Trading Handbook

Foundations to Algorithmic Implementation

Lukas Maximilian Kapferer

lukas@kapferer.or.at
linkedin.com/in/lukas-kapferer
+43 677 61 44 27 44
A-6020 Innsbruck

Version from July 17, 2025

Contents

List of Figures

List of Tables

Part I

Foundations of Financial Markets

1 Market Microstructure

Abstract 1.1: M

rket microstructure studies *how* securities are traded: the rules, protocols, and strategic behavior that transform latent supply and demand into executed prices. Understanding these mechanics is essential for designing trading strategies, measuring costs, and avoiding pathological market conditions such as flash crashes.

1.1 Order Books and Price Formation

Most electronic venues implement a *continuous double auction (CDA)*. Participants submit **limit orders**, which specify a price/size pair, or **market orders**, which demand immediate execution against the best available limits.

Definition 1.1: Limit Order Book

The *limit order book (LOB)* is the queue of outstanding limit orders, ranked by price and (within the same price) by time priority.

Figure **??** shows a stylised snapshot:

1.1.1 Bid–Ask Spread

Let P_b be the highest bid and P_a the lowest ask. The **quoted spread** is $S_q = P_a - P_b$. Liquidity takers implicitly pay half the spread on average.

Example 1.1: Spread Cost

Suppose you buy 1000 shares of XYZ at the ask of \$100.02 and immediately sell at the bid of \$100.00. Your round-trip cost is \$0.02 per share, i.e. \$20 total.

1.2 Liquidity, Depth and Resiliency

1.2.1 Instantaneous Liquidity Metrics

Key metrics include:

- **Depth** at top-of-book: $\sum_{i:P_i=P_b} Q_i$
- **Order-to-Trade Ratio**: number of displayed orders per executed share
- **XLM*:** smallest cost to execute a round trip of size Q

1.3 Market Impact and Implementation Shortfall

Assume your execution trajectory generates an average price $\bar{P}_{\text{exec}}$. The *implementation shortfall* is $\text{IS} = (\bar{P}_{\text{exec}} - P_0) \times Q$, where P_0 is the decision price.

1.3.1 Empirical Power Law

Empirical studies suggest

$$\text{Price Impact} \approx \eta \left(\frac{Q}{V}\right)^{\gamma}, \quad \gamma \approx 0.5,$$

where V is daily volume and η a stock-specific constant (Almgren & Chriss, 2005).

1.4 Order Types and Venue Features

Beyond vanilla limits/markets, exchanges offer:

- **ICEBERG**: display only a portion of true size.
- **PEG**: auto-updates price relative to midpoint/primary quote.
- **IOC/FOK**: immediate-or-cancel / fill-or-kill time constraints.

1.5 Case Study: The 2010 Flash Crash

A large sell order in E-mini futures interacted with high-frequency liquidity depletion, causing a 9 % intra-day plunge in the S&P 500 within minutes. Post-mortems highlighted the role of *stop-loss cascades* and insufficient circuit breakers.[1]

[1] See CFTC/SEC joint report 2010.

Key Takeaways

1. Execution cost decomposes into spread + impact + slippage.
2. LOB state is *state-dependent*; supply curves are endogenous.
3. Microstructural phenomena impose practical limits on theoretical models.

2 Asset Classes Overview

2.1 Equities

Common vs preferred shares, voting rights, corporate actions (dividends, splits, buybacks). Global notation:

$$\text{Total Return} = \frac{P_t + D_t}{P_0} - 1.$$

2.2 Fixed Income

2.2.1 Discount Bond Pricing

For a zero-coupon bond maturing at T with yield y: $P_0 = \exp(-yT)$. In Python:

```
import numpy as np
def zero_price(y, T):
    return np.exp(-y * T)
```

2.3 Foreign Exchange (FX)

Spot vs forwards, covered interest parity:

$$F_{0,T} = S_0 \frac{(1 + r_d T)}{(1 + r_f T)}.$$

2.4 Commodities

Convenience yield, storage costs, backwardation vs contango.

2.5 Cryptoassets

Permissionless ledgers, consensus risks, on-chain vs off-chain volume.

Snapshot Table

Class	Typical Volatility	Primary Drivers
Equities	15–25 %	Earnings, sentiment
Treasuries	3–8 %	Macro rates, Fed policy
FX majors	6–12 %	Yield differentials

Key Takeaways

- Asset classes differ in contract structure, liquidity, and information flows.
- Correlation structures shift in crises ("flight to quality").

3 Time Value of Money

3.1 Discounting and Compounding

A cash flow C at time T has present value $PV = C/(1+r)^T$ under annual compounding. Continuous compounding gives $PV = C\,e^{-rT}$.

Definition 3.1: Yield Curve

A *yield curve* plots term-structure $r(T)$. Bootstrapping derives zero rates from coupon-bearing bonds.

3.1.1 Duration and Convexity

$$D = -\frac{1}{P}\frac{\mathrm{d}P}{\mathrm{d}y}, \quad C = \frac{1}{P}\frac{\mathrm{d}^2P}{\mathrm{d}y^2}.$$

These measure first- and second-order sensitivity to rate shifts.

