Volatile Crypto Risk Modeling

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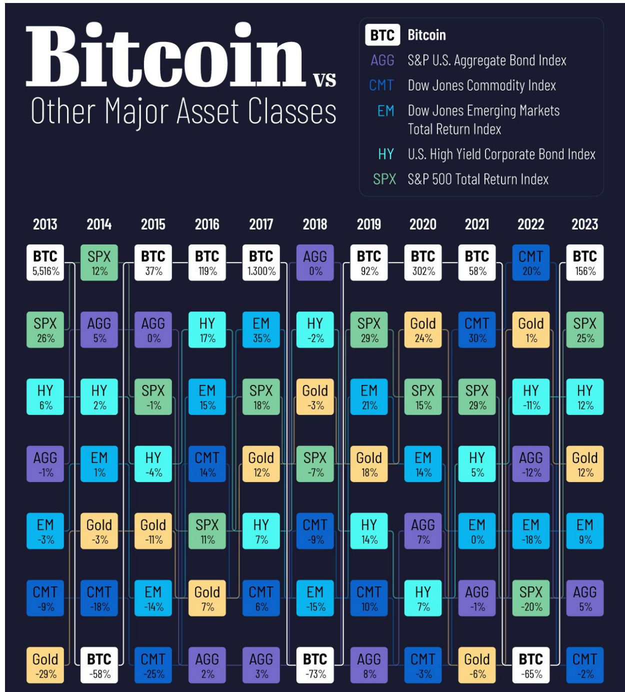
Introduction: Forecasting Bitcoin Volatility with GARCH(1,1)

- Crypto Market & Significance of Volatility Prediction:
  - Traders and Investors: Struggle with unpredictable losses and portfolio risks.
  - Exchanges and Platforms: Require reliable systems to monitor and respond to market instability.
- How the GARCH Model Helps:
  - GARCH(1,1)
  - Potential Gains (Serial → Parallel)
- Key Terms:
  - Volatility
    - Degree of variation in an asset's price over time, measured as variance
    - High volatility == large price swings
  - Volatility Clustering
    - Phenomenon where high-volatility periods are followed by high-volatility periods
  - GARCH(1,1)



Challenges

Key Focus Areas & Challenges:

- Parallelization of Tasks:
  - Efficiently distributing tasks such as autocorrelation analysis, GARCH fitting, and forecasting across multiple cores or nodes.
  - Handling interdependencies in computations
- Volatility Clustering:
  - Crypto prices exhibit clustering patterns that are hard to predict.
- Scalability
  - Scaling the model to analyze additional assets (e.g., Ethereum) becomes feasible with parallel systems.

Implementation Step 1. Data Collection and Preprocessing

Granularity of Data: 1 minute

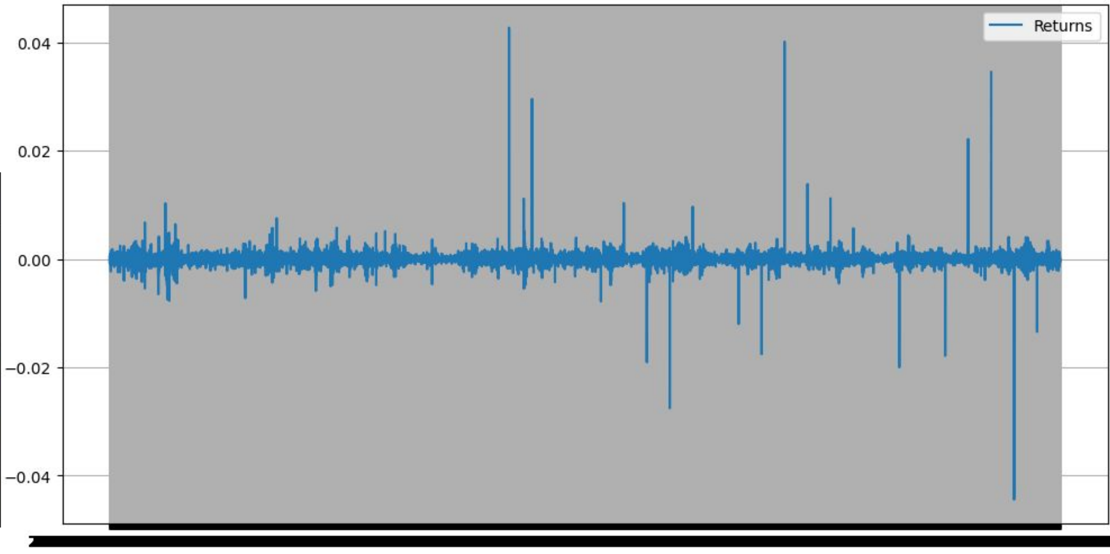
Frequency of Data: Daily

Crypto Target: Bitcoin

Duration/Length: 2 years (11/5/2022 ~ 11/5/2024)

