

# VaR Backtesting and Risk Management

Week 7 — Financial Management: Volatility, Risk, and AI

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2026 Spring

# Today's Roadmap

- 1 The Story: The Regulator Calls
- 2 The Logic of Backtesting
- 3 Kupiec Unconditional Coverage Test
- 4 Christoffersen Conditional Coverage Test
- 5 Basel Traffic Light System
- 6 Stress Testing
- 7 Python Implementation
- 8 Application: The FSA Report
- 9 Key Takeaways

**1**

**The Story: The Regulator Calls**

# The VolTech Challenge

**Scenario:** The Japan FSA wants a full backtesting report in two weeks.

They require: Kupiec test, Christoffersen test, and stress testing under extreme scenarios.

If we fail, the fund holds more capital — less money for investment returns.

## The Core Question

Does our VaR model do what it claims? If we say 99% VaR is breached 1% of the time, can we prove it?

# Today's Learning Objectives

By the end of this session, you will:

1. Define VaR backtesting and explain why regulators require it
2. Implement the Kupiec (POF) unconditional coverage test
3. Implement the Christoffersen conditional coverage test
4. Interpret the Basel traffic light system
5. Design and execute stress tests

# 2

## The Logic of Backtesting

# What Is VaR Backtesting?

**Backtesting** = comparing VaR forecasts against actual losses.

Define the **hit sequence**:

$$I_t = \begin{cases} 1 & \text{if } r_t < -\text{VaR}_t \quad (\text{breach}) \\ 0 & \text{otherwise} \end{cases}$$

A correct model's hit sequence must satisfy:

1. **Unconditional coverage**: proportion of breaches =  $1 - \alpha$
2. **Independence**: breaches should not cluster

# Why Both Properties Matter

**Model A:** 3 breaches in 250 days, spread across Jan, Jun, Nov.

Breach rate =  $1.2\% \approx$  expected  $1\%$ .

→ Passes unconditional coverage.

→ Passes independence.

**Model B:** 3 breaches in 250 days, all in the same week during a crash.

Same breach rate =  $1.2\%$ .

→ Passes unconditional coverage.

→ **Fails independence (clustering!)**

## Key Insight

The Kupiec test catches wrong counts. The Christoffersen test catches clustering. You need **both**.

3

## Kupiec Unconditional Coverage Test

# Kupiec POF Test (1995)

## Kupiec Likelihood Ratio

$$LR_{uc} = -2 \ln \frac{p^x (1-p)^{T-x}}{\hat{p}^x (1-\hat{p})^{T-x}} \sim \chi^2(1)$$

- $T$  = total out-of-sample days
- $x$  = number of breaches
- $p = 1 - \alpha$  = expected breach rate (e.g., 0.01)
- $\hat{p} = x/T$  = observed breach rate

**Decision:** Reject  $H_0$  if  $LR_{uc} > 3.841$  (5% level)

# Kupiec Test: Practical Considerations

For  $T = 250$  days and 99% VaR:

- Expected breaches:  $250 \times 0.01 = 2.5$
- Approximate passing range: 0 to 6 breaches
- $\geq 7$  breaches  $\rightarrow$  likely rejection

## Low Power Warning

With only 250 days, the Kupiec test cannot reliably distinguish between a 1% and a 2% breach rate. This is a fundamental limitation of small samples, not a bug in the test.

4

## Christoffersen Conditional Coverage Test

# Transition Matrix

Define transition probabilities:  $\pi_{ij} = P(l_t = j \mid l_{t-1} = i)$

	$l_t = 0$	$l_t = 1$
$l_{t-1} = 0$	$n_{00}$	$n_{01}$
$l_{t-1} = 1$	$n_{10}$	$n_{11}$

**Independence** means:  $\hat{\pi}_{01} = \hat{\pi}_{11}$

**Clustering** means:  $\hat{\pi}_{11} > \hat{\pi}_{01}$

(Once a breach occurs, more are likely to follow.)