3.2 Forward Rates

Instantaneous forward:

$$f(t) = \frac{\mathrm{d}}{\mathrm{d}T}\big(T\,r(T)\big)_{T=t}$$

Python Example: Spot vs Forward Rates

```
import pandas as pd, numpy as np
times = np.array([0.5, 1, 2, 5])
spot = np.array([0.02, 0.025, 0.03, 0.035])
forward = np.diff(times * spot) / np.diff(times)
pd.DataFrame({"T_start": times[:-1], "f": forward})
```

Key Takeaways

1. Compounding convention matters for quoted yields.
2. DV01 and duration are linear approximations—convexity corrects curvature.

4 Probabilities and Statistics Refresher

4.1 Random Variables

A random variable X has CDF $F_X(x) = \Pr[X \leq x]$. Key families in finance: Normal, log-normal, Student-t, exponential.

4.2 Moments and Estimators

Sample mean $\hat{\mu} = \frac{1}{n} \sum X_i$. Sample variance $\hat{\sigma}^2 = \frac{1}{n-1} \sum (X_i - \hat{\mu})^2$.

Definition 4.1: Central Limit Theorem

As $n \to \infty$,

$$\sqrt{n}\,\frac{\bar{X}_n - \mu}{\sigma} \xrightarrow{d} \mathcal{N}(0, 1).$$

4.3 Hypothesis Testing

Example: two-sample t-test for equal means.

```
from scipy.stats import ttest_ind
stat, p = ttest_ind(sample_A, sample_B, equal_var=False)
```

4.4 Linear Regression

OLS estimator: $\hat{\beta} = (X^\top X)^{-1} X^\top y$. R^2 measures explained variance.

4.5 Maximum Likelihood

Log-likelihood $\ell(\theta) = \sum_i \log f(X_i; \theta)$. Score and Fisher information underpin asymptotic normality.

Key Takeaways

- Estimation error propagates into trading signals—always budget uncertainty.
- Fat-tailed distributions capture extreme-event risk better than Gaussian.

Part II

Financial Instruments & Their Payoffs

5 Cash Instruments

5.1 Equities

Purchasing common stock grants an economic claim on residual cash flows and (often) voting rights. Settlement convention: *T+2* in most developed markets. Key lifecycle events:

- **Dividend Date Trio**: *declaration*, *ex-div*, *payment*.
- **Corporate Actions**: splits, mergers, spin-offs.

5.1.1 Total-Return Decomposition

Let P_t be price and D_t cumulative dividends until t. Total return over Δt:

$$R_{t,t+\Delta t} = \frac{P_{t+\Delta t} - P_t + (D_{t+\Delta t} - D_t)}{P_t}.$$

5.2 Fixed-Income Securities

5.2.1 Coupon-Bearing Bonds

Price is present value of future coupons C_i and face value F:

$$P_0 = \sum_{i=1}^{n} \frac{C_i}{(1+y)^{t_i}} + \frac{F}{(1+y)^T}.$$

Display DV01 in Python:

```
import numpy as np
def dv01(y, cashflows, times):
    # cashflows and times in years
    pv = np.exp(-y*np.array(times))
    return 1e-4 * np.sum(np.array(times) * cashflows * pv)
```

5.3 Money-Market Instruments

Treasury bills, commercial paper, certificates of deposit. Quoting conventions vary (discount rate vs money-market yield).

5.4 Repos

Repurchase agreements combine a spot bond sale and a forward repurchase. Repo rate ρ implies:

$$1 + \rho\Delta t = \frac{P_{\text{sell}}}{P_{\text{buy}}}.$$

Key Takeaways

1. Cash instruments provide the benchmark curves from which forward and derivative prices are bootstrapped.
2. Conventions (day-count, settlement) materially affect quoted yields.

6 Options 101

Abstract 6.1: O

tions grant asymmetric payoffs via the *right* but not the obligation to transact. We formalise terminology, payoff diagrams and no-arbitrage relations that underpin later pricing models.

6.1 Basic Definitions

Call Right to buy the underlying at strike K.

Put Right to sell the underlying at strike K.

European Exercisable only at maturity.

American Exercisable any time up to maturity.

6.2 Payoff Diagrams

S_T

Figure 6.1: European call and put payoffs at maturity.

6.3 Put–Call Parity

$$C - P = S_0 - Ke^{-rT}.$$

Immediate arbitrage if equality violated.

6.4 Moneyness and Delta Approximation

- **Moneyness** $= S_0/K$.
- $\Delta_{\text{call}} \approx N(d_1)$ under Black–Scholes.

6.5 Greeks Primer

Table ?? summarises first-order sensitivities.

Greek	Symbol	Interpretation
Delta	Δ	$\partial C/\partial S$
Gamma	Γ	$\partial^2 C/\partial S^2$
Vega	ν	$\partial C/\partial \sigma$
Theta	Θ	$\partial C/\partial t$

Table 6.1: Primary option Greeks.

Key Takeaways

1. Option structures synthesise non-linear exposures from linear instruments.
2. Parity and monotonicity bounds are model-free sanity checks.

