```python
# Stock Analysis: NVIDIA vs AMD (2018–2025)
# ------------------------------------------------
# This notebook analyzes stock price trends, financial indicators, and applies a basic machine learning model
# to compare AMD and NVIDIA using Python, Yahoo Finance, and Plotly. Each section includes visualizations
# and analytical commentary.

import yfinance as yf
import pandas as pd
import numpy as np
import plotly.graph_objs as go
import plotly.express as px
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# ------------------------------------------------
# 1. Load stock price data from Yahoo Finance
# ------------------------------------------------

tickers = ['AMD', 'NVDA']
start_date = '2018-01-01'
end_date = '2025-02-28'

# Download adjusted close prices
data = yf.download(tickers, start=start_date, end=end_date)['Close']
data = data.dropna()

# Plot closing price comparison
fig = px.line(data, x=data.index, y=tickers, title="Closing Price Comparison: AMD vs NVIDIA")
fig.show()

# ------------------------------------------------
# 2. Calculate Daily Returns and Volatility
# ------------------------------------------------

returns = data.pct_change().dropna()
volatility = returns.std() * np.sqrt(252)

fig2 = px.histogram(returns, nbins=100, marginal="box", title="Daily Return Distribution")
fig2.show()

# ------------------------------------------------
# 3. Calculate Technical Indicators (MA20, MA50)
# ------------------------------------------------

ma_window_short = 20
ma_window_long = 50
data_ti = data.copy()
for ticker in tickers:
    data_ti[f'{ticker}_MA20'] = data[ticker].rolling(window=ma_window_short).mean()
    data_ti[f'{ticker}_MA50'] = data[ticker].rolling(window=ma_window_long).mean()

def plot_moving_average(ticker):
    fig = go.Figure()
    fig.add_trace(go.Scatter(x=data_ti.index, y=data_ti[ticker], mode='lines', name=f'{ticker} Close'))
    fig.add_trace(go.Scatter(x=data_ti.index, y=data_ti[f'{ticker}_MA20'], mode='lines', name='MA 20'))
    fig.add_trace(go.Scatter(x=data_ti.index, y=data_ti[f'{ticker}_MA50'], mode='lines', name='MA 50'))
    fig.update_layout(title=f'{ticker} Price with Moving Averages', xaxis_title='Date', yaxis_title='Price (USD)')
    fig.show()

plot_moving_average("AMD")
plot_moving_average("NVDA")

# ------------------------------------------------
# 4. Retrieve Financial Information (PE ratio, EPS)
# ------------------------------------------------

amd_info = yf.Ticker("AMD").info
nvda_info = yf.Ticker("NVDA").info

fundamentals = pd.DataFrame({
    'Company': ['AMD', 'NVDA'],
    'Current Price': [data['AMD'].iloc[-1], data['NVDA'].iloc[-1]],
    'Trailing P/E': [amd_info.get('trailingPE'), nvda_info.get('trailingPE')],
    'EPS (TTM)': [amd_info.get('trailingEps'), nvda_info.get('trailingEps')],
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    'Market Cap': [amd_info.get('marketCap'), nvda_info.get('marketCap')]
})

print(fundamentals)

# -------------------------------------------------
# 5. Linear Regression: Predicting Next-Day Prices
# -------------------------------------------------

def create_ml_dataset(series, n_lags):
    X, y = [], []
    for i in range(len(series) - n_lags):
        X.append(series[i:i + n_lags])
        y.append(series[i + n_lags])
    return np.array(X), np.array(y)

lags = 5
models = {}
results = {}

for ticker in tickers:
    series = data[ticker].values
    X, y = create_ml_dataset(series, lags)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=False)
