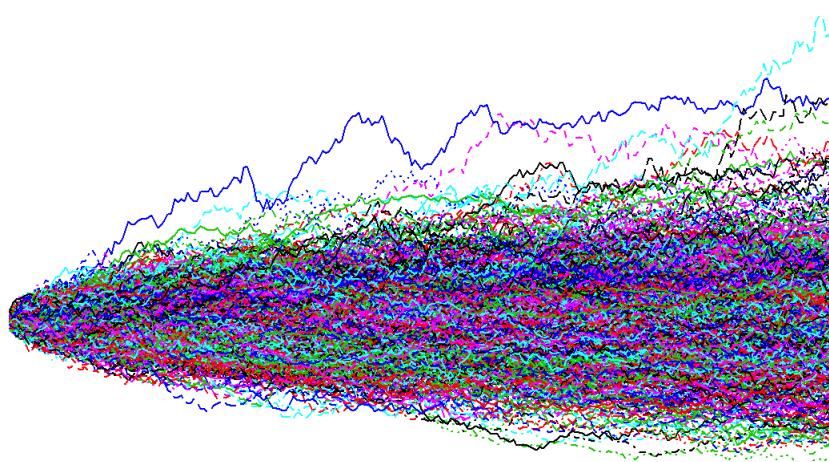


Quantitative Risk Management

MATH 510



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Index of Definitions

This course is based on the ETH course and textbook of the same name, by McNeil, Fray, and Embrechts. The present document is based on this textbook and Prof. Neshlehov's lectures. In order, we will focus on: stochastic volatility, extreme-value theory, multivariate models, risk aggregation, and backtesting.

Cover: index simulation following the stochastic volatility process

DEF 0.1 We will assume good working knowledge of probability and statistics. In addition, we
 DEF 0.2 remind ourselves of the *survivor function* $\bar{F}(x) := \mathbb{P}(X > x) = 1 - F(x)$, as well as the *α -quantile*, where $\alpha \in (0, 1)$, defined to be

$$q_\alpha = F^{-1}(\alpha) = \inf\{x \in \mathbb{R} : F(x) \geq \alpha\}$$

DEF 0.3 In this course, we would like to quantify one's exposure to bad consequences. The likelihood of loss or less-than-expected gains is called *risk*. The following are types of risk:

Risk	Description
Credit Risk	Odds a debtor defaults on payment
Market Risk	Exposure to price fluctuations of bonds, stocks, or derivatives
Operational Risk	Risk relating to circumstantial adverse events (e.g. institutional fraud)
Liquidity Risk	Risk of damage from not having sufficient assets to pay off debts
Model Risk	Risk associated with financial model inaccuracies; closely related to operational risk
Underwriting Risk	Odds that an insured makes a claim on their policy

Risk is necessary: taking this course incurs a risk of a poor grade

The above types of risk interact with each-other. Quantitative risk management aims to model these interactions and hedge against risk.

I LOSS

RISK FACTORS

DEF 1.1 A *portfolio* is a collection of assets or liabilities. Denote by V_t the value of the portfolio at time t . We denote by Δt a *time horizon*, i.e. a duration of time. Assuming that V_t is known, that the composition of the portfolio remains constant over the time horizon, and that there are no payments made, we denote by V_{t+1} the value of the portfolio at time $t + \Delta t$.

Portfolios may include stocks, bonds, derivatives, risky loans, or insurance contracts, for example.

DEF 1.3 We write $\Delta V_{t+1} = V_{t+1} - V_t$. This is a random variable which takes a negative value on losses and a positive value on profits. We say that it follows the *profit-and-loss distribution*. Since we care about managing risk in this course, we prefer that losses are positively indicated. Define *loss* as

$$L_{t+1} = -\Delta V_{t+1} = \begin{cases} V_t - V_{t+1} & \Delta t \text{ is a short horizon} \\ V_t - \frac{V_{t+1}}{1+r_{t,1}} & \Delta t \text{ is a long horizon} \end{cases}$$

Hence, V_{t+k} is the value of the portfolio at time $t + k\Delta t$

Note that, for long time horizons, we must account for the time value of money. If $r_{t,1}$ is the risk-free interest rate, applied over Δt , then $\alpha(1 + r_{t,1})$ at time $t + 1$ is the equivalent

This is akin to the concept of opportunity cost

If one's portfolio consists of insurance policies, $Z_{t,4}$ might be the probability that a claim is made.

in value to α at time t . Hence, V_{t+1} must be adjusted to $V_{t+1}/(1 + r_{t,1})$ to keep L_{t+1} 's time-value of money consistent. Working in " $t + 1$ dollars," one could equivalently write $L_{t+1} = V_t(1 + r_{t,1}) - V_{t+1}$ for long time intervals.

V_t is a function of multiple *risk factors*, denoted by $\mathbf{Z}_t = \langle Z_{t,1}, \dots, Z_{t,d} \rangle$. Thus, we write $V_t = f(t, \mathbf{Z}_t)$ with $f : \mathbb{R}_+ \times \mathbb{R}^d \rightarrow \mathbb{R}$, called the *risk function*. When \mathbf{Z}_t is known, we write $\mathbf{Z}_t = \mathbf{z}_t$. In this case, $f(t, \mathbf{z}_t)$ is called the *realized value* of V_t .

DEF 1.5

DEF 1.6

DEF 1.7

Eg. 1.1 Consider a portfolio of d stocks, and let λ_i denote the number of shares in stock i at time t . Let $S_{t,i}$ denote the price of the stock i . Write

$$Z_{t,i} = \log S_{t,i} : i \in [d]$$

The value of the portfolio is then

$$V_t = \sum_{i=1}^d \lambda_i S_{t,i} = \sum_{i=1}^d \lambda_i e^{Z_{t,i}}$$

This formula is called the *value with log prices*. The purpose of writing $\mathbf{Z}_t = \log(\mathbf{S}_t)$ versus $\mathbf{Z}_t = \mathbf{S}_t$ is purely numerical.