# Christoffersen Test (1998)

## Conditional Coverage Test

$$LR_{cc} = \underbrace{LR_{uc}}_{\text{coverage}} + \underbrace{LR_{ind}}_{\text{independence}} \sim \chi^2(2)$$

- $LR_{uc}$ : Kupiec unconditional coverage (same as before)
- $LR_{ind}$ : independence test using transition counts
- Combined: reject if  $LR_{cc} > 5.991$

## Interpretation

A model can **pass** Kupiec (right count) but **fail** Christoffersen (clustered

5

## Basel Traffic Light System

# Basel Traffic Light Framework

Zone	Breaches (250 d)	Interpretation	Multiplier
Green	0–4	Acceptable	3.0×
Yellow	5–9	Questionable	3.4–3.85×
Red	≥ 10	Rejected	4.0×

## Financial Impact

Red zone = capital multiplier increases from 3.0× to 4.0×. For a fund with \$10B in risk exposure, this means **\$10B more capital** locked up — money that cannot be invested.

## Yellow Zone Details

The yellow zone has graduated multipliers:

Breaches	Multiplier
5	3.40×
6	3.50×
7	3.65×
8	3.75×
9	3.85×

**Key insight:** Banks are strongly motivated to stay in the green zone. VaR model quality has *direct financial consequences*.

# 6

## Stress Testing

# Stress Testing Framework

**Backtesting** = validates model under *normal* conditions

**Stress testing** = evaluates performance under *extreme* scenarios

## Historical stress tests:

- 2008 Global Financial Crisis
- 2020 COVID-19 crash
- 2011 European debt crisis
- 1997 Asian financial crisis

## Hypothetical stress tests:

- Sudden 5% market drop
- VIX spike from 15 to 80
- Simultaneous Asian market crash
- +300 bps interest rate shock

# Interpreting Stress Test Results

For each scenario, compute:

$$\text{VaR Exceedance Ratio} = \frac{\text{Scenario Loss}}{\text{VaR}}$$

Scenario	Loss	VaR Ratio
GFC 2008 (worst day)	-9.47%	3.3×
COVID-19 2020	-12.77%	4.5×
Flash Crash 2010	-3.87%	1.4×
Hypothetical -10%	-10.00%	3.5×

**VaR is not designed for crises.** Stress tests quantify exposure *beyond* VaR.

7

## Python Implementation

# Step 1: VaR Backtest Setup

```
1 import numpy as np, pandas as pd
2 import yfinance as yf
3 from arch import arch_model
4 from scipy import stats
5
6 sp500 = yf.download("^GSPC",
7     start="2015-01-01", end="2024-12-31")
8 prices = sp500["Close"].squeeze()
9 returns = 100 * np.log(
10     prices / prices.shift(1)).dropna()
11
12 window = 1000; alpha = 0.99
13 n_oos = len(returns) - window
14 print(f"Backtest: {n_oos} days")
15 print(f"Expected breaches: {n_oos*0.01:.1f}")
```

## Step 2: Rolling GJR-GARCH VaR

```
1 var_bt = np.full(n_oos, np.nan)
2 for i in range(n_oos):
3     train = returns.iloc[i:i + window]
4     model = arch_model(train, vol="Garch",
5         p=1, o=1, q=1, dist="t")
6     res = model.fit(dispatch="off")
7     fv = res.forecast(horizon=1)
8     vol = np.sqrt(fv.variance.values[-1, 0])
9     nu = res.params["nu"]
10    q = stats.t.ppf(1 - alpha, df=nu)
11    scale = np.sqrt((nu - 2) / nu)
12    var_bt[i] = -(res.params.get("mu", 0)
13        + q * scale * vol)
14
15 breaches = returns.iloc[window:] < -var_bt
16 print(f"Breaches: {breaches.sum()}")
```

## Step 3: Kupiec Test

```
1 def kupiec_test(hits, alpha=0.99):
2     T = len(hits); x = hits.sum()
3     p = 1 - alpha; p_hat = x / T
4     lr = -2 * (x * np.log(p / p_hat) +
5             (T-x) * np.log((1-p) / (1-p_hat)))
6     pval = 1 - stats.chi2.cdf(lr, df=1)
7     return lr, pval
8
9 lr, pval = kupiec_test(breaches)
10 print(f"LR_uc = {lr:.3f}")
11 print(f"p-value = {pval:.4f}")
12 print("PASS" if pval > 0.05 else "FAIL")
```

