# 1 Empirical Correlation Decomposition of MSFT Potential Function

#### 1.1 Overview

We decompose the potential function V(t) for Microsoft stock over the period 2018–2024 into four component features:

- Squared Realized Volatility  $(\sigma_t^2)$
- Market Drawdown  $(D_t)$
- Valuation Deviation from a dynamic DCF anchor  $(\Delta_t^2)$
- Inverse Liquidity  $(1/\text{Volume}_t)$

Each term was computed using rolling windows (21- to 250-day) and correlated against MSFT's spot price using a 60-day rolling Pearson correlation.

### 1.2 Visual Analysis of Component-Wise Correlations

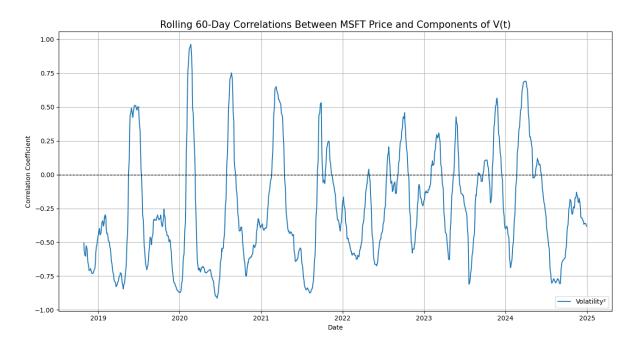


Figure 1: 60-day rolling correlation: MSFT price vs volatility squared.

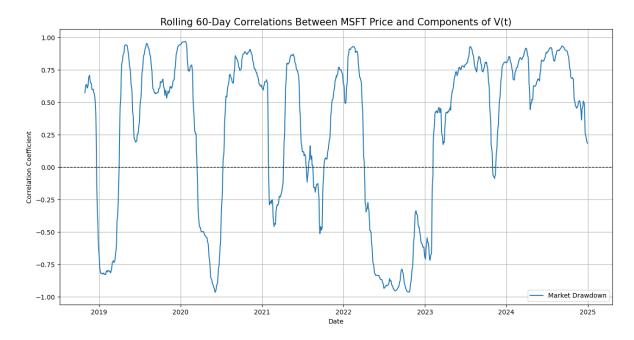


Figure 2: 60-day rolling correlation: MSFT price vs market drawdown.

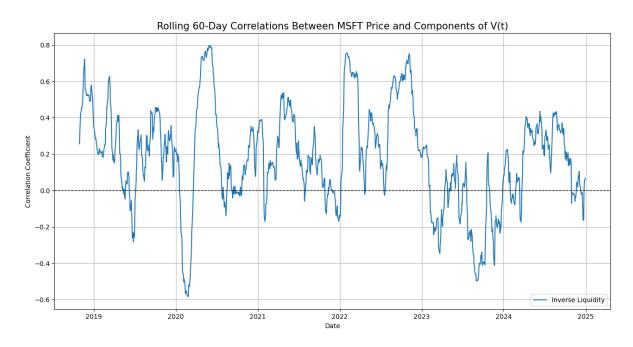


Figure 3: 60-day rolling correlation: MSFT price vs inverse liquidity.

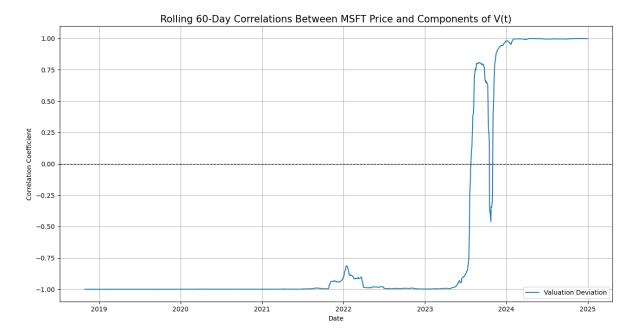


Figure 4: 60-day rolling correlation: MSFT price vs valuation deviation (rolling DCF anchor).