7 Exotic Options and Structured Products

Abstract 7.1: R

al-world risk transfer often demands payoffs beyond vanilla calls and puts. “Exotics” embed path, barrier, or multi-asset features that complicate valuation and hedging.

7.1 Barrier Options

Knock-out call: pays $\max(S_T - K, 0)$ if $S_t < H$ for all t.
Pricing uses reflection principle; closed-forms exist for GBM when $H < K$ (down-and-out).

7.2 Asian Options

Payoff depends on arithmetic average $\bar{S} = \frac{1}{N}\sum_{i=1}^{N} S_{t_i}$.

7.2.1 Monte-Carlo Example

```
import numpy as np
def asian_call_mc(S0, K, r, sigma, T, n_steps, n_paths):
    dt = T/n_steps
    disc = np.exp(-r*T)
    payoffs = []
    for _ in range(n_paths):
        S = S0
        path = []
        for _ in range(n_steps):
            S *= np.exp((r-0.5*sigma**2)*dt +
                        sigma*np.sqrt(dt)*np.random.randn())
            path.append(S)
        payoff = max(np.mean(path) - K, 0)
        payoffs.append(payoff)
    return disc * np.mean(payoffs)
```

7.3 Digital (Binary) Options

Pays fixed amount Q if $S_T > K$. Delta spikes near strike, posing hedging challenges.

7.4 Structured Notes

* Autocallables (contingent coupons) * Range accruals (interest accrues when reference within band) Issuers offset exotic profiles via dynamic hedging or OTC options.

Key Takeaways

- Exotic valuation often requires simulation or PDE methods.
- Liquidity is thinner; model risk and hedging error dominate.

8 Volatility Products

Abstract 8.1: T

ading *volatility* directly—rather than price direction—has spawned instruments such as variance swaps, VIX futures and vol-target ETFs. We formalise payoffs and common pitfalls.

8.1 Implied vs Realised Volatility

Implied σ_{imp} from option prices signifies a *risk-neutral* expectation. Realised volatility σ_{real} is backward-looking.

$$\mathrm{RV}_{t,T} = \sqrt{\frac{252}{n}\sum_{i=1}^{n}\left(\ln S_{t_i} - \ln S_{t_{i-1}}\right)^2}.$$

8.2 Variance Swaps

Floating leg pays RV^2; fixed leg is *variance strike* K_{var}. Replication requires strip of out-of-the-money options:

$$K_{\mathrm{var}} \approx \frac{2e^{rT}}{T}\left[\int_0^{F_0} \frac{P(K)}{K^2}\,K + \int_{F_0}^{\infty} \frac{C(K)}{K^2}\,K\right].$$

8.3 VIX Futures

Cash-settled to the 30-day implied volatility of S&P500.

8.3.1 Term Structure Dynamics

Near-term VIX often in contango except in stress regimes where backwardation signals demand for crash protection.

8.4 Volatility ETNs and Options on VIX

Leveraged / inverse products decay via daily rebalancing mathematics.

Key Takeaways

1. Variance swaps provide pure volatility exposure, but replication assumes continuous hedging across strikes.
2. Vol ETNs embed significant path-dependent decay; position sizing must acknowledge compounding effects.

Part III

Option Pricing & Risk Management

9 Derivation of the Black–Scholes Formula

Abstract 9.1: B

ack–Scholes remains the canonical closed-form option-pricing model. We present an arbitrage-free derivation from first principles, examine assumptions, and provide Python code for numerical evaluation.

9.1 Model Assumptions

1. Underlying follows geometric Brownian motion: $S_t = \mu S_t t + \sigma S_t W_t$.
2. Constant risk-free rate r and volatility σ.
3. No dividends, taxes, or transaction costs (extend later).
4. Continuous trading and frictionless borrowing/lending.

9.2 PDE via Dynamic Hedging

Construct self-financing portfolio $\Pi = C - \Delta S$ with $\Delta = \partial C/\partial S$.
Ito's Lemma $\Rightarrow$

$$C = \left(\partial_t C + \frac{1}{2}\sigma^2 S^2 \partial_{SS} C + rS\partial_S C\right) t + \sigma S \partial_S C W_t.$$

Choose $\Delta = \partial_S C$ to eliminate the W_t term; the hedged portfolio earns risk-free $r\Pi$. Rearranging yields the Black–Scholes PDE:

$$\partial_t C + \frac{1}{2}\sigma^2 S^2 \partial_{SS} C + rS\partial_S C - rC = 0.$$

9.3 Solution for a European Call

With terminal condition $C(S,T) = \max(S - K, 0)$:

$$C(S_0, 0) = S_0 N(d_1) - K e^{-rT} N(d_2),$$

$$d_{1,2} = \frac{\ln(S_0/K) + (r \pm \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}.$$

Python Implementation

```
import numpy as np
from scipy.stats import norm

def bs_call(S0, K, r, sigma, T):
    d1 = (np.log(S0/K) + (r + 0.5*sigma**2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)
    return S0*norm.cdf(d1) - K*np.exp(-r*T)*norm.cdf(d2)
```

9.4 Critical Discussion

* **Volatility smile** contradicts constant-σ assumption. * **Jump risk** and **stochastic rates** break log-normality.
These shortcomings motivate Chapters **??**–**??**.

