APPLIED ECONOMETRICS

MID-TERM PROJECT:
MULTIVARIATE TIME SERIES ANALYSIS

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1. PROBLEM STATEMENT:

The present study employs time series analysis methods to examine the relationship between the financial sector and technology sector, using empirical evidence from the U.S. stock market. The central question guiding the analysis is: ***Do stock price movements of major U.S. information technology firms influence their financial sector?***

	tech	tech	tech	tech	finance	finance	finance	finance	pharma	pharma	pharma	pharma
	MSFT	GOOGL	META	NVDA	JPM	BAC	MA	V	JNJ	PFE	MRK	AZN
Date												
02-01-2014	37.16	27.85586	54.71	0.3965	58.21	16.1	83.414	55.2525	91.03	28.89943	47.22328	29.285
03-01-2014	36.91	27.65265	54.56	0.39175	58.66	16.41	83.081	55.29	91.85	28.95636	47.45229	29.43
06-01-2014	36.13	27.96096	57.2	0.397	59	16.66	82.669	54.9575	92.33	28.98482	47.46183	29.445
07-01-2014	36.41	28.5	57.92	0.4035	58.32	16.5	83.709	55.3775	94.29	29.16508	47.81488	29.255
08-01-2014	35.76	28.55931	58.23	0.409	58.87	16.58	83.684	55.555	94.16	29.36433	47.50954	29.26
09-01-2014	35.53	28.28428	57.22	0.39375	58.76	16.83	84.36	55.4775	94.73	29.34535	47.25191	29.685
10-01-2014	36.04	28.28278	57.94	0.39325	58.49	16.77	83.476	55.2825	94.74	29.11765	47.59542	30.24
13-01-2014	34.98	28.1026	55.91	0.384	57.7	16.43	81	54.725	94.5	28.97533	50.68702	29.81
14-01-2014	35.78	28.76376	57.74	0.396	57.74	16.77	82.171	55.6625	94.72	29.41176	50.57252	31.085
15-01-2014	36.76	28.74424	57.6	0.40025	59.49	17.15	82.337	55.94	94.8	29.58254	50.11451	31.475
16-01-2014	36.89	28.93443	57.19	0.4015	58.99	17.08	82.55	55.4425	94.64	29.57306	50.09542	31.795
17-01-2014	36.38	28.79204	56.3	0.39975	58.11	17.01	81.842	58.045	95.06	29.49715	49.57061	31.865
21-01-2014	36.17	29.12162	58.51	0.40125	58.17	17.01	81.848	57.9825	94.03	29.62998	49.45611	32.5
22-01-2014	35.93	29.15466	57.51	0.40075	57.59	17.15	83.3	58.2475	94.32	29.66793	48.99809	32.695

The dataset, sourced from NASDAQ provides comprehensive observations on stock prices from January 2014 to September 2024 for major firms from a variety of industries, such as Food, Technology, Pharmaceutical and Finance.

To investigate our research question, we filter the dataset to keep the tech sector and one major financial sector firm that will serve as our dependent variable, we will be using the following variables:

- JPM: JPMorgan Chase & Co. stock price (finance) → Dependent variable
- MSFT: Microsoft stock price (tech)
- GOOGL: Google stock price (tech)
- META: Meta stock price (tech)
- NVDA: Nvidia stock price (tech)

Independent variables

```
Dependent Variable (Y): JPM
Independent Variables (X): ['MSFT', 'GOOGL', 'META', 'NVDA']

 Final Analysis DataFrame (JPMC vs. Tech Sector)
```

	JPM	MSFT	GOOGL	META	NVDA
Date					
2014-01-02	58.209999	37.160000	27.855856	54.709999	0.39650
2014-01-03	58.660000	36.910000	27.652653	54.560001	0.39175
2014-01-06	59.000000	36.130001	27.960960	57.200001	0.39700
2014-01-07	58.320000	36.410000	28.500000	57.919998	0.40350
2014-01-08	58.869999	35.759998	28.559309	58.230000	0.40900

2. METHODOLOGY:

- The Augmented Dickey-Fuller (ADF) test to assess stationarity
- Two step Granger Cointegration test
- Granger causality tests (one-way and two-way) to explore causal interactions
- Vector Autoregression (VAR) to analyse short-run dynamics and
- The Johansen cointegration test to examine long-run relationships among the variables.

