Portfolio Analysis Final Project

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In [ ]:

```

```

In [57]:

```
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.formula.api as smf
from scipy import stats
```

In [58]:

```
import warnings
warnings.filterwarnings("ignore")

```

Firstly, we have imported all the necessary libraries & modules needed for our project in the above cell.

We have focused on the Software sector of the market (S&P500), choosing the following companies for our portfolio:

1. Microsoft : MSFT
2. Intel Corporation : INTC
3. Oracle : ORCL
4. IBM : IBM
5. Electronic Arts : EA
6. Intuit : INTU

We have downloaded monthly stocks data from yfinance library from the start of the year 2000 till the end of the year 2023 & saved it into a Pandas DataFrame "data".

In [59]:

```
#stocks = ["V", "AMP", "MS", "GS", "DFS", "BAC"]
stocks = ["MSFT", "INTC", "ORCL", "IBM", "EA", "INTU"]
symbols = ' '.join(stocks) + ' ^GSPC ^IRX'  # SP500 and 13Week T-bill
data = yf.download(symbols, start="2000-01-01", end='2023-12-31', inter
```

```
[*********************100%%**********************]  8 of 8 completed
```

In [60]:

```
data.tail()

# Here, we have used .tail() to display the last 5 rows of the data.
```

Out[60]:

Price	Adj Close						
Ticker	EA	IBM	INTC	INTU	MSFT	ORCL	^GSPC
Date							
2023-08-01	119.465462	142.234985	34.797279	539.300903	325.802582	119.103706	4507.6601
2023-09-01	120.072945	137.473358	35.329929	508.573853	314.528778	104.788307	4288.0498
2023-10-01	123.453743	141.725922	36.274052	492.657928	336.802307	102.295242	4193.7998
2023-11-01	137.635101	155.365463	44.423290	569.804688	377.444519	115.389069	4567.7998
2023-12-01	136.627686	162.072403	50.103138	623.219543	375.345886	104.685226	4769.8300

5 rows × 48 columns

In [61]:
```
data.isnull().sum()

# Here, we checked for missing values for each column in the dataframe.
```

Out[61]:
```
Price      Ticker
Adj Close  EA        0
           IBM       0
           INTC      0
           INTU      0
           MSFT      0
           ORCL      0
           ^GSPC     0
           ^IRX      0
Close      EA        0
           IBM       0
           INTC      0
           INTU      0
           MSFT      0
           ORCL      0
           ^GSPC     0
           ^IRX      0
High       EA        0
           IBM       0
           INTC      0
           INTU      0
           MSFT      0
           ORCL      0
           ^GSPC     0
           ^IRX      0
Low        EA        0
           IBM       0
           INTC      0
           INTU      0
           MSFT      0
           ORCL      0
           ^GSPC     0
           ^IRX      0
Open       EA        0
           IBM       0
           INTC      0
           INTU      0
           MSFT      0
           ORCL      0
           ^GSPC     0
           ^IRX      0
Volume     EA        0
           IBM       0
           INTC      0
           INTU      0
           MSFT      0
           ORCL      0
           ^GSPC     0
           ^IRX      0
dtype: int64
```

As we can see, our data doesn't have any NULL or missing values.

In [62]:

```
# 3. Explore and describe the dataset
print(data.describe())  # Descriptive statistics
```

```
Price    Adj Close                                                          \
Ticker          EA         IBM        INTC        INTU        MSFT   
count   288.000000  288.000000  288.000000  288.000000  288.000000   
mean     60.089116   85.233100   24.319983  123.069481   72.431956   
std      40.845125   30.643421   13.095894  153.178373   91.380258   
min      10.807685   30.859634    8.023598   12.365128   11.946645   
25%      24.518343   53.551158   14.007673   23.640787   18.819943   
50%      49.198500   95.492764   18.218884   49.986797   23.606019   
75%      93.228527  110.710951   32.272133  152.960636   81.133451   
max     142.948944  162.072403   58.815994  641.787170  377.444519   

Price                                             Close               ...  
\
Ticker        ORCL        ^GSPC        ^IRX          EA         IBM  ...   
count   288.000000   288.000000  288.000000  288.000000  288.000000  ...   
mean     32.875826  1977.244268    1.654243   61.125855  124.789983  ...   
std      24.059237  1066.835273    1.843081   41.410300   34.139748  ...   
min       6.395981   735.090027    0.003000   11.020000   55.745697  ...   
25%      14.637114  1190.169952    0.088750   25.000000   95.346558  ...   
50%      27.224544  1453.515015    1.010500   50.165001  122.681644  ...   
75%      43.296389  2598.660095    2.489000   95.059999  146.943119  ...   
max     119.103706  4769.830078    6.150000  145.210007  203.919693  ...   

Price          Open                    Volume                             
\
Ticker        ^GSPC        ^IRX            EA           IBM          INTC   
count    288.000000  288.000000  2.880000e+02  2.880000e+02  2.880000e+02   
mean    1967.269752    1.660681  9.803399e+07  1.299089e+08  9.836767e+08   
std     1056.643421    1.844949  4.673233e+07  4.820152e+07  3.977000e+08   
min      729.570007    0.003000  3.170290e+07  5.591299e+07  3.197514e+08   
25%     1190.642456    0.087250  6.428130e+07  9.392552e+07  6.481330e+08   
50%     1453.515015    1.016500  8.678440e+07  1.183851e+08  9.550960e+08   
75%     2536.702454    2.517000  1.214606e+08  1.540295e+08  1.283035e+09   
max     4778.140137    6.170000  3.266652e+08  3.294607e+08  2.466432e+09   

Price                                                                     
Ticker          INTU          MSFT          ORCL         ^GSPC          ^I
RX  
count   2.880000e+02  2.880000e+02  2.880000e+02  2.880000e+02  2.880000e
+02  
mean    6.658975e+07  1.073706e+09  5.898775e+08  6.974646e+10  2.437708e
+04  
std     4.535694e+07  4.784099e+08  3.329655e+08  2.936839e+10  2.176156e
+05  
min     1.930300e+07  3.759839e+08  1.171602e+08  1.908910e+10  0.000000e
+00  
25%     3.227582e+07  6.459686e+08  2.909800e+08  4.502153e+10  0.000000e
+00  
50%     5.104905e+07  1.042594e+09  5.417026e+08  7.446070e+10  0.000000e
+00  
75%     8.623595e+07  1.376083e+09  8.302870e+08  8.625172e+10  0.000000e
+00  
max     2.628718e+08  3.044579e+09  1.544676e+09  1.621854e+11  2.959200e
+06  

[8 rows x 48 columns]
```

