Trading Simulation Final Report

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Introduction

The SWMDZ Investments team is excited to present our exemplary portfolio performance for the StockTrak Trading Simulation. The portfolio ended the contest with a total return of 4.33% and a Sharpe Ratio of 3.02. The project was an ambition endeavor undertaken over the past few weeks, involving a series of stratic trades based on a blend of Tactical Asset Allocation, ES Futures Breakout Strategy, and Sector Rotation, with the aim to not only maximize returns but also to maintain a balanced risk profile in line with our investment objectives. This report will detail our methodology, the rationale behind our investment decisions, the performance of our portfolio compared to benchmark indices, and the valuable lessons learned throughout this enriching experience. Join us as we delve into the intricate world of finance, exploring the efficacy of our strategies and their impact on portfolio performance.

SWMDZ Investment Objectives

Our main objective was to maximize returns while maintaining a moderately aggressive risk profile. Our investment strategy is broken down into two separate trading strategies: one for ES Futures and one for ETFs. We focused on Tactical Asset Allocation and Sector Rotation strategies to achieve superior market performance, aligning our investments with the dynamic nature of the financial markets.

Portfolio Risk Tolerance

Our portfolio's risk tolerance was strategically calibrated to be moderately aggressive, balancing the pursuit of high returns with a mindful approach to risk management. This tolerance level was a crucial factor in guiding both our ETF and futures trading strategies and combining both strategies allowed us to balance our portfolio's overall risk. While ETFs provided stability and broad market exposure, futures trading offered the potential for higher rewards at a controlled level of risk.

Our ETF investments, spanning various sectors and asset classes, were selected to provide balanced exposure. This diversification aimed to mitigate systemic risks and capitalize on different market conditions. We employed the Capital Asset Pricing Model (CAPM) to evaluate the risk-return profile of each ETF, ensuring our selections aligned with our overall risk tolerance.

Our ES Futures Breakout Strategy adopted a bolder stance, leveraging technical analysis and employing tools such as moving averages and Fibonacci retracements. This method aimed to pinpoint trade setups with high return prospects within a condensed time horizon. Acknowledging the heightened risks associated with the inherent volatility and leverage of futures trading, we enforced rigorous risk management measures. These included the establishment of stop-loss orders and diligent surveillance of our positions to avert significant downturns.

Futures Investment Strategy

The report delves into the strategic approach to trading ES futures with an initial capital of $200,000. The methodology entailed scanning the depth of the market for unusually large positions, scrutinizing major financial reports, and utilizing an analysis of options – particularly delta changes – to gauge momentum and optimize trade positioning. This report reflects on the performance outcomes as illustrated by the cumulative return graph seen in Figure 1 of the Appendix.

Strategic Approach and Analytical Tools:

- **Depth of Market (DOM) Analysis:** The use of DOM scanning was pivotal in identifying large positions that could indicate significant market moves. This insight provided an edge in anticipating market momentum and aligning trades accordingly.
- **Financial Reports Analysis:** Key financial reports were analyzed to understand the macroeconomic environment affecting the ES futures. This analysis helped in predicting market sentiment and potential shifts in price movement.
- **Options Analysis – Delta Change:** Options delta provided a quantifiable measure of the rate of change in the option's price relative to a one-point move in the underlying ES futures. Monitoring delta changes assisted in identifying strong momentum opportunities and potential trend reversals.
- **Support and Resistance Evaluation:** Through options analysis and historical price action, critical support and resistance levels were established. These levels served as targets for entry and exit points, contributing to the precision of the trades.

Futures Transactions of Interest

We trade ES futures for several compelling reasons. Chief among them is the unparalleled liquidity and market depth they offer, which allows for tight bid-ask spreads and efficient order execution, even for large positions. The S&P 500 index, which is tracked by the ES futures, represents a broad spectrum of the U.S. economy, making it an ideal vehicle for gaining exposure to general market trends while also allowing for effective hedging strategies. Additionally, the ES futures market's extended trading hours provide the flexibility to respond to global economic events as they unfold, enabling us to capitalize on opportunities outside of regular market hours. Furthermore, the favorable margin requirements of ES futures amplify our buying power, providing the potential for significant returns on investment. Lastly, the robust regulatory framework of the futures market instills confidence in its integrity and reliability, making ES futures a cornerstone in our trading portfolio.