Key Takeaways

1. Black–Scholes arises from no-arbitrage plus GBM dynamics.
2. Delta-hedging arguments obviate investor risk preferences.
3. Calibration requires implied volatility, not historical.

10 Greeks and Sensitivity Analysis

Abstract 10.1: G

eeks quantify risk in multidimensional parameter space. We derive analytic formulas under Black–Scholes, examine higher-order metrics, and show Python checks using automatic differentiation.

10.1 First-Order Greeks

$$\begin{aligned}
\Delta &= \partial_S C = N(d_1), \\
\Theta &= \partial_t C = -\frac{S\sigma N'(d_1)}{2\sqrt{T}} - rKe^{-rT}N(d_2), \\
\rho &= \partial_r C = KTe^{-rT}N(d_2), \\
\nu &= \partial_\sigma C = S\sqrt{T}N'(d_1).
\end{aligned}$$

10.2 Second-Order Greeks

Gamma $\Gamma = \partial^2_{SS} C = N'(d_1)/(S\sigma\sqrt{T})$. Vanna, vomma, speed for volatility trading desks.

10.3 Python Automatic Differentiation (JAX)

```python
import jax.numpy as jnp
from jax import grad

bs = lambda S, K, r, sigma, T: ...
delta = grad(bs, argnums=0)
gamma = grad(delta, argnums=0)
```

10.4 Greeks Aggregation and Risk Reports

Risk P&L: $\Delta P \approx \Delta \cdot \Delta S + \frac{1}{2}\Gamma(\Delta S)^2 + \nu\Delta\sigma + \dots$

Key Takeaways

- Greeks are partial derivatives; numerical estimation requires step-size control.
- Risk aggregation across portfolios uses position-weighted sums.

11 Numerical Option Pricing Methods

Abstract 11.1: W

en closed-form solutions are unavailable, numerical methods— trees, finite differences, Monte Carlo—step in. We compare accuracy, speed, and implementation complexity.

11.1 Binomial and Trinomial Trees

CRR parameters: $u = e^{\sigma\sqrt{\Delta t}},\ d = 1/u,\ p^* = \frac{e^{r\Delta t}-d}{u-d}$.

11.1.1 American Option Handling

Backwards induction with early-exercise check: $C_i^n = \max\bigl(\text{intrinsic}, e^{-r\Delta t*}[C^{n+1}]\bigr)$.

11.2 Finite-Difference Schemes for the BSM PDE

Implicit, explicit, and Crank–Nicolson grids.

```
def crank_nicolson(M, N, Smax, K, r, sigma, T):
    # M: price steps, N: time steps
    ...
```

11.3 MonteCarlo Simulation

Risk-neutral drift r gives unbiased estimator:

$$C = e^{-rT} \frac{1}{N} \sum_{i=1}^{N} \max\big(S_0 e^{(r-\sigma^2/2)T+\sigma\sqrt{T}Z_i} - K, 0\big).$$

Variance reduction: antithetic variates, control variates (delta hedge).

Comparison Table

Method	Dimension	American?	CPU Complexity
Tree	1D		$O(N^2)$
Finite diff.	1–2D		$O(NM)$
Monte Carlo	High-D	(unless LSM)	$O(NS)$

Key Takeaways

- Choose method based on payoff path-dependence and dimensionality.
- Calibration workflow often mixes analytic and numeric pricers.

12 Stochastic Volatility and Jump Models

Abstract 12.1: W

relax the constant-volatility and continuous-path assumptions. Heston, SABR and Merton jump-diffusion capture skew, smile and kurtosis in observed option markets.

12.1 Heston Model

$$S_t = \mu S_t t + \sqrt{v_t}\, S_t W_t^{(1)},$$
$$v_t = \kappa(\theta - v_t)t + \xi\sqrt{v_t}\, W_t^{(2)},\ W^{(1)} W^{(2)} = \rho\, t.$$

Characteristic-function pricing via Fourier transform (Carr–Madan).

12.2 SABR

Forward F_t dynamics:

$$F_t = v_t F_t^{\beta} W_t^{(1)}, \quad v_t = \nu v_t W_t^{(2)}.$$

Asymptotic implied-vol formula widely used in interest-rate swaptions.

12.3 Jump-Diffusion (Merton)

$S_t/S_t = (\mu - \lambda k)t + \sigma W_t + (J-1)N_t$.
PDF is infinite mixture of normals; option price is weighted sum of Black–Scholes terms.

12.4 Calibration Notes

Non-linear optimisation on implied-vol surface; regularise to avoid over-fitting.

Key Takeaways

- Stochastic vol explains smile curvature; jumps add fat tails.
- Semi-closed-form methods (Fourier, saddle-point) aid speed.

13 Volatility Surface Construction

Abstract 13.1: A

mooth, arbitrage-free volatility surface is fundamental for risk management and exotic pricing. We cover parametrisations (SVI), interpolation schemes, and static arbitrage diagnostics.