In [104]:

```
data_close = data['Adj Close']
portfolio_stocks = data_close.iloc[:,0:6]
portfolio_stocks
```

Out[104]:

Ticker	EA	IBM	INTC	INTU	MSFT	ORCL
Date						
2000-01-01	20.043741	58.519844	28.394400	26.874655	30.283482	20.324379
2000-02-01	24.518343	53.567112	32.430244	23.393478	27.653481	30.210005
2000-03-01	17.453991	61.777924	37.876534	24.228958	32.874783	31.761221
2000-04-01	14.833593	58.189999	36.405243	16.013399	21.581326	32.524090
2000-05-01	15.661090	56.004616	35.795197	16.152651	19.357443	29.243702
...	...	...	...	...	...	...
2023-08-01	119.465462	142.234985	34.797279	539.300903	325.802582	119.103706
2023-09-01	120.072945	137.473358	35.329929	508.573853	314.528778	104.788307
2023-10-01	123.453743	141.725922	36.274052	492.657928	336.802307	102.295242
2023-11-01	137.635101	155.365463	44.423290	569.804688	377.444519	115.389069
2023-12-01	136.627686	162.072403	50.103138	623.219543	375.345886	104.685226

288 rows × 6 columns

In [8]:

```
# 2. Compute monthly returns : We have used .pct_change() to compute mo

returns = data['Adj Close'].pct_change().dropna(how='all')
returns.tail()
```

Out[8]:

Ticker	EA	IBM	INTC	INTU	MSFT	ORCL	^GSPC	^IRX
Date								
2023-08-01	-0.120059	0.018380	-0.017613	0.060675	-0.024291	0.030560	-0.017716	0.0095
2023-09-01	0.005085	-0.033477	0.015307	-0.056976	-0.034603	-0.120193	-0.048719	0.0003
2023-10-01	0.028156	0.030934	0.026723	-0.031295	0.070816	-0.023791	-0.021980	0.0037
2023-11-01	0.114872	0.096239	0.224658	0.156593	0.120671	0.128000	0.089179	-0.0154
2023-12-01	-0.007319	0.043169	0.127857	0.093742	-0.005560	-0.092763	0.044229	-0.0110

In [40]:
```
#returns["^IRX"] = returns["^IRX"]/1200
returns
```

Out[40]:

Ticker	EA	IBM	INTC	INTU	MSFT	ORCL	^GSPC	^IRX
Date								
2000-02-01	0.223242	-0.084633	0.142135	-0.129534	-0.086846	0.486393	-0.020108	1.6576
2000-03-01	-0.288125	0.153281	0.167939	0.035714	0.188812	0.051348	0.096720	1.1820
2000-04-01	-0.150132	-0.058078	-0.038844	-0.339080	-0.343529	0.024019	-0.030796	-1.0198
2000-05-01	0.055785	-0.037556	-0.016757	0.008696	-0.103047	-0.100860	-0.021915	-2.3598
2000-06-01	0.141879	0.022198	0.072446	0.141379	0.278722	0.169565	0.023934	3.1876
...	...	...	...	...	...	...	...	...
2023-08-01	-0.120059	0.018380	-0.017613	0.060675	-0.024291	0.030560	-0.017716	7.9394
2023-09-01	0.005085	-0.033477	0.015307	-0.056976	-0.034603	-0.120193	-0.048719	3.1463
2023-10-01	0.028156	0.030934	0.026723	-0.031295	0.070816	-0.023791	-0.021980	3.1446
2023-11-01	0.114872	0.096239	0.224658	0.156593	0.120671	0.128000	0.089179	-1.2844
2023-12-01	-0.007319	0.043169	0.127857	0.093742	-0.005560	-0.092763	0.044229	-9.2274