DEF 1.8

Risk factors may change over the time horizon. We call time-series changes in risk factors *risk factor changes*, denoted by \mathbf{X}_{t+1} . In particular,

$$\mathbf{X}_{t+1} = \mathbf{Z}_{t+1} - \mathbf{Z}_t$$

Rearranging [Def 1.6](#) gives

$$L_{t+1} = f(t, \mathbf{Z}_t) - f(t + 1, \mathbf{Z}_t + \mathbf{X}_{t+1})$$

"Observable" =
"Known" =
"Realized" =
"Actualized"

When modeling loss, we assume that \mathbf{z}_t is observable. Thus, we are forced only to consider \mathbf{X}_{t+1} as a random variable. If \mathbf{x}_{t+1} is observable, then L_{t+1} is called the *realized loss*. Realized loss is denoted by $l_{[t]}(\mathbf{x}) = L_{t+1}$, especially when we wish to parameterize \mathbf{x}_{t+1} . For simplicity, we drop the subscript, i.e. $\mathbf{x} = \mathbf{x}_{t+1}$. We call this function the *loss operator*.

DEF 1.10

DEF 1.11

We say that L_{t+1} follows a *loss distribution*. The loss distribution is typically right-skewed and has a fat right tail: the probability of heavy profits is small, but it is easy to incur heavy losses.

DEF 1.12

We may use a linearization to obtain the *linearized loss*, denoted $L_{t+1}^\Delta \approx L_{t+1}$.

DEF 1.13

The linearized loss, assuming differentiability of f along t and \mathbf{Z}_t , is given by

$$L_{t+1}^\Delta = -f_t(t, \mathbf{z}_t) - \sum_{i=1}^d f_{z_{t,i}}(t, \mathbf{z}_t) X_{t+1,i}$$

PROP 1.1

PROOF.

Recall $L_{t+1} = f(t, \mathbf{z}_t) - f(t+1, \mathbf{z}_{t+1})$. We will approximate $f(t+1, \mathbf{z}_{t+1})$:

$$f(t+1, \mathbf{z}_{t+1}) \approx f(t, \mathbf{z}_t) + \nabla f(t, \mathbf{z}_t) \cdot (\langle t+1, \mathbf{z}_{t+1} \rangle - \langle t, \mathbf{z}_t \rangle)$$

This is

$$f(t, \mathbf{z}_t) + f_t(t, \mathbf{z}_t) \cdot 1 + \sum_{i=1}^d f_{z_{t,i}}(t, \mathbf{z}_t) X_{t+1,i}$$

Applying to L_{t+1} gives

$$L_{t+1}^\Delta = f(t, \mathbf{z}_t) - \left[f(t, \mathbf{z}_t) + f_t(t, \mathbf{z}_t) + \sum_{i=1}^d f_{z_{t,i}}(t, \mathbf{z}_t) X_{t+1,i} \right] = -f_t(t, \mathbf{z}_t) - \sum_{i=1}^d f_{z_{t,i}}(t, \mathbf{z}_t) X_{t+1,i}$$

as desired. \square

Linearized loss is convenient and easy to understand, but the assumption of its accuracy is a heavy one. An easy improvement would be to consider higher-order Taylor approximations, but the estimation of the necessary derivatives may not be numerically stable.

Eg. 1.2 Following [Example 1.1](#), we compute

$$\mathbf{X}_{t+1} = \mathbf{Z}_{t+1} - \mathbf{Z}_t = \left\langle \log \frac{S_{t+1,1}}{S_{t,1}}, \dots, \log \frac{S_{t+1,d}}{S_{t,d}} \right\rangle$$

DEF 1.14

which, when $\mathbf{Z}_t = \log(\mathbf{S}_t)$, we call *log returns*. Rearranging L_{t+1} :

$$L_{t+1} = \sum_{i=1}^d \lambda_i e^{Z_{t,i}} - \sum_{i=1}^d \lambda_i e^{X_{t+1,i} - Z_{t,i}} = - \sum_{i=1}^d \lambda_i e^{Z_{t,i}} (e^{X_{t+1,i}} - 1) = -V_t \sum_{i=1}^d w_{t,i} (e^{X_{t+1,i}} - 1)$$

DEF 1.15

where $w_{t,i} = \frac{\lambda_i S_{t,i}}{V_t}$ is the *relative weight* of stock i at time t . We also consider $\rho_{t,i} = \lambda_i S_{t,i}$. In the language of operators:

$$l_{[t]}(\mathbf{x}) = -V_t \sum_{i=1}^d w_{t,i} (e^{x_i} - 1)$$

Following [Def 1.13](#),

$$L_{t+1}^\Delta = - \sum_{i=1}^d \lambda_i e^{Z_{t,i}} X_{t+1,i} = -V_t \sum_{i=1}^d w_{t,i} X_{t+1,i} = -\rho_t \cdot \mathbf{X}_{t+1}$$

Thus, if we assume that $\mathbf{X}_{t+1} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ follows the multivariate normal distribution,

$$\mathbb{E}[L_{t+1}^\Delta] = -V_t (\mathbf{w}_t \cdot \boldsymbol{\mu}) = -\rho_t \cdot \boldsymbol{\mu}$$

with $\mathbf{w}_t = \langle w_{t,1}, \dots, w_{t,d} \rangle$. Similarly,

$$\text{Var}(L_{t+1}^\Delta) = V_t^2 \sum_{i=1}^d \text{Var}(w_{t+1} X_{t+1,i}) = V_t^2 (\mathbf{w}_t^T \Sigma \mathbf{w}_t) = \boldsymbol{\rho}_t^T \Sigma \boldsymbol{\rho}_t$$

Note that Σ is a covariance matrix, so $\mathbf{w}_t^T \Sigma \mathbf{w}_t$ is indeed a scalar, as expected.

