Worldwide Stock Market performance analysis post-covid

Import the requried packages:

- Numpy
- Pandas
- Matplotbil
- yFinance

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from pandas_datareader import data as pdr

import yfinance as yf
```

Grab the adjusted close price from: HK HengSeng, US S&P500, UK FTSE, MSCI Developed, MSCI Emerging

- Adjusted close price: the closing price after adjustments for all applicable splits and dividend distributions. It is considered as a more accurate measure of stocks' value.

Timeframe: 2020-01-01 to 2022-11-01

In [2]:
```
stock_indexes_tickers = ["^HSI","^GSPC","^FTSE","XWD.TO","XEM.TO"]

df_indices = pd.DataFrame()

startDate = "2020-01-01"
endDate = "2022-11-01"

for ticker in stock_indexes_tickers:
    df_indices[ticker] = yf.download(ticker, start=startDate, end=endDate)['Adj Close']
```

```
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
```

Examine first 5 and last 5 rows

In [3]:
```
pd.concat([df_indices.head(5), df_indices.tail(5)])
```

Out[3]:

Date	^HSI	^GSPC	^FTSE	XWD.TO	XEM.TO
2020-01-02	28543.519531	3257.850098	7604.299805	54.172573	31.749758
2020-01-03	28451.500000	3234.850098	7622.399902	53.823383	31.220911
2020-01-06	28226.189453	3246.280029	7575.299805	53.823383	31.018990

2020-01-07	28322.060547	3237.179932	7573.899902	53.891285	31.192068
2020-01-08	28087.919922	3253.050049	7574.899902	54.240471	31.384373
2022-10-25	15165.589844	3859.110107	7013.500000	62.980000	25.820000
2022-10-26	15317.669922	3830.600098	7056.100098	62.720001	26.200001
2022-10-27	15427.940430	3807.300049	7073.700195	62.360001	25.959999
2022-10-28	14863.059570	3901.060059	7047.700195	63.689999	25.830000
2022-10-31	14687.019531	3871.979980	7094.500000	63.270000	25.840000

use the describe() function to find out some descriptive statistics

In [4]:
```
df_indices.describe()
```

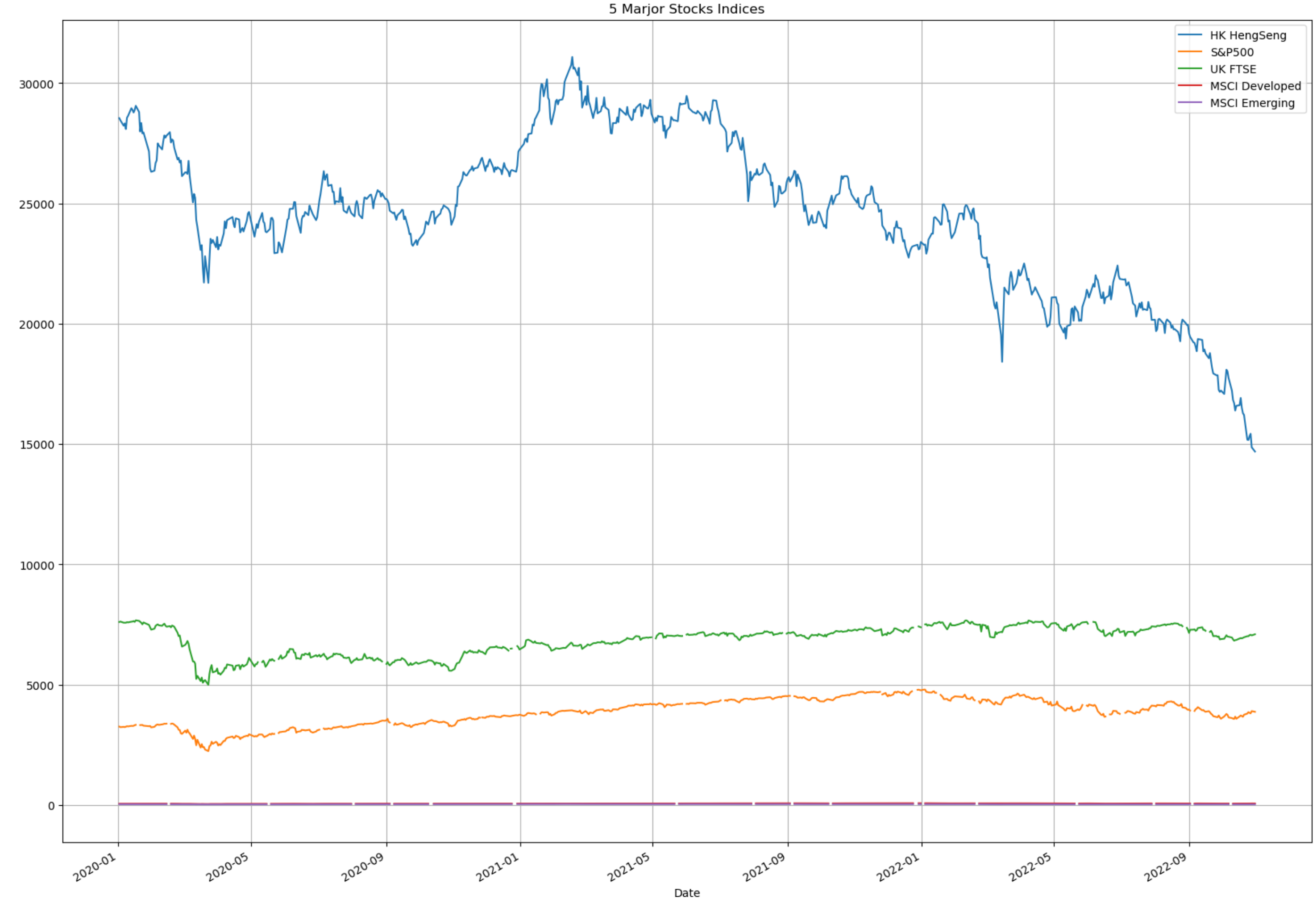
Out[4]:

	^HSI	^GSPC	^FTSE	XWD.TO	XEM.TO
count	699.000000	681.000000	686.000000	682.000000	682.000000
mean	24614.741845	3857.281779	6845.001599	61.420312	32.265581
std	3232.786402	566.385880	598.359129	6.835649	3.539848
min	14687.019531	2237.399902	4993.899902	41.107136	23.797894
25%	22904.405273	3383.540039	6382.974976	55.839919	29.136815
50%	24763.769531	3910.520020	7029.500000	61.900570	32.031298
75%	26782.679688	4349.930176	7299.649902	67.252106	35.111878
