3_2_determine_the_reference_performance

September 21, 2023

0.0.1 Determine The Reference Performance

- Exploratory Data Analysis continued
  - Analyse specific ETFs and Stocks
  - Plot their price charts
  - Compare their performance
  - See how they correlate

[1]:
```
# Import libraries
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib
import seaborn as sns
import os
import pickle
import itertools
```

[2]:
```
# change into Dataset't directory
os.chdir("../dataset")
```

[3]:
```
# Load previously saved pickles

# load objects
with open("3_1_baseline_performance.pckl", "rb") as f:
    %time baseline_performance = pickle.load(f)
```

```
CPU times: user 341 µs, sys: 536 µs, total: 877 µs
Wall time: 846 µs
```

[4]:
```
with open("3_1_avg_stocks.pckl", "rb") as f:
    %time avg_Stocks = pickle.load(f)
```

```
CPU times: user 182 µs, sys: 114 µs, total: 296 µs
Wall time: 271 µs
```

[5]:
```
with open("3_1_avg_etfs.pckl", "rb") as f:
    %time avg_ETFs = pickle.load(f)
```

```
CPU times: user 125 µs, sys: 195 µs, total: 320 µs
Wall time: 271 µs
```

[6]:
```
with open("3_1_stock.pckl", "rb") as f:
    %time Stocks = pickle.load(f)
```

```
CPU times: user 809 ms, sys: 237 ms, total: 1.05 s
Wall time: 1.05 s
```

[7]:
```
with open("3_1_etfs.pckl", "rb") as f:
    %time ETFs = pickle.load(f)
```

```
CPU times: user 16.2 ms, sys: 0 ns, total: 16.2 ms
Wall time: 15.8 ms
```

[8]:
```
# Get symbol real names
ndt_reference = pd.read_csv("ndt_reference.csv")
ndt_reference.head()
```

[8]:
```
   Unnamed: 0 Nasdaq Traded Symbol  \
0           0             Y      A
1           1             Y     AA
2           2             Y    AAA
3           3             Y   AAAU
4           4             Y    AAC

                                       Security Name Listing Exchange  \
0            Agilent Technologies, Inc. Common Stock                N
1                    Alcoa Corporation Common Stock                N
2  Investment Managers Series Trust II AXS First …              P
3                Goldman Sachs Physical Gold ETF Shares                Z
4  Ares Acquisition Corporation Class A Ordinary …              N

  Market Category ETF  Round Lot Size Test Issue Financial Status CQS Symbol  \
0                   N           100.0          N              NaN          A
1                   N           100.0          N              NaN         AA
2                   Y           100.0          N              NaN        AAA
3                   Y           100.0          N              NaN       AAAU
4                   N           100.0          N              NaN        AAC

  NASDAQ Symbol NextShares
0             A          N
1            AA          N
2           AAA          N
3          AAAU          N
4           AAC          N
```

[9]:
```
avg_ETFs = pd.merge(avg_ETFs, ndt_reference[["Symbol", "Security Name"]],␣
↪on="Symbol")
```

[10]:
```
avg_Stocks = pd.merge(avg_Stocks, ndt_reference[["Symbol", "Security Name"]],␣
↪on="Symbol")
```

[11]:
```
print("The list of ETFs")
avg_ETFs[["Symbol", "Security Name", "Current pct_change"]]
```

The list of ETFs

[11]:

	Symbol	Security Name	Current pct_change
0	EWL	iShares Inc iShares MSCI Switzerland ETF	3.013875
1	XLK	SPDR Select Sector Fund - Technology	3.121449
2	EWC	iShares MSCI Canada Index Fund	2.973889
3	XLF	SPDR Select Sector Fund - Financial	2.750948
4	EWO	iShares Inc iShares MSCI Austria ETF	2.584267
5	QQQ	Invesco QQQ Trust, Series 1	3.589787
6	SPY	SPDR S&P 500	3.627273

[12]:
```
print("The list of Stocks")
avg_Stocks[["Symbol", "Security Name", "Current pct_change"]]
```

The list of Stocks

[12]:

	Symbol	Security Name	Current pct_change
0	ZEUS	Olympic Steel, Inc. - Common Stock	11.694638
1	RGR	Sturm, Ruger & Company, Inc. Common Stock	11.702276
2	BWA	BorgWarner Inc. Common Stock	11.707241
3	ECL	Ecolab Inc. Common Stock	11.647079
4	SHYF	The Shyft Group, Inc. - Common Stock	11.645839
5	PZZA	Papa John's International, Inc. - Common Stock	11.787230
6	CASS	Cass Information Systems, Inc - Common Stock	11.583909

0.0.2 Inspect the avarage ETF prices visually

[13]:
```
# Combine ETFs' Close prices in one DataFrame
date_set = False
ETFs_prices = pd.DataFrame()

for index, row in avg_ETFs.iterrows():
    symbol = row["Symbol"]
    if not date_set:
        ETFs_prices["Date"] = ETFs[symbol]["Date"]
        date_set = True
    ETFs_prices[symbol] = ETFs[symbol]["Adj Close"]
```

```python
ETFs_prices.head()
```