3. ANALYSIS:

3.1. Descriptive statistics:

	JPM	MSFT	GOOGL	META	NVDA
count	2718.000000	2718.000000	2718.000000	2718.000000	2718.000000
mean	110.744809	169.804731	75.928304	201.293293	16.742268
std	40.673898	120.606938	42.772069	113.975767	26.963600
min	53.070000	34.980000	24.853001	53.529999	0.384000
25%	68.272501	57.602499	39.684501	118.562498	1.574875
50%	108.820000	128.110001	59.520750	175.794998	5.883500
75%	138.449997	262.940002	112.518875	264.547493	18.331249
max	225.369995	467.559998	191.179993	595.940002	138.070007

- count: The number of observations (data points) for each stock is 2,718, i.e. no missing values are present.
- mean: The average price for each stock over the dataset, for e.g., JPMC is 110.74 USD.
- std: The standard deviation, which measures the data's dispersion or volatility. A higher number (like MSFT's 120.6) means its values were more spread out from the mean.
- min: The minimum (lowest) value observed for each stock, for e.g., JPMC is 53 USD.

3.2. Augmented Dicky-Fuller Test:

Prior to the implementation of time series modelling, it is imperative to ascertain the stationarity characteristics of the variables under examination. The condition of stationarity stipulates that the statistical properties of a series—such as its mean, variance, and autocorrelation—exhibit time invariance. The presence of non-stationarity in data introduces the risk of generating spurious regression outcomes; consequently, unit root testing constitutes an important preliminary diagnostic procedure. Accordingly, this analysis employed the Augmented Dickey-Fuller (ADF) test, applying it to the key variables (JPM, MSFT, GOOGL, META, and NVDA) to evaluate the potential presence of unit roots.

ADF ON ORIGINAL PRICE

```
 Running ADF Test for: 'JPM' Prices
ADF Statistic: 0.3936
p-value: 0.9813
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (0.9813) is > 0.05. We FAIL to reject the Null
  Conclusion: The data IS NON-STATIONARY.

 Running ADF Test for: 'MSFT' Prices
ADF Statistic: 0.9205
p-value: 0.9934
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (0.9934) is > 0.05. We FAIL to reject the Null
  Conclusion: The data IS NON-STATIONARY.
```

```
 Running ADF Test for: 'GOOGL' Prices
ADF Statistic: 0.2597
p-value: 0.9754
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (0.9754) is > 0.05. We FAIL to reject the Null
  Conclusion: The data IS NON-STATIONARY.

 Running ADF Test for: 'META' Prices
ADF Statistic: 1.0132
p-value: 0.9944
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (0.9944) is > 0.05. We FAIL to reject the Null
  Conclusion: The data IS NON-STATIONARY.

 Running ADF Test for: 'NVDA' Prices
ADF Statistic: 4.2225
p-value: 1.0000
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (1.0000) is > 0.05. We FAIL to reject the Null
  Conclusion: The data IS NON-STATIONARY.
```