Example of Trades taken: On November 27th, our vigilance was rewarded when our monitoring systems detected an influx of sizable buy orders arriving in the order book just 10 seconds before the market's opening bell. This anomaly piqued our interest, and soon after the market opened, we observed a substantial wave of sell orders being placed, notably out of the money. This confluence of activity triggered a buy signal from our algorithm, prompting us to execute a timely trade. The accuracy of our system's predictive capabilities was validated as this strategic move generated a remarkable return of $5,000. This instance exemplifies the efficacy of our code in translating market patterns into profitable opportunities.

By introducing our code, we've significantly enhanced our decision-making process for executing buy or sell orders in the futures market. The algorithm's primary function is to dissect the order book in search of abnormally large positions, a hallmark of potentially market-moving trades. By doing so, it provides us with a granular view of market sentiment and participant actions, enabling us to discern whether these positions are likely to instigate a bullish or bearish momentum. With this insight, our buy/sell decisions are no longer just reactive responses to market changes; instead, they are proactive, informed choices backed by comprehensive data analysis. This strategic edge allows us to position our trades in alignment with—or in anticipation of—significant market shifts triggered by these large positions, ensuring that we are on the favorable side of the trade execution.

ETF Investment Strategy

The ETF trades were made based on an algorithm created in Python that generates a minimized risk portfolio and a maximized risk portfolio based on the chosen ETFs, the total investment ($800,000), the risk-free rate, the end date, a target expected CAPM return for the minimized risk portfolio, and a target beta for the maximized return portfolio. We chose a target expected return of 13% for the minimized risk portfolio and a target beta of 1.25 for the maximized return portfolio, and the risk-free rate and end date are updated manually every time the code is run.

The algorithm fetches historical data from January 1, 2022, until the specified end date (the current date when the program is run) for the chosen ETFs from Yahoo Finance. For each ETF, the beta and expected return based on the CAPM is calculated using its historical data. Optimization was done through optimization functions that determine the optimal weights for each ETF that collectively minimize the overall portfolio risk while meeting the target return of 13%. Similarly, the program optimizes the portfolio weights to maximize return while adhering to a target beta of 1.25. Once the optimal weights are obtained, the weights are converted into practical buy-sell decisions, determining the number of shares to buy for each ETF based on the available investment amount and current market prices. Visualization through pie charts, generated by the PIES function, provides a clear representation of the allocation of funds among different ETFs in the minimized risk and maximized return portfolios. The visualization component aids in understanding the portfolio composition resulting from the optimization, offering insights into risk-minimizing and return-maximizing strategies.

After running the program on Day 1, the team determined that we would make trades based only on the minimized risk portfolio with a target expected return of 13%. Based on the optimized weights for the minimized risk portfolio, the algorithm calculates the exact number of shares to purchase/hold for each ETF within the total budget of $800,000 by fetching the current minute-by-minute market prices of each ETF.

ETF Transactions of Interest

Our ETF portfolio was diversified across various sectors, including technology, emerging markets, fixed income and bond markets, commodities, consumer staples, broad market exposure, etc. The following ETFs were held in our portfolio from the first day of ETF trading:

- 1. IEMG (iShares Core MSCI Emerging Markets ETF): Chosen for its diversification benefits and potential high returns from emerging market economies

    - Beta: 0.94
    - P/E Ratio TTM: 11.27
    - Expense Ratio: 0.09%
- 2. BND (Vanguard Total Bond Market ETF): Chosen for its broad exposure to the U.S. bond market so that it provides a counterbalance to the volatility of the stock market
    - Beta: 1.00
    - Expense Ratio: 0.05%
- 3. MBB (iShares MBS ETF): Chosen for its focus on mortgage-based securities, providing diversification away from equities
    - Beta: 1.01
    - Expense Ratio: 0.04%
- 4. IVV (iShares Core S&P 500 ETF): Chosen for exposure to the S&P 500 with low cost
    - Beta: 1.00
    - P/E Ratio TTM: 22.95
    - Expense Ratio: 0.03%
- 5. SPY (SPDR S&P 500 ETF Trust): Chosen for diversified, broad market exposure that mirrors the S&P 500 Index performance
    - Beta: 1.00
    - P/E Ratio TTM: 22.94
    - Expense Ratio: 0.09%
- 6. IWF (ISHARES RUSSELL 1000 GROWTH ETF): Chosen to capitalize on growth-oriented companies by investing in U.S. large-cap growth stocks
    - Beta: 1.10
    - P/E Ratio TTM: 32.13
    - Expense Ratio: 0.19%
- 7. VOO (Vanguard S&P 500 ETF): Chosen for exposure to the S&P 500 with low expense ratio
    - Beta: 1.00
    - P/E Ratio TTM: 22.70
    - Expense Ratio: 0.04%
- 8. VIGI (Vanguard International Dividend Appreciation ETF): Chosen for potential capital growth in international markets
    - Beta: 0.89
    - P/E Ratio TTM: 19.50
    - Expense Ratio: 0.16%
- 9. SCHD (Schwab U.S. Dividend Equity ETF): Chosen for focus on high-dividend-paying companies and potential for lower volatility
    - Beta: 0.84
    - P/E Ratio TTM: 13.62
    - Expense Ratio: 0.06%
- 10. GSG (iShares S&P GSCI Commodity-Indexed Trust): Chosen for exposure to broad range of commodities
    - Beta: 1.13
    - P/E Ratio TTM: 4.60
    - Expense Ratio: 0.75%

