Quantitative Trading

Models, Market Structure, and Systematic Strategies

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Outline

- **Core Concepts of Trading**
  - Instruments, Profit Mechanics, and Time Horizons
- **The Quantitative Approach**
  - Data-driven Signals: Alpha, Risk, and Execution
- **Stylized Facts of Financial Markets**
  - Heavy Tails, Volatility Clustering, and Non-Stationarity
- **Modeling Market Dynamics**
  - Jumps, Leverage Effects, and Path Dependence
- **Microstructure and Cross-Asset Effects**
  - Noise, Frictions, and Global Contagion

Course Reference:
Futuretesting Quantitative Strategies
`http://ssrn.com/abstract=4647103`

Trading: Core Concepts

- Trading is the act of buying and selling financial instruments to generate profit.
- Instruments include equities, bonds, derivatives, FX, commodities, and crypto-assets.
- Profit arises from anticipating price movements:
  - Go **long** to benefit from rising prices
  - Go **short** to benefit from falling prices
- Trading typically operates over short- to medium-term horizons: from seconds to weeks.
- At its core, trading seeks to answer a single question:

  Where are prices likely to move next, and with what risk?

Key challenge: forecasts are uncertain, noisy, and time-dependent.

Trading Styles and Time Horizons

Trading strategies can be classified by their investment horizon and decision frequency.

- **High-frequency trading (HFT):**
  - Time horizon: milliseconds to seconds
  - Relies on speed, microstructure effects, and order book dynamics
- **Intraday trading:**
  - Positions opened and closed within the same trading day
  - Exploits short-term price patterns and liquidity imbalances
- **Swing / short-term trading:**
  - Time horizon: days to weeks
  - Focuses on momentum, mean reversion, and volatility regimes
- **Medium-term / systematic trading:**
  - Time horizon: weeks to months
  - Often model-driven and portfolio-based

Key insight: different horizons imply different data, risks, and modelling assumptions.

Why Quantitative Trading?

Financial markets generate vast amounts of data, but prices are noisy, adaptive, and highly competitive.

- Human intuition struggles to consistently process high-dimensional, fast-moving market data.
- Quantitative trading uses mathematical models, statistics, and algorithms to identify and exploit patterns in prices, volumes, and order flow.
- Decisions are rule-based, systematic, and reproducible, reducing behavioural biases.
- Models can be rigorously backtested, stress-tested, and monitored over time.

Core idea:

$$\text{Data} \longrightarrow \text{Model} \longrightarrow \text{Signal} \longrightarrow \text{Trade}$$

Key challenge: separating genuine signal from noise in a non-stationary environment.

Alpha, Risk, and Execution

Any trading strategy can be decomposed into three tightly coupled components.

- **Alpha (signal):**
  - A forecast of future returns or relative price movements
  - Can arise from momentum, mean reversion, carry, volatility, or cross-asset relationships
- **Risk management:**
  - Controls exposure to market, factor, and tail risks
  - Determines position sizing, leverage, and diversification
- **Execution:**
  - Translates signals into trades under liquidity and transaction cost constraints
  - Poor execution can destroy otherwise profitable alpha

Key principle: alpha generation, risk control, and execution cannot be designed in isolation.

Data in Quantitative Trading

Quantitative trading relies critically on data quality, availability, and interpretation.

- **Market data:**
  - Prices, returns, volumes, order book data
  - Available at multiple frequencies (daily, intraday, tick-level)
- **Derived data:**
  - Volatility measures, factors, technical indicators
  - Cross-sectional rankings and signals
- **Alternative data:**
  - News, text, macro indicators, flows, sentiment
  - Often noisy, delayed, and difficult to validate

Key challenge: financial data are noisy, non-stationary, and subject to selection and survivorship biases.

Models as Approximations of Reality

Quantitative trading relies on models to transform noisy data into actionable decisions.

- A model is a simplified representation of market dynamics, not a description of reality.
- All models embed assumptions about distributions, dependence, stationarity, and market behaviour.
- Simpler models are interpretable and robust, but may miss important features.
- More complex models can capture richer dynamics, but risk overfitting and instability.

Model risk:

- Incorrect assumptions can lead to systematic losses.
- Model performance degrades when market regimes change.

Key principle: models should be judged by robustness and economic plausibility, not only in-sample fit.

Stylised Facts of Financial Markets

Empirical studies show that financial time series exhibit robust statistical regularities, known as *stylised facts*.

- These features are observed across asset classes, markets, and time periods.
- They persist despite changes in technology, regulation, and market participants.
- Stylised facts describe how markets behave in practice, not how models assume they behave.

Examples include:

- Heavy-tailed return distributions
- Volatility clustering and persistence
- Non-stationarity and regime changes
- Jumps, asymmetries, and nonlinear dynamics
- Cross-asset dependence and contagion

Key message: successful trading models must respect these empirical constraints.

Characteristics of Financial Time Series

Financial time series differ fundamentally from the data encountered in classical statistics.

