High Frequency Trading and Market Making Strategies in a Multi Order Book Market

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Motivation & Research Questions

Why now? Fragmented markets: similar prices, *heterogeneous liquidity* (depth, latency, fees).

Key questions

1. How to extend Avellaneda–Stoikov to N order books with a shared inventory q_t?
2. How to model **dynamic volatility** for optimal MM strategies?
3. What is the *P&L–risk* frontier when coordinating quotes across order books? (work in progress)

Baseline: Avellaneda–Stoikov (single order book)

Objective: maximize terminal utility under risk aversion γ.

Key components:

- **Reservation price**: $r_t = S_t - q_t \, \gamma \, \sigma^2 \, (T - t)$
- **Optimal half–spread**: $\delta_t^* = f(\gamma, \sigma, T - t)$
- **Quotes**: $p_t^{ask} = r_t + \delta_t^*, \quad p_t^{bid} = r_t - \delta_t^*$

Insight: Volatility σ is crucial but often assumed constant $\rightarrow$ **important limitation**

Theoretical validation on real BTC data

Methodology: Test of the pure AS model on Bitcoin multi–exchange time series.

Rigorous setup:

- **Theoretical fidelity**: decreasing time horizon $(T - t)$, full temporal spread, NO practical tweaks
- **Data**: tick–by–tick BTC from Binance, Coinbase, Kraken, Bitfinex, OKX
- **Robustness**: multi–seed validation (10 seeds) for statistical significance

Key results:

- **Inventory strategy** systematically outperforms symmetric (win rate 80%)
- **Risk control**: Inventory strategy shows lower drawdowns and managed inventory volatility

Empirical confirmation of AS theoretical validity in crypto high-frequency markets

Upgrade I: Dynamic volatility modeling

Problem: Avellaneda–Stoikov assumes constant $\sigma \rightarrow$ suboptimal under volatility clustering.

Our solution: multi–regime dynamic model

- **Rolling estimation**: $\hat{\sigma}_t$ from moving tick windows
- **Regime detection**: automatic identification of high/low vol periods
- **Real–time adaptation**: spreads adjust dynamically to σ_t

$$\delta_t^* = \delta_t^*(\gamma, \hat{\sigma}_t, T - t) \quad \text{instead of constant } \sigma$$

Dynamic vs Static Volatility: Cross–Exchange Analysis

Research Goal

Demonstrate the **methodological superiority** of dynamic volatility models over traditional static ones in the HFT market making context.

Methodology

- **Data**: Bitcoin 1-second HFT
- **Period**: July 2025 (1 month)
- **Rolling Window**: 120 seconds
- **Exchanges**: 5 main platforms

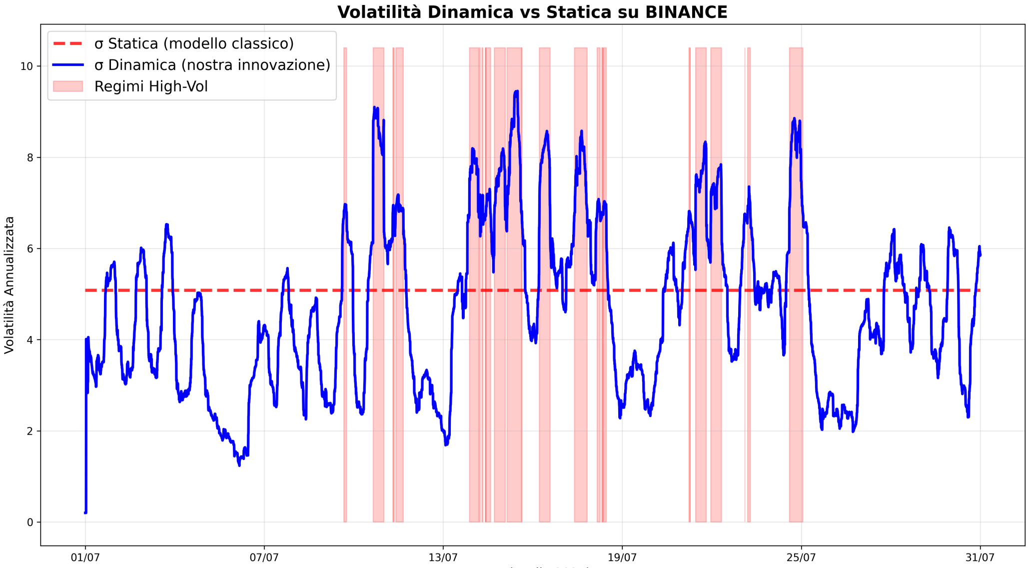
Hypotheses

Dynamic volatility:

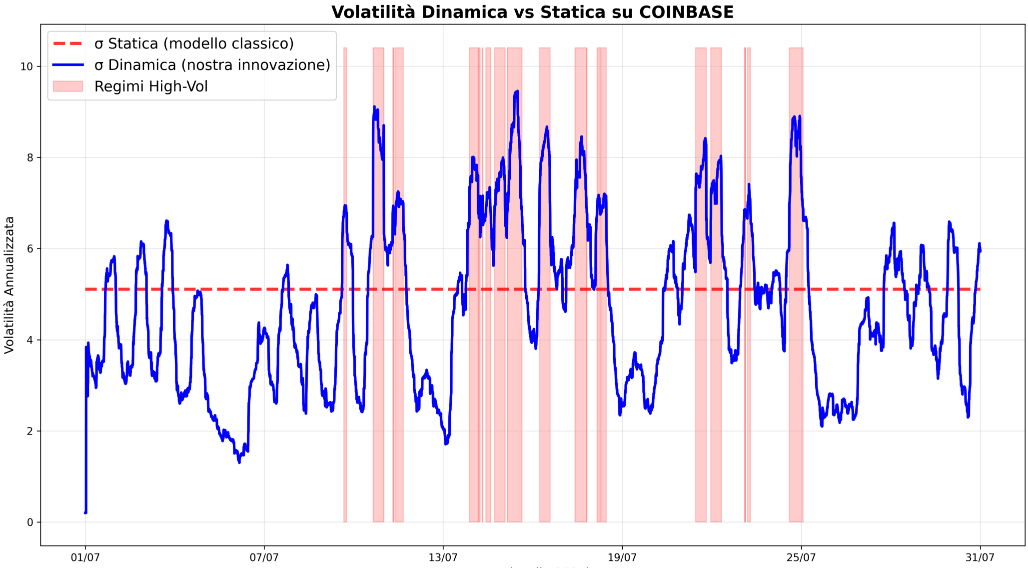
- Better captures **market regimes**
- Is more **responsive** to price shocks
- Shows **cross-exchange robustness**
- Improves trading performance

We now analyze results for each exchange...

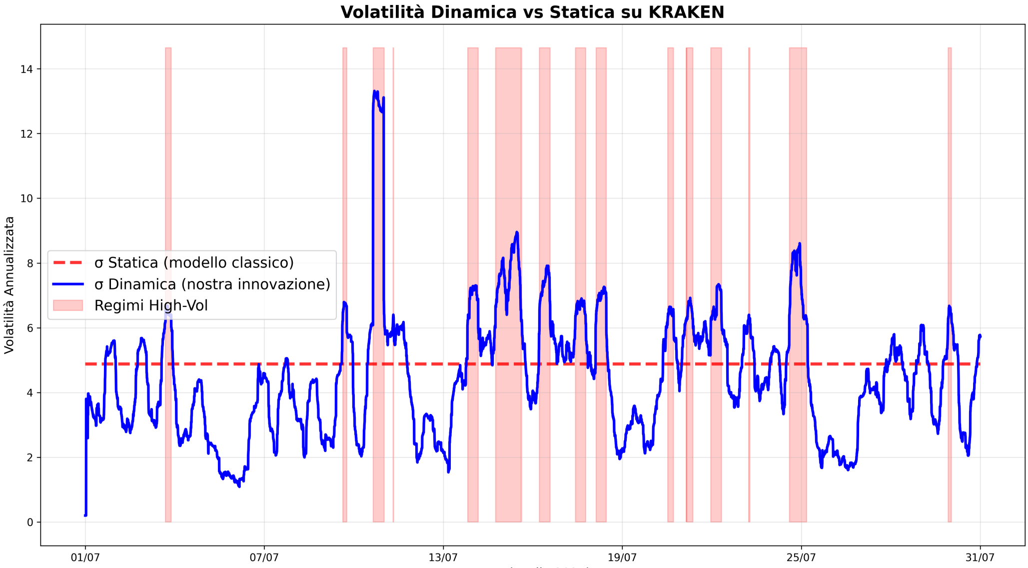
Exchange Analysis: BINANCE - Market Leader