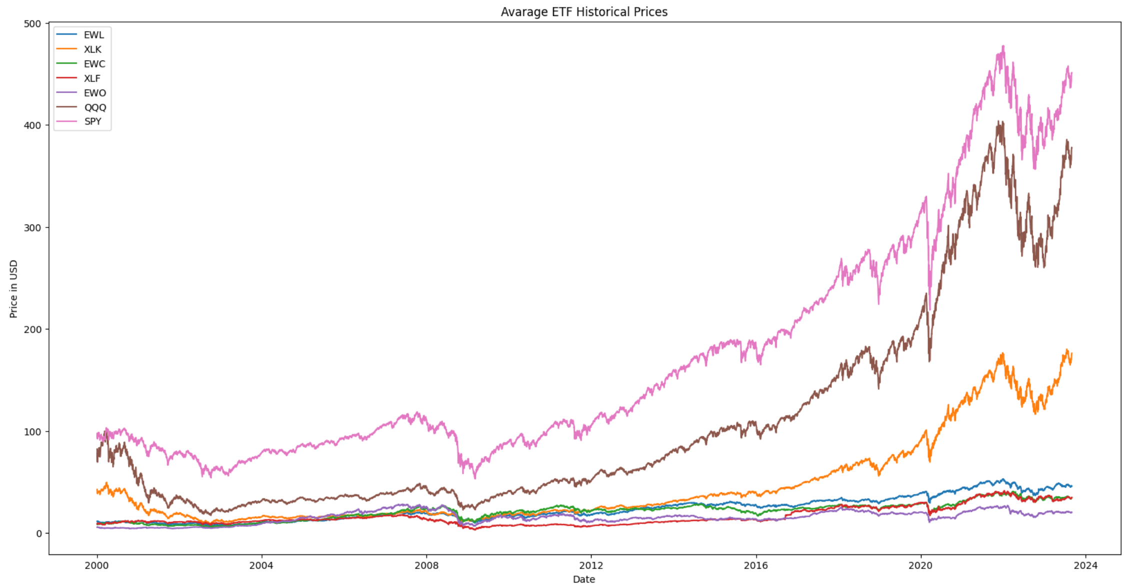
[13]:
```
                  Date        EWL        XLK       EWC       XLF       EWO  \
Date
2000-01-03  2000-01-03  11.442809  42.751957  8.789878  9.248327  5.655271
2000-01-04  2000-01-04  11.094737  40.583042  8.393343  8.844025  5.615444
2000-01-05  2000-01-05  11.225265  39.980549  8.558568  8.774538  5.695096
2000-01-06  2000-01-06  11.225265  38.655117  8.459435  9.159883  5.695096
2000-01-07  2000-01-07  11.573333  39.329876  8.591611  9.311501  6.053528

                  QQQ        SPY
Date
2000-01-03  82.267441  97.506668
2000-01-04  76.623764  93.693573
2000-01-05  74.670212  93.861176
2000-01-06  69.542053  92.352676
2000-01-07  78.143234  97.716209
```

[14]:
```python
ETFs_prices.describe()
```

[14]:
```
               EWL          XLK          EWC          XLF          EWO  \
count  5955.000000  5955.000000  5955.000000  5955.000000  5955.000000
mean     23.335496    45.981338    21.064742    16.221625    15.402936
std      11.788383    42.536913     8.311273     8.972495     6.072450
min       6.658945     8.930201     5.766855     3.068984     4.365574
25%      12.720385    17.639490    13.852406     9.976231    11.859705
50%      19.742582    26.014860    22.679607    12.776107    15.266085
75%      31.259892    56.355822    26.029679    22.618418    20.112888
max      53.020000   180.259995    40.660000    41.419998    28.348576

               QQQ          SPY
count  5955.000000  5955.000000
mean    106.564825   171.326537
std      98.931966   112.604175
min      17.417257    53.155308
25%      36.403812    88.301949
50%      61.093704   112.424484
75%     142.035995   233.683655
max     403.989990   477.709991
```

[15]:
```python
# Plot ETFs' prices
plt.figure(figsize=(20,10))

for column in ETFs_prices.columns[1:]:
    plt.plot(ETFs_prices.index, ETFs_prices[column], label=column)

plt.xlabel("Date")
```

```
plt.ylabel("Price in USD")
plt.legend()
plt.title("Avarage ETF Historical Prices")
plt.show()
```



[16]:
```
# Calculate daily returns and isu it for correlation

ETFs_prices_daily_change = ETFs_prices[[column for column in ETFs_prices.
    ↪columns[1:]]].pct_change(1)
ETFs_prices_daily_change.head()
```

