# Hypothesis Testing of Standard Assumptions Theoretical Financial Mathematics

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### Introduction

In the theory of mathematical finance and modeling, it's often assumed that log returns of stock/index are normally distributed. This mini project investigates if the log returns of stocks of our chosen are normally distributed.

We will consider 5 years' daily log returns of 10 real-world stocks and explore the followings:

- 1. Test if there are periods of time when the log-returns of a stock have evidence of normal distribution.
- 2. Test if removing extremal return data creates a distribution with evidence of being normal.
- 3. Create a personalized portfolio of stocks with historical log return data that is normally distributed.
- 4. Test if the portfolio created in Mini Project 1 has significant periods of time with normally distributed log returns.
- 5. Perform full-period normality tests on several individual stocks to identify any that exhibit normal log return behavior.

#### 1 Preliminaries

**Data Used:** We downloaded adjusted closing prices for 10 large-cap stocks: AAPL, MSFT, GOOGL, TSLA, NVDA, KO, JNJ, PG, PEP, and XOM. Daily log returns were calculated as:

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right)$$

Normality Test: Throughout we test normality with

- Shapiro-Wilk (SW),
- Jarque-Bera (JB),
- Anderson–Darling  $(AD)^1$ .

<sup>&</sup>lt;sup>1</sup>Accept normality at 5% significance if AD statistic < critical value<sub>5%</sub>.

## 2 Rolling 6-Month Normality Test

For each stock we applied the AD test to a rolling 126-day window.

Ticker	% windows normal	Comment
XOM	80.3%	Most Gaussian-like
AAPL, NVDA, MSFT	5961%	Frequent local normality
GOOGL	33.6%	Rarely normal
Consumer-staple set	pprox 42%	Intermittent normality

**Conclusion.** Some stocks do exhibit local periods of normal behavior.

## 3 Normality After Removing Extremes

Define the  $\alpha$ -trimmed return sample

$$r_t^{(\alpha)} = \begin{cases} r_t & \text{if } q_\alpha \le r_t \le q_{1-\alpha}, \\ \text{(discard)} & \text{otherwise,} \end{cases}$$

where  $q_{\alpha}$  is the empirical  $\alpha$ -quantile.

- With  $\alpha = 1\%$ , only **XOM** passed AD.
- With  $\alpha = 3\%$ , five stocks passed: **JNJ**, **KO**, **NVDA**, **TSLA**, **XOM**.

**Conclusion.** Fat tails drive most rejections of normality; removing 3% of extremes makes several equities Gaussian-like.

# 4 Constructing a Normal Portfolio

Using the trimmed data from Task 2, we selected the 5 stocks with best normality test results and created an equal-weight portfolio. Portfolio returns were computed as:

$$R_t = \sum_{i=1}^{5} w_i \, r_{i,t}^{\text{(trimmed)}} \quad \text{with } w_i = 0.2$$

Test Results on Portfolio:

- Shapiro-Wilk p = 0.3058
- Jarque–Bera p = 0.9508
- Anderson–Darling: Passed at 5% significance

Conclusion: A well-chosen and trimmed stock portfolio can produce log returns that are approximately normally distributed.

## 5 Task 4: Testing Mini Project 1 Portfolio

We took the portfolio weights from Mini Project 1 for both high-risk and low-risk portfolios and tested their rolling normality using 126-day windows.

#### Portfolio Details:

• High-Risk: TSLA, KO, PG, PEP, XOM

• Low-Risk: GOOGL, KO, JNJ, PG, PEP, XOM

#### Results:

- High-Risk Portfolio passed in 80.85% of periods.
- Low-Risk Portfolio passed in 69.86% of periods.

**Conclusion:** Both portfolios from Mini Project 1 exhibit frequent periods of normal log return behavior.

## 6 Full-Period Normality for Individual Stocks

We tested the entire 5-year log return series for each of the 10 stocks using:

- Shapiro-Wilk Test
- Jarque-Bera Test
- Anderson–Darling Test

#### **Summary:**

- None of the 10 stocks passed all three tests.
- Most had low *p*-values, indicating deviation from normality.
- Visual inspection (histograms and Q-Q plots) supported heavy tails and skewness.

Conclusion: Over long time horizons, individual stock log returns do not follow a normal distribution.

### 7 Conclusion

- Log returns are rarely normal over long periods, but often locally normal.
- Removing outliers and constructing portfolios can improve normality.
- Statistical tests and visual tools are both essential for diagnosing normality.