max	31084.939453	4796.560059	7674.600098	74.289253	39.841946

The row counts are roughly the same, because the trading days differs in each stock market throughout the year. Conventionally, we would usually consider 251 trading days per year.

Next, I will try to plot a line chart to get a visual representation of the data.

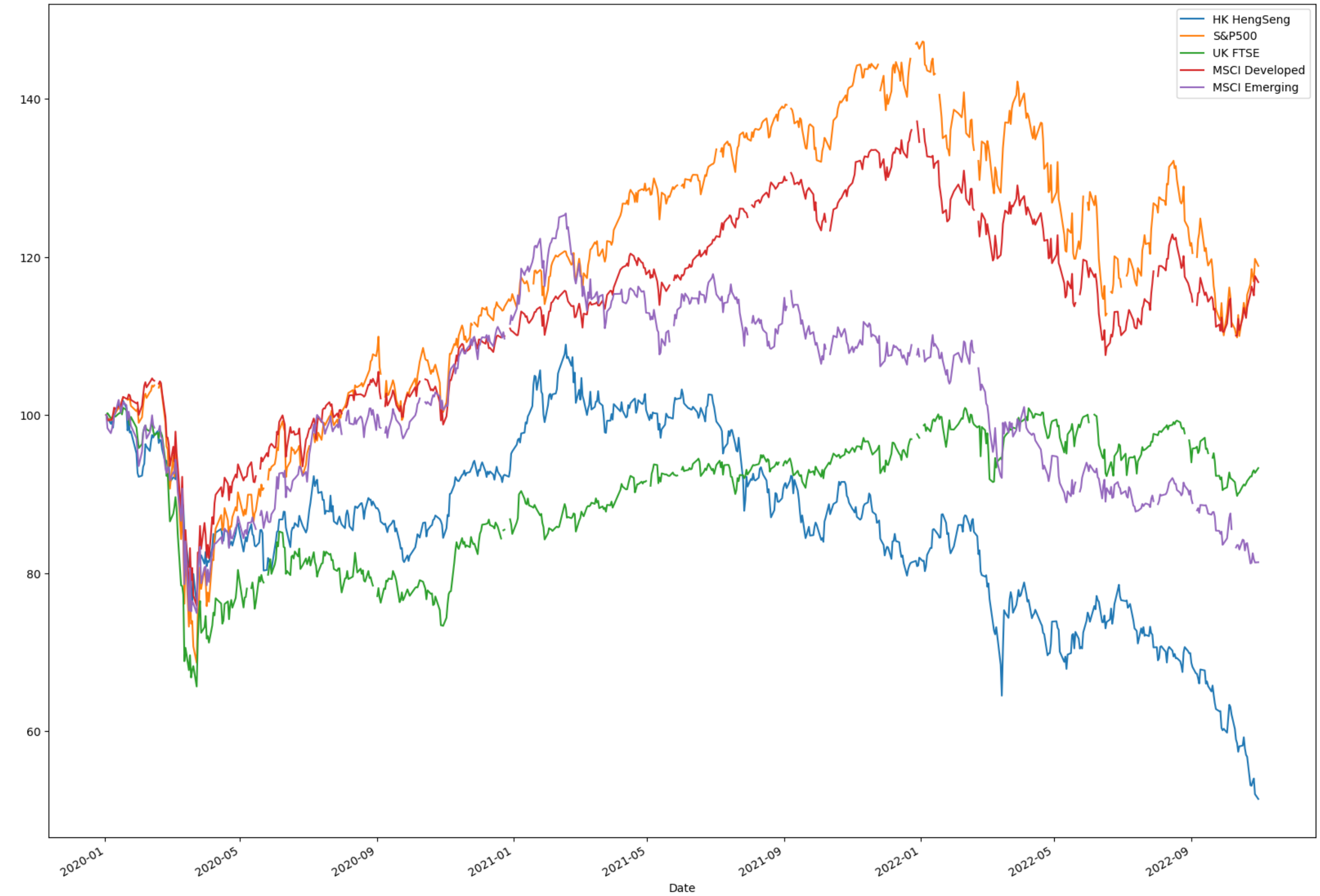
In [5]:
```
df_indices.plot(kind='line',title="5 Marjor Stocks Indices",grid=True,figsize=(20,15))
plt.legend(["HK HengSeng", "S&P500", "UK FTSE", "MSCI Developed", "MSCI Emerging"])
plt.show()
```



The line chart above does not really give any insightful information, simply because the these indices are scaled differently. Therefore, a mathematical trick called data normalization should be applied, so that all the indices start at 100. The formula is as follow:

$$ Normalized\, index = \frac{P_{t}}{P_{0}}\ * 100 $$
Normalize these 5 indices to compare relative changes

In [6]:
```
indices_normalized = ((df_indices/df_indices.iloc[0])*100)
indices_normalized.plot(kind="line",figsize=(20,15))
plt.legend(["HK HengSeng", "S&P500", "UK FTSE", "MSCI Developed", "MSCI Emerging"])
plt.show()
```



Some preliminary observations:

- All 5 markets indices plummetd at the beginning of Covid-19 pandemic
- A general upward trend can be seen from SP500 and MSCI developed. A general downward trend is shown for MSCI Emerging and HSI.

1.Analysis for HK HengSeng, S&P500, UK FTSE indices

We are interested in finding out how these markets correlate to each other. Therefore, I will conduct a correlation and analysis by simply using the corr() method. This will produce a correlation matrix

In [7]:
```
df_indices.iloc[:,0:3].corr()
```

Out[7]:

	^HSI	^GSPC	^FTSE
^HSI	1.000000	-0.016302	-0.152492
^GSPC	-0.016302	1.000000	0.763011
^FTSE	-0.152492	0.763011	1.000000

The above matrix shows that SP500 and FTSE are positively correlated, and HSI is negatively correlated with the other two. Next, the std() will be used to find out standard deviation.

In [8]:
```
df_indices.iloc[:,0:3].std()
```

```
^HSI      3232.786402
```

Out[8]:
```
^GSPC      566.385880
^FTSE      598.359129
dtype: float64
```

1.1 ROI (rate on investment) analysis

Calculate the daily rate of return for first 3 markets. The daily ROI is calculated as:

$$ daily\,ROI = \frac{P_{t}}{P_{t-1}}\ - 1 $$

In [9]:
```
df_indices_daily_roi = pd.DataFrame()