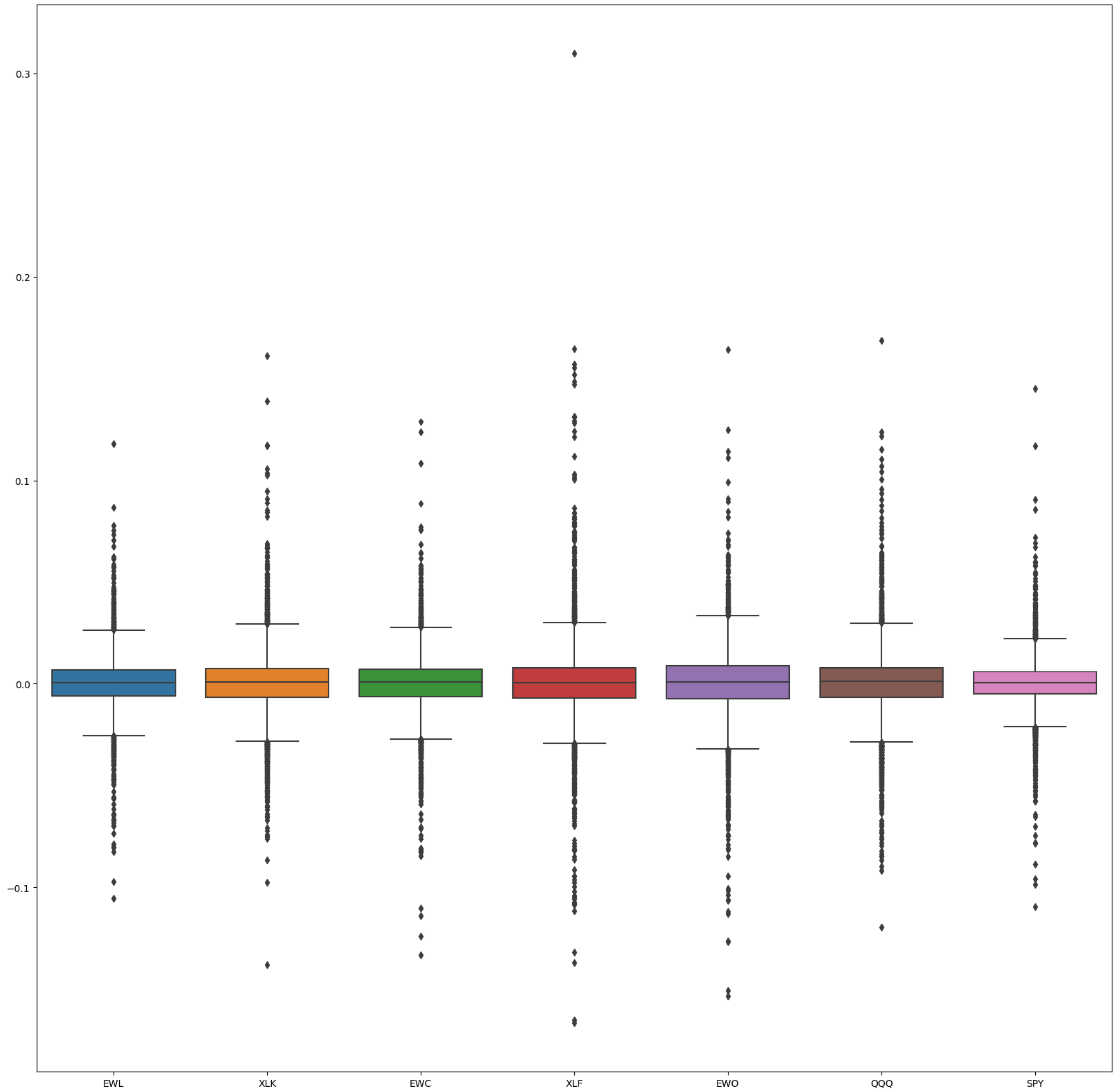
[16]:
```
                 EWL       XLK       EWC       XLF       EWO       QQQ  \
Date
2000-01-03       NaN       NaN       NaN       NaN       NaN       NaN
2000-01-04 -0.030418 -0.050733 -0.045113 -0.043716 -0.007042 -0.068602
2000-01-05  0.011765 -0.014846  0.019685 -0.007857  0.014184 -0.025495
2000-01-06  0.000000 -0.033152 -0.011583  0.043916  0.000000 -0.068677
2000-01-07  0.031008  0.017456  0.015625  0.016552  0.062937  0.123683

                 SPY
Date
2000-01-03       NaN
2000-01-04 -0.039106
2000-01-05  0.001789
2000-01-06 -0.016072
2000-01-07  0.058077
```

[17]:
```python
# Show the correlation
plt.subplots(figsize=(20,20))
sns.heatmap(ETFs_prices_daily_change.corr(), annot=True, fmt=".2%")
```

[17]: <Axes: >

[18]:
```python
# Plot the returns width their percentiles
plt.subplots(figsize=(20,20))
sns.boxplot(ETFs_prices_daily_change)
```

[18]: <Axes: >



[19]:
```
# Check the co-variance for the symbols
ETFs_prices_daily_change.cov()
```

[19]:

	EWL	XLK	EWC	XLF	EWO	QQQ	SPY
EWL	0.000174	0.000124	0.000121	0.000152	0.000145	0.000125	0.000116
XLK	0.000124	0.000269	0.000145	0.000195	0.000128	0.000266	0.000177
EWC	0.000121	0.000145	0.000207	0.000170	0.000153	0.000143	0.000131
XLF	0.000152	0.000195	0.000170	0.000360	0.000185	0.000194	0.000192
EWO	0.000145	0.000128	0.000153	0.000185	0.000291	0.000127	0.000133
QQQ	0.000125	0.000266	0.000143	0.000194	0.000127	0.000299	0.000182
SPY	0.000116	0.000177	0.000131	0.000192	0.000133	0.000182	0.000154

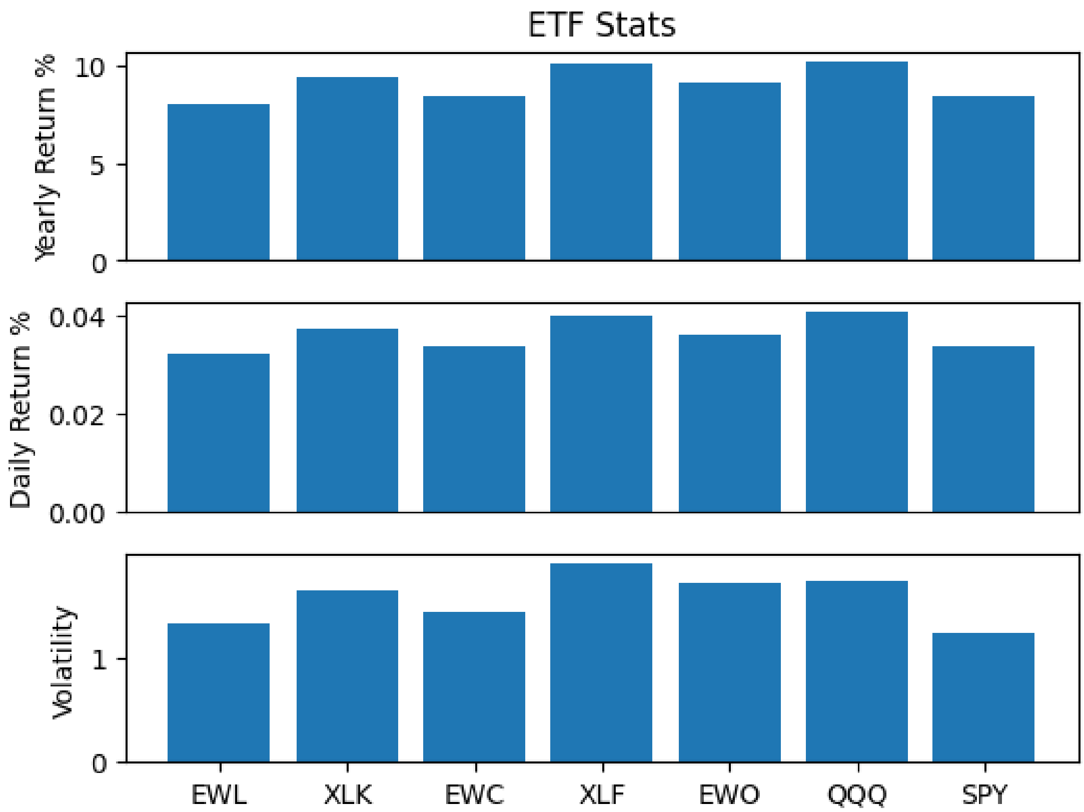
[20]:
```python
# Calculate volatilitiy
ETFs_stats = pd.DataFrame()
ETFs_stats["Volatility"] = (ETFs_prices_daily_change.std() * 100)

# Calculate avarage daily returns %
ETFs_stats["Daily Return %"] = (ETFs_prices_daily_change.mean() * 100)

# Calculate avarage yearly returns % (approx to 252 avarage trading days / year)
ETFs_stats["Yearly Return %"] = (ETFs_prices_daily_change.mean() * 100 * 252)

ETFs_stats
```