ADF ON FIRST DIFFERENCES

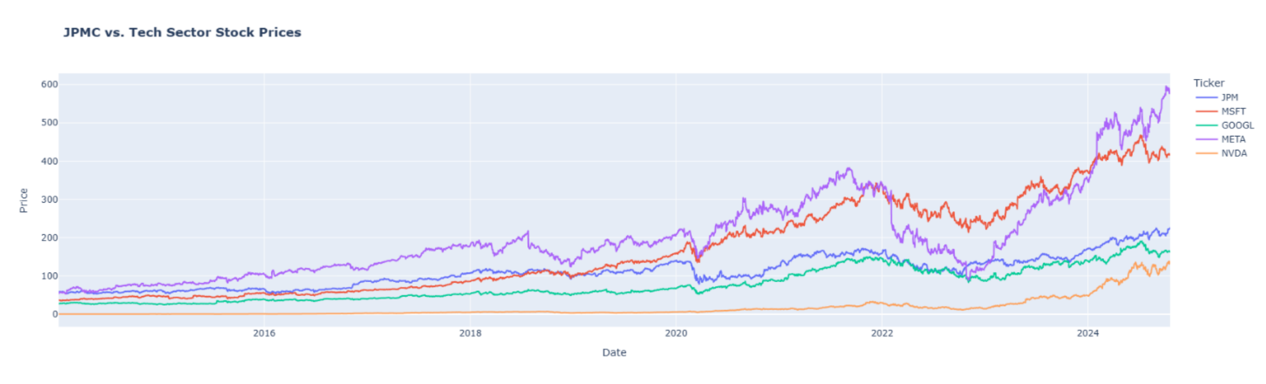
```
 Running ADF Test for: 'JPM' First Difference (Re
ADF Statistic: -13.0464
p-value: 0.0000
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (0.0000) is <= 0.05. We REJECT the Null
  Conclusion: The data IS STATIONARY.

 Running ADF Test for: 'MSFT' First Difference (R
ADF Statistic: -11.7009
p-value: 0.0000
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (0.0000) is <= 0.05. We REJECT the Null
  Conclusion: The data IS STATIONARY.
```

```
 Running ADF Test for: 'GOOGL' First Difference (R
ADF Statistic: -11.6519
p-value: 0.0000
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (0.0000) is <= 0.05. We REJECT the Null
  Conclusion: The data IS STATIONARY.

 Running ADF Test for: 'META' First Difference (Re
ADF Statistic: -17.4678
p-value: 0.0000
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (0.0000) is <= 0.05. We REJECT the Null
  Conclusion: The data IS STATIONARY.

 Running ADF Test for: 'NVDA' First Difference (Re
ADF Statistic: -8.1214
p-value: 0.0000
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (0.0000) is <= 0.05. We REJECT the Null
  Conclusion: The data IS STATIONARY.
```

<u>Left column:</u> This output confirms that the raw price data for JPM, MSFT, GOOGL, META, and NVDA are all non-stationary. Null Hypothesis assumes that the data has a unit root, which means it is non-stationary. Since all p-values are greater than 0.05, we fail to reject the null hypothesis for all five series. This is a typical finding for stock prices and indicates that further steps, such as differencing (e.g., calculating daily returns), are needed before they can be used in many time series models.

<u>Right column:</u> While the original price data was non-stationary, this output confirms that the first-differenced data (i.e., the daily price changes) for all five stocks is stationary. he p-value for every single differenced series is 0.0000. Since all p-values are less than 0.05, we reject the null hypothesis for all five series. This transformation makes the data suitable for use in standard time series models like VAR or VECM. Thus, **all stock price series are confirmed to be Integrated of Order 1: I(1).**

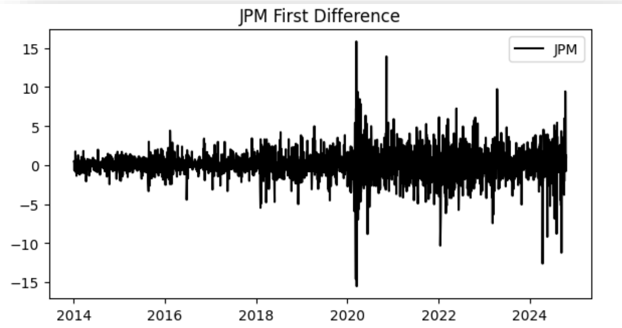
3.3. Graphical Representation:

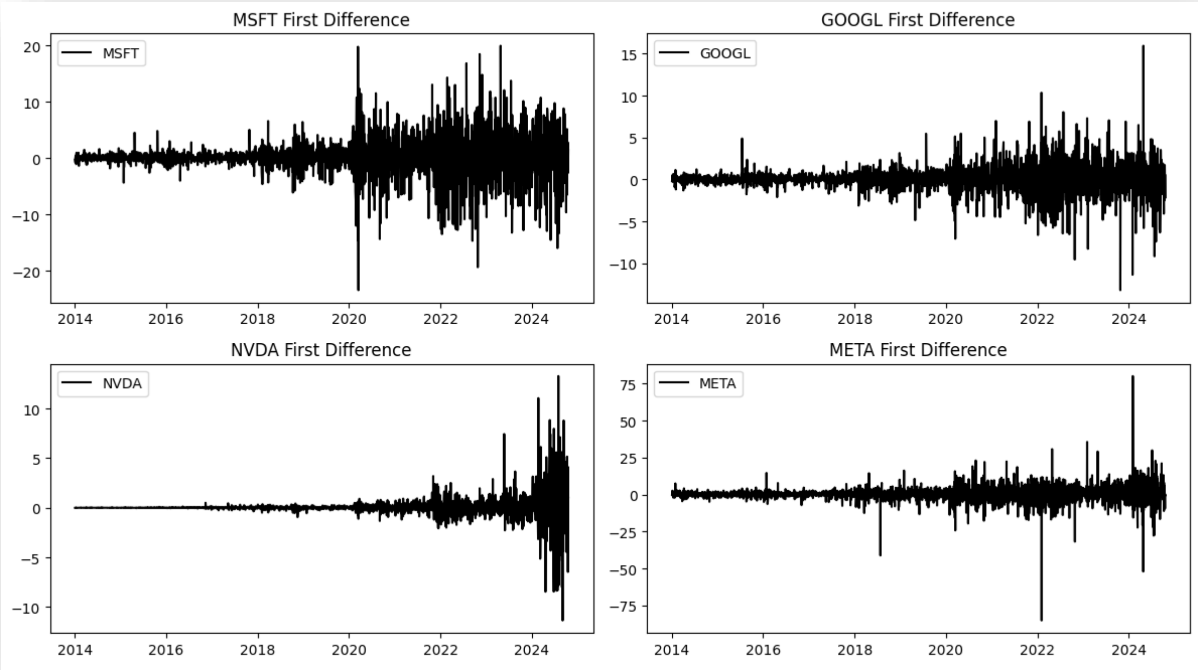


The above **plot visually confirms the results of the initial Augmented Dickey-Fuller** (ADF) tests. This is a time series plot charting the raw price levels of JPM, MSFT, GOOGL, META, and NVDA from 2014 to late 2024. The most prominent feature of all five lines is a clear upward trend. None of the series fluctuate around a constant average price. Instead, their mean value is clearly changing (increasing) over time. The first set of ADF tests (on the raw prices) concluded that all five series were non-stationary. This plot is the visual proof of that statistical finding. The strong, persistent trends are the reason the ADF tests failed to reject the null hypothesis, as the statistical properties (specifically the mean) are not constant over time.

Now, the five plots below provide the visual representation of the first-differenced data we tested in the second set of Augmented Dicky-Fuller (ADF) tests. Each chart shows the "first difference" for a stock. This is the day-to-day change in price. Unlike the first plot of raw prices (which showed strong upward trends), all five of these series appear stationary. They do not have a persistent trend. They fluctuate around a stable mean, which is zero.

They **visually confirm the results of the ADF tests on the first-differenced data** (where all p-values were 0.0000). The statistical test proved the data was stationary, and this plot shows what that stationary data looks like.