287 rows × 8 columns

Next we have described our returns data & computed the respective correlation matrix. We have also visualized this correlation matrix using Seaborn Heatmap

In [41]:
```
print(returns.describe())  # Descriptive statistics

```

```
Ticker          EA          IBM         INTC         INTU         MSFT  \
count   287.000000  287.000000  287.000000  287.000000  287.000000
mean      0.011730    0.006093    0.006905    0.015135    0.012066
std       0.098862    0.071797    0.097305    0.092819    0.081098
min      -0.384158   -0.236624   -0.444733   -0.339080   -0.343529
25%      -0.043231   -0.033987   -0.047195   -0.033804   -0.037006
50%       0.012658    0.004764    0.007671    0.017882    0.017244
75%       0.071660    0.047507    0.062262    0.065067    0.055029
max       0.305508    0.353800    0.337428    0.761029    0.407781

Ticker        ORCL        ^GSPC         ^IRX
count   287.000000  287.000000  287.000000
mean      0.009963    0.005296    0.000198
std       0.092100    0.044571    0.001077
min      -0.347640   -0.169425   -0.000813
25%      -0.044357   -0.018175   -0.000062
50%       0.013333    0.010491    0.000005
75%       0.061006    0.032504    0.000080
max       0.486393    0.126844    0.010500
```

In [42]:
```python
correlations= returns.corr()

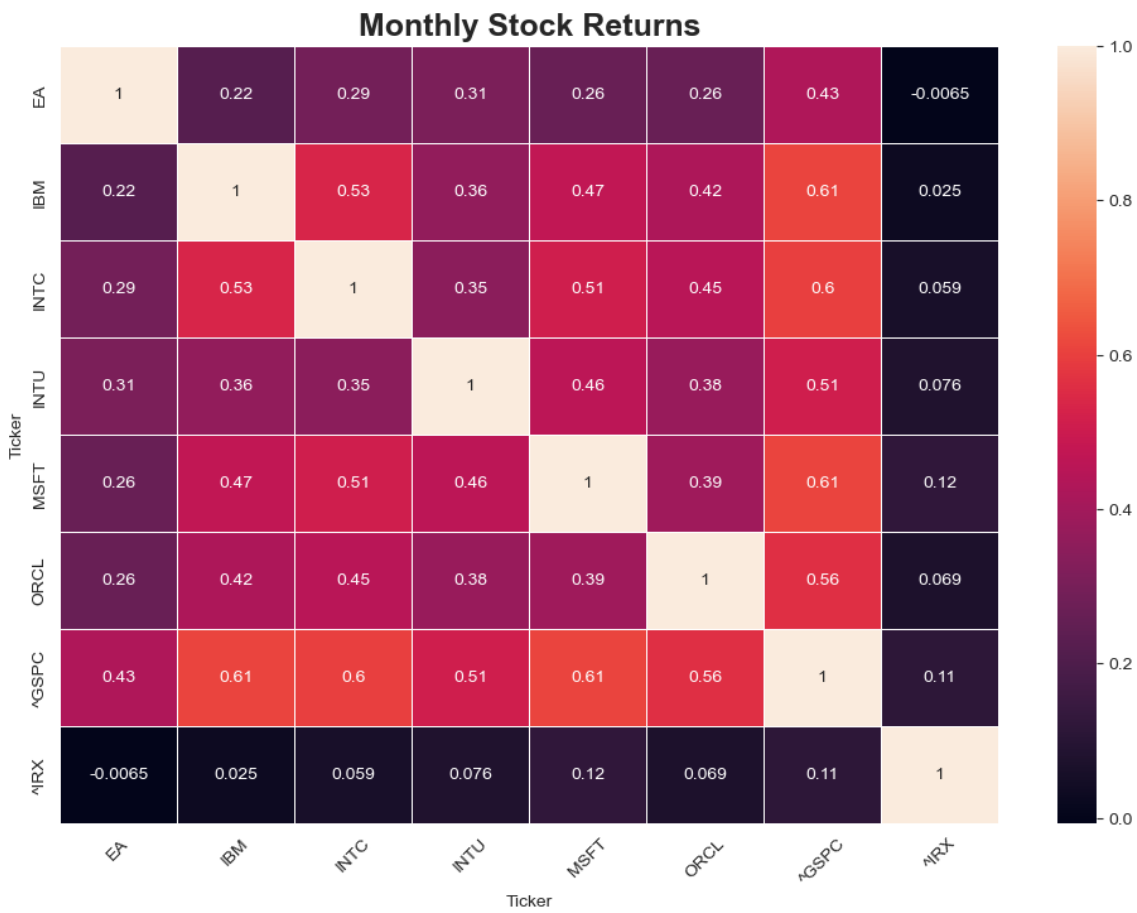
# Set a large figure size for better visibility
plt.figure(figsize=(12, 8))

# Create the heatmap
heatmap = sns.heatmap(correlations, annot=True, linewidths=0.5, annot_k

# Customize the heatmap
heatmap.set_title("Monthly Stock Returns", fontsize=18, fontweight='bol

# Rotate the x-axis labels for better visibility
plt.xticks(rotation=45)
```