- 11. KBWP (Invesco KBW Property & Casualty Insurance ETF): Chosen for exposure to property and casualty insurance sector
    - Beta: 0.64
    - P/E Ratio TTM: 16.59
    - Expense Ratio: 0.35%
- 12. XLP (Consumer Staples Select Sector SPDR Fund): Chosen for focus on consumer staples and potential to provide stability during market volatility
    - Beta: 0.62
    - P/E Ratio TTM: 24.01
    - Expense Ratio: 0.10%

On Day 1 (October 27th), the program yielded the following optimized weights for the minimized risk portfolio: 15.80% of BND with 1855 shares, 15.40% of MBB with 1434 shares, 5.20% of IVV with 98 shares, 5.10% of SPY with 98 shares, 2.30% of IWF with 69 shares, 5.20% of VOO with 108 shares, 5.70% of VIGI with 656 shares, 8.70% of SCHD with 1014 shares, 13.30% of GSG with 4851 shares, 10.60% of KBWP with 972 shares, 12.10% of XLP with 1423 shares, and 0.60% of IEMG with 101 shares. The program also generates a pie chart for visualization of the portfolio composition which is seen in Figure 2 of the Appendix.

ETF Buy/Sell Decision Analysis

The number of shares specified by the algorithm, which can be seen in Table 1 of the Appendix, were bought for each ETF on the first day. After Day 1, the code was updated and ran every trading day, and trades were made if the optimized weights were significantly different than the previous trade's weights. Trades were tracked in an Excel sheet so that we can easily see and analyze differences in weights. Trades were made by subtracting the previous shares held by the number of new shares to hold, and then buying or selling the difference if it was positive or negative, respectively. This process can be seen in Table 2 of the Appendix.

Buy/Sell decisions were ultimately made through the Python optimization process which returned the optimal weights that collectively minimize overall portfolio risk while meeting the target return of 13%. Once the optimal weights are obtained, the weights are converted into practical buy-sell decisions, determining the number of shares to hold for each ETF based on the available investment amount and current market prices. In summary, the decision-making process involves mathematical optimization to find optimal weights for each ETF based on MPT principles, with subsequent steps converting these weights into actionable buy-sell decisions.

Portfolio Returns Calculations & Performance Measures

As of Monday, November 27, 2023, the portfolio had achieved a total return of 4.33% over the trading period, with an average daily return of 0.1180% and an average weekly return of 0.6727%, reflecting consistent performance and increase in value. The total market return during the same period was 6.25% with a standard deviation of 0.00885, while our portfolio returns had a standard deviation of 0.0114, reflecting a moderate level of volatility in daily returns. While both our total return and standard deviation were slightly lower than the ^GSPC benchmark, the portfolio demonstrated a lower risk and volatility with a low portfolio beta of 0.387. The leptokurtic return distribution with negative skew suggests a higher frequency of negative returns and a higher probability of extreme returns compared to the normal distribution.

Our portfolio demonstrated robust performance, particularly in terms of risk-adjusted returns. The portfolio significantly outperformed the expected return based on its beta with a positive Jensen’s alpha of 0.1037. The Sharpe Ratio of 3.02 suggests a high level of excess return per unit of risk taken, and this is reinforced by the Treynor Ratio of 0.624716 which implies a strong return rate per unit of market risk. The negative Information Ratio shows that the portfolio underperformed relative to the benchmark, which is seen in the overall return (4.33% vs 6.25% for the market), and points towards an area of improvement in closely tracking the market benchmark.