# calcuate the daily ROI iteratively and store these data into a dataframe
for ticker in stock_indexes_tickers[0:3]:
    df_indices_daily_roi[ticker + ' daily ROI'] = (df_indices[ticker]/df_indices[ticker]
df_indices_daily_roi
```

Out[9]:

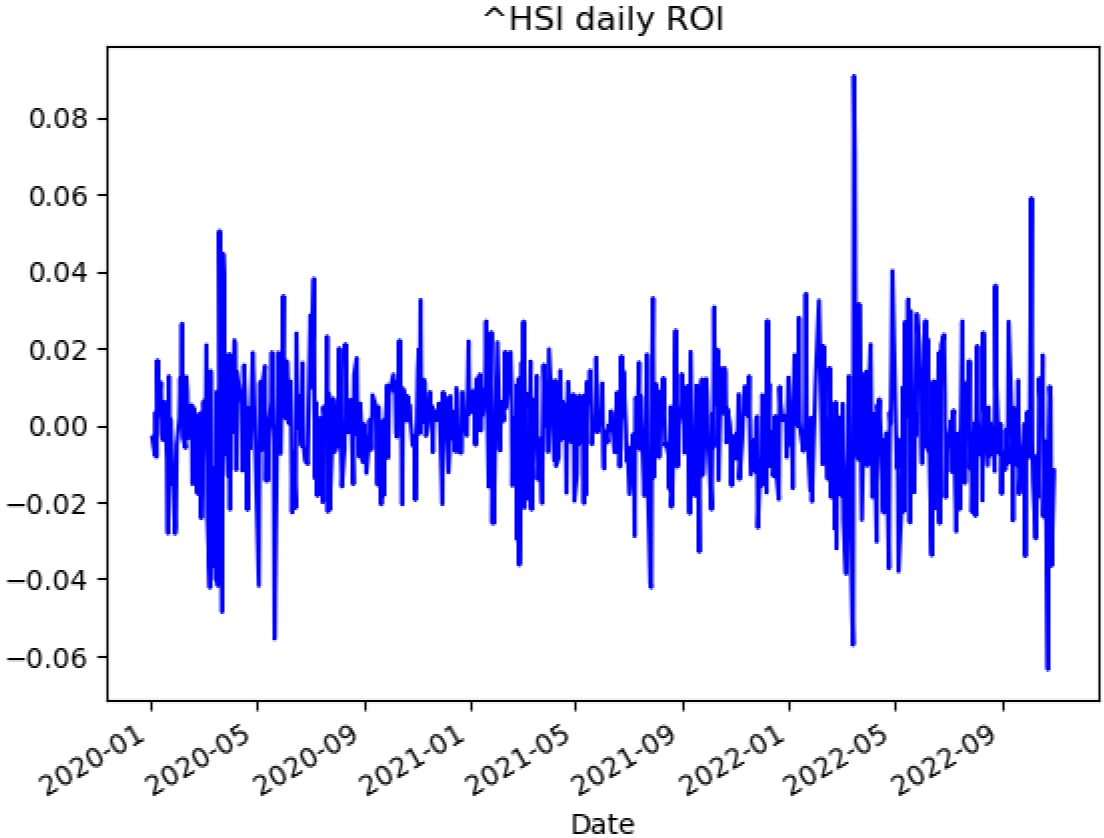
Date	^HSI daily ROI	^GSPC daily ROI	^FTSE daily ROI
2020-01-02	NaN	NaN	NaN
2020-01-03	-0.003224	-0.007060	0.002380
2020-01-06	-0.007919	0.003533	-0.006179
2020-01-07	0.003397	-0.002803	-0.000185