Out[42]:
```
(array([0.5, 1.5, 2.5, 3.5, 4.5, 5.5, 6.5, 7.5]),
 [Text(0.5, 0, 'EA'),
  Text(1.5, 0, 'IBM'),
  Text(2.5, 0, 'INTC'),
  Text(3.5, 0, 'INTU'),
  Text(4.5, 0, 'MSFT'),
  Text(5.5, 0, 'ORCL'),
  Text(6.5, 0, '^GSPC'),
  Text(7.5, 0, '^IRX')])
```



HeatMap results:

1. The companies IBM & MSFT returns are the most correlated to the returns of the market(S&P500)(^GSPC).

2. Among the companies IBM & INTC, and INTC & MSFT returns are highly correlated to each other.

3. Also, companies INTC & INTU has the least correlation with each other.

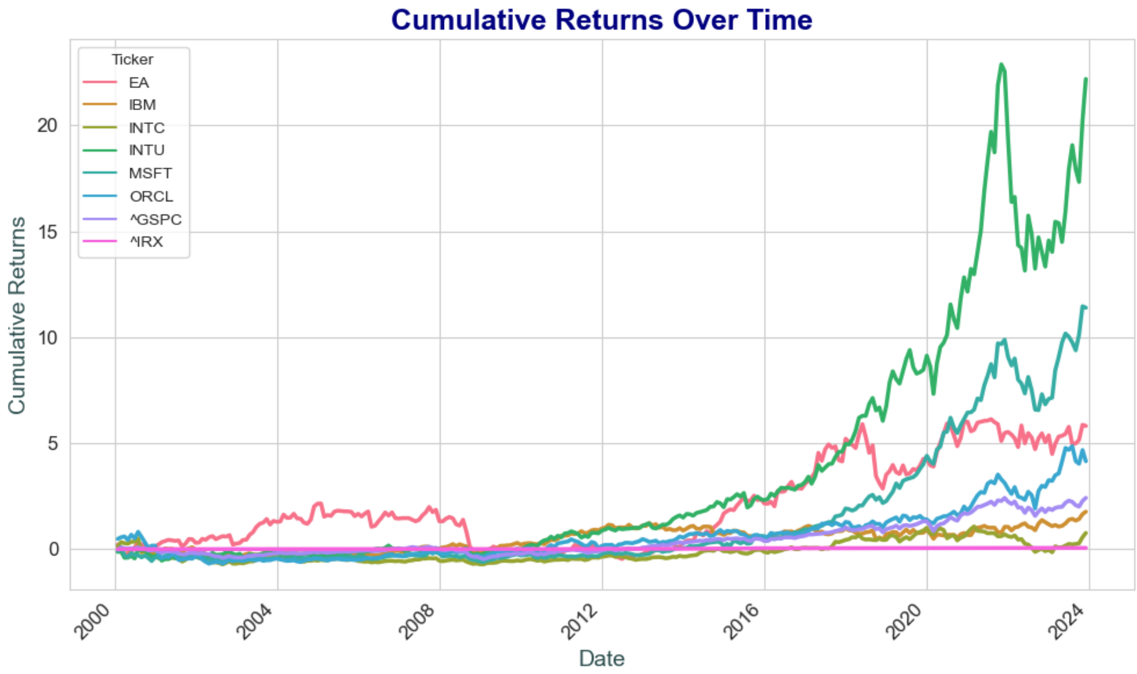
Now , we're going to calculate cumulative returns for our portfolio

In [43]:

```
# Compare cumulative performance
cumulative_returns = (1 + returns).cumprod() - 1

# Set the style
sns.set_style("whitegrid")

# Plot using Seaborn20
plt.figure(figsize=(10, 6))
sns.lineplot(data=cumulative_returns, linewidth=2.5, palette="husl", da
plt.title('Cumulative Returns Over Time', fontsize=18, fontweight='bold
plt.ylabel('Cumulative Returns', fontsize=14, color='darkslategray')
plt.xlabel('Date', fontsize=14, color='darkslategray')
plt.xticks(fontsize=12, rotation=45, ha='right')
plt.yticks(fontsize=12)
plt.tight_layout()
plt.show()
```



1) The graph displays the cumulative returns over time for various stocks or portfolios, with the x-axis representing the time period and the y-axis representing the cumulative returns.