Calculate Logarithmic Returns … $R_t = \ln(\frac{P_t}{P_{t-1}})$

	Timestamp	Open	High	Low	Close	Volume
0	2024-09-05 00:00:00	58060.0	58061.0	58060.0	58061.0	0.001793
1	2024-09-05 00:01:00	58029.0	58029.0	57995.0	58022.0	0.023644
2	2024-09-05 00:02:00	58022.0	58038.0	58022.0	58038.0	0.072100
3	2024-09-05 00:03:00	58069.0	58069.0	58049.0	58049.0	0.144172
4	2024-09-05 00:04:00	58082.0	58086.0	58082.0	58086.0	0.000962



Step 2. Test the Data

Autocorrelated Analysis

$$ACF(k) = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2}$$

- Applied the test from 0 to 60
- Check if ACF is used to check if the series is stationary
- high ACF at long lags

$$|ACF(k)| \geq \pm 1.96\sqrt{(T)}$$

Step 3. GARCH Model

GARCH(Generalized Autoregressive Conditional Heteroskedasticity) is a statistical model for analyzing and predicting time series volatility.

Basic Principles(**GARCH(1,1)**): $\sigma_t^2 = \omega + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2$

- σ_t^2: Current volatility.
- ω: Long Term Average Variance
- α: Weight for recent Error
- β: Weight for recent variance
- ε_{t-1}^2: Previous residual (squared).
- σ_{t-1}^2: Previous period's variance.

requirement: $\omega > 0,\ \alpha > 0,\ \beta > 0,\ \alpha + \beta < 1$

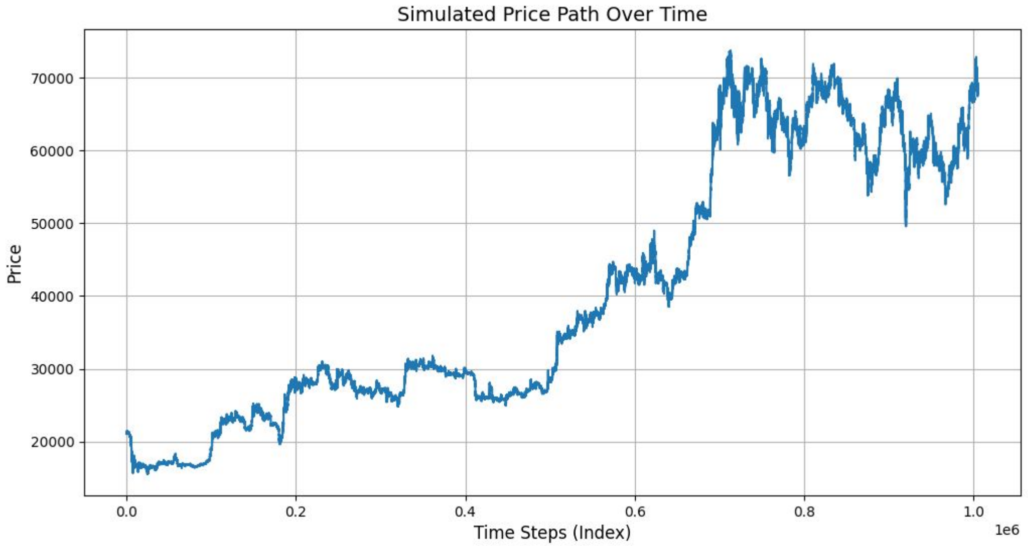
Features:

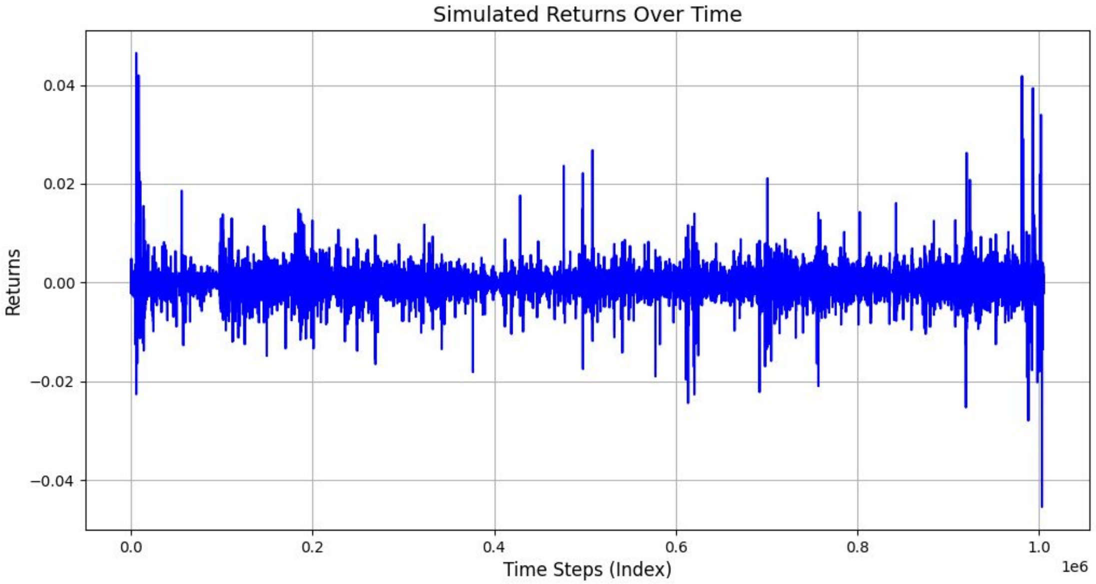
- Captures **volatility clustering**: Large changes are followed by large changes, small changes by small changes.
- Models **time-dependent heteroskedasticity**: Variance evolves dynamically with time.