Active vs. Passive Portfolio

Our active portfolio outperformed the passive portfolio, demonstrating the effectiveness of our strategic approach. The active portfolio's value stands at $1,043,326.06, compared to the passive portfolio's $1,014,547.62. This translates to a return of 4.33% for the active portfolio, significantly higher than the 1.45% return of the passive one.

The key driver behind this performance disparity is our precision in executing the active portfolio strategy. We employed a Sector Rotation Strategy, which involves shifting our investment allocation among various market sectors based on our analysis of economic and market conditions. This approach allows us to capitalize on sectors showing potential for growth while avoiding or minimizing exposure to those expected to underperform.

Additionally, we implemented Tactical Asset Allocation, adjusting the percentages of assets in various ETF categories in response to market changes. This was guided by the Capital Asset Pricing Model, which provided expected price insights, enabling us to identify and take advantage of mispricing's promptly. This dynamic and responsive approach to asset allocation added significant value to our portfolio, distinguishing it from the more static nature of the passive portfolio.

Overall, these strategies allowed us to actively manage risks and exploit market opportunities more effectively than the passive approach, leading to the superior performance of our active portfolio.

Conclusion

In conclusion, the StockTrak Trading Simulation presented by SWMDZ Investments has been a profound learning experience, offering valuable insights into the complexities of financial markets and investment strategies. Our journey, guided by tactical asset allocation and sector rotation strategies, demonstrated the potential and challenges of active portfolio management. While our active portfolio outperformed the passive portfolio, this endeavor highlighted key areas for improvement, particularly in managing the risks associated with high kurtosis and negative skewness.

The simulation also sheds light on the importance of monitoring and adapting to market conditions, underscoring the dynamic nature of investment strategies. Furthermore, our reliance on a Python-based algorithm for ETF trading decisions reinforced the significance of technology in modern financial analysis, though it also revealed limitations in predictive accuracy. This experience has deepened our understanding of market efficiency and the impact of behavioral biases on investment decisions.

Moving forward, we aim to integrate these learnings into our future endeavors, continuously refining our approach to achieve a balance between risk and reward in the ever-evolving landscape of investment management.