Eg. 1.3 Consider a portfolio with one standard European call on a stock S with maturity T and exercise price K . The value of European options is modeled by the Black-Scholes equation:

$$V_t = C^{BS}(t, S_t, r_t, \sigma_t)$$

where S_t and σ_t is the price and volatility of the underlying stock, respectively, and r_t is the risk-free interest rate. We write $\mathbf{Z}_t = \langle \log(S_t), r_t, \sigma_t \rangle$. The Black-Scholes equation satisfies

$$\frac{\partial C^{BS}}{\partial t} + \frac{\sigma^2}{2} S^2 \frac{\partial^2 C^{BS}}{\partial S^2} + rS \frac{\partial C^{BS}}{\partial S} - rC^{BS} = 0$$

Differentiating C^{BS} gives "the Greeks"

$$C_t^{BS}(\text{theta}) \quad C_r^{BS}(\text{rho}) \quad C_\sigma^{BS}(\text{vega}) \quad C_S^{BS}(\text{delta})$$

with $C_z^{BS} = S_t \times C_S^{BS}$. One can compute the linearized loss to be

$$L_{t+1}^\Delta = -C_t^{BS} - S_t C_S^{BS} X_{t+1,1} - C_r^{BS} X_{t+1,2} - C_\sigma^{BS} X_{t+1,3}$$

Note that

$$\mathbf{X}_{t+1} = \left\langle \log\left(\frac{S_{t+1}}{S_t}\right), r_{t+1} - r_t, \sigma_{t+1} - \sigma_t \right\rangle$$

Stylized Loan Portfolio

This is an example of a similar flavor to [Example 1.2](#), but deserves a section of its own.

We will consider a stylized loan portfolio. Let the time horizon Δt be one year (with this horizon, we should account for the time value of money).

We lend to m obligors. For each obligor i , let k_i denote the amount to be paid at the end of the present time period, consisting of the loan principle plus interest. Since this payment is made at time $t + 1$, $e_i = \frac{k_i}{1+r_{t,1}}$, called the exposure, is the present-day money value of this payment, where $r_{t,1}$ is the risk-free interest rate.

There is a possibility that an obligor defaults. Let $Y_{t,i}$ be an indicator variable, called the default state, that detects whether an obligor defaults by time t . We will assume $Y_{t,i} = 0$ and $\mathbb{E}[Y_{t+1,i}] = p_i$. In case of default, the lender may recover a portion of the loan, i.e. $(1 - \delta_i)k_i$, where $\delta_i \in (0, 1]$. The expected shortfall associated with obligor i is the difference between [the present-dollar value of the loan payment at time $t + 1$] and [the

present-dollar expected loan payment at time $t + 1$]

$$\frac{k_i}{1+r_{t,i}} - \underbrace{\left[p_i(1-\delta_i) \frac{k_i}{1+r_{t,i}} + (1-p_i) \frac{k_i}{1+r_{t,i}} \right]}_{e_i(1-p_i\delta_i)} = p_i\delta_i \frac{k_i}{1+r_{t,i}} = p_i\delta_i e_i$$

The value of the loan itself, then, is the [present-dollar loan payment's value] minus the [expected shortfall], or $e_i - p_i\delta_i e_i$. Note that this is exactly [the present-dollar expected loan payment at time $t + 1$], which we already computed. The value of whole the portfolio is given by

$$V_t = \sum_{i=1}^m e_i - p_i\delta_i e_i = \sum_{i=1}^m e_i(1 - p_i\delta_i)$$

At time $t + 1$, we assume that all obligors have paid off the principle. Hence, V_{t+1} encapsulates the actualized payoff made at time $t + 1$. However, if the loan payments continued into a second year, we would add on to V_{t+1} an estimation of the expected loan payment at time $t + 2$. In the former case, we have

$$V_{t+1} = \sum_{i=1}^m Y_{t,i}(1 - \delta_i)k_i + (1 - Y_{t,i})k_i = k_i(1 - Y_{t,i}\delta_i)$$

We adjust for the time value of money in the next calculation:

$$L_{t+1} = V_t - \frac{V_{t+1}}{1+r_{t,1}} = \sum_{i=1}^m e_i(1 - \delta_i p_i) - e_i(1 - Y_{t,i}\delta_i) = \sum_{i=1}^m e_i\delta_i(Y_{t,i} - p_i)$$

Determining Loss Distributions

In order to determine the loss distribution ([Def 1.12](#)), one must model risk factor changes \mathbf{X}_{t+1} , given a known mapping $f(t, \mathbf{Z}_t) = V_t$. We distinguish between:

1. The conditional distribution of risk factor changes, as a function of all information up to time t . We call the resulting loss distribution is called the *conditional loss distribution*. Note that an estimation of risk factor changes which relies on historical data is *not* necessarily a conditional distribution.
2. The stationary distribution of risk factor changes. The resulting loss distribution is called the *unconditional loss distribution*.

DEF 1.16

DEF 1.17

VARIANCE-COVARIANCE METHOD

We will first consider an analytical method for the unconditional distribution of L_{t+1} . Assume that \mathbf{X}_{t+1} has a multivariate normal distribution, and write $\mathbf{X}_{t+1} \sim \mathcal{N}(\boldsymbol{\mu}, \Sigma)$. Suppose also that the linearized loss, written as

$$L_{t+1}^\Delta = -(c_t + \mathbf{b}_t^T \mathbf{X}_{t+1})$$

This is not new: c_t denotes the partial of the realized value with respect to t , and \mathbf{b}_t denotes the partials with respect to \mathbf{z}_t .

is sufficiently accurate, i.e. $L_{t+1}^\Delta = L_{t+1}$. Consequently,

$$L_{t+1}^\Delta \sim \mathcal{N}(-c_t - \mathbf{b}_t^T \boldsymbol{\mu}, \mathbf{b}_t^T \Sigma \mathbf{b}_t)$$

In this case, the mean vector $\boldsymbol{\mu}$ and covariance matrix Σ are estimated from past data. Hence, inference about the loss distribution are made using these estimates:

$$L_{t+1}^\Delta \sim \mathcal{N}(-c_t - \mathbf{b}_t^T \hat{\boldsymbol{\mu}}, \mathbf{b}_t^T \hat{\Sigma} \mathbf{b}_t)$$

The estimation of L_{t+1} in this manner is called the *Variance-Covariance Method*. Of its advantages: it is easy to implement and understand, and it is a closed solution, which eases compute requirements. However, we rely on heavy assumptions. In particular, linearized loss is crude, and the normality assumption may seriously underestimate the tail of the loss distribution.