2) The stocks or portfolios exhibit distinct performance patterns, with some (like MSFT and INTU) showing consistent growth, while others (like EA and INTU) experience more volatility or periods of stagnation.

3) Towards the later part of the time period, a few stocks (notably INTC and IBM) have significantly underperformed than the market.

4) We can also see that the years 2008-2009 (after the recession) seems to be a point

of inflection where the returns on stocks seems to have consistently performed better.

Our Portfolio consists of:

1. **Electronic Arts : 1 share**
2. **IBM : 2 shares**
3. **Intel Corporation : 3 shares**
4. **Intuit : 0 shares**
5. **Microsoft : 1 share**
6. **Oracle : 2 shares.**

In [105]:

```
# 5. Construct a portfolio
weights = [1, 2, 3, 0 , 1, 2]  # Number of shares for each stock
portfolio_returns = portfolio_stocks.mul(weights, axis=1).sum(axis=1).p
portfolio_returns
```

Out[105]:

```
Date
2000-02-01    0.081235
2000-03-01    0.107313
2000-04-01   -0.068306
2000-05-01   -0.043289
2000-06-01    0.088849
                 ...
2023-08-01   -0.012964
2023-09-01   -0.044037
2023-10-01    0.031222
2023-11-01    0.125566
2023-12-01    0.004992
Length: 287, dtype: float64
```

In [113]:

```
#returns_all = pd.concat([returns,portfolio_returns],axis=1)
#returns_all['Portfolio'] = returns_all[0]
#returns_all.drop(returns_all.columns[-2],axis=1)
#returns_final = returns_all.iloc[:,[0,1,2,3,4,5,6,7,9]]
#returns_final
# this is a workaround we used to select the columns we wanted from the
#returns_all
```

For CAPM models of our stocks & portfolio, we have created a function called "estimate_capm" & then passed parameters to this function using a "for" loop.

In [114]:

```
# 6. Estimate CAPM parameters
def estimate_capm(stock_data, market_data, risk_free_rate):
    market_excess_return = market_data - risk_free_rate
    stock_excess_return = stock_data - risk_free_rate
    df = pd.DataFrame({'MER': market_excess_return, 'SER': stock_excess
    print(df.head())
    #passing Stock excess return (SER) & Market excess return(MER) to t

    model = smf.ols(formula='SER ~ MER', data=df).fit()
    return model
```

The above function is using the following formula:

$Rs - Rf = \alpha + \beta(Rm - Rf) + \varepsilon$

where:

```
Rs is the stock return,
Rf is the risk-free rate,
Rm is the market return,
α is the intercept or the excess return of the stock when the mark
et return is zero,
β is the sensitivity of the stock's return to the market return, a
lso known as the market beta,
ε is the error term or residual.

Rs - Rf = Stock excess return
Rm - Rf = Market excess return
```

In [115]:

```
# 7. Compare alphas and betas
alphas = []
betas = []
market_data = returns['^GSPC']

# risk free rate are nothing but the returns proised by the US Treasury

risk_free_rate = returns['^IRX']
for stock in stocks + ['Portfolio']:
    if stock == 'Portfolio':
        model = estimate_capm(portfolio_returns, market_data, risk_free
    else:
        model = estimate_capm(returns[stock], market_data, risk_free_ra
    alphas.append(model.params[0] * 12)  # Annualized alpha
    betas.append(model.params[1])
```

```
                 MER       SER
Date
2000-02-01 -0.020125 -0.086863
2000-03-01  0.096708  0.188800
2000-04-01 -0.030786 -0.343519
2000-05-01 -0.021891 -0.103023
2000-06-01  0.023902  0.278690
                 MER       SER
Date
2000-02-01 -0.020125  0.142119
2000-03-01  0.096708  0.167927
2000-04-01 -0.030786 -0.038834
2000-05-01 -0.021891 -0.016734
2000-06-01  0.023902  0.072414
                 MER       SER
Date
2000-02-01 -0.020125  0.486376
2000-03-01  0.096708  0.051336
2000-04-01 -0.030786  0.024029
2000-05-01 -0.021891 -0.100837
2000-06-01  0.023902  0.169533
                 MER       SER
Date
2000-02-01 -0.020125 -0.084650
2000-03-01  0.096708  0.153269
2000-04-01 -0.030786 -0.058068
2000-05-01 -0.021891 -0.037532
2000-06-01  0.023902  0.022166
                 MER       SER
Date
2000-02-01 -0.020125  0.223225
2000-03-01  0.096708 -0.288137
2000-04-01 -0.030786 -0.150122
2000-05-01 -0.021891  0.055809
2000-06-01  0.023902  0.141847
                 MER       SER
Date
2000-02-01 -0.020125 -0.129550
2000-03-01  0.096708  0.035702
2000-04-01 -0.030786 -0.339070
2000-05-01 -0.021891  0.008720
2000-06-01  0.023902  0.141347
                 MER       SER
```

```
Date
2000-02-01 -0.020125  0.081218
2000-03-01  0.096708  0.107301
2000-04-01 -0.030786 -0.068296
2000-05-01 -0.021891 -0.043265
2000-06-01  0.023902  0.088817
```