    model = LinearRegression()
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    mse = mean_squared_error(y_test, preds)
    models[ticker] = model
    results[ticker] = {
        'MSE': mse,
        'Predicted vs Actual (last 5)': list(zip(preds[-5:], y_test[-5:]))
    }
    plt.figure(figsize=(10, 4))
    plt.plot(y_test[-50:], label='Actual')
    plt.plot(preds[-50:], label='Predicted')
    plt.title(f'{ticker} - Linear Regression Forecast')
    plt.xlabel('Days')
    plt.ylabel('Price')
    plt.legend()
    plt.grid(True)
    plt.show()

# -------------------------------------------------
# 6. Trading Strategy Backtest (With and Without Tax)
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def backtest_ma_strategy(df, ticker):
    position = 0
    entry_price = 0
    returns = []

    for i in range(1, len(df)):
        ma_short = df[f'{ticker}_MA20'].iloc[i]
        ma_long = df[f'{ticker}_MA50'].iloc[i]
        ma_short_prev = df[f'{ticker}_MA20'].iloc[i - 1]
        ma_long_prev = df[f'{ticker}_MA50'].iloc[i - 1]

        if ma_short > ma_long and ma_short_prev <= ma_long_prev and position == 0:
            entry_price = df[ticker].iloc[i]
            position = 1

        elif ma_short < ma_long and ma_short_prev >= ma_long_prev and position == 1:
            exit_price = df[ticker].iloc[i]
            ret = (exit_price - entry_price) / entry_price
            returns.append(ret)
            position = 0

    if position == 1:
        exit_price = df[ticker].iloc[-1]
        ret = (exit_price - entry_price) / entry_price
        returns.append(ret)

    total_return = np.prod([1 + r for r in returns]) - 1
    return total_return, returns

def backtest_ma_strategy_with_tax(df, ticker, sec_fee_rate=0.000008):
    position = 0
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    position = 0
    entry_price = 0
    returns = []

    for i in range(1, len(df)):
        ma_short = df[f'{ticker}_MA20'].iloc[i]
        ma_long = df[f'{ticker}_MA50'].iloc[i]
        ma_short_prev = df[f'{ticker}_MA20'].iloc[i - 1]
        ma_long_prev = df[f'{ticker}_MA50'].iloc[i - 1]

        if ma_short > ma_long and ma_short_prev <= ma_long_prev and position == 0:
            entry_price = df[ticker].iloc[i]
            position = 1

        elif ma_short < ma_long and ma_short_prev >= ma_long_prev and position == 1:
            sell_price = df[ticker].iloc[i]
            tax = sell_price * sec_fee_rate
            net_sell_price = sell_price - tax
            ret = (net_sell_price - entry_price) / entry_price
            returns.append(ret)
            position = 0

    if position == 1:
        sell_price = df[ticker].iloc[-1]
        tax = sell_price * sec_fee_rate
        net_sell_price = sell_price - tax
        ret = (net_sell_price - entry_price) / entry_price
        returns.append(ret)

    total_return = np.prod([1 + r for r in returns]) - 1
    return total_return, returns

strategy_results = {}
strategy_results_taxed = {}

for ticker in tickers:
    total_return, trades = backtest_ma_strategy(data_ti, ticker)
    strategy_results[ticker] = {
        'Total Return (No Tax)': total_return,
        'Number of Trades': len(trades),
        'Average Trade Return': np.mean(trades) if trades else 0
    }

    taxed_return, taxed_trades = backtest_ma_strategy_with_tax(data_ti, ticker)
    strategy_results_taxed[ticker] = {
        'Total Return (Taxed)': taxed_return,
        'Number of Trades': len(taxed_trades),