- Asset returns exhibit complex dynamics driven by human behaviour, institutional constraints, and market microstructure.
- Statistical properties evolve over time: means, variances, and dependencies are not stable.
- Extreme events, regime shifts, and feedback effects are intrinsic features, not anomalies.
- As a result, many standard assumptions fail:
  - Normality
  - Independence
  - Stationarity, Linearity

Implication for trading: models must be robust to noise, instability, and structural change rather than optimised for idealised settings.

Heavy Tails and Non-Gaussian Returns

Extreme events are the rule, not the exception

- Financial returns deviate strongly from the normal distribution.
- Empirical distributions exhibit **fat (heavy) tails**: large moves occur far more frequently than Gaussian models predict.
- Both extreme losses *and* extreme gains are common.
- Classical models systematically underestimate tail risk.
- Crisis events are not statistical outliers — they are structural features of markets.

Implication for trading and risk management:

- Volatility and drawdowns are underestimated under normality.
- Risk metrics based on Gaussian assumptions (e.g. parametric VaR) can fail catastrophically.
- Robust strategies must be designed for tail events, not average behaviour.

Example: Intraday Jump Event (1.27% Move)

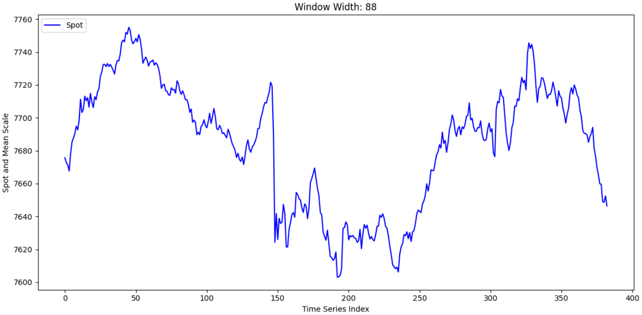

Figure 1: Spot FTSE, 1-minute chart — 09/04/25.

- A sudden price jump of 1.27% occurs within minutes.
- Such moves are incompatible with continuous Gaussian diffusion models.
- Intraday jumps dominate short-horizon risk and P&L.
- Stop-losses, leverage, and execution speed become critical.

Example: Regime Change

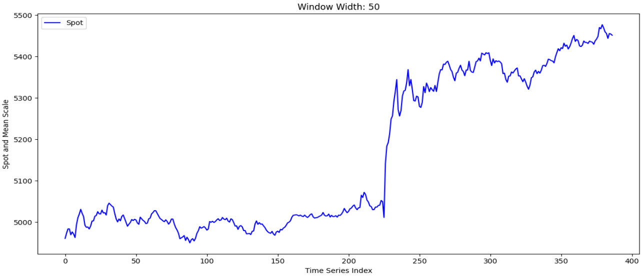

Figure 2: Spot S&P 500 (GSPC), 1-minute chart — 09/04/25.

- Market behaviour shifts abruptly from calm to highly volatile.
- Statistical properties (volatility, correlations, liquidity) change within minutes.
- Models calibrated in one regime fail in another.
- Successful strategies must detect and adapt to regime transitions.

Mathematical Formulation and Implications

- Empirical return distributions often exhibit excess kurtosis and power-law tails:

$$P\big(|X_t| > x\big) \sim x^{-\alpha}, \qquad \alpha \in (2,4)$$

- Heavy tails imply that extreme events decay slowly relative to Gaussian assumptions.
- Depending on α, higher-order moments may be unstable or ill-defined.

- Consequences for modelling and risk:
  - Variance and tail risk estimates become unreliable.
  - Gaussian-based Value-at-Risk severely underestimates crash probability.
  - Linear models fail to capture downside risk asymmetry.

Takeaway: risk in financial markets is dominated by tail behaviour, not average fluctuations.

Volatility Clustering and Persistence

- Financial markets exhibit **volatility clustering**:
  - High-volatility periods tend to follow high volatility.
  - Calm periods tend to persist.
- While raw returns may be weakly autocorrelated, their magnitudes are not.
- This violates the assumption of i.i.d. returns.
- Formally, squared (or absolute) returns exhibit positive serial dependence:

$$\operatorname{Cov}\left(r_t^2, r_{t+h}^2\right) > 0 \quad \text{for small } h$$

- This behaviour is well captured by ARCH/GARCH-type models and stochastic volatility frameworks.

Trading implication:

- Risk is time-varying and predictable to some extent.
- Position sizing, leverage, and stop distances should adapt to current volatility regimes.

Non-Stationarity and Structural Breaks

- Financial time series are inherently **non-stationary**.
- Key statistical properties evolve over time:
  - Mean returns, Volatility
  - Correlations and higher moments
- These changes reflect macroeconomic cycles, policy shifts, liquidity conditions, and market sentiment.

- **Structural breaks** are abrupt, persistent changes in market behaviour.
- Common causes include:
  - Central bank interventions
  - Regulatory changes
  - Crises and systemic shocks
  - Changes in market microstructure

Implication for trading:

- Models calibrated on historical data can fail suddenly.
- Adaptive, rolling, and regime-aware methods are essential for robustness.