3.4. Two-Step Granger Test:

```
 Running OLS Regression (JPM ~ META)
                            OLS Regression Results
==============================================================================
Dep. Variable:                    JPM   R-squared:                       0.834
Model:                            OLS   Adj. R-squared:                  0.834
Method:                 Least Squares   F-statistic:                 1.364e+04
Date:                Fri, 31 Oct 2025   Prob (F-statistic):               0.00
Time:                        15:41:23   Log-Likelihood:                -11488.
No. Observations:                2718   AIC:                         2.298e+04
Df Residuals:                    2716   BIC:                         2.299e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         45.1462      0.645     69.940      0.000      43.881      46.412
META           0.3259      0.003    116.779      0.000       0.320       0.331
==============================================================================
Omnibus:                      167.889   Durbin-Watson:                   0.018
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              212.557
Skew:                           0.584   Prob(JB):                     6.98e-47
Kurtosis:                       3.717   Cond. No.                         470.
==============================================================================
```

The Engle-Granger test is used to determine if two (or more) time series that are individually non-stationary nevertheless move together in a way that implies a stable, long-run relationship.

We first run an OLS regression with JPM as the dependent variable and META as the independent variable. This step assumes that both JPM and META are non-stationary and integrated of the same order. The residuals represent the error in the relationship, or the short-term deviation from the long-run equilibrium path.

Next, we test the residuals for stationarity by using ADF test again. Null Hypothesis assumes the residuals are non-stationary (they have a unit root). This would mean the variables are not cointegrated, and the regression in previous step would be spurious. Result: The ADF test on the residuals gives a p-value of 0.0075. Since the p-value (0.0075) is less than 0.05, we reject the null hypothesis. **The residuals are stationary.**

Since the linear combination of the two non-stationary variables (JPM and META) results in a stationary series (the residuals), **we conclude that JPM and META are cointegrated**. This confirms that a stable, long-run equilibrium relationship exists between them.

```
 Running ADF Test for: OLS Residuals (JPM ~ META)
ADF Statistic: -3.5190
p-value: 0.0075
Critical Values:
        1%: -3.4328
        5%: -2.8626
        10%: -2.5673

Interpretation:
  p-value (0.0075) is <= 0.05. Residuals ARE STATIONARY.
  Conclusion: The variables ARE COINTEGRATED.
```

The rest of the OLS regressions (JPM and MSFT, etc.) and stationarity tests on the consequent residuals obtained show that they are not cointegrated. Thus, we consider only JPM and META in this section due to the presence of cointegration.

3.4.1. Granger Causality:

The Granger Causality test is performed to determine if the past values of one time series can be used to predict the future values of another. This test is performed on the stationary (first-differenced) data from earlier.

I. Lag Selection:

- Optimal Lag (AIC): 10
- Optimal Lag (BIC): 0
- Chosen Lag: 1

The output shows a discrepancy between two common criteria, AIC and BIC, for selecting the optimal number of lags. The analysis has proceeded using 1 lag. This means the test is specifically asking: "Does the value of stock X yesterday help predict the value of stock Y today?"

II. The Hypothesis Test:

- Decision Rule: p-value < 0.05 then reject H0.
- Null Hypothesis (H0): Variable X does NOT Granger-cause Variable Y.
- Alternative Hypothesis (H1): Variable X DOES Granger-cause Variable Y.

```
Optimal Lag Length (AIC): 10
Optimal Lag Length (BIC): 0
→ Using 1 lags for Granger causality tests.

===== ONE-WAY GRANGER CAUSALITY TEST SUMMARY =====

Independent (X) Dependent (Y)  Lag  F-stat  p-value Granger_Cause?
          MSFT           JPM     1  0.3873   0.5338             NO
         GOOGL           JPM     1  0.0933   0.7601             NO
          META           JPM     1  2.6296   0.1050             NO
          NVDA           JPM     1  0.2325   0.6297             NO

Decision rule: p-value < 0.05 → Reject Hₒ → X Granger-causes Y.

===== TWO-WAY GRANGER CAUSALITY TEST SUMMARY =====

Independent (X) Dependent (Y)  Lag  F-stat  p-value Granger_Cause?
           JPM          MSFT     1 12.0702   0.0005            YES
          MSFT           JPM     1  0.3873   0.5338             NO
           JPM         GOOGL     1  5.1804   0.0229            YES
         GOOGL           JPM     1  0.0933   0.7601             NO
           JPM          META     1  7.1290   0.0076            YES
          META           JPM     1  2.6296   0.1050             NO
           JPM          NVDA     1  2.3303   0.1270             NO
          NVDA           JPM     1  0.2325   0.6297             NO

Decision rule: p-value < 0.05 → Reject Hₒ → X Granger-causes Y.
```