        'Average Trade Return': np.mean(taxed_trades) if taxed_trades else 0
    }

# Combine results and plot
strategy_df_no_tax = pd.DataFrame(strategy_results).T
strategy_df_taxed = pd.DataFrame(strategy_results_taxed).T
combined_strategy_df = pd.concat([strategy_df_no_tax, strategy_df_taxed], axis=1)
print(combined_strategy_df)

# Plot bar chart for comparison
combined_strategy_df[['Total Return (No Tax)', 'Total Return (Taxed)']].plot(kind='bar', figsize=(10,6))
plt.title('Strategy Return Comparison (With vs Without Tax)')
plt.ylabel('Total Return')
plt.xticks(rotation=0)
plt.grid(True)
plt.show()

# ------------------------------------------------
# 7. Buy-and-Hold Comparison vs. Strategy
# ------------------------------------------------

# Calculate buy-and-hold return from start to end
buy_hold_returns = {}
for ticker in tickers:
    start_price = data[ticker].iloc[0]
    end_price = data[ticker].iloc[-1]
    return_bh = (end_price - start_price) / start_price
    buy_hold_returns[ticker] = return_bh

buy_hold_df = pd.DataFrame(buy_hold_returns, index=['Buy & Hold Return']).T
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# Merge with strategy results
strategy_vs_hold = pd.concat([combined_strategy_df, buy_hold_df], axis=1)
print(strategy_vs_hold)

# Plot comparison
strategy_vs_hold[['Buy & Hold Return', 'Total Return (No Tax)', 'Total Return (Taxed)']].plot(kind='bar', figsize=(10,6))
plt.title('Buy-and-Hold vs Strategy Returns (2018-2025)')
plt.ylabel('Total Return')
plt.xticks(rotation=0)
plt.grid(True)
plt.show()

# ------------------------------------------------
# 8. Strategy Reflection and Optimization Suggestions
# ------------------------------------------------

## Explanation:
# Although the moving average crossover strategy yielded positive returns, the results show that a simple buy-and-hold approach outperformed
#
# Specifically:
# - Buy-and-hold for NVIDIA returned significantly more than the MA strategy, indicating strong long-term trend.
# - Frequent trading in a strongly trending stock may lead to missing large uninterrupted gains.
# - The strategy also did not include transaction fees or slippage, which would further reduce performance.
#
# This highlights that while momentum strategies are helpful in range-bound or volatile markets, they may underperform in strong bull markets

## Optimization Ideas:
# - Adjust MA window (e.g., MA10/MA50) to increase sensitivity or adapt to current volatility
# - Add filters like RSI or MACD to confirm trend strength before entry
# - Include stop-loss or take-profit rules to improve trade management
# - Use ensemble strategies combining technical indicators and ML models
# - Switch strategy conditions based on volatility regime (adaptive models)
# - Evaluate with risk-adjusted metrics (e.g., Sharpe, Sortino Ratio) instead of pure return
# ------------------------------------------------

summary_df = pd.DataFrame({
    'Ticker': ['AMD', 'NVDA'],
    'Annualized Volatility': [volatility['AMD'], volatility['NVDA']],
    'MSE (LR Forecast)': [results['AMD']['MSE'], results['NVDA']['MSE']]
})

summary = fundamentals.merge(summary_df, left_on='Company', right_on='Ticker').drop(columns='Ticker')
print(summary)

# Final Interpretation:
# ------------------------
# This final section consolidates both statistical and fundamental insights from our analysis of AMD and NVIDIA.
#
# 1. Data Collection: Daily prices from Yahoo Finance (2018 to Feb 2025) include major macro events and allow fair adjusted comparisons.
