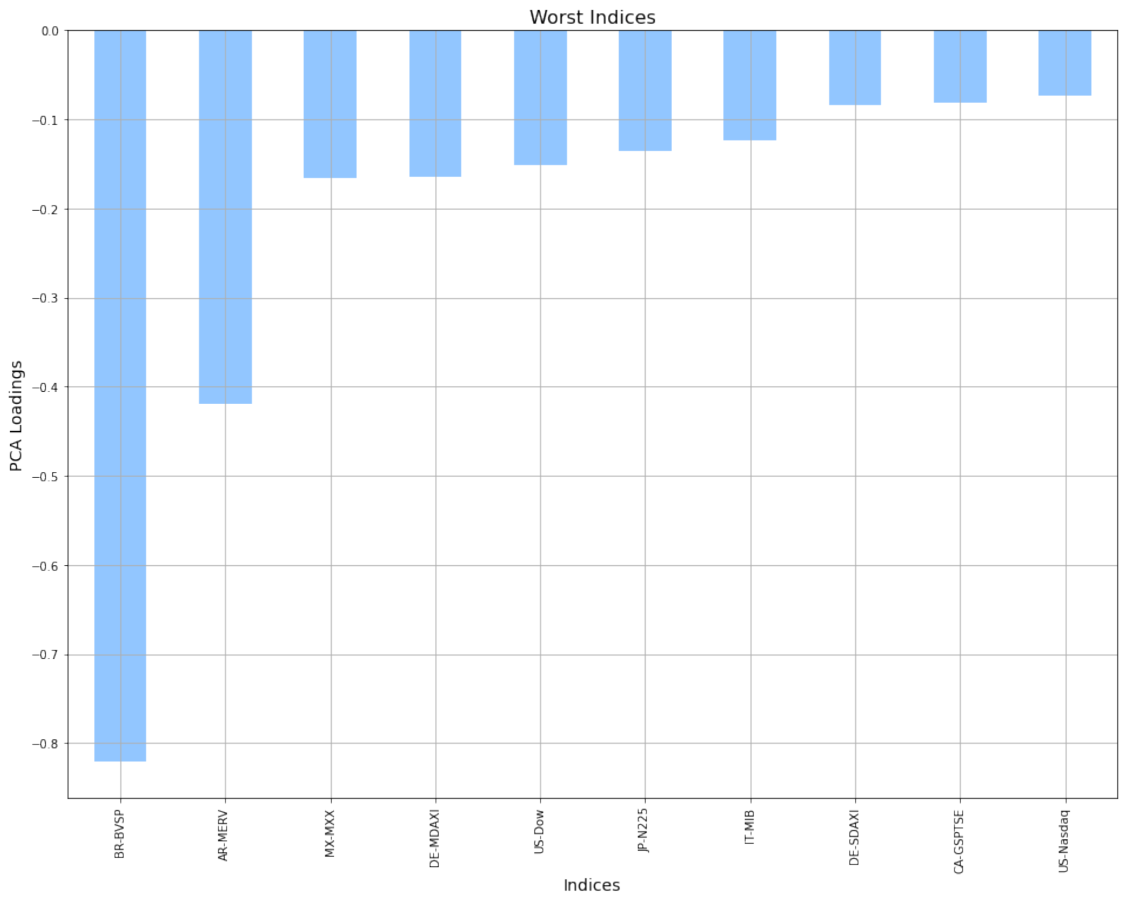
While it is about 'degree of impact', we may verify how large each extent is.

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

        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 [9]: pca_dr = PCA(1).fit(daily_return1)
        daily_return_factors = pd.Series(index=daily_return1.columns, data=pca_dr.components_[(
        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 Analysis

5.1 K-Means Clustering

```
In [10]: 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.com

         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

print("RESULTS:")

groups
```

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

```
Out[10]:      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
```

5.1.1 Visualization

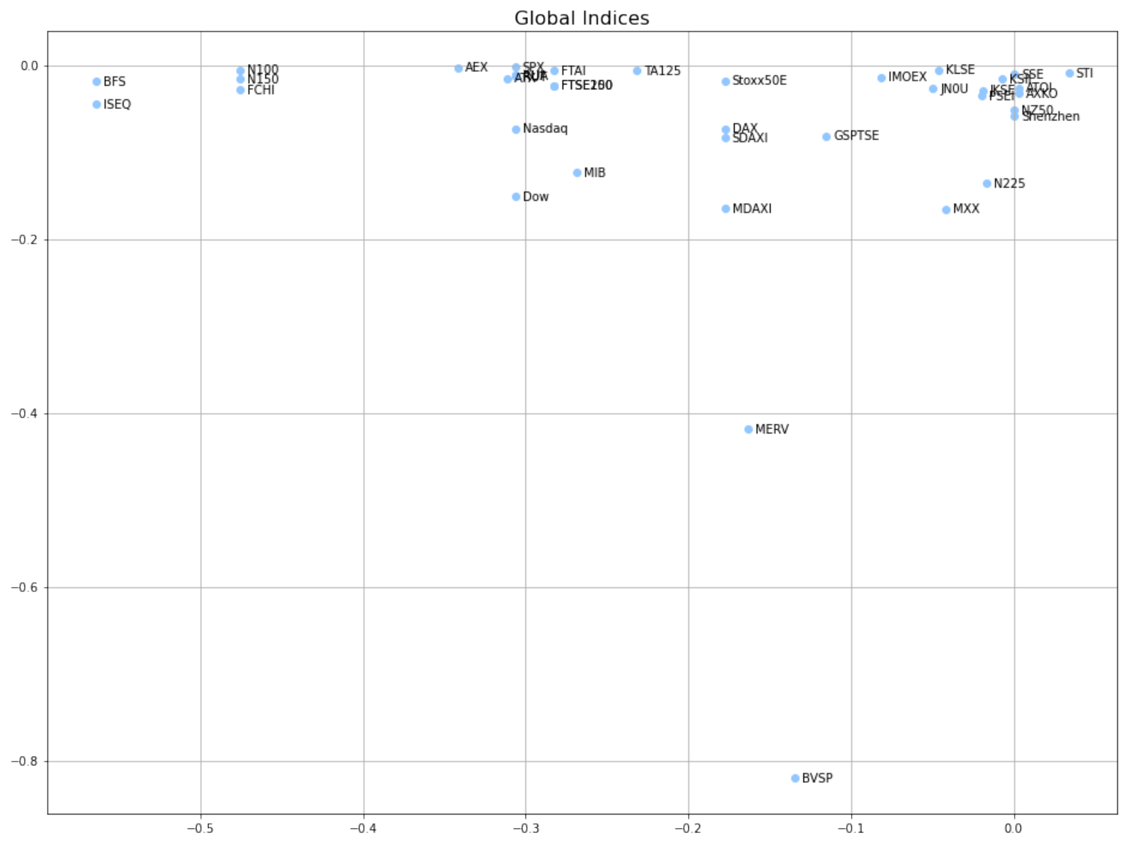
As a data scientist, I add “visualization” to let my analysis more intuitive and straightforward.

```
In [11]: 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, label
             plt.annotate(label,
                          xy = (x_pos, y_pos),
                          xytext=(6,0),
                          textcoords='offset points',
                          ha='left',
                          va='center'
                         )

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



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 [12]: import statsmodels.formula.api as smf

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

         GLSAR.summary()
```

```
Out[12]: <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:                        10:46:19   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
         ==============================================================================
         """
```

5.3 Takeaways

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**.

6 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