[20]:

	Volatility	Daily Return %	Yearly Return %
EWL	1.317572	0.032046	8.075710
XLK	1.639194	0.037189	9.371595
EWC	1.437909	0.033559	8.456826
XLF	1.897438	0.040048	10.092181
EWO	1.705665	0.036099	9.096845
QQQ	1.729070	0.040520	10.210945
SPY	1.241737	0.033448	8.428791

[21]:
```python
# Plot ETFs Stats

plt.figure(figsize=(40, 10))
fig, axis = plt.subplots(3, 1)


axis[2].bar(ETFs_stats.index, ETFs_stats["Volatility"])
axis[2].set_ylabel("Volatility")

axis[1].bar(ETFs_stats.index, ETFs_stats["Daily Return %"])
axis[1].set_ylabel("Daily Return %")
axis[1].xaxis.set_visible(False)

axis[0].set_title("ETF Stats")
axis[0].bar(ETFs_stats.index, ETFs_stats["Yearly Return %"])
axis[0].set_ylabel("Yearly Return %")
axis[0].xaxis.set_visible(False)
plt.show()
```

```
<Figure size 4000x1000 with 0 Axes>
```



0.0.3 Inspect the avarage Stocks prices visually

And add some additional symbols of some knows companies like Coca Cola, Apple, Shell and IBM.

[22]:
```
# Add additional symbols and refresh security names
avg_Stocks.drop(columns=["Security Name"], inplace=True)

avg_Stocks = pd.concat([avg_Stocks,␣
 ↪baseline_performance[baseline_performance["Symbol"] == "KO"]])
avg_Stocks = pd.concat([avg_Stocks,␣
 ↪baseline_performance[baseline_performance["Symbol"] == "AAPL"]])
avg_Stocks = pd.concat([avg_Stocks,␣
 ↪baseline_performance[baseline_performance["Symbol"] == "SHEL"]])
avg_Stocks = pd.concat([avg_Stocks,␣
 ↪baseline_performance[baseline_performance["Symbol"] == "IBM"]])

avg_Stocks = pd.merge(avg_Stocks, ndt_reference[["Symbol", "Security Name"]],␣
 ↪on="Symbol")
```

[23]:
```
avg_Stocks
```

```
[23]:    Symbol  First Date  First Adj Close Highest Adj Close Date  \
0     ZEUS  2000-01-03         4.378227             2008-06-30
1      RGR  2000-01-03         4.076435             2021-06-30
2      BWA  2000-01-03         3.249329             2014-07-09
3      ECL  2000-01-03        14.446023             2021-12-29
4     SHYF  2000-01-03         1.290543             2021-11-17
5     PZZA  2000-01-03         6.033363             2021-11-04
6     CASS  2000-01-03         3.042775             2018-06-22
7       KO  2000-01-03        11.361526             2022-04-21
8     AAPL  2000-01-03         0.859423             2023-07-31
9     SHEL  2000-01-03        59.375000             2007-10-29
10     IBM  2000-01-03        63.795197             2022-12-13

    Highest Adj Close Lowest Adj Close Date  Lowest Adj Close  \
0           69.836151            2000-10-25          1.705803
1           87.934952            2008-11-20          3.048036
2           51.952221            2000-02-24          2.537365
3          235.639999            2000-02-29         10.828531
4           54.250000            2000-12-28          0.418953
5          140.009995            2000-12-19          4.426346
6           57.866196            2000-10-25          2.700127
7           66.209999            2003-03-10          8.191070
8          196.449997            2003-04-17          0.201463
9           87.949997            2020-03-18         21.620001
10         150.570007            2002-10-09         30.766453

   Current Adj Close Date  Current Adj Close    ETF  Highest pct_change  \
0              2023-09-01          55.580002  False           14.950784
1              2023-09-01          51.779999  False           20.571535
2              2023-09-01          41.290001  False           14.988602
3              2023-09-01         182.699997  False           15.311756
4              2023-09-01          16.320000  False           41.036567
5              2023-09-01          77.150002  False           22.205963
6              2023-09-01          38.290001  False           18.017575
7              2023-09-01          59.310001  False            4.827562
8              2023-09-01         189.460007  False          227.583518
9              2023-09-01          62.849998  False            0.481263
10             2023-09-01         147.940002  False            1.360209

    Lowest pct_change  Current pct_change  \
0           -0.610390           11.694638
1           -0.252279           11.702276
2           -0.219111           11.707241
3           -0.250414           11.647079
4           -0.675367           11.645839
5           -0.266355           11.787230
6           -0.112610           11.583909
```

```
7           -0.279052           4.220250
8           -0.765583         219.450168
9           -0.635874           0.058526
10          -0.517731           1.318983

                                       Security Name
0                  Olympic Steel, Inc. - Common Stock
1           Sturm, Ruger & Company, Inc. Common Stock
2                        BorgWarner Inc. Common Stock
3                            Ecolab Inc. Common Stock
4                The Shyft Group, Inc. - Common Stock
5      Papa John's International, Inc. - Common Stock
6        Cass Information Systems, Inc - Common Stock
7                Coca-Cola Company (The) Common Stock
8                          Apple Inc. - Common Stock
9   Shell PLC American Depositary Shares (each rep…
10  International Business Machines Corporation Co…
```