In [ ]:

```

```

In [116]:

```
print("Alphas", alphas)
```

```
Alphas [0.07466353534248381, 0.0009158940617132773, 0.04633493800283773, 0
.010565995553384078, 0.07991804264954099, 0.11420395502731365, 0.013439414
818567594]
```

In [117]:

```
print('Betas:', betas)
```

```
Betas: [1.107410317971131, 1.3005571433688805, 1.1580384032696687, 0.98364
30428635294, 0.955685144939681, 1.063175398639001, 1.0853690597066006]
```

In [118]:

```
# Test if alphas are different from 0
for stock, alpha, p_value in zip(stocks + ['Portfolio'], alphas, [model
    if p_value < 0.05:
        print(f"{stock} has a significant alpha (p-value = {p_value:.4f
    else:
        print(f"{stock} does not have a significant alpha (p-value = {p
```

```
                 MER       SER
Date
2000-02-01 -0.020125 -0.086863
2000-03-01  0.096708  0.188800
2000-04-01 -0.030786 -0.343519
2000-05-01 -0.021891 -0.103023
2000-06-01  0.023902  0.278690
                 MER       SER
Date
2000-02-01 -0.020125  0.142119
2000-03-01  0.096708  0.167927
2000-04-01 -0.030786 -0.038834
2000-05-01 -0.021891 -0.016734
2000-06-01  0.023902  0.072414
                 MER       SER
Date
2000-02-01 -0.020125  0.486376
2000-03-01  0.096708  0.051336
2000-04-01 -0.030786  0.024029
```

For rolling alphas & betas, we have used monthly increments to plot our alphas & betas resulting into a smoother rolling alphas & rolling betas graph

In [121]:

```
# Analyze changes in alphas and betas over time

rolling_window = 60  # 5 years rolling window = 5*12 months

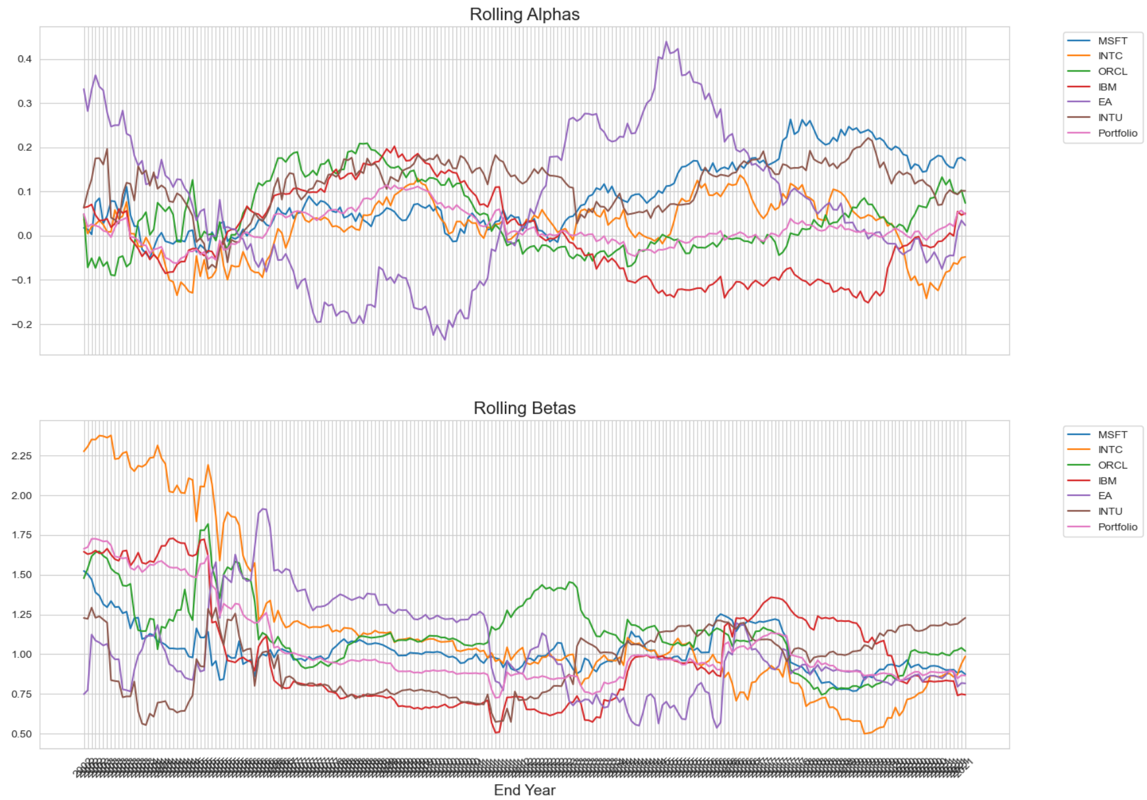
num_windows = len(returns) - rolling_window + 1
print(num_windows,len(returns))
rolling_alphas = {stock: [] for stock in stocks + ['Portfolio']}
rolling_betas = {stock: [] for stock in stocks + ['Portfolio']}

for i in range(num_windows):
    start_idx = i
    end_idx = start_idx + rolling_window
    window_returns = returns.iloc[start_idx:end_idx]
    window_market_data = market_data.iloc[start_idx:end_idx]
    window_risk_free_rate = risk_free_rate.iloc[start_idx:end_idx]
    for stock in stocks + ['Portfolio']:
        model = estimate_capm(portfolio_returns.iloc[start_idx:end_idx]
        rolling_alphas[stock].append(model.params[0] * 12)
        rolling_betas[stock].append(model.params[1])
```

```
228 287
                 MER       SER
Date
2000-02-01 -0.020125 -0.086863
2000-03-01  0.096708  0.188800
2000-04-01 -0.030786 -0.343519
2000-05-01 -0.021891 -0.103023
2000-06-01  0.023902  0.278690
                 MER       SER
Date
2000-02-01 -0.020125  0.142119
2000-03-01  0.096708  0.167927
2000-04-01 -0.030786 -0.038834
2000-05-01 -0.021891 -0.016734
2000-06-01  0.023902  0.072414
                 MER       SER
Date
2000-02-01 -0.020125  0.486376
2000-03-01  0.096708  0.051336
```