13.1 Market Data Cleaning

1. Remove crossed markets.
2. Convert quotes (delta, moneyness) to strikes.
3. Smooth bid-ask midpoints before fitting.

13.2 SVI Parametrisation

Total implied variance $w(k)$: $w = a + b\big(\rho(k - m) + \sqrt{(k - m)^2 + \sigma^2}\big)$.
No-butterfly no-calendar constraints enforce arbitrage-free region.

13.3 Calibration Pipeline

Global–local routine: global differential-evolution seed, then local L-BFGS-B.

13.4 Density Recovery

Breeden–Litzenberger: $q(K) = e^{rT} \partial_{KK} C(K, T)$.

Key Takeaways

1. Surface must satisfy calendar- and butterfly-arbitrage constraints.
2. SVI dominates equity desks; natural extensions exist for rates.

14 Risk Measurement

Abstract 14.1: W

formalise Value-at-Risk, Expected Shortfall, stress testing, and scenario generation, emphasising implementation details relevant to options portfolios.

14.1 Value-at-Risk (VaR)

$\mathrm{VaR}_\alpha = \inf\{x \mid \Pr(L \le x) \ge \alpha\}$.
Historical, parametric (variance–covariance), and Monte Carlo approaches.

14.2 Expected Shortfall (ES)

$\text{ES}_\alpha = [L \mid L > \text{VaR}_\alpha]$.
Coherent; regulatory standard (FRTB).

14.3 Stress Testing

Design historical and hypothetical shocks (vol spike, correlation breakdown). Full-reval vs parametric approximations.

14.4 Back-testing Framework

Coverage test: reject if number of VaR exceptions exceeds binomial bounds.

Key Takeaways

- ES supersedes VaR for tail risk; implementation cost modest.
- Back-testing validates both data quality and model assumptions.

15 Portfolio Management and Allocation

Abstract 15.1: W

bridge option-centric risk analytics with portfolio theory: CAPM, multi-factor models, risk-parity, and Kelly sizing.

15.1 CAPM Refresher

$E[R_i] = r_f + \beta_i(E[R_m] - r_f)$.

15.2 Factor Models

Fama–French 3-/5-factor, momentum, quality minus junk (QMJ). Estimation in Python:

```
import pandas as pd, statsmodels.api as sm
Y = asset_returns
X = sm.add_constant(factor_returns)
results = sm.OLS(Y, X).fit(cov_type='HAC', cov_kwds={'maxlags':5})
```

15.3 Risk-Parity and Vol-Target Portfolios

Allocate weights inversely to vol or marginal contribution to risk.

15.4 Kelly Criterion

Optimal growth weight: $w^* = \Sigma^{-1}(\mu - r\mathbf{1})$.
Discuss leverage constraints and drawdown risk.

Key Takeaways

1. Allocation frameworks must integrate derivative Greeks for holistic risk.
2. Kelly optimality maximises long-run growth but increases variance.

Part IV

Trading Strategies & Execution

16 Discretionary vs Systematic Trading Styles

Abstract 16.1: T

ading philosophies span a spectrum from human intuition to fully automated decision-making. We contrast discretionary and systematic approaches in terms of signal generation, execution, governance and scalability.

16.1 Taxonomy

- **Discretionary**: portfolio manager synthesises macro news, order flow, and qualitative insights to make directional bets.
- **Quantitative Systematic**: rules-based models translate data into positions; execution often automated.

16.2 Edge Identification

Discretionary edge: information asymmetry, situational awareness. Systematic edge: statistical regularities, speed, breadth.

16.3 Risk Governance

Humans prone to bias and style drift; systems vulnerable to model error and regime change. $\Rightarrow$ implement *kill switches*, exposure limits, and real-time monitoring.

Key Takeaways

1. Neither style dominates universally—hybrid teams increasingly common.
2. Discipline and post-trade review close the loop on both fronts.

17 Momentum, Mean Reversion & Statistical Arbitrage

Abstract 17.1: W

formalise two cornerstone factors—momentum and mean reversion—and demonstrate a simple pairs-trade back-test in Python.

17.1 Cross-Sectional Momentum

Return over look-back L: $R_{t,L} = P_t/P_{t-L}-1$. Long top decile, short bottom decile (Jegadeesh–Titman).

17.2 Mean Reversion in Spreads

Cointegration of pair (X_t, Y_t): $S_t = \ln X_t - \beta \ln Y_t$. If S_t reverts to mean μ, design threshold entry.

Python Snippet

```python
import statsmodels.api as sm, numpy as np, pandas as pd
beta = sm.OLS(np.log(X), sm.add_constant(np.log(Y))).fit().params[1]
spread = np.log(X) - beta*np.log(Y)
z = (spread - spread.mean())/spread.std()
signals = (z > 2) * -1 + (z < -2) * 1
```

17.3 Risk Controls

Half-life estimation for stop-loss windows; market neutrality reduces beta risk but not residual correlation breakdown.

Key Takeaways

- Factor premia persist but exhibit crowding and crash risk.
- Robustness checks: out-of-sample decay, sub-period consistency.