III. Interpretation of Results:

One-Way Summary (Tech Stocks onto JPM): This block tests the hypothesis that the tech stocks (Independent, X) Granger-cause JPM (Dependent, Y). Based on a 1-day lag, there is no statistical evidence that past price movements in MSFT, GOOGL, META, or NVDA help predict JPM's price movements.

Two-Way Summary (All Pairs): This block tests for causality in both directions. These results suggest a one-way predictive relationship (Granger causality) from JPM to MSFT, GOOGL, and META. There is no evidence of a reverse relationship (from those tech stocks to JPM) or any relationship with NVDA in either direction, at the chosen 1-day lag.

Thus, **JPM Granger-causes MSFT, GOOGL, and META**.

3.4.2. Vector Auto-Regressive Model:

While the above tests assess causality in a bivariate setting, the VAR model extends this analysis by capturing interdependencies among all variables simultaneously. This formulation aligns with the unrestricted Granger equations, but the VAR model nests all such equations jointly — allowing simultaneous estimation of interdependencies among the variables. A VAR model is a system-based approach where all variables (JPM, MSFT, GOOGL, META, NVDA) are treated as endogenous, meaning each variable is modelled as a function of its own past values and the past values of all other variables in the system.

The output shows the results of setting up a Vector Autoregressive (VAR) model and then using it to perform a multivariate Granger Causality test.

I. Lag Selection:

Before fitting the VAR model, we must choose the optimal number of past periods (lags) to include. The AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) are used. The goal is to find the lag number that minimizes these criteria, balancing model fit with simplicity. The Lag Selection Summary table shows that both AIC and BIC are minimized at Lag 10. Therefore, the analysis proceeds by building a VAR model where each variable is predicted by the past 10 values of *all five* variables.

II. Multivariate Granger Causality: This test checks if the lags of an entire group of variables are useful for predicting another variable (or group). This is different from the pairwise tests ran earlier.

A. Do Tech Stocks (as a group) predict JPM?

The group ['MSFT', 'GOOGL', 'META', 'NVDA'] does not Granger-cause 'JPM'. This tests if the past 10 lags of all four tech stocks, taken together, are jointly useless in predicting 'JPM'. The p-value is 0.000 (since the test statistic 2.069 is greater than the critical value 1.395). Since $p < 0.05$, we reject the null hypothesis. This provides strong evidence that the past values of the tech stocks, as a group, do have statistically significant predictive power for JPM's price changes.

B. Does JPM predict Tech Stocks (as a group)?

'JPM' does not Granger-cause the group ['MSFT', 'GOOGL', 'META', 'NVDA']. This tests if the past 10 lags of 'JPM' are jointly useless in predicting the price changes of the four tech stocks. The p-value is 0.000 (since the test statistic 2.079 is greater than the critical value 1.395). Since $p < 0.05$, we reject the null hypothesis. This provides strong evidence that JPM's past price changes do have statistically significant predictive power for the group of tech stocks.

```
Lag Selection Summary (AIC & BIC):
 Lag  AIC  BIC
   0   10    0
   1   10    0
   2   10    0
   3   10    0
   4   10    0
   5   10    0
   6   10    0
   7   10    0
   8   10    0
   9   10    0
  10   10    0

VAR model fitted with 10 lags.
```