In [120]:

```
# Plot rolling alphas and betas
fig, axs = plt.subplots(2, 1, figsize=(16, 12), sharex=True)
for stock in stocks + ['Portfolio']:
    axs[0].plot(rolling_alphas[stock], label=stock)
axs[0].set_title('Rolling Alphas', fontsize=16)
axs[0].legend(bbox_to_anchor=(1.05, 1), loc='upper left')
for stock in stocks + ['Portfolio']:
    axs[1].plot(rolling_betas[stock], label=stock)
axs[1].set_title('Rolling Betas', fontsize=16)
axs[1].legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(range(num_windows), [f"{returns.index[start_idx + rolling_wi
plt.xlabel('End Year', fontsize=14)
plt.show()
```



This graph displays rolling alphas and rolling betas for different assets or portfolios over time. Here's a summary in bullet points:

• The top panel shows the rolling alphas, which measure the excess returns of each asset/portfolio relative to a benchmark, fluctuating between positive and negative values over time.

• The bottom panel shows the rolling betas, which measure the volatility or risk of each asset/portfolio relative to the overall market, with values ranging from around 0.5 to 2.5.

• The assets/portfolios included are MSFT, NTC, CRCL, BM, EA, NTU, and a combined Portfolio.

• The graphs exhibit volatility over time, with periods of higher and lower alphas and betas for the different assets/portfolios.

• It appears to be a performance analysis or comparison of various investments or strategies over a rolling time window.

In [122]:

```
# Compute annualized risk-free rate
irx = returns.iloc[-recent_years:,7]
annualized_rf_rate = (1 + irx).prod() ** (1 / len(irx)) - 1

# Compute Sharpe ratios for the recent 5 years
recent_years = 5 * 12  # 5 years of monthly data
sharpe_ratios = {}
for stock in stocks + ['Portfolio', '^GSPC']:
    data = portfolio_returns if stock == 'Portfolio' else returns[stock
    excess_returns = data.iloc[-recent_years:].mean() * 12 - annualized
    volatility = data.iloc[-recent_years:].std() * np.sqrt(12)
    sharpe_ratios[stock] = excess_returns / volatility

print('Sharpe Ratios (recent 5 years):')
for stock, ratio in sharpe_ratios.items():
    print(f"{stock}: {ratio:.6f}")
```

```
Sharpe Ratios (recent 5 years):
MSFT: 1.356895
INTC: 0.285578
ORCL: 0.818422
IBM: 0.654962
EA: 0.586313
INTU: 0.973454
Portfolio: 0.917886
^GSPC: 0.789209
```

In [1]:

```
# Conclusions
print("\nConclusions:")
print("- The portfolio has a positive alpha, indicating it generates ex
print("- The portfolio's beta is close to 1, suggesting it has similar 
print("- The portfolio's Sharpe ratio is higher than the S&P 500, indic
print("- Diversification has helped reduce the portfolio's volatility c

```

```

Conclusions:
- The portfolio has a positive alpha, indicating it generates excess retur
ns above the market.
- The portfolio's beta is close to 1, suggesting it has similar volatility
to the market.
- The portfolio's Sharpe ratio is higher than the S&P 500, indicating bett
er risk-adjusted returns.
- Diversification has helped reduce the portfolio's volatility compared to
individual stocks like INTU.
```