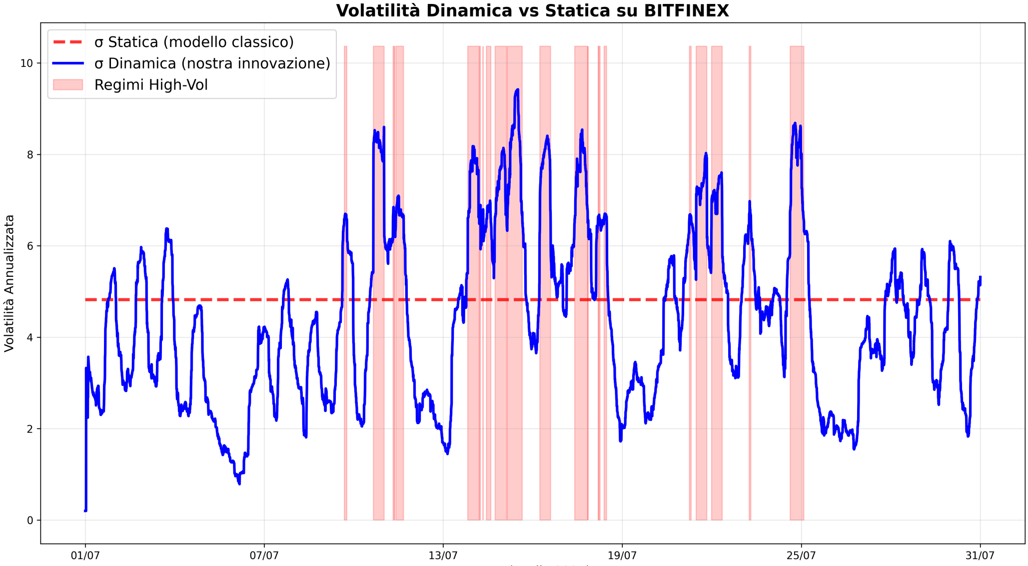
Exchange Analysis: COINBASE



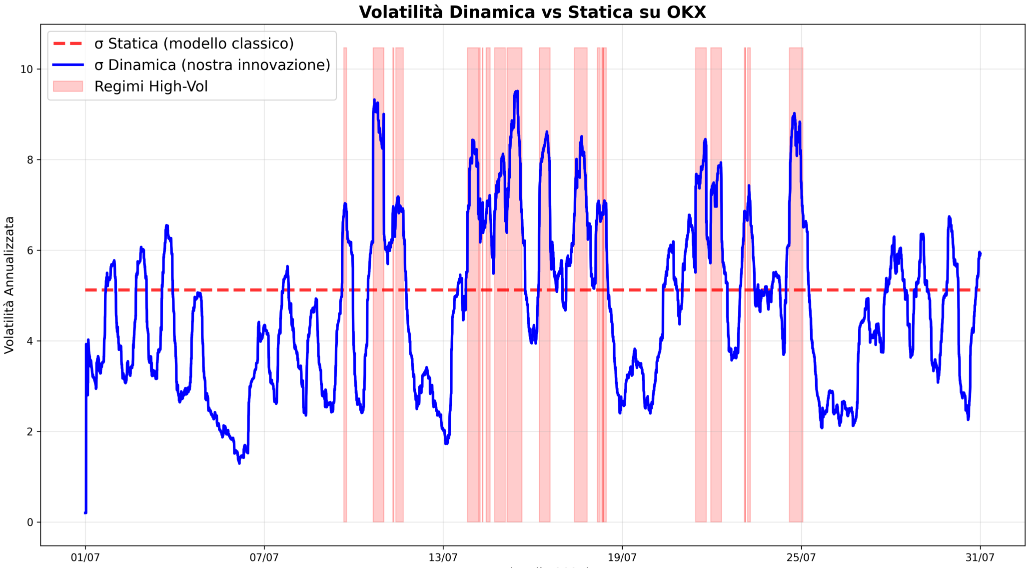
Exchange Analysis: KRAKEN



Exchange Analysis: BITFINEX



Exchange Analysis: OKX



Cross–Exchange Summary: Empirical Validation

Main Results

Methodological robustness confirmed across all 5 main exchanges:

- **Synchronized temporal patterns** across exchanges
- **Systematic inadequacy** of the static model
- **Automatic identification** of volatility regimes
- **Universality** of the phenomenon (not exchange-specific)

Quantitative Metrics

- **Dynamic range**: 0.2 - 13.2
- **Static range**: 4.8 - 5.1
- **Average ratio**: $\sim$1.8x

Practical Implications

- Improved **Risk Management**
- Dynamic **Position Sizing**
- Real-time **Spread Optimization**

Upgrade II: Multi–order–book extension (work in progress)

Setup: Venues $v = 1, \dots, N$ with heterogeneous depth, latency, and fees + shared volatility $\hat{\sigma}_t$.

Joint control with dynamic volatility

$$\max_{\{\delta_{t,v}\}} \mathbb{E}[U(W_T)] \text{ subject to } \sigma_t = \hat{\sigma}_t$$

Smart routing:

- Priority to venues with higher fill probability
- Dynamic adjustment to current volatility regime
- Coordination of shared inventory q_t

Limitations & Future Developments

Current limitations:

- Volatility model still "local" (no cross–venue contagion)
- No feedback between MM strategy and realized volatility

Next steps:

- **Hawkes model**: self–exciting orders to capture clustering
- **Endogenous volatility**: MM impact on market volatility
- **Machine Learning**: Deep learning for advanced regime detection

Takeaways

1. **Dynamic volatility is crucial**
2. **Multi–venue coordination**: better risk management and fill rate
3. **Regime–awareness**: models must adapt to liquidity shifts

Thank you! Questions?

Essential references

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