Jumps and Discontinuities

- Asset prices often exhibit sudden, discrete jumps.
- These moves are too abrupt to be explained by continuous diffusion models.
- Common drivers include:
  - Earnings announcements and macro releases
  - Geopolitical and policy events
  - Liquidity shocks and forced deleveraging
- A more realistic return model incorporates jumps explicitly:

$$dX_t = \mu \, dt + \sigma \, dW_t + J_t \, dN_t$$

- W_t: Brownian motion (continuous risk)
- N_t: Poisson process (jump arrivals), J_t: random jump size

Jumps and Discontinuities

Trading implication:

- Jump risk dominates short-horizon P&L.
- Stop-losses, leverage, and overnight exposure must be designed for discontinuities.
- Continuous-time hedging arguments break down in the presence of jumps.

Leverage Effects and Asymmetric Volatility

- Volatility responds asymmetrically to returns:
  - Negative returns increase volatility more than positive returns.
- This phenomenon is known as the **leverage effect**.

- Economic intuition:
  - Falling asset prices increase financial leverage.
  - Higher leverage raises perceived risk and volatility.
  - Margin calls and risk limits amplify downside moves.

- Consequences for modelling and trading:
  - Volatility dynamics are direction-dependent.
  - Symmetric models underestimate downside risk.
  - Asymmetric GARCH and stochastic volatility models are required.

Trading implication: downside risk grows faster than upside opportunity.

Autocorrelation in Higher Moments

- Raw returns exhibit little serial correlation:
  - Information is rapidly incorporated into prices.
  - Arbitrage eliminates predictable return patterns.
- Higher moments behave very differently:
  - Volatility is strongly autocorrelated.
  - Skewness and kurtosis vary persistently over time.
- Formal observation:

$$Cov(r_t^2, r_{t+h}^2) > 0 \quad \text{for small } h$$

- This persistence underpins:
  - GARCH and stochastic volatility models
  - Volatility forecasting and risk targeting
  - Dynamic option pricing and hedging

Key insight: predictability exists primarily in risk, not returns.

Path Dependence and Memory Effects

- Financial markets are path-dependent:
  - Outcomes depend on how the current state was reached.
  - Identical prices can imply different risks depending on history.
- Context matters for shock propagation:
  - A -2% move during a bull market differs from the same move after a drawdown.
  - Volatility response depends on recent return sequences.
- Modelling implications:
  - Violates the Markov assumption.
  - Simple state-based models miss long memory effects.
  - Motivates models with memory, filters, or latent states.

Trading implication: history conditions risk, even when prices repeat.

Asymmetry and Nonlinear Dynamics

- Market reactions are inherently asymmetric:
  - A -1% move typically has a stronger impact than a $+1\%$ move.
  - Downside shocks trigger disproportionate responses.
- Sources of nonlinearity:
  - Loss aversion and behavioural asymmetry.
  - Margin calls, stop-loss cascades, and forced deleveraging.
  - Liquidity evaporation during stress periods.
- Implications for modelling and trading:
  - Linear models underestimate tail risk and volatility spikes.
  - Volatility depends on both magnitude and sign of returns.
  - Asymmetric and nonlinear models are required for realistic risk estimation.

Key insight: market dynamics are convex in losses and concave in gains.

Market Microstructure Noise and Frictions

- At high frequencies, observed prices are noisy:
  - Quotes reflect trading mechanics, not true fundamental value.
  - Noise dominates signal at very short horizons.
- Key sources of microstructure noise:
  - Bid–ask bounce and discrete price grids.
  - Latency, asynchronous trading, and execution delays.
  - Order book dynamics and hidden liquidity.
- Modelling implications:
  - Naively computed high-frequency returns are biased.
  - Volatility is overstated at short sampling intervals.
  - Requires filtering, aggregation, or noise-robust estimators.

Trading implication: speed increases noise before it increases information.

Cross-Asset Spillovers and Contagion

- Financial markets are interconnected:
  - Shocks propagate across assets, sectors, and regions.
  - Losses rarely remain isolated during stress periods.
- Dependence structures are state-dependent:
  - Correlations rise sharply during crises.
  - Diversification benefits weaken when risk is highest.
- Modelling implications:
  - Linear correlation fails to capture tail co-movement.
  - Extreme events exhibit strong tail dependence.
  - Requires dynamic correlation and copula-based models.

Risk insight: assets diversify in calm markets, but converge in crises.

Implications for Modelling and Trading

- Financial time series violate classical assumptions:
  - Non-Gaussian returns with heavy tails
  - Time-varying volatility and regime shifts
  - Asymmetry, memory, and nonlinear dynamics
- Consequences for quantitative models:
  - Linear, stationary models underestimate risk.
  - Standard error metrics miss economically relevant behaviour.
  - Backtests can appear stable while hiding tail fragility.
- Practical takeaway:
  - Models must align with empirical market structure.
  - Risk must be modelled dynamically, not averaged.
  - Robustness matters more than precision.

Core message: markets reward disciplined adaptation, not static optimisation.

The end

Thank You !