18 Options Strategies

Abstract 18.1: S

reads, straddles and volatility targeting translate option building blocks into actionable trades. We analyse payoff geometry, Greek exposure and typical use-cases.

18.1 Vertical Spreads

Bull call (long K_1, short $K_2 > K_1$) caps upside, lowers premium.

18.2 Calendar Spreads

Long near-term gamma vs short far-term vega; theta profile inverted.

18.3 Straddle vs Strangle

ATM straddle: high gamma, vega; strangle cheaper but needs larger move.

18.4 Delta-Hedged Volatility Trades

18.4.1 Gamma Scalping

P&L decomposition: $\Delta P \approx \frac{1}{2}\Gamma(\Delta S)^2 - \frac{1}{2}\sigma_{\mathrm{imp}}^2 S^2 \Gamma \Delta t$.
Positive expectancy if realised vol exceeds implied.

Key Takeaways

1. Risk budget expressed in Greeks guides sizing.
2. Transaction costs erode theoretical edge—execution crucial.

19 Event-Driven & Macro Strategies

Abstract 19.1: C

talyst-based trades exploit discrete events—mergers, earnings, policy decisions—while macro strategies allocate across rates, FX and commodities driven by economic cycles.

19.1 Merger Arbitrage

Spread = target price – consideration. Probability-weighted payoff $E[P] = pV_{\text{deal}} + (1-p)V_{\text{busted}}$.

19.2 Earnings Plays

Implied move from straddle: $\sigma_{\text{earn}} = \sqrt{\frac{2}{T}}\,\frac{C_{ATM}+P_{ATM}}{S_0}$.
Back-test delta-hedged straddle into earnings.

19.3 Macro Trend Following

CTA models on futures; time-series momentum with risk parity sizing.

Key Takeaways

- Event windows compress liquidity—size accordingly.
- Success hinges on probability and timing estimation, not just directional view.

20 High-Frequency Trading Concepts

Abstract 20.1: M

llisecond horizons demand specialised infrastructure. We survey market-making, latency arbitrage and execution algorithms, focusing on practical implementation.

20.1 Latency Budget

Propagation + encoding + exchange matching latency. Colocation reduces fibre round-trip from $\sim$40µs to8µs.

20.2 Market-Making Model

Inventory process q_t; Avellaneda–Stoikov quotes:

$$\delta^{\pm} = \pm\frac{1}{\gamma}\ln\left(1+\frac{\gamma}{k}\right)+\frac{2q_t}{k}\sigma^2(T-t).$$

20.3 Order-Anticipation Strategies

Detect large iceberg orders via imbalance signals.

20.4 Regulatory Considerations

MiFIDII RTS-6, SEC Rule 15c3-5 (risk controls), market-maker obligations.

Key Takeaways

1. Edge decays with technology diffusion; constant investment required.
2. Inventory risk transforms micro P&L into macro exposure.

21 Behavioral Biases & Trading Psychology

Abstract 21.1: C

gnitive biases distort decision quality. Recognising and mitigating them is essential for both discretionary and quantitative traders.

21.1 Common Biases

Overconfidence Excessive belief in one's forecasting skill.

Loss Aversion Utility curvature steeper for losses than gains.

Disposition Effect Selling winners, holding losers.

Recency Over-weighting latest outcomes.

21.2 Debiasing Techniques

Checklists, pre-mortems, algorithmic overrides.

21.3 Psychological Metrics

Sharpe adjusted for stress (ulcer index), sleep-monitor feedback loops.

Key Takeaways

- Structural alpha often arises from exploiting others' biases.
- Governance frameworks institutionalise discipline.

Part V

Trading Infrastructure & Algorithmic Implementation

22 Order Routing & Market Connectivity

Abstract 22.1: F

st and reliable connectivity determines execution quality. We dissect network architectures, connectivity protocols (FIX, ITCH/OUCH) and smart order-routing (SOR) algorithms that optimise venue selection.

22.1 Connectivity Topology

- **Direct Market Access (DMA)** – broker pipes orders straight to exchange gateways.
- **Sponsored Access** – client bypasses broker systems but uses broker's membership (must pass "15c3-5" filters).
- **Colocation** – servers hosted in exchange data centre; round-trip latencies $< 100\,\mu s$.

22.2 Protocols

FIX 4.x Human-readable tag = value pairs; survives middle-/back-office because of extensibility.

ITCH/OUCH Binary, sequence-numbered; carries full L2 feed and nanosecond timestamps.

22.3 Smart Order Routing (SOR)

Algorithm partitions a parent order across venues i with probability proportional to depth and historical fill rates:

$$w_i = \frac{D_i^\alpha}{\sum_j D_j^\alpha},$$

where $\alpha \in [0, 1]$ tunes aggressiveness vs liquidity.

22.4 Risk Controls

* Pre-trade checks: notional, share and price collars. * Kill-switches triggered by runaway fills or connectivity loss.

Key Takeaways

1. Latency matters but deterministic jitter and fail-over matter more.
2. FIX is lingua franca; binary feeds power sub-millisecond decisioning.