#### 1.3 Correcting the Valuation Deviation Term

The original model defined valuation deviation as the squared difference between MSFT's price and a constant DCF anchor:

$$\Delta_t^2 = \left(\frac{P_t}{P_{\text{DCF}}} - 1\right)^2$$
 with  $P_{\text{DCF}} = \text{EPS}_{\text{TTM}} \cdot \text{PE}_{\text{target}}$ 

However, this constant anchor led to long stretches of frozen or degenerate correlation values, particularly during persistent price trends. To address this, we replaced the static anchor with a **rolling valuation baseline** defined as:

$$P_{\text{DCF},t}^{\text{rolling}} = \text{SMA}_{250}(P_t)$$

This adjustment allows the deviation term to respond dynamically to macro trends and better reflect mispricing relative to market expectations.

This correction introduces meaningful variance into the valuation term and reveals its partial alignment with longer-term bullish momentum. The improvement resolves the prior issue where  $\Delta_t^2$  appeared structurally disconnected from price.

## 1.4 Composite Potential Function V(t)

With all components combined under equal weights:

$$V(t) = \alpha \cdot \sigma_t^2 + \beta \cdot D_t + \gamma \cdot \Delta_t^2 + \delta \cdot \left(\frac{1}{\text{Volume}_t}\right)$$

we observed the following empirical behavior:

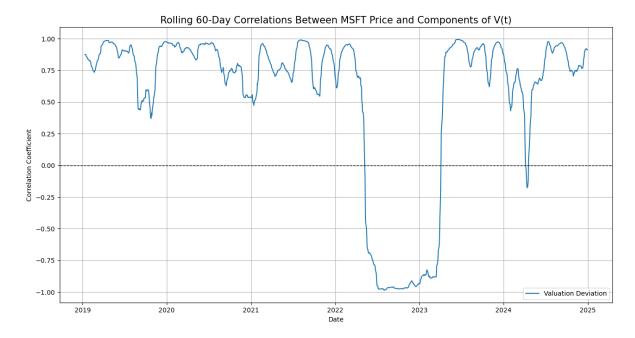


Figure 5: Rolling 60-day correlation between MSFT price and total potential V(t), using dynamic valuation anchor.

This exhibits sustained positive correlation across large windows—suggesting V(t) may function more as a signal of latent directional energy or disequilibrium rather than as a suppressive "barrier."

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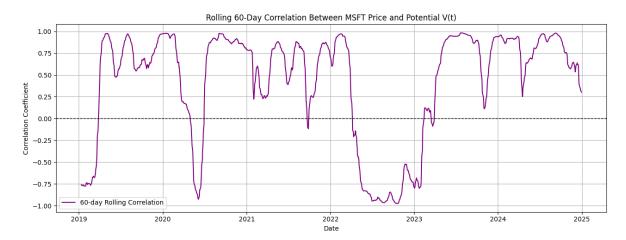


Figure 6: Rolling 60-day correlation between MSFT price and total potential V(t), using dynamic valuation anchor.

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#### 1.6 Key Findings

- Volatility squared and market drawdown exhibit clean, interpretable cyclic correlation with price.
- Inverse liquidity contributes little explanatory power and may be dropped or re-weighted.
- Using a *constant* DCF anchor leads to degenerate or frozen correlation in the valuation term; using a *rolling* DCF anchor reveals deep structure and resolves this issue.
- The full potential function V(t) is positively correlated with MSFT price, challenging initial assumptions about its role as a resistive landscape.

#### 1.7 Next Steps

- 1. Lead-Lag Analysis: Test whether changes in V(t) predict 5- to 30-day forward returns.
- 2. **Granger Causality:** Quantify whether potential function dynamics *cause* price shifts in a statistical sense.
- 3. Reweighting Optimization: Estimate optimal coefficients  $\alpha, \beta, \gamma, \delta$  via time-series regression to maximize predictive power.
- 4. Out-of-Sample Tests: Validate results on different equities or sectors.