DEF 1.18

Granted, we can use the t -distribution to achieve heavy tailed-ness

This also estimates the *unconditional* loss distribution

Note: this method is identical to the brief analysis we include at the end of [Example 1.2](#).

HISTORICAL SIMULATION METHOD

Alternatively, we use an empirical distribution based on historical data $\mathbf{X}_{t-n+1}, \dots, \mathbf{X}_t$. To do so, we construct the historically simulated loss data:

$$\tilde{L}_s = f(t, \mathbf{z}_t) - f(t + 1, \mathbf{z}_t + \mathbf{X}_s) : s \in [t - n + 1, t]$$

Then, we average these estimates to yield a final estimation of the loss distribution:

$$\mathbb{P}(L_{t+1} \leq x) \approx \frac{1}{n} \sum_{s=1}^n \mathbb{1}(\tilde{L}_{t-n+s} \leq x)$$

If \mathbf{X}_s are IID, the convergence of the empirical distribution to the true distribution is ensured. (Real-life risk factor changes are not IID.) Note that this method can only estimate the unconditional loss distribution.

Past performance does not indicate future gains. The historical simulation method is akin to driving by only looking through the rear view mirror

MONTE CARLO METHOD

We create a model for risk factor changes, based on data $\mathbf{X}_{t-n+1}, \dots, \mathbf{X}_t$, to simulate m new data points $\tilde{\mathbf{X}}_{t+1}^{(1)}, \dots, \tilde{\mathbf{X}}_{t+1}^{(m)}$. Using this data, we construct simulated future loss data:

$$\tilde{L}_s = f(t, \mathbf{z}_t) - f(t + 1, \mathbf{z}_t + \mathbf{X}_{t+1}^{(m)}) : m \in [M]$$

As before, we average these estimates into a final loss distribution

$$\mathbb{P}(L_{t+1} \leq x) \approx \frac{1}{M} \sum_{m=1}^M \mathbb{1}(\tilde{L}_{t+1}^{(m)} \leq x)$$

This method can potential circumvent a lack of historical data with a better model, more simulations with the model (i.e. $M \gg 0$), or more models. However, this method is potentially expensive, and it relies on training a suitably accurate model.

The Monte Carlo Method is akin to driving by using the rear view mirror to view a front-facing funny mirror.
Slightly better.

RISK MEASURES

In order to simplify our view of a portfolio's exposure to risk, we employ mappings from risk distributions to \mathbb{R} , called risk measures. Historically, risk measurement has been comprised of the following methods:

Notational Risk is simply derived from the sum total of the values of the portfolio's securities.

Scenario-Based One predicts (e.g. via Markov chains) future scenarios, and measures the expected maximum future loss of the portfolio against these scenarios.

Loss-Based We provide statistical descriptions of the loss distribution, or an estimate of it.

Building on the previous section, we will primarily concern ourselves with the last method. However, we consider some examples for each.

Eg. 1.4 Using the notational method, we weigh assets by their riskiness. For instance, when measuring operational risk, we might use

$$\alpha \frac{\sum_{i=1}^3 \max(G^{t-i}, 0)}{\sum_{i=1}^3 \mathbb{1}(G^{t-i} > 0)}$$

where $\alpha \approx 0.15$ and G is gross annual income. This measure tracks the average gross income over the past 3 years, excluding years where incoming is 0 or negative. Heuristically, our operational risk (i.e. risk of loss by internal mismanagement) is proportional to cash flows processed by the institution.

Eg. 1.5 Using the scenario-based method, we consider some fixed risk factor changes $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$, with associated weights $\{w_1, \dots, w_n\}$ describing their likelihood of occurring. A scenario-based risk assessment is

$$\psi(L) = \max\{w_i L(\mathbf{x}_i)\}_{i \in [n]}$$

where L is a loss function.

Eg. 1.6 The oldest loss-based measure simply used the variance of the *P&L* distribution as a risk measure. However, this approach requires the existence of a second moment.

DEF 1.19 A *coherent risk measure* is a function $\rho : \mathcal{M} \rightarrow \mathbb{R} : L \mapsto \rho(L)$ on the space of random variables \mathcal{M} representing losses. We view $\rho(L)$ has the total amount of equity capital required to back a position with loss function L . It satisfies the following:

Monotonicity For all $L_1, L_2 \in \mathcal{M}$ with $L_1 \geq L_2$ almost surely,

$$\rho(L_1) \geq \rho(L_2)$$

Recall the notion of almost surely:
 $\mathbb{P}(L_1 \geq L_2) = 1$

Invariance For any $L \in \mathcal{M}$ and $\ell \in \mathbb{R}$,

$$\rho(L + \ell) = \rho(L) + \ell$$

Subadditivity For any $L_1, L_2 \in \mathcal{M}$, we have

$$\rho(L_1 + L_2) \leq \rho(L_1) + \rho(L_2)$$

Homogeneity For any $L \in \mathcal{M}$ and $\lambda \geq 0 \in \mathbb{R}$,

$$\rho(\lambda L) = \lambda \rho(L)$$

These axioms are informed by practice and financial intuition:

- M.** If we are confident that L_1 is a riskier position than L_2 , then surely we would require more equity to back the first position
- I.**
- S.** A diversification of our portfolio should not create extraneous risk (if fact, this is usually considered a good thing). If this were not the case, an institution could reduce risk capital by splitting into subsidiaries.
- H.** $\rho(L + \dots + L) \leq n\rho(L)$ by subadditivity. But we are not diversifying our portfolio, so it seems silly that we could reduce our risk by simply multiplying the size of our portfolio. Hence, this holds with equality. In fact, a "don't put your eggs in one basket" argument suggests $\rho(nL) > n\rho(L)$, but this is prevented by subadditivity. This last point has sparked much debate over the validity of the last two axioms.

A coherent risk measure is convex, i.e. for all $L_1, L_2 \in \mathcal{M}$ and $\lambda \in (0, 1)$

PROP 1.2

$$\rho(\lambda L_1 + (1 - \lambda)L_2) \leq \lambda \rho(L_1) + (1 - \lambda)\rho(L_2)$$

However, the converse is not true.