[24]:

```python
# Combine ETFs' Close prices in one DataFrame
date_set = False
Stocks_prices = pd.DataFrame()

for index, row in avg_Stocks.iterrows():
    symbol = row["Symbol"]
    if not date_set:
        Stocks_prices["Date"] = Stocks[symbol]["Date"]
        date_set = True
    Stocks_prices[symbol] = Stocks[symbol]["Adj Close"]

Stocks_prices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 5955 entries, 2000-01-03 to 2023-09-01
Data columns (total 12 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Date    5955 non-null   object
 1   ZEUS    5955 non-null   float64
 2   RGR     5955 non-null   float64
 3   BWA     5955 non-null   float64
 4   ECL     5955 non-null   float64
 5   SHYF    5955 non-null   float64
 6   PZZA    5955 non-null   float64
 7   CASS    5955 non-null   float64
 8   KO      5955 non-null   float64
 9   AAPL    5955 non-null   float64
 10  SHEL    5955 non-null   float64
```

```
 11  IBM     5955 non-null   float64
dtypes: float64(11), object(1)
memory usage: 604.8+ KB
```

[25]:
```
Stocks_prices.describe()
```

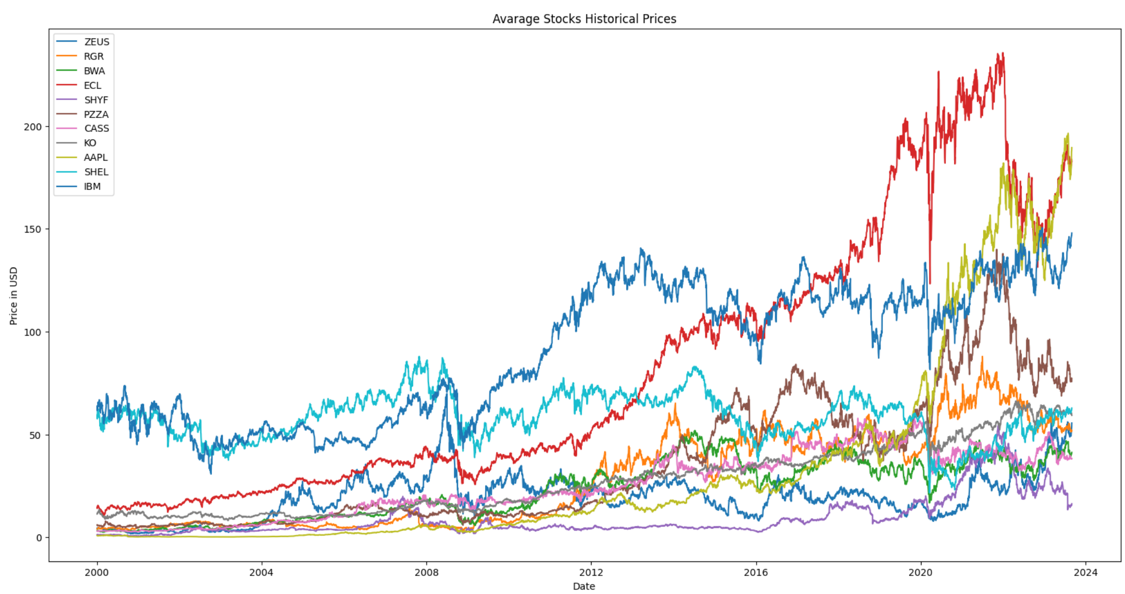
[25]:
```
              ZEUS          RGR          BWA          ECL         SHYF  \
count  5955.000000  5955.000000  5955.000000  5955.000000  5955.000000
mean     19.470901    28.205683    23.119777    81.985614     9.136387
std      10.995246    22.848867    14.060410    63.812341     9.587340
min       1.705803     3.048036     2.537365    10.828531     0.418953
25%      12.383190     6.231582     9.733729    28.331012     3.748859
50%      19.877592    22.553392    25.502546    48.914669     4.949563
75%      25.503544    47.871002    34.606873   126.496151    10.697322
max      69.836151    87.934952    51.952221   235.639999    54.250000

              PZZA         CASS           KO         AAPL         SHEL  \
count  5955.000000  5955.000000  5955.000000  5955.000000  5955.000000
mean     35.252638    25.156406    27.490260    32.888863    58.399237
std      31.984205    15.623892    16.443189    48.544423    11.242674
min       4.426346     2.700127     8.191070     0.201463    21.620001
25%       9.669167    10.561713    11.825697     1.794894    51.035000
50%      16.464876    21.987619    24.242241    12.088393    59.139999
75%      58.103527    38.586596    38.854361    37.552719    66.174999
max     140.009995    57.866196    66.209999   196.449997    87.949997

               IBM
count  5955.000000
mean     90.580729
std      32.529035
min      30.766453
25%      56.778316
50%     100.670609
75%     119.403328
max     150.570007
```

[26]:
```
Stocks_prices.head()
```

[26]:
```
                  Date      ZEUS       RGR       BWA        ECL      SHYF  \
Date
2000-01-03  2000-01-03  4.378227  4.076435  3.249329  14.446023  1.290543
2000-01-04  2000-01-04  4.378227  4.047928  3.249329  14.062716  1.234022
2000-01-05  2000-01-05  4.378227  3.990915  3.265077  14.613727  1.281123
2000-01-06  2000-01-06  4.264506  3.990915  3.223083  15.260563  1.347063
2000-01-07  2000-01-07  4.548805  4.190461  3.312321  15.260563  1.337643

                PZZA      CASS         KO      AAPL    SHEL         IBM
```

```
Date
2000-01-03  6.033363  3.042775  11.361526  0.859423  59.375  63.795197
2000-01-04  5.751430  2.927953  11.374119  0.786965  57.625  61.629768
2000-01-05  5.666849  2.927953  11.474890  0.798481  59.750  63.795197
2000-01-06  5.666849  2.927953  11.487485  0.729382  61.000  62.695278
2000-01-07  5.793720  2.927953  12.243238  0.763932  63.063  62.420292
```