Unlike the simpler pairwise tests (which used 1 lag and found a one-way relationship), this more comprehensive 10-lag VAR model suggests a **bi-directional Granger causality between JPM and the block of tech stocks**. Information appears to flow in both directions.

```
Multivariate Granger Causality Results:
Granger causality F-test. H_0: ['MSFT', 'GOOGL', 'META', 'NVDA'] do not Granger-cause JPM. Conclusion: reject H_0 at 5% significance level.
================================================
Test statistic Critical value p-value      df
------------------------------------------------
         2.069          1.395   0.000 (40, 13280)
------------------------------------------------
Granger causality F-test. H_0: JPM does not Granger-cause [MSFT, GOOGL, META, NVDA]. Conclusion: reject H_0 at 5% significance level.
================================================
Test statistic Critical value p-value      df
------------------------------------------------
         2.079          1.395   0.000 (40, 13280)
------------------------------------------------
```

3.5. Johansen Cointegration Test:

While the Engle–Granger two-step method is useful for testing cointegration between two variables, it is limited to bivariate analysis and cannot effectively capture multiple long-run equilibrium relationships within a system of more than two variables. To address this limitation, the Johansen cointegration test was employed, as it provides a multivariate framework for identifying and estimating multiple cointegrating vectors simultaneously.

I. The Cointegration Test:

```
 Johansen Cointegration Test Statistics
Trace Statistics:
[7.18008981e+01 4.13041670e+01 2.33578343e+01 9.62764458e+00
 7.12344200e-02]
Trace 5% Critical Values:
[69.8189 47.8545 29.7961 15.4943  3.8415]

Max-Eigen Statistics:
[30.4967311  17.94633264 13.73018974  9.55641016  0.07123442]
Max-Eigen 5% Critical Values:
[33.8777 27.5858 21.1314 14.2639  3.8415]
H0: r ≤ 0 rejected at 5% ⇒ At least 1 cointegrating vector(s)
H0: r ≤ 1 not rejected ⇒ 1 cointegrating relationship(s)
H0: r ≤ 2 not rejected ⇒ 2 cointegrating relationship(s)
H0: r ≤ 3 not rejected ⇒ 3 cointegrating relationship(s)
H0: r ≤ 4 not rejected ⇒ 4 cointegrating relationship(s)
```

The output shows the statistical test used to determine how many cointegrating relationships exist. The Johansen Test is run to find the "cointegrating rank" (denoted as r) of the system. This rank is the number of stable, long-run equilibrium relationships among the five variables (JPM, MSFT, GOOGL, META, NVDA) we have considered in our analysis.

It uses two statistics, the Trace Statistic and the Max-Eigen (Maximum Eigenvalue) Statistic.

H0: r = 0 (No cointegration): The test checks if there are zero cointegrating relationships. The hypothesis is rejected since there is at least 1 cointegrating vector.

H0: r <= 1 (At most 1 relationship): Now, the test checks if there is more than one relationship. This hypothesis is not rejected.

Since the test rejected r=0 but failed to reject r<=1, the analysis concludes that there is **exactly one cointegrating relationship (r=1)** among the five stock prices.

II. The VECM Framework & Potential Vectors:

```
VECM: Δyt = Π yt-1 + Γ1 Δyt-1 + ... + ut

Eigenvalues (λ):
[1.11985418e-02 6.60524270e-03 5.05740062e-03 3.52273557e-03
 2.63048313e-05]

Estimated β (Cointegrating vectors):
          beta1     beta2     beta3     beta4     beta5
JPM    0.003857 -0.065093  0.031168 -0.033004  0.020138
MSFT  -0.037957 -0.010969  0.007225  0.009794 -0.024161
GOOGL  0.122979  0.052397 -0.046994 -0.015381  0.009210
META  -0.010774  0.022801  0.006168 -0.005136  0.004730
NVDA   0.002288 -0.035246 -0.057152  0.022765  0.042405

=> Interpretation:
Each column of β defines a potential long-run cointegrating relation among variables.

Number of non-zero eigenvalues (rank Π): 5
```

The output shows the underlying structure of the Vector Error Correction Model (VECM) that the Johansen test is built on.