Appendix

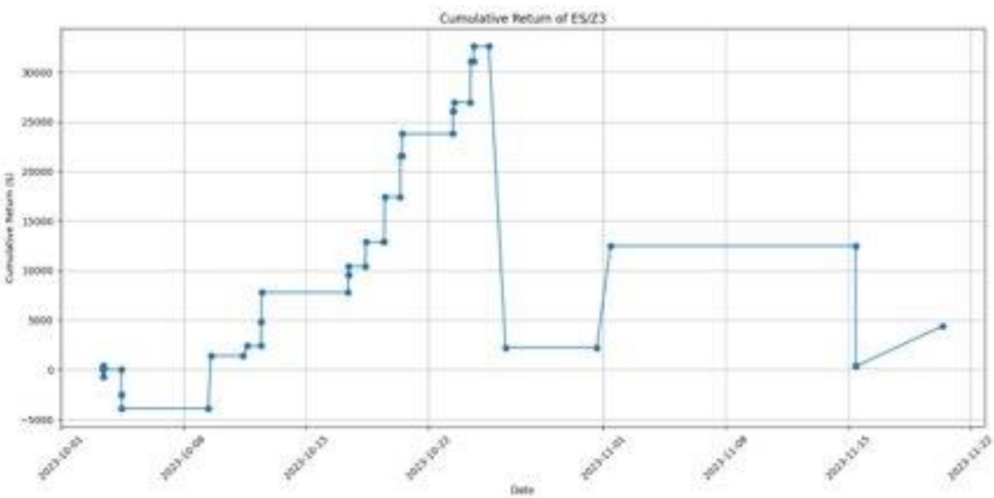

Figure 1: Cumulative Return Graph of ES Futures

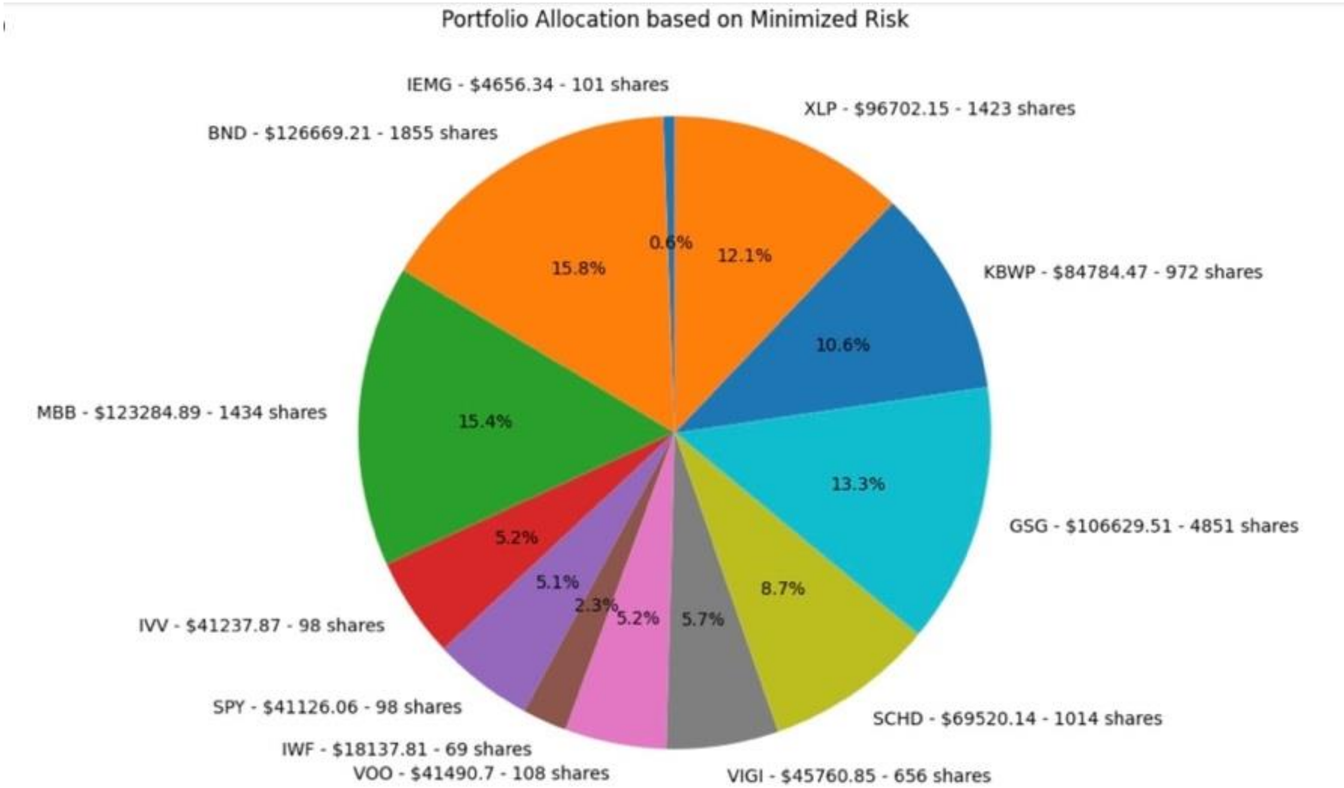

Figure 2: Initial Shares Bought for Each ETF on Day 1

ETFs	Percentages	Shares Bought
BND	15.80%	1855
MBB	15.40%	1434
IVV	5.20%	98
SPY	5.10%	98
IWF	2.30%	69
VOO	5.20%	108
VIGI	5.70%	656
SCHD	8.70%	1014
GSG	13.30%	4851
KBWP	10.60%	972
XLP	12.10%	1423
IEMG	0.60%	101

Table 1: Initial Optimized Portfolio Weights for Minimized Risk Portfolio

	Trade 1 (Oct. 27)			Trade 2 (Nov. 3)			
ETFs	**Percentages**	**Shares Bought**	**Buy/Sell**	**Percentages**	**Num of Shares**	**Difference**	**Buy/Sell**
BND	15.80%	1855	Buy	12.00%	1388	-467	Sell
MBB	15.40%	1434	Buy	11.80%	1077	-357	Sell
IVV	5.20%	98	Buy	6.80%	124	26	Buy
SPY	5.10%	98	Buy	6.70%	125	27	Buy
IWF	2.30%	69	Buy	5.30%	157	88	Buy
VOO	5.20%	108	Buy	6.80%	136	28	Buy
VIGI	5.70%	656	Buy	7.00%	781	125	Buy
SCHD	8.70%	1014	Buy	8.50%	975	-39	Sell
GSG	13.30%	4851	Buy	10.80%	3960	-891	Sell
KBWP	10.60%	972	Buy	9.50%	853	-119	Sell
XLP	12.10%	1423	Buy	10.20%	1185	-238	Sell
IEMG	0.60%	101	Buy	4.50%	764	663	Buy