[27]:
```python
# Plot ETFs' prices
plt.figure(figsize=(20,10))

for column in Stocks_prices.columns[1:]:
    plt.plot(Stocks_prices.index, Stocks_prices[column], label=column)

plt.xlabel("Date")
plt.ylabel("Price in USD")
plt.legend()
plt.title("Avarage Stocks Historical Prices")
plt.show()
```



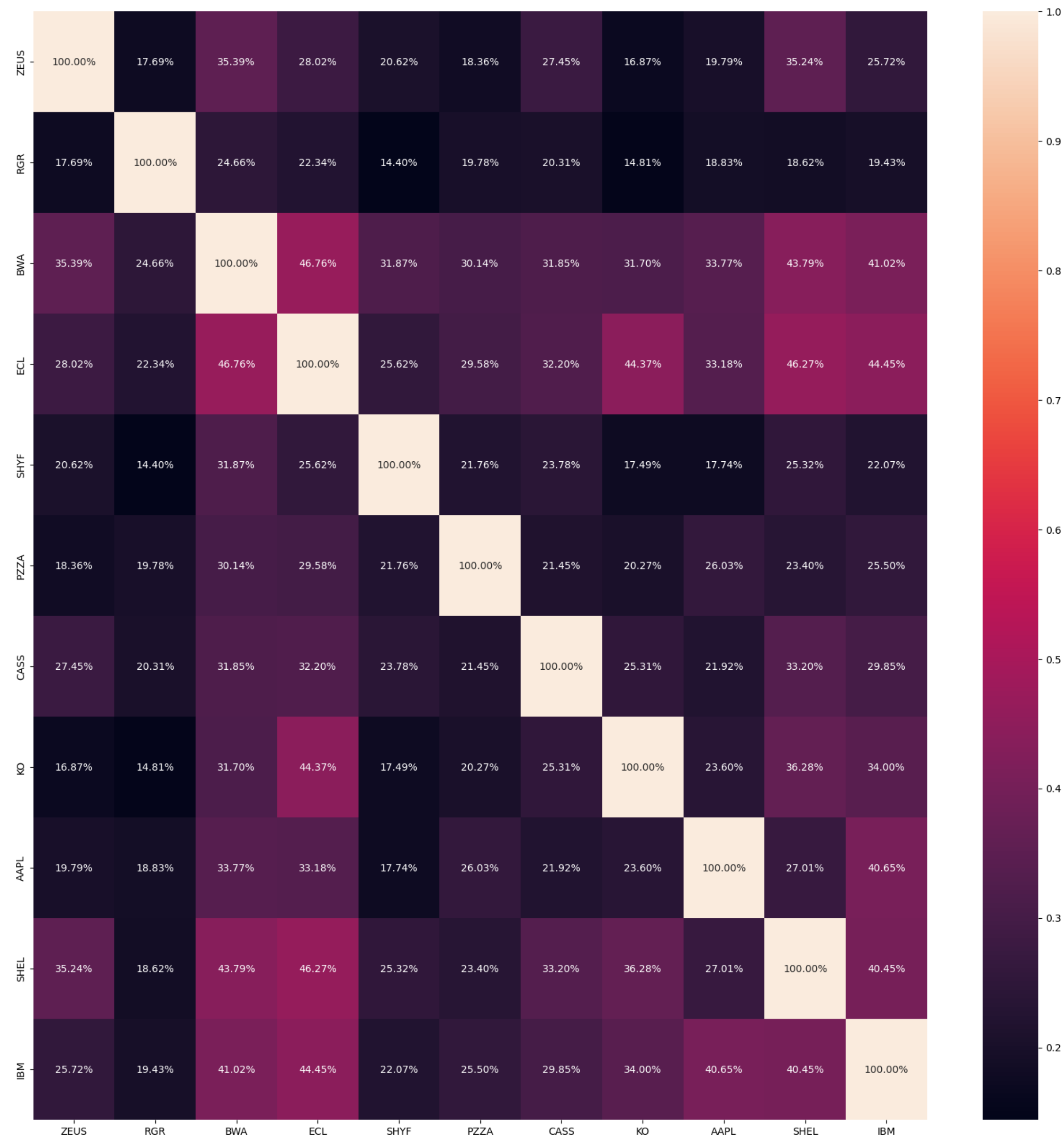
[28]:
```python
# Calculate daily returns and isu it for correlation

Stocks_prices_daily_change = Stocks_prices[[column for column in Stocks_prices.
 ↪columns[1:]]].pct_change(1)
Stocks_prices_daily_change.head()
```

[28]:
```
                ZEUS       RGR       BWA       ECL      SHYF      PZZA  \
Date
```

```
2000-01-03        NaN       NaN       NaN       NaN       NaN       NaN
2000-01-04  0.000000 -0.006993  0.000000 -0.026534 -0.043796 -0.046729
2000-01-05  0.000000 -0.014084  0.004847  0.039182  0.038168 -0.014706
2000-01-06 -0.025974  0.000000 -0.012861  0.044262  0.051471  0.000000
2000-01-07  0.066666  0.050000  0.027687  0.000000 -0.006993  0.022388

                CASS        KO      AAPL      SHEL       IBM
Date
2000-01-03        NaN       NaN       NaN       NaN       NaN
2000-01-04 -0.037736  0.001108 -0.084310 -0.029474 -0.033943
2000-01-05  0.000000  0.008860  0.014633  0.036876  0.035136
2000-01-06  0.000000  0.001098 -0.086538  0.020921 -0.017241
2000-01-07  0.000000  0.065789  0.047369  0.033820 -0.004386
```