2020-01-08	-0.008267	0.004902	0.000132
...	...	...	...
2022-10-25	-0.000995	0.016267	-0.000071
2022-10-26	0.010028	-0.007388	0.006074
2022-10-27	0.007199	-0.006083	0.002494
2022-10-28	-0.036614	0.024626	-0.003676
2022-10-31	-0.011844	-0.007454	0.006640

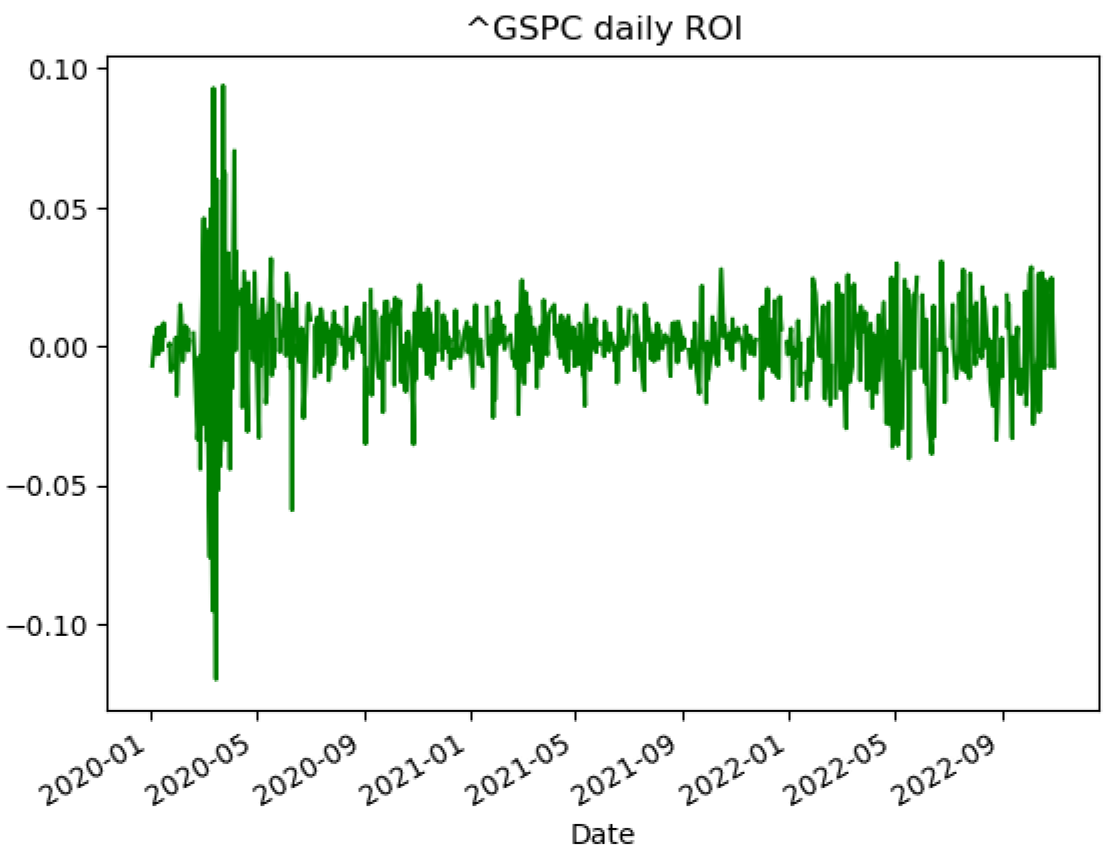
699 rows × 3 columns

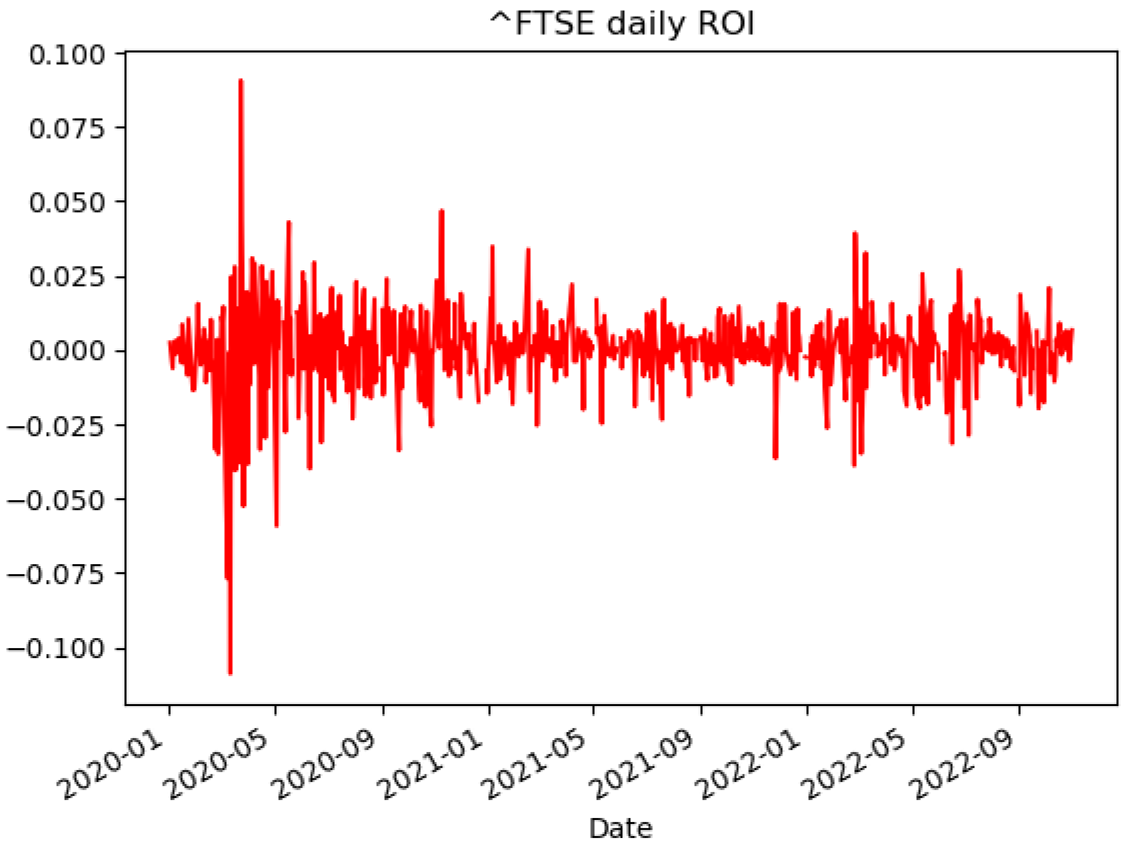
Plot these 3 columns

In [10]:
```
# random color generator
from itertools import cycle
cycol = cycle('bgrcmk')