Table 2: Example of Buy/Sell Decisions/Calculations

Portfolio Metrics	
Total Return	4.3286%
Average Daily Return	0.1180%
Average Weekly Return	0.6727%
Standard Deviation of Returns	1.1406%
Skewness of Returns	-1.333454
Kurtosis of Returns	5.867851

Table 3: Portfolio Performance Measures

CAPM	
Portfolio Beta	0.387018
Sharpe Ratio	3.018827
Jensen’s Alpha	0.103707
Treynor Ratio	0.624716
Information Ratio	-0.038034
CAPM E[r]	3.4654%
Average Daily Market Return	0.1636%

Total Market Return	6.2548%
Market Standard Deviation	0.8849%

Table 4: CAPM Metrics

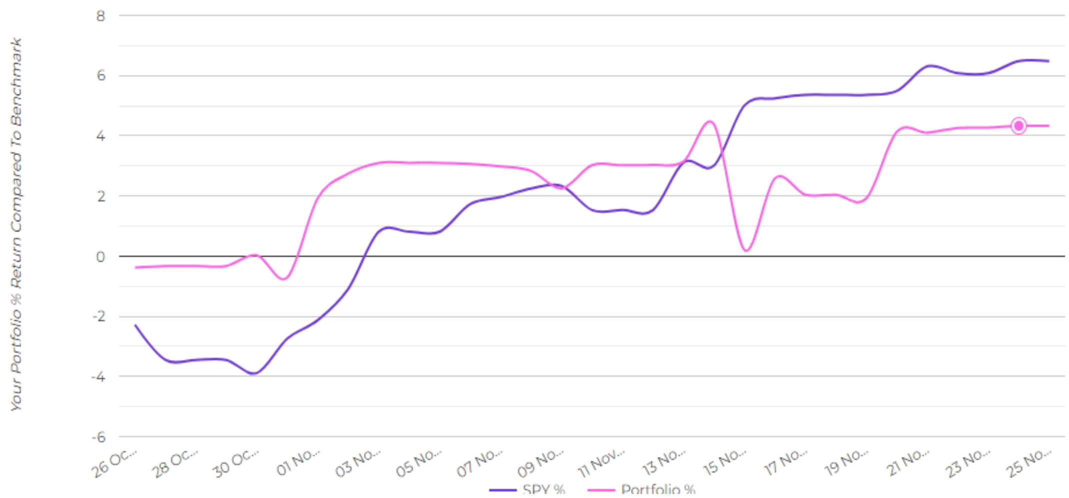

Figure 3: Portfolio Return Compared to Benchmark

```python
#Inputs:
risk_free_rate = 0.0555 # needs updated every time we run the code
end_date = "2023-11-27" # needs updated every time we run the code
ETFs = ['IEMG','BND','MBB','IVV','SPY','IWF','VOO','VIGI','SCHD','GSG','KBWP','XLP']
target_rtn = 0.13
target_beta = 1.25
total_investment = 800000 # other 200k for futures
#Functions:
def Beta(x, y):
    coef = np.cov(x, y)
    beat = coef[0][1]
    box = coef[0][0]
    return beat / box
def Capital_Asset_Pricing_Model(rf, rm, beta):
    return rf + beta*(rm - rf)
def downloadData(end_date,ETFs):
    #data from 1/1/2022 til now
    datasets = {tick:yf.download(tick, start = "2022-01-01", end = end_date) for tick in ETFs}
    close = np.array([datasets[tick]['Adj Close'].values.tolist() for tick in ETFs]).T
    #current prices
    current_prices = {}
    for tick in ETFs:
      data = yf.download(tick,period='1d',interval='1m')
      if not data.empty:
        current_prices[tick] = data['Adj Close'][-1]
    return close, current_prices
```