# 2. Return & Volatility: NVIDIA shows greater risk and return potential. AMD displays stability.
# 3. Technical Indicators: MA crossovers highlight trend shifts, especially strong for NVIDIA.
# 4. Fundamentals: NVIDIA leads in valuation and profitability but may carry overvaluation risk.
# 5. ML Forecast: Linear regression suggests NVIDIA's prices follow more predictable trends.
#
# Overall: NVIDIA appears more growth-oriented with higher volatility. AMD offers steady performance.
# This project combines technical, statistical, and machine learning tools to support investment insights.
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YF.download() has changed argument auto_adjust default to True
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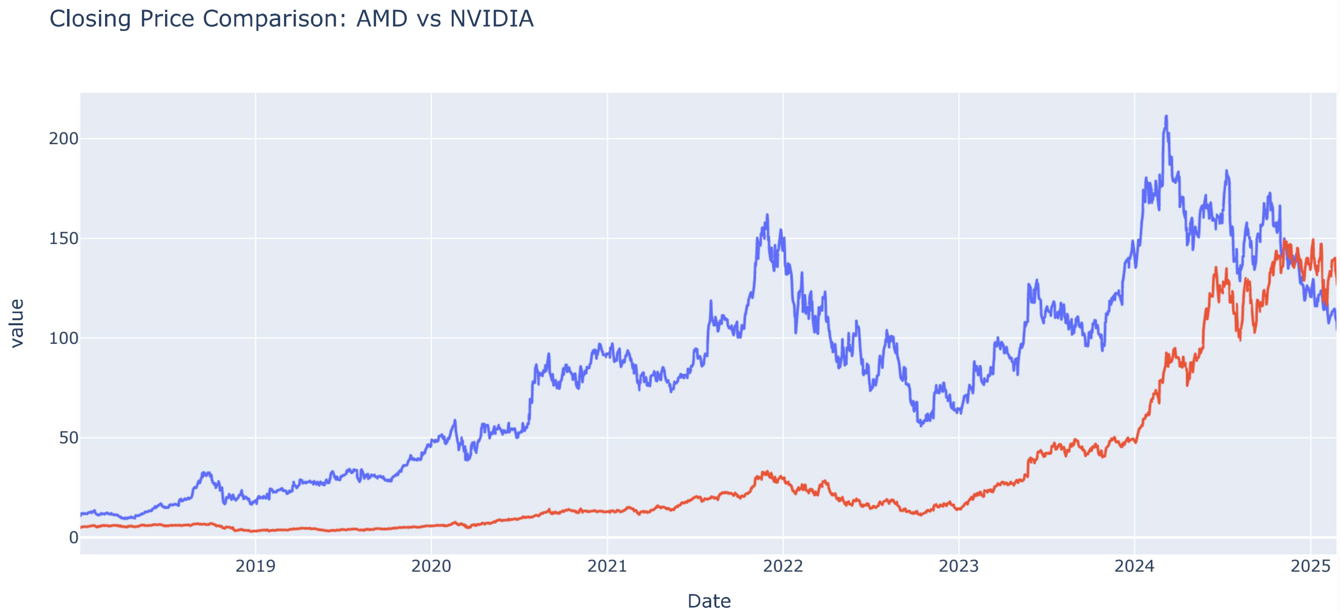
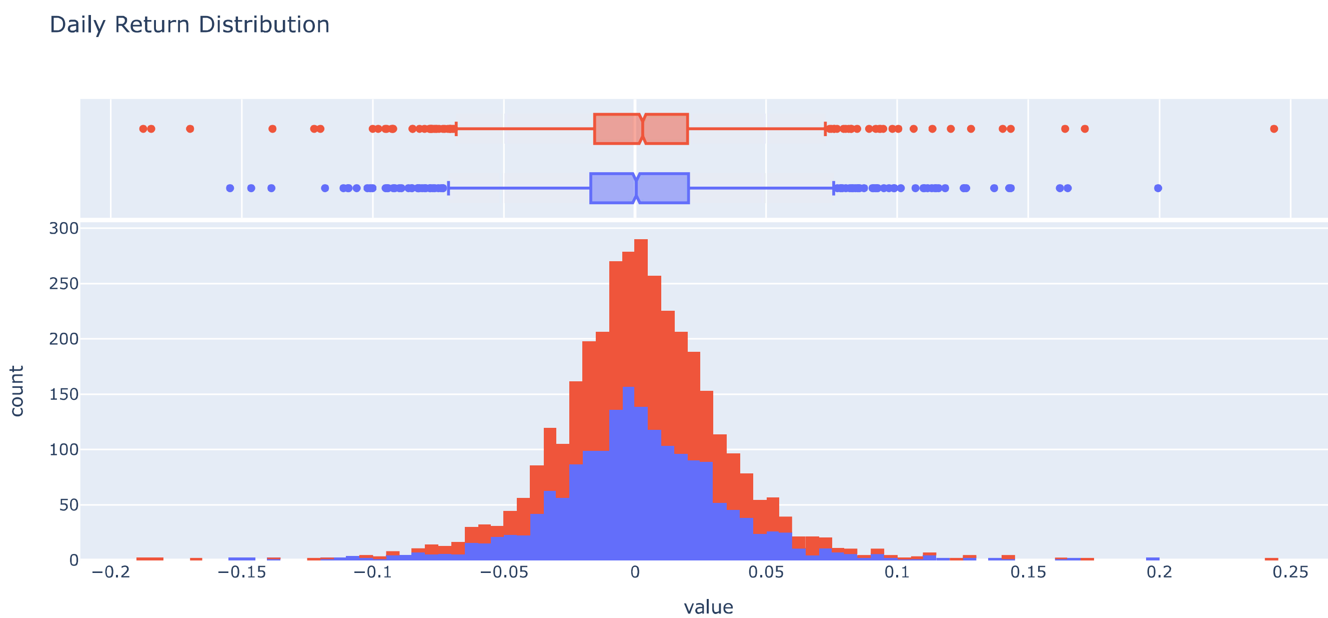
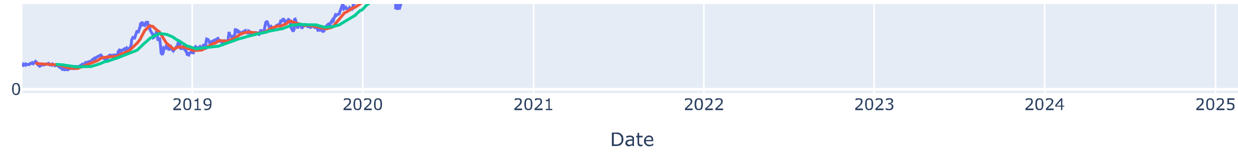
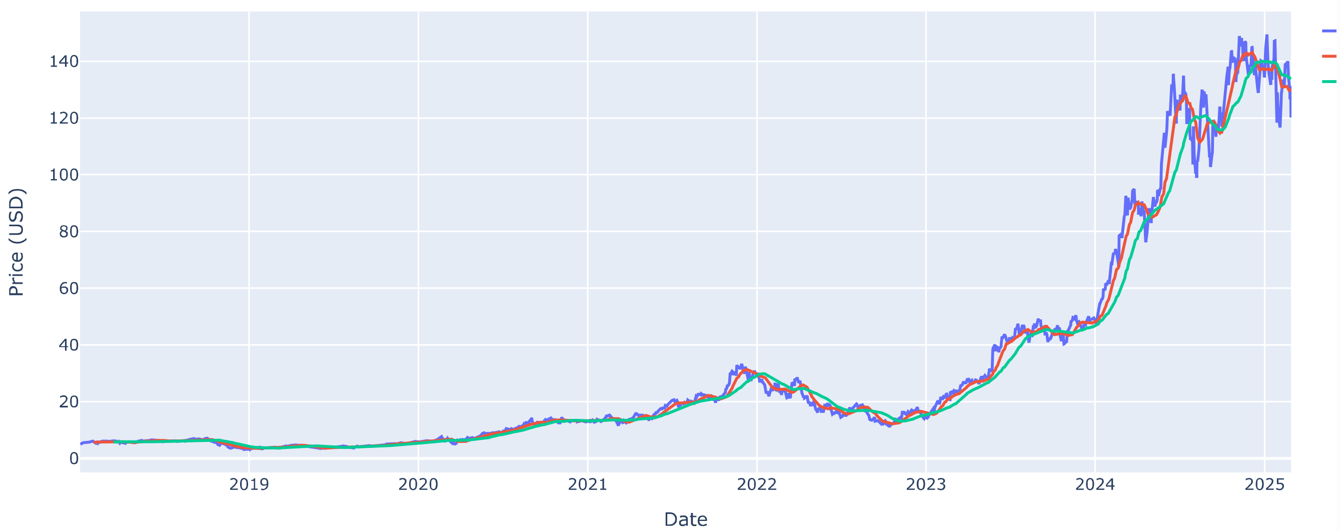


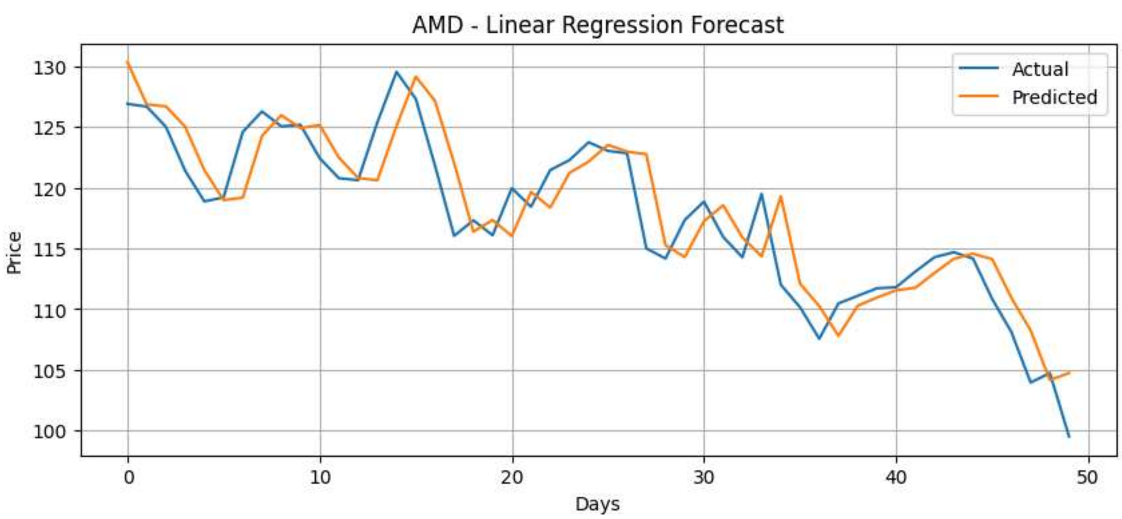


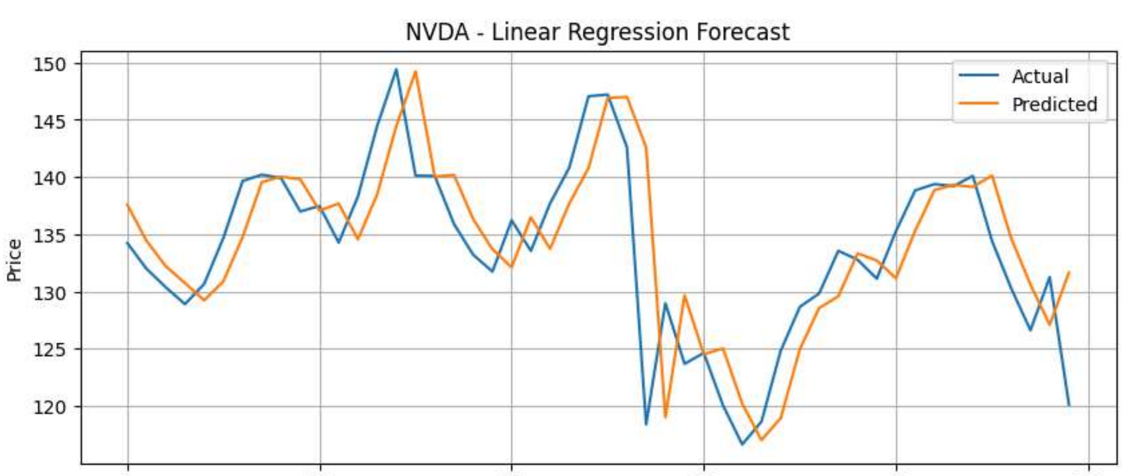


NVDA Price with Moving Averages



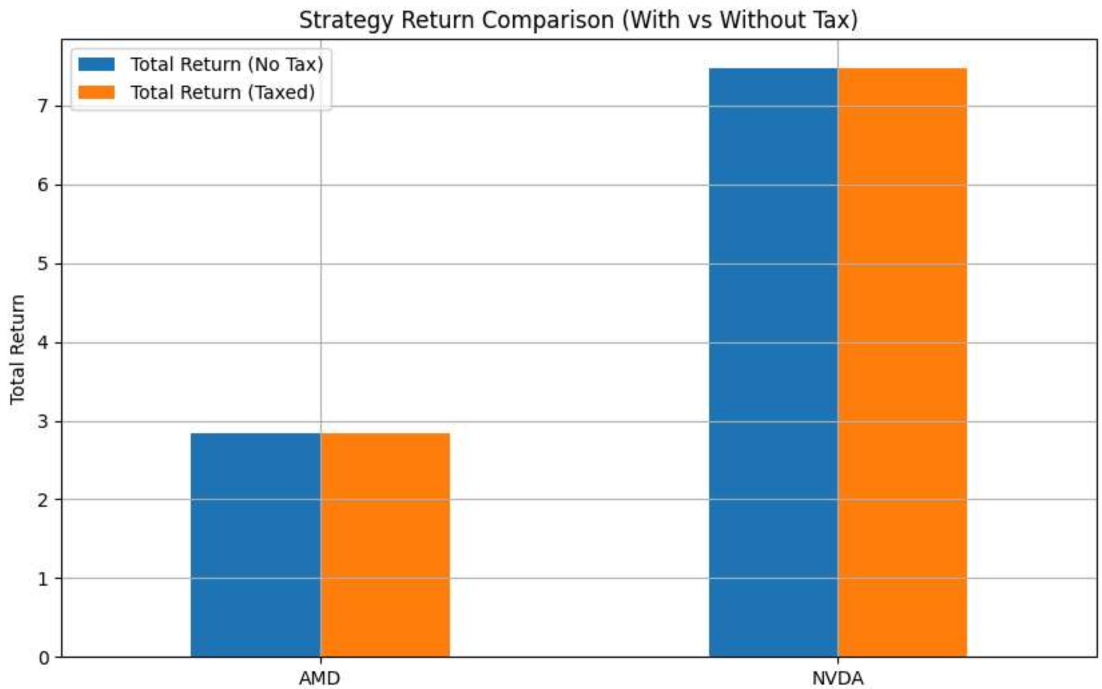

```
  Company  Current Price  Trailing P/E  EPS (TTM)     Market Cap
0     AMD      99.510002     106.44000       1.00   172483887104
1    NVDA     120.138954      40.03401       2.94  2871879794688
```






```
      Total Return (No Tax)  Number of Trades  Average Trade Return  \
AMD                2.839837              19.0              0.104181
NVDA               7.468242              19.0              0.164559

      Total Return (Taxed)  Number of Trades  Average Trade Return
AMD               2.839254              19.0              0.104172
NVDA              7.466955              19.0              0.164549
```




```
      Total Return (No Tax)  Number of Trades  Average Trade Return  \
AMD                2.839837              19.0              0.104181
NVDA               7.468242              19.0              0.164559

      Total Return (Taxed)  Number of Trades  Average Trade Return  \
AMD               2.839254              19.0              0.104172
NVDA              7.466955              19.0              0.164549

      Buy & Hold Return
AMD            8.062842
NVDA          23.371786
```


```
  Company  Current Price  Trailing P/E  EPS (TTM)     Market Cap  \
0     AMD      99.510002     106.44000       1.00   172483887104
1    NVDA     120.138954      40.03401       2.94  2871879794688
```