23 Data Engineering for Traders

Abstract 23.1: H

gh-quality data is the fuel of systematic trading. We cover tick vs bar aggregation, storage formats, vendor APIs, and real-time pipelines built with open-source tooling.

23.1 Tick, Quote, Trade

Tick Event-driven record of any book update.

Quote Snapshot of top-of-book bid/ask at fixed interval.

Trade Executed prints; basis for VWAP.

23.2 Storage Choices

- **Columnar** (‘Parquet‘, ‘Feather‘) – compressable, splittable.
- **Time-series DB** (‘kdb+‘, ‘Influx‘, ‘TimescaleDB‘) – nanosecond indexing.
- **Object store** (S3, MinIO) + metadata catalogue (‘Iceberg‘, ‘Delta Lake‘).

23.3 Real-Time Pipeline: Kafka → Flink → DuckDB

```
# consume exchange feed, normalise JSON → Avro
flink run --jar normaliser.jar
# materialise 1-min bars into DuckDB for back-tester
```

23.4 Data Quality KPIs

Missing rate, out-of-sequence messages, crossed-book detection.

Key Takeaways

- Schema-on-read beats rigid relational models for heterogeneous feeds.
- Version control your data (Delta/Apache Iceberg) as strictly as code.

24 Backtesting Architecture in Python

Abstract 24.1: A

obust back-tester separates market simulation, strategy logic and broker emulation. We implement a minimal event-driven engine using ‘pandas‘ and showcase pitfalls like look-ahead bias.

24.1 Core Components

1. **Event Queue** – market, signal, order, fill events.
2. **Execution Handler** – slippage + commission model.
3. **Portfolio** – positions, cash, realised P&L.

Skeleton Code

```
class MarketEvent: pass
class DataHandler:
    def get_next(self): ...
class Strategy:
    def calculate_signals(self, event): ...
class ExecutionHandler:
    def execute_order(self, order): ...
```

24.2 Vectorised vs Event-Driven

Vectorised (‘vectorbt‘, ‘bt‘) is fast but struggles with intraday order book logic; event-driven (‘zipline‘, QuantConnect) is granular but slower.

24.3 Performance Metrics

Sharpe, Sortino, tail ratio, turnover, max drawdown, time under water.

Key Takeaways

- Decouple concerns—replace execution layer for paper- vs live-trading.
- Always "warm up" indicators to avoid initialisation artefacts.

25 Execution Algorithms

Abstract 25.1: V

AP, TWAP, POV and implementation shortfall algorithms split parent orders to balance impact, risk and opportunity cost. We formalise cost models and provide pseudo-code.

25.1 Cost Model

Total cost:

$$C = \text{Spread} + \text{Market Impact} + \text{Timing Risk}.$$

Almgren–Chriss optimum minimises $\lambda[\text{Cost}] + [\text{Cost}]$.

25.2 VWAP Trajectory

Allocate slice $Q_i = Q \frac{V_i}{\sum_j V_j}$ where V_i is predicted volume in slice i.

Python Pseudo-Code

```
volume_profile = forecast_volume(bars)
slices = order_size * volume_profile / volume_profile.sum()
for bar, qty in zip(bars, slices):
    send_child_order(qty, limit=bar.vwap*1.0005)
```

25.3 Percent of Volume (POV)

Child order size $= \eta \times$ lit volume.

25.4 Benchmark Evaluation

Implementation shortfall vs decision price; use ‘benchly‘ open-source lib.

Key Takeaways

- Information leakage grows with schedule determinism—randomise.
- Real-time volume forecasts beat static curves in volatile sessions.

26 Machine Learning in Trading

Abstract 26.1: W

cover feature engineering, model validation, and deployment patterns for both batch and online learning, emphasising open-source libraries (‘scikit-learn‘, ‘PyTorch‘, ‘xgboost‘).

26.1 Feature Pipeline

- Price-derived: returns, volatility, order-imbalance.
- Alternative: news sentiment, satellite, on-chain metrics.

Use ‘sklearn.compose.ColumnTransformer‘ to prevent look-ahead leakage.

26.2 Cross-Validation Scheme

Purged walk-forward CV (De Prado) removes overlapping label leakage.

Example

```
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(gap=5, n_splits=5, test_size=20)
```

26.3 Online Learning

Hedge incremental drift with ‘river‘, adaptive hyper-params.

26.4 Model Governance

* Feature store versioning (Feast). * Explainability (SHAP) for compliance.

Key Takeaways

- Data leakage is enemy 1—temporal CV is mandatory.
- Deployment model accuracy; latency, monitoring, rollback matter.

27 Risk & Performance Monitoring Dashboards

Abstract 27.1: R

al-time dashboards consolidate positions, Greeks, risk limits and performance attribution. We outline architecture and show a minimal ‘Plotly Dash‘ example.

27.1 Key Components

1. **Data Ingestion** – Kafka topics: positions, orders, market data.
2. **Aggregation Service** – Redis or PostgreSQL for snapshots.
3. **Front-End** – web framework (Dash/Streamlit) or Grafana.

27.2 Performance Attribution

Brinson–Fachler for long-only; Carino for leverage; option desks add Greek attribution.