Figure 4: Python Initial Functions and Inputs

```python
def betaCAPM(close, risk_free_rate):
  #Rates
  rate_of_return = close[:-1]/close[1:] - 1
  X = rate_of_return.T
  X0 = X[0]
  market_rate = close.T[0][0] / close.T[0][-1] - 1
  BETA, CAPM = [], []
  #Appending to lists
  for x in X:
    beta = Beta(X0, x)
    capm = Capital_Asset_Pricing_Model(risk_free_rate, market_rate, beta)
    BETA.append(beta)
    CAPM.append(capm)
  return BETA,CAPM
```

Figure 5: Python Helper Function

```python
def MinimizeRisk(beta, capm, target_return):
    beta, capm = np.array(beta), np.array(capm)
    def objective(W):
        return W @ beta
    def constraint(W):
        return W @ capm - target_return
    def constraint2(W):
        return W @ np.ones(len(W)) - 1
    def constraint3(W):
        return W
    W = np.ones(len(beta))
    cons = [{'type':'ineq','fun':constraint},
            {'type':'eq','fun':constraint2},
            {'type':'ineq','fun':constraint3}]
    res = minimize(objective, W, method='SLSQP', bounds=None, constraints=cons)
    return res.x
def MaximizeReturn(beta, capm, target_beta):
    beta, capm = np.array(beta), np.array(capm)
    def objective(W):
        return -(W @ capm)
    def constraint(W):
        return -(W @ beta - target_beta)
    def constraint2(W):
        return W @ np.ones(len(W)) - 1
    def constraint3(W):
        return W
    W = np.ones(len(beta))
    cons = [{'type':'ineq','fun':constraint},
            {'type':'eq','fun':constraint2},
            {'type':'ineq','fun':constraint3}]
    res = minimize(objective, W, method='SLSQP', bounds=None, constraints=cons)
    return res.x
```

Figure 6: Python Optimization Functions

```python
def PIES(minrisk, maxretn, ETFs, BETA, CAPM, titleA, titleB,total_investment,current_prices):
  fig = plt.figure(figsize=(8, 16))
  ax = fig.add_subplot(211)
  #ay = fig.add_subplot(212)
  ax.set_title(titleA)
  #ay.set_title(titleB)
  s_tickers = [f'{i} | Beta: {round(j, 3)}' for i, j in zip(ETFs, BETA)]
  ax.pie(minrisk, labels=s_tickers, autopct='%1.1f%%')
  #ay.pie(np.abs(maxretn), labels=s_tickers, autopct='%1.1f%%')
  plt.tight_layout()
  plt.show()
  minriskpercentages = minrisk/minrisk.sum()
  maxretpercentages = maxretn/maxretn.sum()
  minrisklist = [f'{p:.1f}' for p in minriskpercentages * 100]
  maxretlist = [f'{p:.1f}' for p in maxretpercentages * 100]

  norm_minrisk = minrisk/np.sum(minrisk)
  portfolio_values = norm_minrisk*total_investment
  initial_shares_to_buy = {tick: portfolio_values[i]/current_prices[tick] for i, tick in enumerate(ETFs)}
  return minrisklist, maxretlist,initial_shares_to_buy
```

Figure 7: Python Function for Visualization and Calculation of Shares to Buy/Hold

```python
#Downloading data
close = downloadData(end_date,ETFs)
current_prices = getCurrentPrices(ETFs)
BETA,CAPM = betaCAPM(close,risk_free_rate)

#Portfolio Optimization
minrisk = MinimizeRisk(BETA, CAPM, target_rtn)
maxretn = MaximizeReturn(BETA, CAPM, target_beta)
dot = lambda x, y: np.sum([i*j for i, j in zip(x, y)])
minimized_risk = dot(minrisk, BETA) #beta
maximized_return = dot(maxretn, CAPM) #capm E[r]

#Visualization
titleA = f'Minimized Risk Portfolio\nTargetCAPM: {target_rtn}\nPortfolio Beta: {round(minimized_risk, 3)}'
titleB = f'Maximized Return Portfolio\nTargetBeta: {target_beta}\nPortfolio Return: {round(maximized_return, 3)}'
minriskpercentages, maxretpercentages, shares = PIES(minrisk, maxretn, ETFs, BETA, CAPM, titleA, titleB, total_investment, current_prices)
weights = pd.DataFrame({
    'ETF': ETFs,
    'Minimized Risk Weights': minriskpercentages,
    #'Max Return Weights':maxretpercentages,
    'Shares to Hold': shares.values()
    })
print(weights)
```

Figure 8: Python Code of Main Execution