for index_roi in df_indices_daily_roi:
    df_indices_daily_roi[index_roi].plot(title=index_roi, color=next(cycol))
    plt.show()
```


^HSI daily ROI
0.08
0.06
0.04
0.02
0.00
−0.02
−0.04
−0.06
2020-01
2020-05
2020-09
2021-01
2021-05
2021-09
2022-01
2022-05
2022-09
Date


^GSPC daily ROI
0.10
0.05
0.00
−0.05
−0.10
2020-01
2020-05
2020-09
2021-01
2021-05
2021-09
2022-01
2022-05
2022-09
Date



Some observations：

- High volitity at the beginning of Covid-19
- The volitility for HSI seems to be higher

Count the positive and negative trading days

In [11]:
```
df_pos_neg = pd.DataFrame()

for ticker in stock_indexes_tickers[0:3]:
    df_pos_neg[ticker + ' count'] = np.sign(df_indices_daily_roi[ticker + " daily ROI"])
    print(df_pos_neg[ticker + ' count'].value_counts())
```

```
-1.0    353
 1.0    345
Name: ^HSI count, dtype: int64
 1.0    351
-1.0    311
Name: ^GSPC count, dtype: int64
 1.0    360
-1.0    311
 0.0      1
Name: ^FTSE count, dtype: int64
```

Generally speaking, for FTSE and SP500, there exists positive >> negative. For HSI, it is roughly the same.

Calculate the annual rate of returns:

In [12]:
```
df_indices_daily_roi.mean()*250
```

Out[12]:
```
^HSI daily ROI    -0.207574
^GSPC daily ROI    0.104690
^FTSE daily ROI   -0.016438
dtype: float64
```

SP500 has +10% annual ROI!!! Whereas HSI investors experienced a -20% annual ROI

In [13]:
```
df_indices_daily_roi.describe()
```

Out[13]:

	^HSI daily ROI	^GSPC daily ROI	^FTSE daily ROI
count	698.000000	662.000000	672.000000
mean	-0.000830	0.000419	-0.000066
std	0.015583	0.016461	0.013742
min	-0.063563	-0.119841	-0.108738
25%	-0.008920	-0.006692	-0.005274
50%	-0.000294	0.001001	0.000702
75%	0.007792	0.008309	0.006091
max	0.090818	0.093828	0.090530

Correlation & volatilty analysis for ROI (rate of return)

In [14]:
```
df_indices_daily_roi.corr()
```

Out[14]:

	^HSI daily ROI	^GSPC daily ROI	^FTSE daily ROI
^HSI daily ROI	1.000000	0.228519	0.429581
^GSPC daily ROI	0.228519	1.000000	0.600076
^FTSE daily ROI	0.429581	0.600076	1.000000

In [15]:
```
df_indices_daily_roi.std()
```

Out[15]:
```
^HSI daily ROI     0.015583
^GSPC daily ROI    0.016461
^FTSE daily ROI    0.013742
dtype: float64
```

1.2 Anlysis for the developed world vs the emerging world

Covid-19 definitely has different scales of impact for the developed world and the emering world. There are a number of reasons, such as financial market regulations, social welfare & stability, monetary policies etc.

I am interesed in finding out how Covid-19 impact the developed market and the emeringing market respectively. First, I will grab the dataframe for MSCI developed economies and MSCI emerging economies, then examine the first and last 5 rows

In [16]:
```
df_indices.iloc[:,3:5]
```

Out[16]:

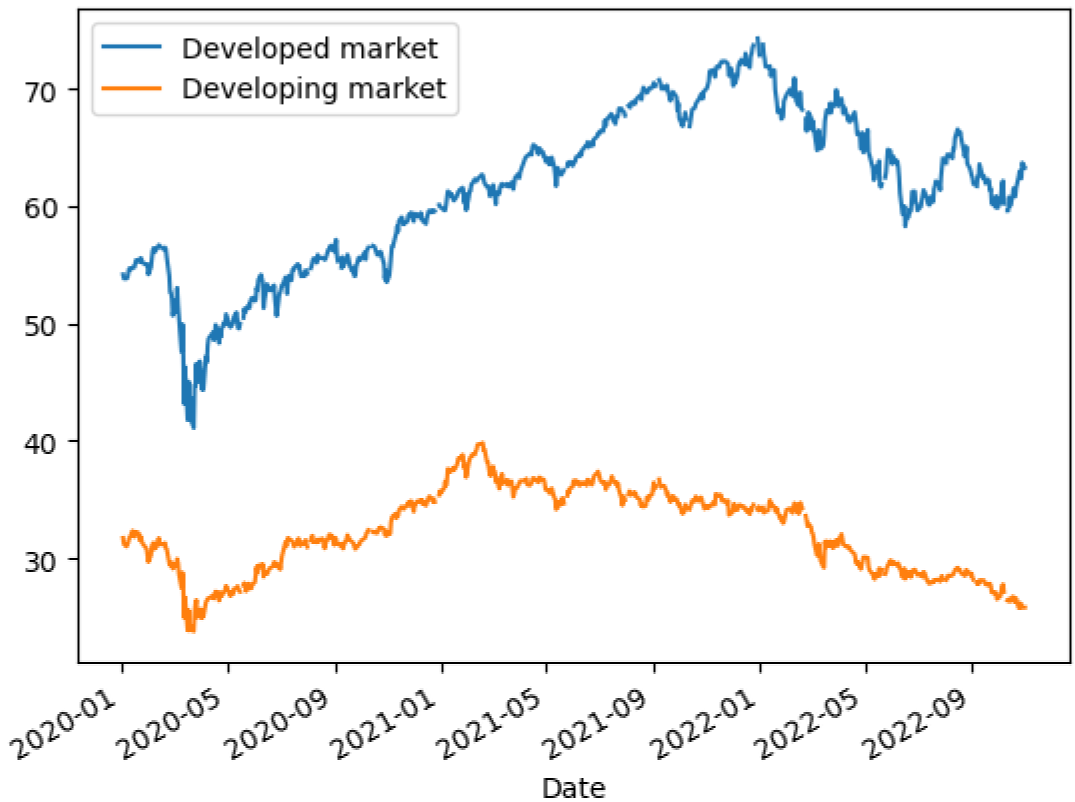
	XWD.TO	XEM.TO
Date		
2020-01-02	54.172573	31.749756
2020-01-03	53.823383	31.220915
2020-01-06	53.823383	31.018991

2020-01-07	53.891285	31.192064
2020-01-08	54.240467	31.384367
...	...	...
2022-10-25	62.980000	25.820000
2022-10-26	62.720001	26.200001
2022-10-27	62.360001	25.959999
2022-10-28	63.689999	25.830000
2022-10-31	63.270000	25.840000

699 rows × 2 columns

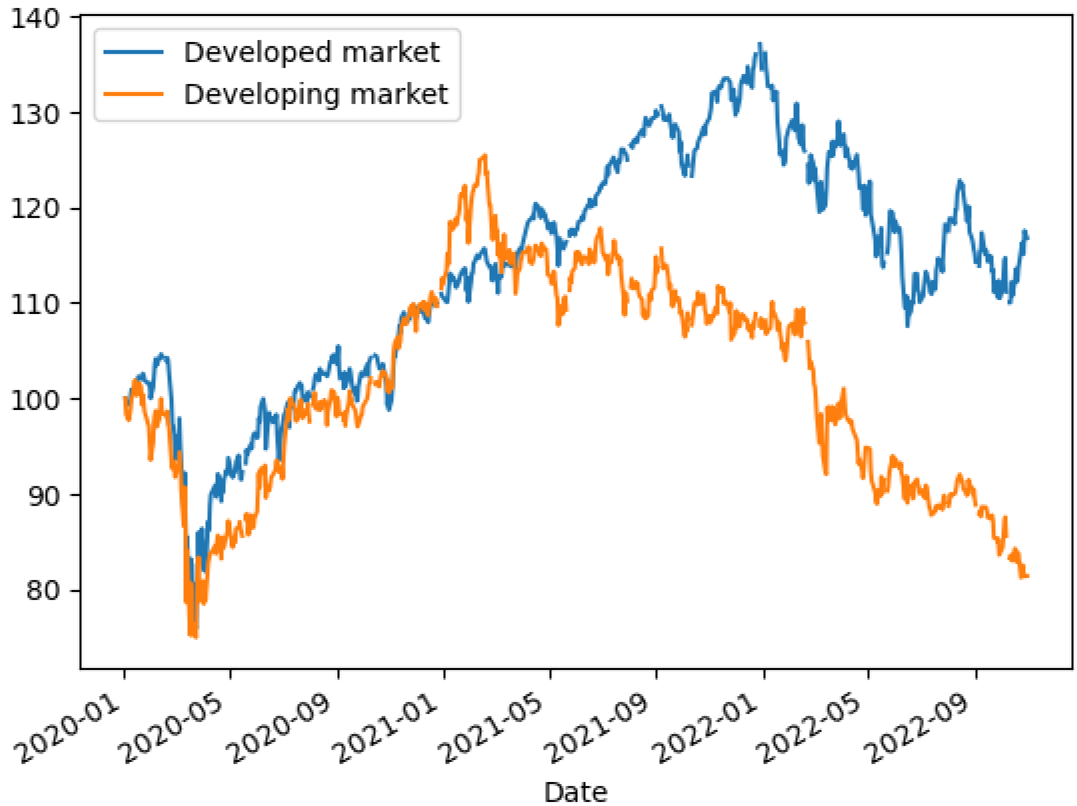
Plot the dataframe

In [17]:
```
df_indices.iloc[:,3:5].plot()
plt.legend(["Developed market","Developing market"])
plt.show()
```



Plot the normalized graph

In [18]:
```
indices_normalized_MSCI = ((df_indices.iloc[:,3:5]/df_indices.iloc[0,3:5])*100)
indices_normalized_MSCI.plot()
plt.legend(["Developed market","Developing market"])
plt.show()
```



Observations:

- A general upward trend for the developed market, and a general downward trend to the emerging market.
- Both markets have downward trend since 2022-01, because of the FED rate hikes since 2022-01

Calculate the ROI (rate on investment)

Simple rate of return:

$$ daily\,ROI = \frac{P_{t}}{P_{t-1}}\ - 1 $$

In [19]:

```
df_indices_daily_roi_MSCI = pd.DataFrame()
for ticker in stock_indexes_tickers[3:5]:
    df_indices_daily_roi_MSCI[ticker + ' daily ROI'] = (df_indices[ticker]/df_indices[ti

# Examine the first and last 5 rows
df_indices_daily_roi_MSCI
```

Out[19]:

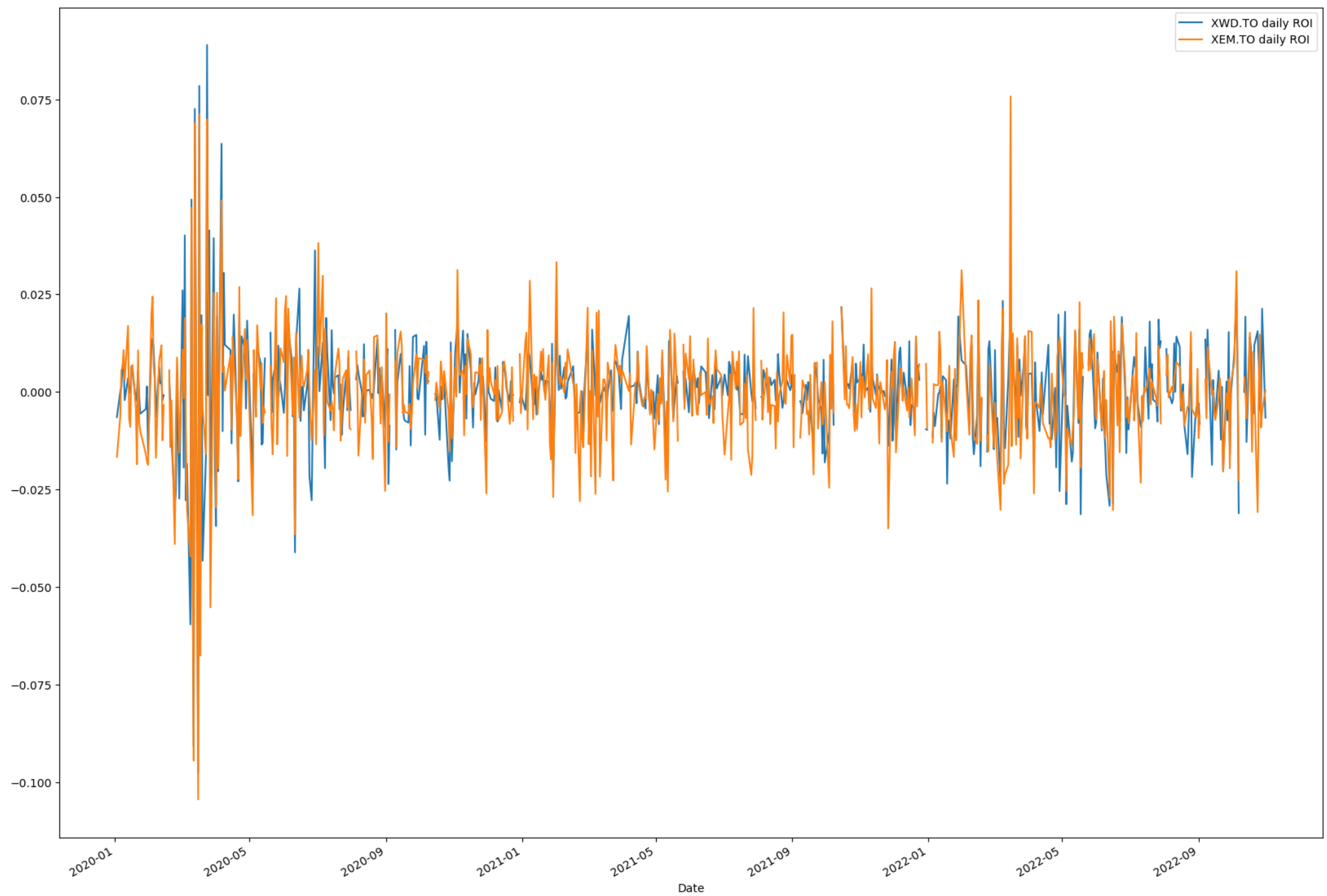
Date	XWD.TO daily ROI	XEM.TO daily ROI
2020-01-02	NaN	NaN
2020-01-03	-0.006446	-0.016657
2020-01-06	0.000000	-0.006468
2020-01-07	0.001262	0.005580
2020-01-08	0.006479	0.006165
...	...	...
2022-10-25	0.007519	0.001163
2022-10-26	-0.004128	0.014717

2022-10-27	-0.005740	-0.009160
2022-10-28	0.021328	-0.005008
2022-10-31	-0.006594	0.000387

699 rows × 2 columns

Plot the ROI

In [20]:
```
df_indices_daily_roi_MSCI.plot(figsize=(20,15))
plt.show()
```



Calculate the annual ROI

In [21]:
```
df_indices_daily_roi_MSCI.mean()*250
```

Out[21]:
```
XWD.TO daily ROI     0.070763
XEM.TO daily ROI    -0.053153
dtype: float64
```

The divergence is pretty obvious. The developed market has a positive annual ROI of 7%, while the emerging market has a negative 5%.

Calculate the standard deviation

In [22]:
```
df_indices_daily_roi_MSCI.std()
```

Out[22]:
```
XWD.TO daily ROI     0.013774
XEM.TO daily ROI     0.014566
dtype: float64
```

2. S&P500 sector performance analysis

The Covid-19 pandemic has different impacts on different industries. Here, I would want to find out which industries go above the market and vice versa.

Analyze the performance for the following sectors: IT, Financials, energy, industrials, Consumer Staples, Consumer Discretionary, healthcare

In [15]:

```
df_sp500_indices = pd.DataFrame()

# respective tickers for: IT, Financials, Energy, industrials, Consumer Staples, Consume
indices_tickers = ["^SP500-45","^SP500-40","^GSPE","^SP500-20","^SP500-30","^SP500-25","
indices_sector_names = ["IT","Financials","Energy","Industrials","Consumer Staples", "Co

startDate = "2020-01-01"
endDate = "2022-11-01"