Python Dash Snippet

```
import dash, dash_core_components as dcc, dash_html_components as html
import plotly.graph_objects as go

app = dash.Dash(__name__)
app.layout = html.Div([
    dcc.Graph(id='pnl',
              figure=go.Figure({'data':[{'x':dates,'y':pnl}]})
)])
if __name__ == '__main__':
    app.run_server(debug=True)
```

27.3 Alerting

Define rules: VaR breach, drawdown > XIntegrate with PagerDuty / Slack.

Key Takeaways

1. Single source of truth avoids reconciliation nightmares.
2. Visual latency should be $< 1\,\mathrm{s}$ for actionable risk.

Part VI

Governance, Regulation & Ethics

28 Regulatory Landscape

Abstract 28.1: C

pital-markets regulation balances market integrity, investor protection and systemic stability. We map the key statutory frameworks across regions—MiFIDII, Dodd–Frank, EMIR, Basel III—and outline the evolving crypto-asset rule-set.

28.1 Europe

MiFIDII/ MiFIR Best-execution RTS 27/28, SI regime, algorithmic trading controls (Article 17).

EMIR Clearing, trade repository reporting, margin for non-cleared OTC derivatives.

28.2 United States

- **Dodd–Frank Title VII** – swaps execution facilities, mandatory clearing, Volcker Rule.
- **Reg ATS Rule15c3-5** – market-access risk filters.

28.3 Basel III and FRTB

Capital charges for market, counterparty and operational risk; standardised vs internal-model approaches; ES at 97.5

28.4 Crypto-Asset Regulation

MiCA (EU), UK FCA PS 20/10, U.S. state "BitLicenses". Travel-rule compliance for VASPs.

Key Takeaways

1. Regional rules differ but converge on transparency and systemic-risk reduction.
2. Algorithmic trading is explicitly supervised (pre- and post-trade controls, kill-switches).

29 Compliance Programs

Abstract 29.1: E

fective compliance is continuous, data-driven and woven into trading workflows. We detail trade surveillance, best-execution testing, and regulatory reporting obligations.

29.1 Trade Surveillance

Market-Manipulation Patterns Spoofing, layering, quote stuffing.

Insider Dealing Unusual volume ahead of material events.

SQL Pattern Example

```sql
SELECT trader_id, COUNT(*) AS cancels
FROM orders
WHERE action='CANCEL'
  AND timestamp BETWEEN :t0 AND :t1
GROUP BY trader_id
HAVING cancels > 10 * executed;
```

29.2 Best-Execution Testing

Compare realised execution price to volume-weighted NBBO benchmark; RTS-28 disclosure in EU.

29.3 Regulatory Reporting

- **EMIR / CFTC Part 45** – swap data repositories.
- **MiFIR Transaction Reporting** – 65 fields incl. algo identifier.
- **CAT** (U.S.) – order lifecycle from origination to execution.

Key Takeaways

- Automation and audit-trails are mandatory; manual processes fail at scale.
- Surveillance models require continuous calibration to new tactics.

30 Operational Risk & Resilience

Abstract 30.1: O

erational failures—cyber-attacks, system outages, third-party breaches— can dwarf market losses. We cover frameworks (BCM, NIST CSF), cyber-defence layers, cloud risk and incident response.

30.1 Risk Taxonomy

- **Technology** – software bugs, latency amplification.
- **People** – privilege misuse, key-person dependency.
- **Process** – flawed change management, poor documentation.

30.2 Business-Continuity Management (BCM)

* Recovery-time objective (RTO) * Recovery-point objective (RPO) * Tier-0 hot-hot datacentres with $\leq 15\,\mathrm{min}$ RPO.

30.3 Cyber-Security Controls

Zero-trust network segmentation, MFA, SOC 2 and ISO 27001 certification, red-team exercises.

30.4 Cloud and Third-Party Risk

Shared-responsibility model; vendor lock-in; regulatory localisation (e.g. EU DORA).

30.5 Incident Response Playbook

Detection → Containment → Eradication → Recovery → Post-mortem (blameless).

Key Takeaways

1. Resilience is architectural—cannot be patched after go-live.
2. Board-level ownership and rehearsed run-books cut downtime impact.

31 Ethical Considerations

Abstract 31.1: B

yond formal legality lies the normative realm: market fairness, data privacy and social responsibility. We discuss manipulation grey zones, AI ethics and sustainable investing lenses.

31.1 Market Manipulation vs Legitimate Strategy

- Quote spoofing vs genuine passive liquidity.
- Information asymmetry vs illegal insider information.

31.2 DataPrivacy

GDPR lawful bases, data-minimisation, differential privacy for alt-data.

31.3 AI Ethics

Bias amplification, model explainability mandates (EU AI Act), human-in-the-loop overrides.

31.4 ESG and Fiduciary Duty

Integration of environmental and social metrics in portfolio selection; green-washing risks.

Key Takeaways

- “Could” “should”: legal permissibility does not guarantee stakeholder acceptance.
- Transparency and accountability build long-run licence to operate.

Bibliography

Almgren, R., & Chriss, N. (2005). *Optimal execution of portfolio transactions*. Journal of Risk.