This follows immediately from subadditivity and homogeneity. □

PROOF.

Any function $\rho : \mathcal{M} \rightarrow \mathbb{R} : L \mapsto \rho(L)$, whether it satisfies the axioms of [Def 1.19](#), is simply called a *risk measure*.

DEF 1.20

Given a tolerance $\alpha \in (0, 1)$, *Value at Risk*, a primary risk measure, is defined to be

DEF 1.21

$$\text{VaR}_\alpha(L) = q_\alpha(F_L) = F_L^{-1}(\alpha) = \inf\{x \in \mathbb{R} : F_L(x) \geq \alpha\}$$

where F_L is the CDF of the loss distribution. In other words, $\text{VaR}_\alpha(L)$ is the α -quantile of F_L . With probability at least α we would see losses in the range $(-\infty, \text{VaR}_\alpha(L)]$.

Since $\text{VaR}_\alpha(L)$ provides a boundary between "likely" and "unlikely" losses, we frequently put $\alpha = 0.95$.

Observe that $x_0 = \text{VaR}_\alpha(L)$ if and only if $\mathbb{P}(L \leq x_0) \geq \alpha$ and $\mathbb{P}(L \leq x) < \alpha$ whenever $x < x_0$.

PROP 1.3

$\text{Var}_\alpha(L)$ is not coherent. In particular, it does not satisfy subadditivity, but it satisfies the other axioms of [Def 1.19](#).

PROP 1.4

PROOF.

As proof of the fact that VaR does not satisfy subadditivity, we'll consider a worked (counter)example.

Consider a portfolio of 50 defaultable bonds with independent defaults. Default on each bond is IID $Y_i \sim \text{Ber}(0.02)$. The current price of bonds is 95, with a face value equal to 100. In **Portfolio A**, we buy 100 units of bond 1. In **Portfolio B**, we buy 2 units of each bond. The value of each portfolio is 9500.

Intuitively, we understand Portfolio A to be riskier. However, we'll see that VaR shows the opposite.

$$L_i = 95 - 100(1 - Y_i) \implies \mathbb{P}(L_i \leq x) = \begin{cases} 1 & x \leq 95 \\ 0 & x < -5 \\ 0.98 & x \in [-5, 95) \end{cases}$$

Then, with a tolerance of $\alpha = 0.95$, $\text{VaR}_\alpha(L_i) = -5$. We conclude that

$$\text{VaR}_\alpha(L^A) = \text{VaR}_\alpha(100L_1) = 100\text{VaR}_\alpha(L_1) = -500$$

Noting that $L^B = \sum_{i=1}^{50} 2L_i = -500 + 200 \sum_{i=1}^{50} Y_i$, we have that

$$L^B \sim -500 + 200\text{Bin}(50, 0.02)$$

It follows that $\text{VaR}_\alpha(L^B) = -500 + 200\text{VaR}_\alpha(\text{Bin}(50, 0.02))$, which, one can calculate, is $-500 + 200 \cdot 3 = 100$. Hence, $\text{VaR}_\alpha(L^A) < \text{VaR}_\alpha(L^B)$, which contradicts subadditivity. \square

DEF 1.22

Alternatively, we use the *expected shortfall* as a risk measure, defined to be

$$\text{ES}_\alpha(L) = \mathbb{E}[L | L \geq \text{VaR}_\alpha(L)]$$

In other words, assuming that we incur losses above the α -quantile, how much should we expect to lose? This is akin to a bad-case scenario estimation. If $\alpha = 0.95$, $\text{ES}_\alpha(L)$ describes the expected loss among only extreme (probability < 0.05) losses.

PROP 1.5

If L is a continuous distribution, then $\text{ES}_\alpha(L)$ is a coherent risk measure.

PROOF.

Axioms 1, 2, and 4 of [Def 1.19](#) are inherited from $\text{VaR}_\alpha(L)$. For subadditivity, note that

$$\text{ES}_\alpha(L) = \frac{1}{1-\alpha} \mathbb{E}(L \mathbb{1}(L \geq \text{VaR}_\alpha(L)))$$

We will show

$$(1 - \alpha)[\text{ES}_\alpha(L_1) + \text{ES}_\alpha(L_2) - \text{ES}_\alpha(L_1 + L_2)] \geq 0 \quad \star$$

Let $I_i := \mathbb{1}(L_i \geq \text{VaR}_\alpha(L_i))$ for $i = 1, 2$, and $I_{12} = \mathbb{1}(L_1 + L_2 \geq \text{VaR}_\alpha(L_1 + L_2))$. Then

$$\begin{aligned} \star &\iff \mathbb{E}(L_1 I_1 + L_2 I_2 - (L_1 + L_2) I_{12}) \geq 0 \\ &\iff \mathbb{E}(L_1(I_1 - I_{12})) + L_2(I_2 - I_{12}) \geq 0 \end{aligned}$$

We show that

$$\begin{aligned}\mathbb{E}(L_1(I_1 - I_{12})) &\geq \mathbb{E}[\text{VaR}_\alpha(L_1)(I_1 - I_{12})] = \text{VaR}_\alpha(L_1)\mathbb{E}(I_1 - I_{12}) \\ &= \mathbb{E}[I_1] - \mathbb{E}[I_{12}] = \mathbb{P}(L_1 \geq \text{VaR}(L_1)) - \mathbb{P}(L_1 + L_2 \geq \text{VaR}_\alpha(L_1)) = 0\end{aligned}$$

The L_2 case is symmetric. If $I_1 = 1$, then $I_1 - I_{12} \geq 0$. Conversely, if $I_1 = 0$, then $I_1 - I_{12} \leq 0$. Hence

$$\mathbb{E}((L_1 - \text{VaR}_\alpha(L_1))(I_1 - I_{12})) \geq 0 \quad \square$$

If L has continuous density f , then

$$\text{ES}_\alpha(L) = \frac{1}{1-\alpha} \int_{\text{VaR}_\alpha(L)}^{\infty} xf(x)dx$$

We can view $L|L \geq \text{VaR}_\alpha(L)$ as a variable with CDF

$$\begin{aligned}G(x) &= \mathbb{P}(L \leq x | L \geq \text{VaR}_\alpha(L)) = \begin{cases} 0 & x < \text{VaR}_\alpha(L) \\ \frac{\mathbb{P}(L \in [\text{VaR}_\alpha(L), x])}{\mathbb{P}(L \geq \text{VaR}_\alpha(L))} & x \geq \text{VaR}_\alpha(L) \end{cases} \\ &= \frac{F_L(x) - F_L(\text{VaR}_\alpha(L))}{1-\alpha} = \frac{F_L(x) - \alpha}{1-\alpha} : x \geq \text{VaR}_\alpha(L)\end{aligned}$$

PROOF.