# Grab the adjusted close price
for i in range(0, len(indices_tickers)):
    df_sp500_indices[indices_tickers[i] + "-" + indices_sector_names[i]] = yf.download(i
```

```
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
```

In [16]:

```
df_sp500_indices
```

Out[16]:

Date	^SP500-45-IT	^SP500-40-Financials	^GSPE-Energy	^SP500-20-Industrials	^SP500-30-Consumer Staples	^SP500-25-Consumer Discretionary	^SP500-35-Healthcare	^GSPC-Market
2020-01-02	1639.119995	516.210022	460.339996	700.049988	641.669983	999.010010	1190.449951	3257.850098
2020-01-03	1621.680054	510.519989	458.769989	699.229980	640.549988	990.500000	1180.329956	3234.850098
2020-01-06	1626.380005	510.230011	462.339996	699.039978	642.070007	994.119995	1187.270020	3246.280029
2020-01-07	1624.589966	506.820007	461.390015	698.179993	637.390015	992.869995	1184.410034	3237.179932
2020-01-08	1641.380005	509.559998	453.359985	699.780029	640.260010	994.369995	1192.030029	3253.050049
...	...	...	...	...	...	...	...	...
2022-10-25	2251.110107	548.530029	670.219971	770.330017	740.340027	1156.260010	1514.030029	3859.110107
2022-10-26	2200.830078	550.140015	679.340027	772.979980	745.150024	1144.030029	1530.989990	3830.600098
2022-10-27	2173.330078	554.250000	681.190002	781.820007	745.429993	1135.780029	1522.180054	3807.300049

2022-10-28	2271.629883	568.030029	685.710022	800.419983	761.969971	1132.369995	1547.849976	3901.060059
2022-10-31	2241.129883	563.909973	689.830017	797.710022	757.250000	1124.520020	1546.640015	3871.979980

714 rows × 8 columns

Obatin some descriptive statistics about the indices dataframe and verify the row counts are roughly the same.

In [17]:
```
df_sp500_indices.describe()
```

Out[17]:

	^SP500-45-IT	^SP500-40-Financials	^GSPE-Energy	^SP500-20-Industrials	^SP500-30-Consumer Staples	^SP500-25-Consumer Discretionary	^SP500-35-Healthcare	^GSPC-Market
count	714.000000	714.000000	714.000000	714.000000	714.000000	714.000000	714.000000	714.000000
mean	2300.405839	533.338026	408.336723	758.014341	706.040224	1267.824120	1385.067913	3858.978503
std	416.442853	98.363353	127.553657	113.702801	65.022566	201.785299	162.086162	566.568854
min	1239.390015	293.549988	179.940002	412.059998	500.950012	707.130005	870.989990	2237.399902
25%	2034.697479	449.360008	295.332504	685.807495	660.237488	1128.239990	1238.350037	3382.377502
50%	2328.960083	549.459991	391.735001	773.259979	715.820007	1285.750000	1431.474976	3913.535034
75%	2641.787537	621.649979	520.592499	857.119980	755.062500	1424.430054	1525.184998	4351.917358
max	3107.459961	688.849976	698.429993	905.630005	841.989990	1673.270020	1664.579956	4796.560059

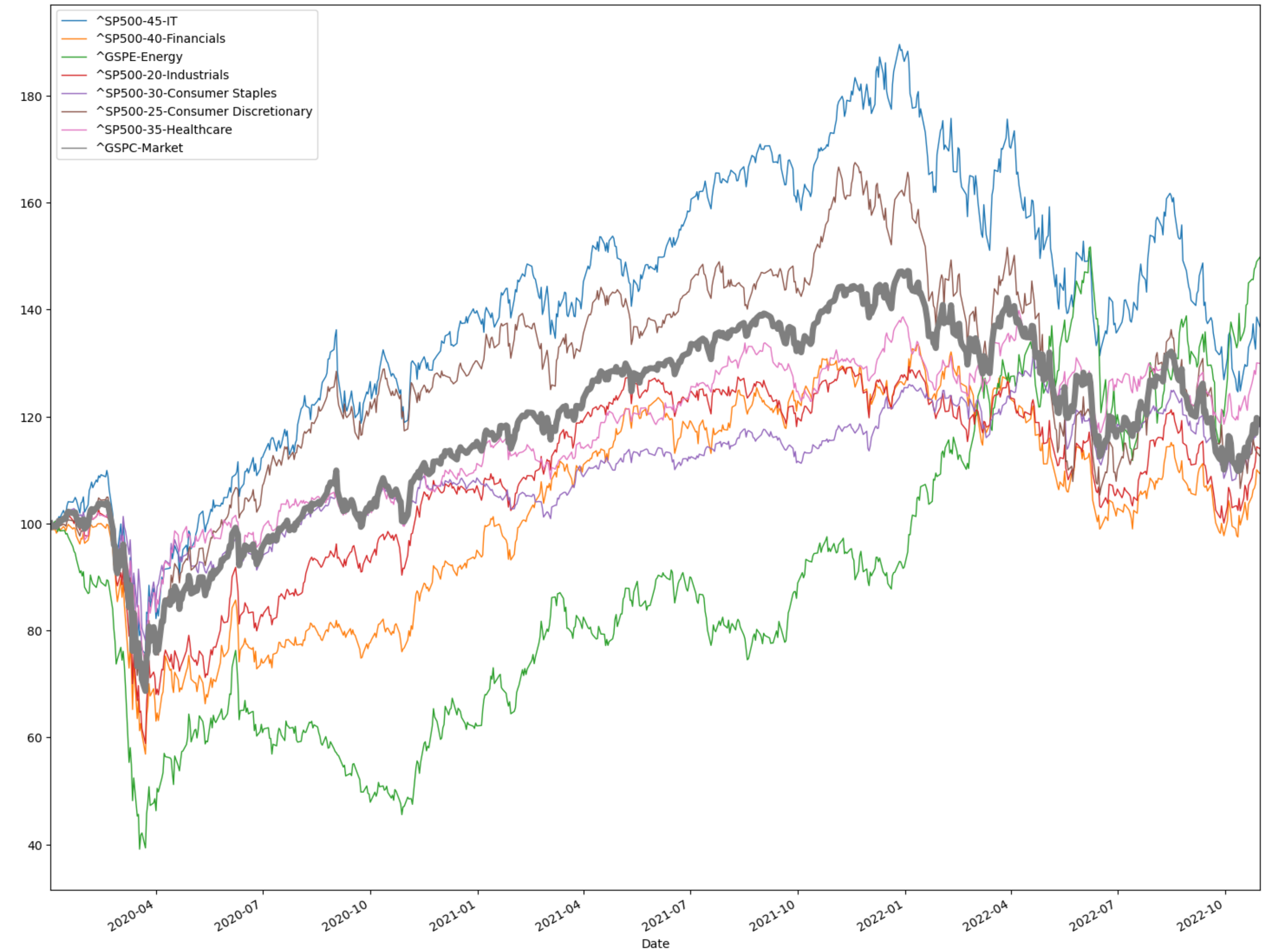
Plot the normalized data. The formula to obtain normalized data is as followed:

$$ Normalized\, index = \frac{P_{t}}{P_{0}}\ * 100 $$
The SP500 index is highlighted as grey color and bolded.

In [19]:
```
fig, ax = plt.subplots()
((df_sp500_indices/df_sp500_indices.iloc[0])*100).plot(figsize=(18,15),lw=1,ax=ax)