## Step 4: Christoffersen Test

```
1 def christoffersen_test(hits, alpha=0.99):
2     h = hits.astype(int).values
3     n00=n01=n10=n11=0
4     for t in range(1, len(h)):
5         if h[t-1]==0 and h[t]==0: n00+=1
6         elif h[t-1]==0 and h[t]==1: n01+=1
7         elif h[t-1]==1 and h[t]==0: n10+=1
8         else: n11+=1
9     pi01 = n01/max(n00+n01,1)
10    pi11 = n11/max(n10+n11,1)
11    # ... compute LR_ind and LR_cc
12    return lr_cc, pval
13
14 lr_cc, pval = christoffersen_test(breaches)
15 print(f"LR_cc = {lr_cc:.3f}, p = {pval:.4f}")
```

## Step 5: Basel Traffic Light

```
1 def basel_zone(n_breaches):
2     if n_breaches <= 4:
3         return "GREEN", 3.0
4     elif n_breaches <= 9:
5         mult = {5:3.4, 6:3.5, 7:3.65,
6                 8:3.75, 9:3.85}
7         return "YELLOW", mult[n_breaches]
8     else:
9         return "RED", 4.0
10
11 last_250 = breaches.iloc[-250:]
12 zone, mult = basel_zone(last_250.sum())
13 print(f"Zone: {zone}, Mult: {mult}x")
```

## Step 6: Stress Testing

```
1 scenarios = {
2     "GFC 2008":      -0.0947,
3     "COVID 2020":   -0.1277,
4     "Flash Crash":  -0.0387,
5     "Hypo -5%":     -0.05,
6     "Hypo -10%":    -0.10,
7 }
8 current_var = var_bt[-1]
9 for name, loss in scenarios.items():
10     ratio = abs(loss)*100 / current_var
11     flag = "!!!" if abs(loss)*100 > current_var \
12         else ""
13     print(f"{name:20s} {ratio:.2f}x {flag}")
```

# 8

## **Application: The FSA Report**

# FSA Backtesting Summary

Metric	Nikkei 225	S&P 500
Breach rate	1.4%	1.0%
Kupiec $p$ -value	0.265	1.000
Christoffersen $p$	0.144	0.571
Basel zone	Green	Green

**Conclusion:** GJR-GARCH with  $t$ -distribution passes all regulatory requirements for both indices.

**Key advantage:** Model adapts daily — recovers from crisis shocks faster than Historical Simulation.

9

**Key Takeaways**

## Six Things to Remember

1. **Backtesting validates VaR:** Compare predictions against actual losses using the hit sequence  $I_t$
2. **Kupiec test:** Tests unconditional coverage — is the total breach rate correct? ( $\chi^2(1)$ )
3. **Christoffersen test:** Tests coverage *and* independence — are breaches clustered? ( $\chi^2(2)$ )
4. **Basel traffic light:** Green (0–4), Yellow (5–9), Red ( $\geq 10$ ) with direct capital impact
5. **Stress testing complements backtesting:** Normal conditions vs. extreme scenarios — both required
6. **GJR-GARCH +  $t$ :** Consistently achieves green zone, outperforming simpler models

# Mission 7: The FSA Backtesting Report

## Deliverables

1. Rolling 99% VaR with GJR-GARCH( $t$ ) for Nikkei & S&P
2. Kupiec and Christoffersen tests for both indices
3. Basel traffic light classification (last 250 days)
4. Backtest visualization (returns + VaR + breaches)
5. Stress tests: 3 historical + 2 hypothetical scenarios
6. 300-word executive summary letter to the FSA

**Bonus:** Compare 3 VaR methods (HS, GARCH-normal, GJR-GARCH- $t$ ) and determine which performs best.

# Next Week Preview

## Week 8: AI in Finance

David: “QuantStar is pitching a pure ML risk system — random forests, LSTMs. They claim 50% better accuracy.”

Dr. Lin: “Better accuracy by what measure? Against what benchmark? With what interpretability?”

**Topics:** Machine learning for risk, model interpretability, AI + GARCH hybrid approaches