Hence, $L|L \geq \text{VaR}_\alpha(L)$ will have PDF $\frac{f(x)}{1-\alpha}$ when $x \geq \text{VaR}_\alpha(L)$, and 0 otherwise. \square

Eg. 1.7 Suppose $L \sim \mathcal{N}(\mu, \sigma^2)$. We know $L \stackrel{d}{=} \mu + \sigma L^*$, where $L^* \sim \mathcal{N}(0, 1)$. Then

$$\begin{aligned}\mathbb{P}(L \leq x) &= F_L(x) = \mathbb{P}(\mu + \sigma L^* \leq x) \\ &= \mathbb{P}(L^* \leq \frac{x-\mu}{\sigma}) = \Phi\left(\frac{x-\mu}{\sigma}\right) =: \alpha\end{aligned}$$

where Φ is the CDF of $\mathcal{N}(0, 1)$. Then

$$\Phi\left(\frac{x-\mu}{\sigma}\right) = \alpha \iff \frac{x-\mu}{\sigma} = \Phi^{-1}(\alpha) \iff x = \mu + \sigma\Phi^{-1}(\alpha)$$

We conclude that $\text{VaR}_\alpha(L) = \mu + \sigma\text{VaR}_\alpha(L^*) = \mu + \sigma\Phi^{-1}(\alpha)$.

Eg. 1.8 Similarly, under the same assumptions, we compute $\text{ES}_\alpha(L)$. This is

$$\begin{aligned}\text{ES}_\alpha(L) &= \mathbb{E}(\mu + \sigma L^* | \mu + \sigma L^* \geq \text{VaR}_\alpha(L)) = \mathbb{E}(\mu + \sigma L^* | \mu + \sigma L^* \geq \mu + \sigma\text{VaR}_\alpha(L^*)) \\ &= \mathbb{E}(\mu + \sigma L^* | L^* \geq \text{VaR}_\alpha(L^*)) = \mu + \sigma\mathbb{E}(L^* | L^* \geq \text{VaR}_\alpha(L^*)) \\ &= \mu + \sigma\text{ES}_\alpha(L^*)\end{aligned}$$

We must now calculate $\text{ES}_\alpha(L^*)$ directly, using [Prop 1.3](#):

$$\text{ES}_\alpha(L^*) = \frac{1}{1-\alpha} \int_{\Phi^{-1}(\alpha)}^{\infty} \phi(x) x dx$$

where $\mathcal{N}(0, 1)$ follows the PDF ϕ . But this has the property that $\phi'(x) = -x\phi(x)$, so we conclude

$$\text{ES}_\alpha(L^*) = \frac{1}{1-\alpha} [-\phi(x)]_{\Phi^{-1}(\alpha)}^{\infty} = \frac{\phi(\Phi^{-1}(\alpha))}{1-\alpha}$$

$$\text{and hence } \text{ES}_\alpha(L) = \mu + \sigma \frac{\phi(\Phi^{-1}(\alpha))}{1-\alpha}$$

DEF 1.23 The *shortfall-to-quatile ratio* is

$$\lim_{\alpha \rightarrow 1} \frac{\text{ES}_\alpha(L)}{\text{VaR}_\alpha(L)}$$

PROP 1.7 When $L^* \sim \mathcal{N}(0, 1)$, we have

$$\lim_{\alpha \rightarrow 1} \frac{\text{ES}_\alpha(L^*)}{\text{VaR}_\alpha(L^*)} = \lim_{\alpha \rightarrow 1} \frac{\frac{1}{1-\alpha} \phi(\Phi^{-1}(\alpha))}{\Phi^{-1}(\alpha)} = \lim_{x \rightarrow \infty} \frac{\frac{1}{1-\Phi(x)} \phi(x)}{x} = \lim_{x \rightarrow \infty} \frac{\phi(x)}{1-\Phi(x)}$$

Using L'Hopital's rule,

$$\lim_{x \rightarrow \infty} \frac{\frac{\phi(x)}{x}}{1-\Phi(x)} = \lim_{x \rightarrow \infty} \frac{1+x^2}{x^2} = 1$$

Hence, when $L \sim \mathcal{N}(\mu, \sigma^2)$, the shortfall-to-quantile ratio also goes to 1.

Eg. 1.9 If L follows the Pareto distribution with parameter $\theta > 0$, i.e.

$$F_L(x) = 1 - x^{-\theta} : x \geq 1$$

From this, we derive the PDF $L(x) = \theta x^{-\theta-1} : x \geq 1$. Computing VaR_α :

$$1 - x^{-\theta} = \alpha \implies x = \text{VaR}_\alpha(L) = (1 - \alpha)^{-1/\theta}$$

Similarly,

$$\text{ES}_\alpha(L) = \frac{1}{1-\alpha} \int_{(1-\alpha)^{-1/\theta}}^{\infty} x \theta x^{-\theta-1} dx = \frac{1}{1-\alpha} \int_{(1-\alpha)^{-1/\theta}}^{\infty} \theta x^{-\theta} dx$$

Note that this integral only converges when $\theta > 1$. Computing the integral gives

$$\text{ES}_\alpha(L) = \frac{\theta}{\theta-1} (1 - \alpha)^{-1/\theta} = \frac{\theta}{\theta-1} \text{VaR}_\alpha(L)$$

$$\text{Hence, } \frac{\text{ES}_\alpha(L)}{\text{VaR}_\alpha(L)} = \frac{\theta}{\theta-1}$$

Suppose F_L is continuous and $\mathbb{E}[|L|] < \infty$. Then, for $\alpha \in (0, 1)$

$$\text{ES}_\alpha(L) = \int_\alpha^1 \text{VaR}_u(L) du$$

PROP 1.8

II Financial Time Series

STATISTICAL CHARACTERIZATIONS

Autocorrelation

Some pertinent examples include log-returns or commodity prices.