# highlight the S&P500 market line
for line in ax.get_lines():
    if line.get_label() == '^GSPC-Market':
        line.set_linewidth(5)

ax.margins(x=0)
plt.show()
```



Some observations:

- Since Covid-19, IT and Consumer Discretionary have performed stronger than the market.
- The enery sector(^GSPE) was hit the hardest because of the decline in demand of transportation. Since 2022-01, the enery sector skyrocketed because of the Russian-Ukrain conflict.

Perform a correlation analysis

In [27]:
```
df_sp500_indices.corr()
```

Out[27]:

	^SP500-45-IT	^SP500-40-Financials	^GSPE-Energy	^SP500-20-Industrials	^SP500-25-Consumer	^SP500-35-Healthcare	^GSPC-Market
^SP500-45-IT	1.000000	0.899024	0.462132	0.924409	0.951003	0.926396	0.984649
^SP500-40-Financials	0.899024	1.000000	0.614347	0.964111	0.828395	0.897416	0.955870
^GSPE-Energy	0.462132	0.614347	1.000000	0.532239	0.239398	0.703193	0.536330
^SP500-20-Industrials	0.924409	0.964111	0.532239	1.000000	0.890592	0.894130	0.969609
^SP500-25-Consumer	0.951003	0.828395	0.239398	0.890592	1.000000	0.800793	0.930430
^SP500-35-Healthcare	0.926396	0.897416	0.703193	0.894130	0.800793	1.000000	0.945810
^GSPC-Market	0.984649	0.955870	0.536330	0.969609	0.930430	0.945810	1.000000

To obtain the annual ROI (rate of investment) for these S&P500 IT index, make a get request and it will return a JSON object containing all the key info

In [28]:
```
from pprint import pprint

# create a dump function to examine all the properties within the object
def dump(obj):
  for attr in dir(obj):
    print("obj.%s = %r" % (attr, getattr(obj, attr)))

SP500_IT = yf.Ticker("^SP500-45")
```

Examine the JSON data that is returned from Yahoo finance. Here, we specially look at the info property, which contains all the key data

In [29]:
```
SP500_IT.info
```

Out[29]:

```
{'exchange': 'SNP',
 'shortName': 'S&P 500 Information Technology ',
 'longName': 'S&P 500 Information Technology (Sector)',
 'exchangeTimezoneName': 'America/New_York',
 'exchangeTimezoneShortName': 'EST',
 'isEsgPopulated': False,
 'gmtOffSetMilliseconds': '-18000000',
 'quoteType': 'INDEX',
 'symbol': '^SP500-45',
 'messageBoardId': 'finmb_INDEXSP500-45',
 'market': 'us_market',
 'previousClose': 2327.4,
 'regularMarketOpen': 2327.4,
 'twoHundredDayAverage': 2625.775,
 'trailingAnnualDividendYield': None,
 'payoutRatio': None,
 'volume24Hr': None,
 'regularMarketDayHigh': 2334.86,
 'navPrice': None,
 'averageDailyVolume10Day': 558440840,
 'totalAssets': None,
 'regularMarketPreviousClose': 2327.4,
 'fiftyDayAverage': 2868.988,
 'trailingAnnualDividendRate': None,
 'open': 2327.4,
 'toCurrency': None,
 'averageVolume10days': 558440840,
 'expireDate': None,
 'yield': None,
 'algorithm': None,
 'dividendRate': None,
 'exDividendDate': None,
 'beta': None,
 'circulatingSupply': None,
 'startDate': None,
 'regularMarketDayLow': 2295.17,
 'priceHint': 2,
 'currency': 'USD',
 'regularMarketVolume': 544238582,
 'lastMarket': None,
 'maxSupply': None,
 'openInterest': None,
 'marketCap': None,
 'volumeAllCurrencies': None,
 'strikePrice': None,
 'averageVolume': 458239642,
```

```
 'priceToSalesTrailing12Months': None,
 'dayLow': 2295.17,
 'ask': 0,
 'ytdReturn': None,
 'askSize': 0,
 'volume': 544238582,
 'fiftyTwoWeekHigh': 3079.53,
 'forwardPE': None,
 'maxAge': 1,
 'fromCurrency': None,
 'fiveYearAvgDividendYield': None,
 'fiftyTwoWeekLow': 2188.2,
 'bid': 0,
 'tradeable': False,
 'dividendYield': None,
 'bidSize': 0,
 'dayHigh': 2334.86,
 'coinMarketCapLink': None,
 'regularMarketPrice': 2304.92,
 'preMarketPrice': None,
 'logo_url': 'https://logo.clearbit.com/S&P.com'}
```

Extract some of the key technical data, and store these data into a pd dataframe:

- twoHundredDayAverage
- fiftyDayAverage
- fiftyTwoWeekHigh
- fiftyTwoWeekLow

In [30]:

```
df_sp500_IT = pd.DataFrame.from_dict(
    {'250 days average':[SP500_IT.info['twoHundredDayAverage']],
     '52 days average':[SP500_IT.info['fiftyDayAverage']],
     '52 weeks high':[SP500_IT.info['fiftyTwoWeekHigh']],
     '52 weeks low':[SP500_IT.info['fiftyTwoWeekLow']]
    }
)

df_sp500_IT
```

Out[30]:

	250 days average	52 days average	52 weeks high	52 weeks low
0	2625.775	2868.988	3079.53	2188.2

Calculate the maximum annual ROI (return on investment for last 52 weeks).
To find the maximum annual ROI, take the logrithmic return of (max/min)

In [31]:

```
sp500_IT_max_return = np.log(df_sp500_IT['52 weeks high']/df_sp500_IT['52 weeks low'])
sp500_IT_max_return
```

Out[31]:

```
0    0.341698
dtype: float64
```