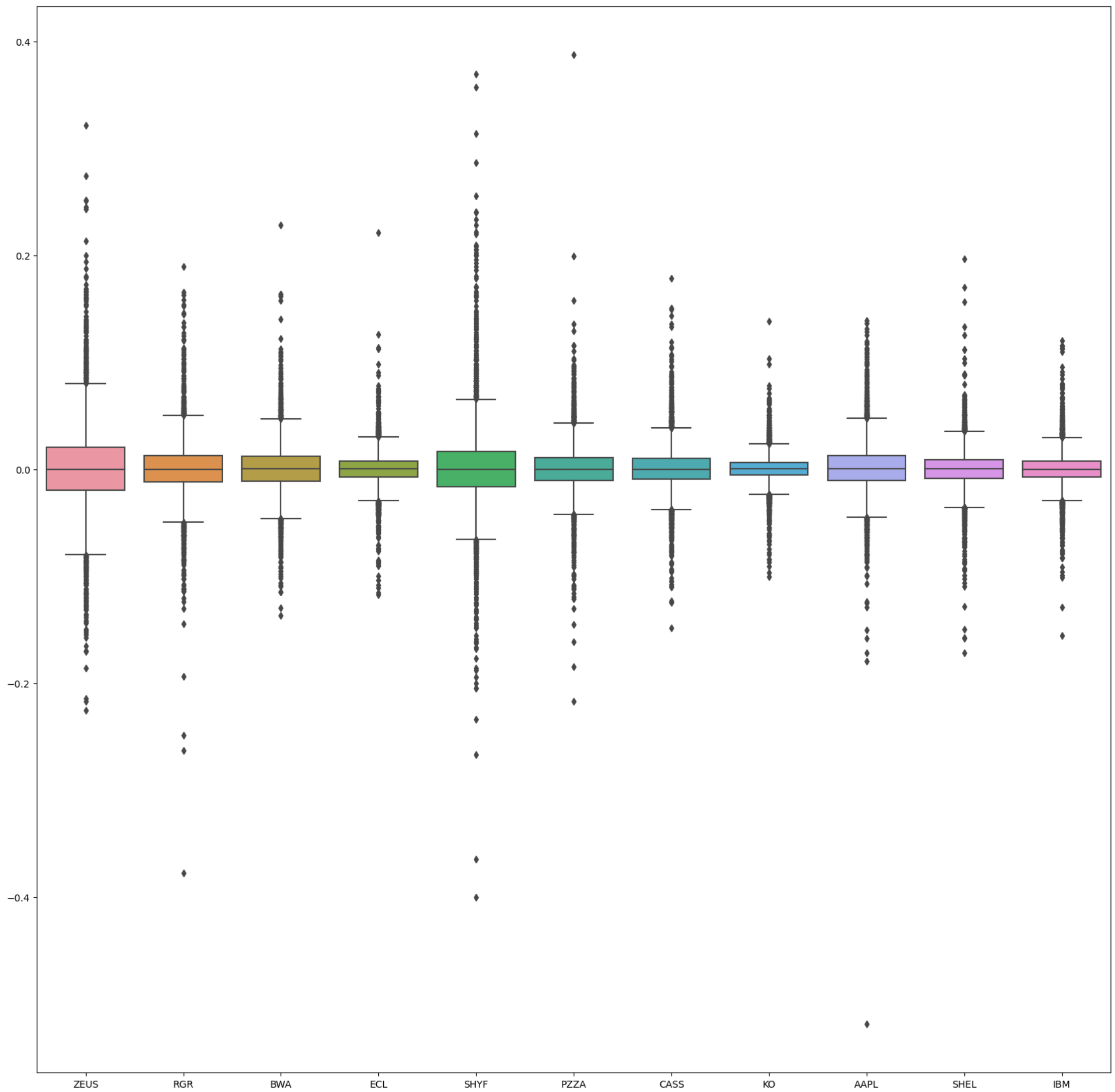
[29]:
```python
# Show the correlation
plt.subplots(figsize=(20,20))
sns.heatmap(Stocks_prices_daily_change.corr(), annot=True, fmt=".2%")
```

[29]: <Axes: >



[30]:
```
# Plot the returns width their percentiles
plt.subplots(figsize=(20,20))
sns.boxplot(Stocks_prices_daily_change)
```

[30]:
```
<Axes: >
```



[31]:
```
# Check the co-variance for the symbols
Stocks_prices_daily_change.cov()
```

[31]:

	ZEUS	RGR	BWA	ECL	SHYF	PZZA	CASS \
ZEUS	0.001567	0.000184	0.000322	0.000176	0.000309	0.000167	0.000233
RGR	0.000184	0.000694	0.000149	0.000093	0.000144	0.000120	0.000115
BWA	0.000322	0.000149	0.000527	0.000170	0.000278	0.000159	0.000157
ECL	0.000176	0.000093	0.000170	0.000251	0.000154	0.000108	0.000109
SHYF	0.000309	0.000144	0.000278	0.000154	0.001438	0.000190	0.000193
PZZA	0.000167	0.000120	0.000159	0.000108	0.000190	0.000531	0.000106
CASS	0.000233	0.000115	0.000157	0.000109	0.000193	0.000106	0.000460
KO	0.000088	0.000051	0.000096	0.000092	0.000087	0.000061	0.000071
AAPL	0.000195	0.000123	0.000193	0.000131	0.000167	0.000149	0.000117

```
SHEL   0.000258  0.000091  0.000186  0.000136  0.000177  0.000100  0.000132
IBM    0.000167  0.000084  0.000154  0.000116  0.000137  0.000096  0.000105

             KO      AAPL      SHEL       IBM
ZEUS   0.000088  0.000195  0.000258  0.000167
RGR    0.000051  0.000123  0.000091  0.000084
BWA    0.000096  0.000193  0.000186  0.000154
ECL    0.000092  0.000131  0.000136  0.000116
SHYF   0.000087  0.000167  0.000177  0.000137
PZZA   0.000061  0.000149  0.000100  0.000096
CASS   0.000071  0.000117  0.000132  0.000105
KO     0.000172  0.000077  0.000088  0.000073
AAPL   0.000077  0.000618  0.000124  0.000166
SHEL   0.000088  0.000124  0.000341  0.000123
IBM    0.000073  0.000166  0.000123  0.000269
```