Stationary \neq IID. In particular, we may not (*probably do not*) have independence between time-steps.

A *time series* is a collection $(X_t : t \in \mathbb{Z})$ of random variables.

DEF 2.1

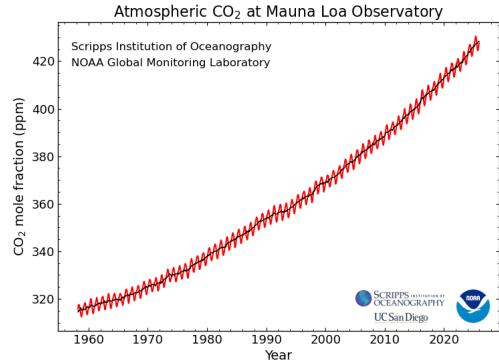
We call a time series X_t *strictly stationary*, or that it follows a stationary distribution, if

DEF 2.2

$$(X_{t_1}, \dots, X_{t_n}) \stackrel{d}{=} (X_{t_1+h}, \dots, X_{t_n+h})$$

for any choice of $t \in \mathbb{Z}^n$ and $h \in \mathbb{Z}_+$, which we call *lag*. This is akin to the notion of time homogeneity of Markov chains. Setting $n = 1$, X_t has the same distribution over all $t \in \mathbb{Z}$.

DEF 2.3



For instance, the above chart does not follow a stationary distribution.

For a time series X_t , with $\mathbb{E}[X_t^2] < \infty \forall t \in \mathbb{Z}$, we define

$$\mu(t) = \mathbb{E}[X_t] \quad \gamma(s, t) = \text{cov}(X_s, X_t)$$

called the *mean function* and *autocovariance function*, respectively.

DEF 2.4

For a series that satisfies $\mathbb{E}[X_t^2] < \infty \forall t \in \mathbb{Z}$, we call it *covariance stationary* if

DEF 2.5

DEF 2.6

$$\mu(t) = \mu \quad \forall t \in \mathbb{Z} \quad \text{and} \quad \gamma(s, t) = \gamma(s + h, t + h) \quad \forall t, s, h \in \mathbb{Z}$$

In this case, we write $\gamma(h) := \gamma(h, 0)$.

If X_t is strictly stationary with $\mathbb{E}[X_t^2] < \infty$, then it is covariance stationary.

PROP 2.1

DEF 2.7 Let X_t be covariance stationary. The *autocorrelation function*, also called serial correlation, is given by

$$\rho(h) = \text{cor}(X_h, X_0) = \frac{\gamma(h)}{\gamma(0)}$$

This definition is consistent with the usual notion of correlation, i.e.

$$\text{cor}(X, Y) = \frac{\text{cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}}$$

Shape

In addition to time-dependent correlations, we are also interested in the broader distribution of returns. For instance, we expect heavier tails on the side of positive loss. Skewness and kurtosis help us quantify these characteristics.

DEF 2.8 Let X have mean μ and variance σ^2 . Suppose $\mathbb{E}[|Y|^3] < \infty$. Then the *skewness* of X is

$$\beta := \mathbb{E}\left[\left(\frac{Y - \mu}{\sigma}\right)^3\right] = \frac{\mathbb{E}[(Y - \mu)^3]}{\mathbb{E}[(Y - \mu)^2]^{3/2}}$$

If $\beta < 0$, we say that X is *left skewed*. Similarly, when $\beta > 0$, we say that X is *right skewed*.

DEF 2.10

A left skewed distribution typically has large mass on its right side, and similarly for a right skewed distribution. The naming convention describes how a left skewed variable's mean is to the left of both its median and mode.

DEF 2.11 Let X have mean μ and variance σ^2 . Suppose $\mathbb{E}[|Y|^4] < \infty$. Then the *kurtosis* of X is

$$\kappa := \mathbb{E}\left[\left(\frac{Y - \mu}{\sigma}\right)^4\right] = \frac{\mathbb{E}[(Y - \mu)^4]}{\mathbb{E}[(Y - \mu)^2]^2}$$

A large kurtosis indicates a higher concentration around the variable's mean. We call such distributions *heteroscedastic*.

DEF 2.12

A normal variable has skew $\beta = 0$ and kurtosis $\kappa = 3$. For an arbitrary variable X , we call $\kappa_X - 3$ its *excess kurtosis*. Variables with positive excess kurtosis are heavy-tailed.

White Noise

Finally, we are interested in distributions that serve as "randomness" for future models.

DEF 2.14

A *white noise process* X_t is a covariance stationary time series with $\gamma(0) = \sigma^2$ and $\mathbb{E}[X_t] = 0$, whose autocorrelation function is given by

$$\rho(0) = 1 \quad \rho(h) = 0 \quad \forall h \neq 0$$

In other words, this is a series which shows no autocorrelation. We write $X_t \sim \text{WN}(0, \sigma^2)$.

DEF 2.15

Similarly, a *strict white noise* process X_t is any process of IID random variables with finite variance σ^2 . In this case, we write $X_t \sim \text{SWN}(0, \sigma^2)$ when $\mathbb{E}[X_t] = 0$.

Let \mathcal{F}_t denote the history of X_i up to time t . We say that X_t is a *martingale difference* with respect to \mathcal{F} if $\mathbb{E}[|X_t|] < \infty \forall t \in \mathbb{Z}$, and

$$\mathbb{E}[X_t | \mathcal{F}_{t-1}] = 0 \quad \forall t \in \mathbb{Z}$$

The *volatility* of a time series X_t , where $\mathbb{E}[X_t^2] < \infty \forall t \in \mathbb{Z}$, is

$$\sigma_t = \sqrt{\text{Var}(X_t | \mathcal{F}_{t-1})} \quad \forall t \in \mathbb{Z}$$

If X_t is a martingale difference, and $\mathbb{E}[X_t^2] < \infty$, then X_t is a white noise process.