- VECM Equation: This is the general form of the model. The $\pi = \alpha\beta'$ term is the most important part, as it contains the long-run information.
- Eigenvalues (λ): These are the statistical values used to compute the Trace and Max-Eigen statistics. The **rank r = 1 means that only the first eigenvalue is statistically significant.**
- Estimated β (Cointegrating vectors): This matrix shows all five-potential long-run relationships. However, we have concluded that only one of them is valid (the first column, β1). The other four are not statistically significant long-run relationships.

III. The Estimated VECM Coefficients (for r=1):

```
 Estimated α (Adjustment Coefficients)
          alpha
JPM    0.000476
MSFT   0.000590
GOOGL  0.000478
META   0.001515
NVDA   0.000484

 Estimated β (Cointegrating Vector)
            beta
JPM     1.000000
MSFT    5.514688
GOOGL -19.032394
META    2.337679
NVDA    0.615506
```

This output shows the estimated coefficients for the VECM, given the conclusion from the test that r= 1.

Estimated β (Cointegrating Vector): This is the single cointegrating vector (corresponding to β1), which has been normalized so that the coefficient for JPM is 1.0. This vector defines the specific long-run equilibrium relationship:

1.0(JPM) + 5.51(MSFT) – 19.03(GOOGL) + 2.34(META) + 0.62(NVDA) = equilibrium

This equation is the long-run path that these stocks tend to follow together.

Estimated α (Adjustment Coefficients): This column shows the "speed of adjustment" for each variable. It measures how quickly each stock's price returns to the long-run equilibrium after a short-term shock. For example, the α for META is 0.001515. This coefficient indicates how strongly META's price changes in response to a deviation from the equilibrium in the previous period. For the system to be stable, at least one of these coefficients must be statistically significant and have the correct sign to pull the system back to equilibrium.

4. CONCLUSION:

The study provides strong statistical evidence that the stock price series of JPMorgan (JPM), Microsoft (MSFT), Google (GOOGL), Meta (META), and Nvidia (NVDA) are deeply interconnected. As confirmed by the Augmented Dickey-Fuller (ADF) tests, the raw price levels of all five stocks are non-stationary and integrated of order one, I(1). The first-differenced series, representing daily returns, were found to be stationary, which is a prerequisite for subsequent cointegration and causality analysis.

The central finding is the confirmation of a stable long-run equilibrium relationship among these assets. The Engle-Granger test first indicated a pairwise cointegrating relationship between JPM and META. More comprehensively, the Johansen cointegration test robustly confirmed the presence of one significant cointegrating vector (r=1) for the system as a whole. This implies that while the individual stock prices may drift apart in the short term, a persistent economic force tethers them together over the long run.

The analysis of short-term dynamics, conducted within a Vector Autoregressive (VAR) framework, revealed complex predictive relationships. While simple pairwise tests with a single lag suggested a one-way Granger causality from JPM to the tech stocks, a more robust 10-lag multivariate test established a bi-directional Granger causality. This indicates that predictive information flows in both directions: past movements in JPM can help predict the tech stock block, and past movements in the tech stock block can, in turn, help predict JPM. The existence of cointegration validates the use of a Vector Error Correction Model (VECM) as the appropriate framework for any future forecasting or impulse-response analysis, as it correctly incorporates both the short-run dynamics and the long-run equilibrium adjustments.

In summary, **the price movements of these firms from two different sectors are not independent**. They are bound by a long-run cointegrating relationship and exhibit complex, bi-directional short-term dynamics. Thus, the stock market data provides evidence of the U.S. tech sector having an influence over their financial sector.