Experimental Results of Serial vs Parallel

Predict result:

From 2024/11/05 to 2025/11/04

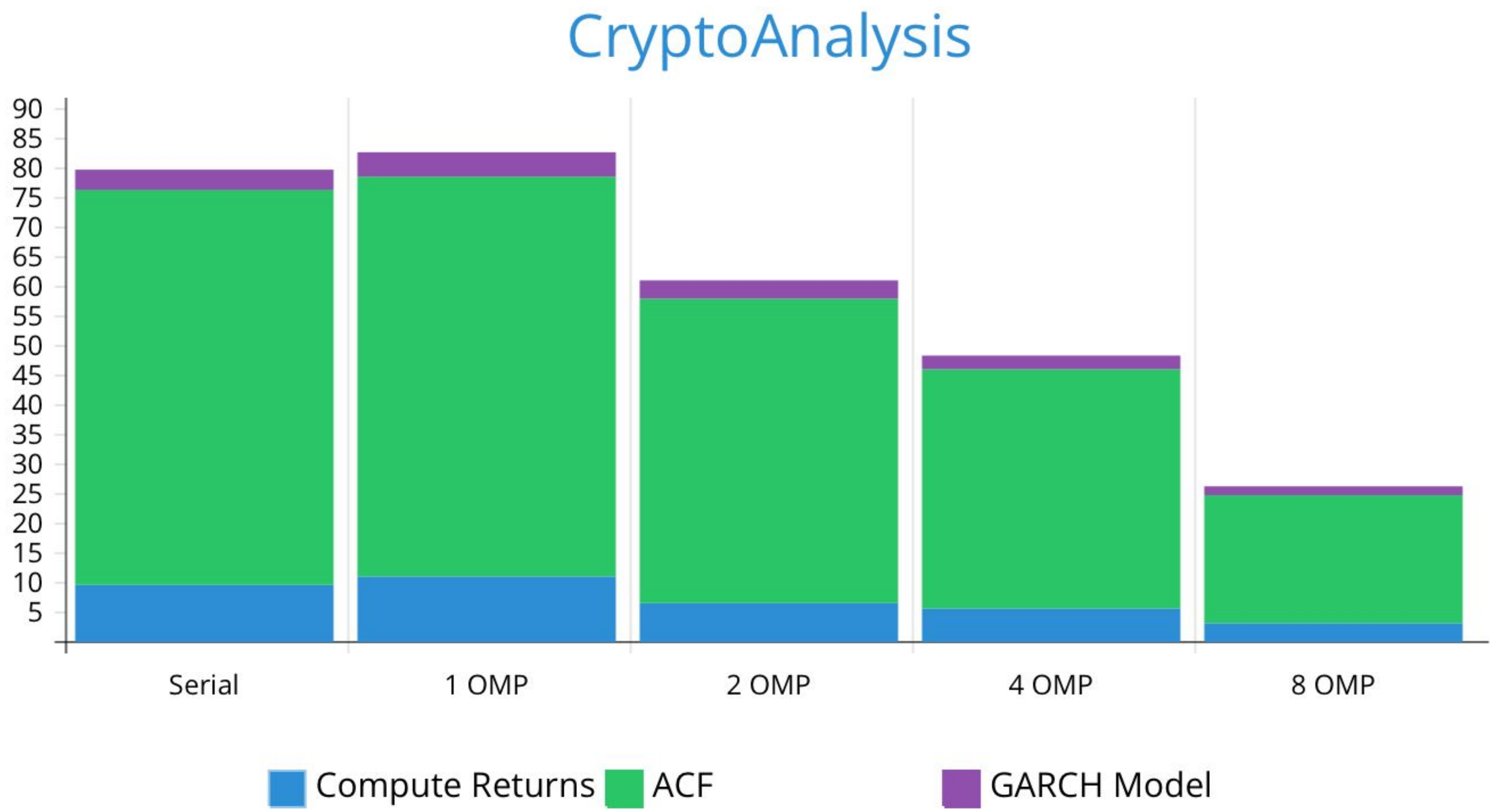




Bitcoin price simulation suggests a potential upward trend over the next year, favoring long-term holding.

However, returns show high volatility with occasional extremes, making short-term trading significantly risky.

Benefit of Using OMP



Step 4. Takeaway

Project Reflection

- **Too Optimistic for the Time Limit**
- **Great Structure to Attempt the Project**
- Lot of High Frequency Trading follows some sort of pattern and require quick analysis

Future Plans:

- Refine dashboard for real-time risk visualization.
- Explore advanced models like EVT and regime-switching models for rare event prediction.
- Explore better parallelization Algorithms

$$\sigma_{t+1}^2 = \omega + \alpha * \epsilon_t^2 + \beta * \sigma_t^2$$