[32]:

```
# Calculate volatilitiy
Stocks_stats = pd.DataFrame()
Stocks_stats["Volatility"] = (Stocks_prices_daily_change.std() * 100)

# Calculate avarage daily returns %
Stocks_stats["Daily Return %"] = (Stocks_prices_daily_change.mean() * 100)

# Calculate avarage yearly returns % (approx to 252 avarage trading days / year)
Stocks_stats["Yearly Return %"] = (Stocks_prices_daily_change.mean() * 100 *␣
 ↪252)

Stocks_stats
```

[32]:

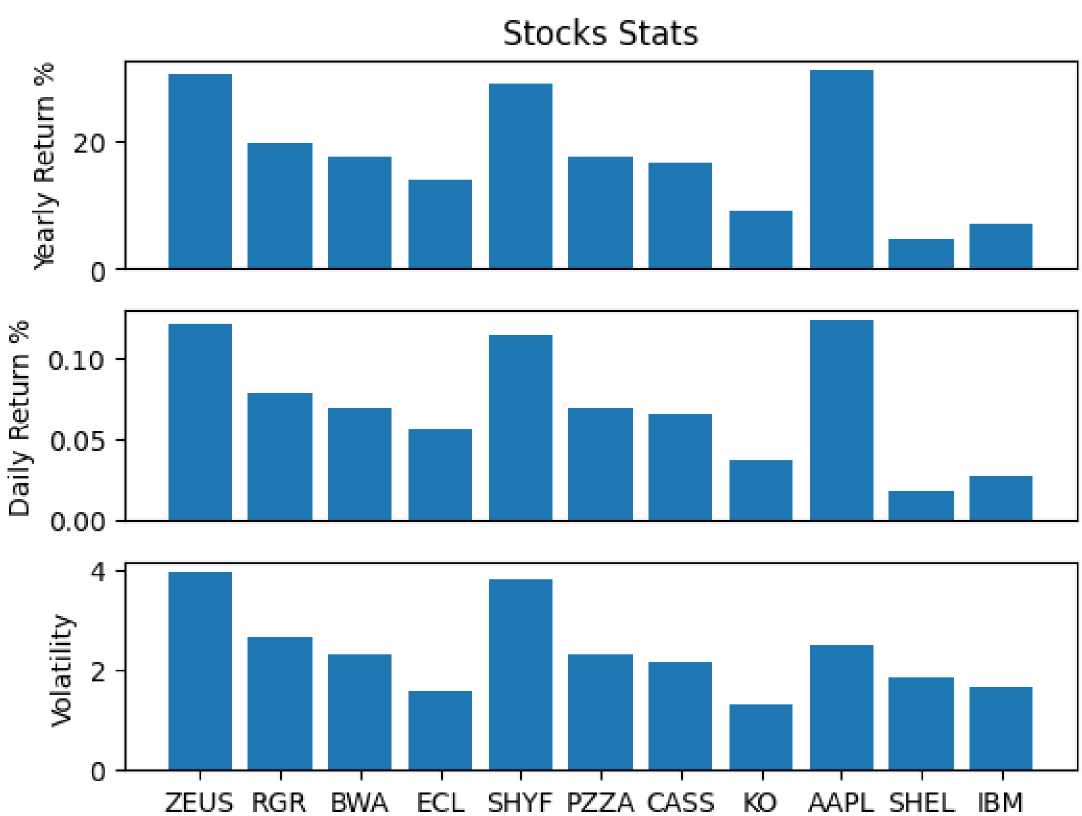
```
      Volatility  Daily Return %  Yearly Return %
ZEUS    3.958510        0.120413        30.343988
RGR     2.633768        0.077949        19.643053
BWA     2.296525        0.068978        17.382415
ECL     1.584878        0.055159        13.900117
SHYF    3.791752        0.114222        28.783838
PZZA    2.303858        0.069161        17.428600
CASS    2.144626        0.065467        16.497573
KO      1.312269        0.036371         9.165557
AAPL    2.486965        0.122889        30.968136
SHEL    1.847852        0.018083         4.556985
IBM     1.639524        0.027587         6.952034
```

[33]:

```
# Plot Stocks Stats

plt.figure(figsize=(40, 10))
fig, axis = plt.subplots(3, 1)
```

```
axis[2].bar(Stocks_stats.index, Stocks_stats["Volatility"])
axis[2].set_ylabel("Volatility")

axis[1].bar(Stocks_stats.index, Stocks_stats["Daily Return %"])
axis[1].set_ylabel("Daily Return %")
axis[1].xaxis.set_visible(False)

axis[0].set_title("Stocks Stats")
axis[0].bar(Stocks_stats.index, Stocks_stats["Yearly Return %"])
axis[0].set_ylabel("Yearly Return %")
axis[0].xaxis.set_visible(False)
plt.show()
```

```
<Figure size 4000x1000 with 0 Axes>
```



0.0.4 Save the temporary generated data objects for later use

[34]:
```
# import libraries
import pickle
```

[35]:
```
# dump objects
with open("3_2_etfs_prices.pckl", "wb") as f:
    %time pickle.dump(ETFs_prices, f)
```

```
CPU times: user 394 µs, sys: 279 µs, total: 673 µs
Wall time: 677 µs
```

[36]:
```
# dump objects
with open("3_2_stocks_prices.pckl", "wb") as f:
    %time pickle.dump(Stocks_prices, f)
```

```
CPU times: user 636 µs, sys: 64 µs, total: 700 µs
Wall time: 704 µs
```