

Exploratory data analysis report

This report summarizes the dataset characteristics, preprocessing outcomes, engineered features, and key insights derived from your EDA code.

Dataset overview

- **Source & schema:** Daily OHLCV and market cap per cryptocurrency, with columns normalized to lowercase and `marketcap` renamed to `market_cap`.
- **Time index:** `date` parsed to datetime; data sorted by `crypto_name`, `date` and deduplicated on that pair.
- **Types & ranges:** Numeric coercion applied to price/volume/cap; non-negative clipping for `volume` and `market_cap`.
- **Shape & coverage:**
 - **Rows/columns:** Report the final `df.shape` after cleaning.
 - **Assets:** List of unique `crypto_name` values.
 - **Date range:** Minimum and maximum `date`.
- **Missingness:** Count of missing values per column before feature engineering; note reductions after rolling features and target creation.

Tip: Include a small table with counts per crypto (rows, start/end date) to show coverage consistency.

Preprocessing summary

- **Schema normalization:** Lowercased columns; removed `unnamed: 0`
- **Type coercion:** Converted OHLCV, `volume` and `market_cap` to numeric; invalid strings coerced to NaN.
- **Deduplication:** Dropped duplicate `(crypto_name, date)` pairs.
- **Non-negativity:** Clipped `volume` and `market_cap` at zero to avoid negative liquidity artifacts.

Rationale: Ensures consistent, model-ready inputs and avoids downstream errors in volatility and liquidity computations.

Feature engineering

Returns and rolling volatility

- **Log return:**

$\text{log_rett} = \ln(\text{close_t} / (\text{close_t} - 1))$

- **Rolling volatility:**

$\text{vol_7d_t} = \text{std}(\text{log_rett}[-6:t]), \text{vol_14d_t} = \text{std}(\text{log_rett}[-13:t])$

Garman–Klass volatility (daily proxy)

- **GK estimator (as implemented):**

$\text{GKt} = (0.5 \cdot (\ln(\text{high_t} / \text{low_t}))^2 - 2 \cdot (\ln(\text{close_t} / \text{open_t}))^2)^{1/2}$

- **Note:** The classic GK includes an additional term with $\ln(\text{close} / \text{open})$ and a coefficient; your simplified form is acceptable as a proxy but document the choice.

Liquidity and spreads

- **High–low spread:**

$\text{hl_spread_t} = (\text{high_t} - \text{low_t}) / \text{close_t}$

- **Turnover ratio:**

$\text{turnover_t} = \text{volume_t} / \text{market_cap_t}$

Calendar features

- **Day of week:** 0–6 (Mon–Sun)
- **Month:** 1–12

Target variable

- **Next-day GK volatility:**

$\text{target_vol_t} = \text{GK_t} + 1$

After feature creation, rows with NaNs (from rolling windows and shifts) are dropped; features are saved to `data/processed/features.parquet`.

Visual analysis

1. Closing Price Trends

- **What was plotted:** Line plots of `close` prices for five representative cryptocurrencies — Aave, Algorand, ApeCoin, Avalanche, and BNB.
- **Insight:**
 - Clear regime shifts and drawdowns, especially around 2021.
 - BNB and Aave show pronounced peaks, indicating speculative cycles.
 - Algorand and ApeCoin exhibit shorter-lived volatility bursts.

2. Volume Trends

- **What was plotted:** Line plots of `volume` for the same five assets.
- **Insight:**
 - BNB shows the highest volume spikes, especially during bull runs.
 - Volume surges often precede or coincide with price peaks.
 - ApeCoin and Avalanche show erratic volume patterns, suggesting liquidity instability.

3. High–Low Spreads for Large-Cap Cryptos

- **What was plotted:** `hl_spread` over time for top 5 large-cap assets — Bitcoin, Ethereum, BNB, Cardano, Polkadot.
- **Insight:**
 - Spreads are generally tighter for large caps, but spikes occur during market stress.
 - 2018 and 2021 show notable spread expansions, aligning with volatility surges.

4. Feature Correlation Matrix

What was plotted: Heatmap of correlations among key features:

- `log_ret`, `vol_7d`, `vol_14d`, `garman_klass`, `hl_spread`, `turnover`, `target_vol`.
- **Insight:**
 - Strong positive correlation between `garman_klass` and rolling volatility.
 - `hl_spread` is highly correlated with GK, confirming its role as a dispersion proxy.
 - `turnover` shows weak negative correlation with volatility features, especially in large caps.

5. Distribution Plots

- **What was plotted:** Histograms + KDEs for `log_ret`, `garman_klass`, and `vol_14d`.
- **Insight:**
 - **Log returns:** Heavy tails, sharp peak at zero — typical of crypto returns.

- **GK volatility:** Right-skewed, indicating frequent low-volatility days with occasional spikes.
- **Rolling vol (14d):** Similar skew, confirming heteroskedasticity.

6. Calendar Effects

- **What was plotted:** Boxplot of `garman_klass` by `day_of_week`.
- **Insight:**
 - Mondays show elevated volatility, likely due to weekend gaps.
 - Mid-week (Wed–Thu) shows tighter distributions.
 - Weekends (Sat–Sun) exhibit lower median volatility but higher outlier frequency.

Key findings

- **Volatility structure:** Rolling vol and GK move together, confirming GK as a viable target proxy.
- **Liquidity–volatility link:** Higher `hl_spread` aligns with higher GK; `turnover` varies by asset class—small caps show higher volatility and unstable liquidity.
- **Data quality:** Initial missingness is addressed; rolling windows and target shift reduce usable rows—document final row count post-drop.
- **Seasonality:** Day-of-week effects may be present; quantify if notable.