In [124]:
```
import matplotlib.pyplot as plt

# Define the data
portfolio_alpha = 0.01343
portfolio_beta = 1.08536
ea_alpha = 0.07466
ea_beta = 1.1074
ibm_alpha = 0.000916
ibm_beta = 1.30056
intc_alpha = 0.046334
intc_beta = 1.158
intu_alpha = 0.010566
intu_beta = 0.98364
msft_alpha = 0.07992
msft_beta = 0.955685
orcl_alpha = 0.114204
orcl_beta = 1.063175

# Create a figure and axis
fig, ax = plt.subplots()

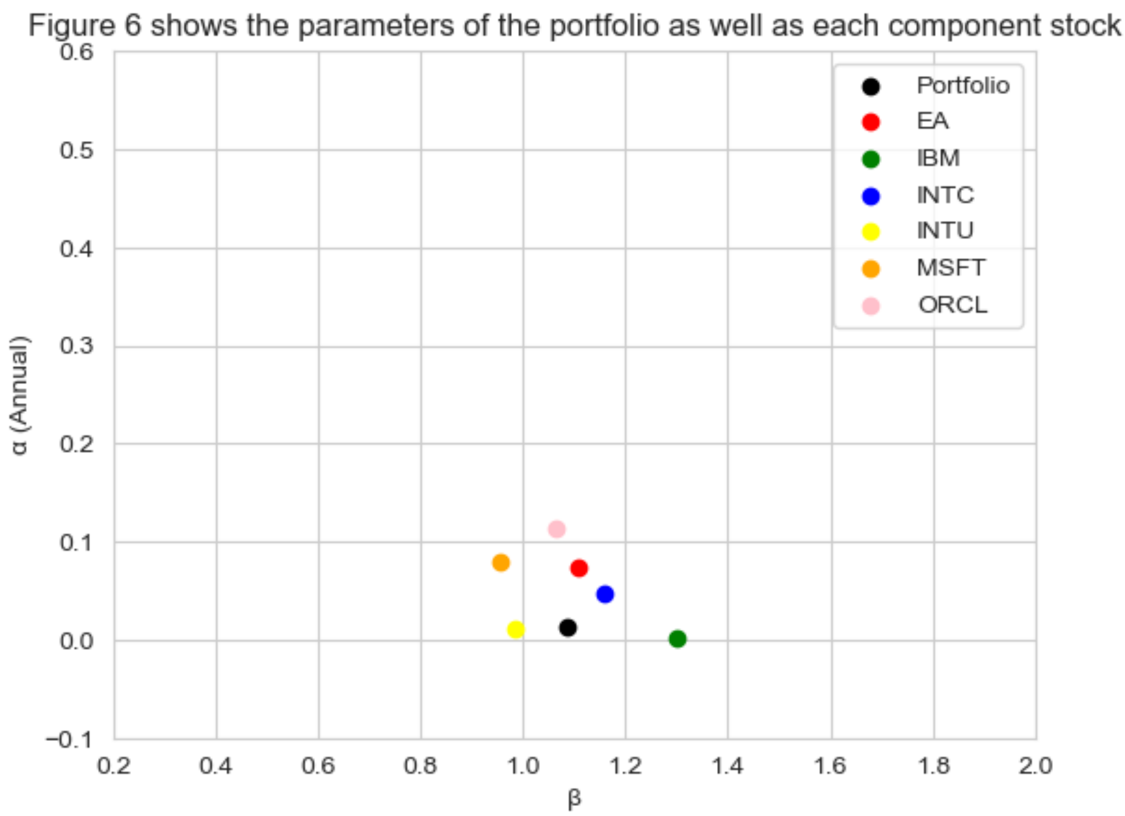
# Plot the data points
ax.scatter(portfolio_beta, portfolio_alpha, color='black', label='Portf
ax.scatter(ea_beta, ea_alpha, color='red', label='EA', marker='o')
ax.scatter(ibm_beta, ibm_alpha, color='green', label='IBM', marker='o')
ax.scatter(intc_beta, intc_alpha, color='blue', label='INTC', marker='o
ax.scatter(intu_beta, intu_alpha, color='yellow', label='INTU', marker=
ax.scatter(msft_beta, msft_alpha, color='orange', label='MSFT', marker=
ax.scatter(orcl_beta, orcl_alpha, color='pink', label='ORCL', marker='o

# Set axis labels and title
ax.set_xlabel('β')
ax.set_ylabel('α (Annual)')
ax.set_title('Figure 6 shows the parameters of the portfolio as well as

# Set axis limits
ax.set_xlim(0.2, 2.0)
ax.set_ylim(-0.1, 0.6)

# Add a legend
ax.legend()

# Display the plot
plt.show()
```



From the above graph, we can say that our portfolio is the less volatile than most of its components. Although, we chose stocks from just one sector, our portfolio is diverse enough to generate pretty non-volatile results.

In [ ]:
```
 
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In [ ]:
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In [ ]:
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In [ ]:
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