We show

1. $\mathbb{E}[X_t] = 0$
2. $\text{cov}(X_s, X_t) = 0 : s < t$

For (1), we have $\mathbb{E}[X_t] = \mathbb{E}_{\mathcal{F}_{t-1}}[\mathbb{E}[X_t | \mathcal{F}_{t-1}]] = \mathbb{E}_{\mathcal{F}_{t-1}}[0] = 0$. For (2), we have $\text{cov}(X_s, X_t) = \mathbb{E}[X_s X_t] = \mathbb{E}_{\mathcal{F}_{t-1}}[\mathbb{E}[X_s X_t | \mathcal{F}_{t-1}]] = \mathbb{E}_{\mathcal{F}_{t-1}}[X_s \mathbb{E}[X_t | \mathcal{F}_{t-1}]] = 0$, noting that $X_s \in \mathcal{F}_{t-1}$. \square

Estimators and Tests

For the following, let X_1, \dots, X_n be time-series observations.

Estimators for the skewness β and kurtosis κ are given by

$$\hat{\beta}_n := \frac{\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^3}{\left[\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \right]^{3/2}} \quad \hat{\kappa}_n := \frac{\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^4}{\left[\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \right]^2}$$

The *sample autocovariance*, an estimator of $\gamma(h) = \text{Cov}(X_h, X_0)$, is given by

$$\hat{\gamma}(h) = \frac{1}{n} \sum_{t=1}^{n-h} (X_t - \bar{X})(X_{t+h} - \bar{X})$$

It follows that

$$\hat{\rho}(h) := \frac{\hat{\gamma}(h)}{\hat{\gamma}(0)}$$

is an estimator for the autocorrelation function. We call this the *sample autocorrelations*, and $h \mapsto \hat{\rho}(h) : h \geq 0$ the *correlogram*.

The *Jarque–Berra statistic* is

$$T_n = \frac{n}{6} \left(\hat{\beta}_n^2 + \frac{1}{4} (\hat{\kappa}_n - 3)^2 \right)$$

If $X \sim \mathcal{N}(\mu, \sigma^2)$, where μ and σ are unknown, then $T_n \sim \chi_2^2$.

Hence, we may use T_n to reject the null hypothesis that "X is normally distributed."

The *Ljung–Box statistic* is

$$Q_n = n(n+2) \sum_{j=1}^h \frac{\hat{\rho}(j)^2}{n-j}$$

Under the assumption that X_1, \dots, X_n is a strict white noise, $Q_n \sim \chi_h^2$ for large n .

Stylized Facts of Financial Time Series

DEF 2.23 A *stylized fact* is an assumption about the empirical behavior of a financial time series.

Let X_t be a financial time series. We assume it is covariance-stationary and strictly stationary. The following are common stylized facts that we will wish to replicate in the following section.

1. X_t are not IID, but show very little autocorrelation. In other words, X_t should form a white noise, but a strict white noise.
2. $|X_t|$ exhibits large autocorrelation.
3. $\mathbb{E}[X_t | \mathcal{F}_{t-1}] \approx 0$.
4. Volatility, i.e. $\text{Var}(X_t | \mathcal{F}_{t-1})$, varies over time.
5. Extreme returns appear in clusters.
6. X_t has a leptokurtic distribution, i.e. is heavy-tailed.

MODELLING FINANCIAL TIME SERIES

We will consider parameterized models for financial time series, which will (hopefully) satisfy stylized facts.

Classical ARMA Models

MOVING AVERAGE PROCESS

DEF 2.24 The series X_t forms a *moving average process* with lag q , and we denote $\text{MA}(q)$, if there are coefficients $\theta_i \in \mathbb{R}$ which satisfy

$$X_t = \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t \quad t \in \mathbb{Z}$$

DEF 2.25 where $(\varepsilon_t) \sim \text{WN}(0, \sigma_\varepsilon^2)$, which we refer to as *innovations*. We observe autocorrelation up to lag q , and no autocorrelation whatsoever for larger lags.

AUTOREGRESSIVE PROCESS

DEF 2.26 The series X_t forms an *autoregressive process* with lag p , and we denote $\text{AR}(p)$, if there are coefficients $\phi_j \in \mathbb{R}$ which satisfy

$$X_t = \sum_{j=1}^p \phi_j X_{t-j} + \varepsilon_t \quad t \in \mathbb{Z}$$

where $(\varepsilon_t) \sim \text{WN}(0, \sigma_\varepsilon^2)$ are our innovations, as before. We observe strong autocorrelation up to lag p , which gradually decays outside of this window. Note that, as the autoregressive process is a solution to a stochastic differential equation, simulations must be done iteratively, with an initial condition. In contrast, the moving average process can be computed at once.

Eg. 2.1 We will compute an AR(1) process. We have

$$\begin{aligned}
 X_t &= \phi X_{t-1} + \varepsilon_t \\
 &= \phi(\phi X_{t-2} + \varepsilon_{t-1}) + \varepsilon_t = \phi^2 X_{t-2} + \phi \varepsilon_{t-1} + \varepsilon_t \\
 &= \phi^2(\phi X_{t-3} + \varepsilon_{t-2}) + \phi \varepsilon_{t-1} + \varepsilon_t = \phi^3 X_{t-3} + \phi^2 \varepsilon_{t-2} + \phi \varepsilon_{t-1} + \varepsilon_t \\
 &\vdots \\
 &= \phi^k X_{t-k} + \sum_{i=0}^{k-1} \phi^i \varepsilon_{t-i}
 \end{aligned}$$

So $X_t \approx \lim_{k \rightarrow \infty} \phi^k X_{t-k} + \sum_{i=0}^{\infty} \phi^i \varepsilon_{t-i}$. The summation only converges when $|\phi| < 1$, in which case $X_t \approx \sum_{i=0}^{\infty} \phi^i \varepsilon_{t-i}$. This is a necessary condition for a solution to exist.

ARMA PROCESS

We combine ideas from autoregressive and moving average processes. The series X_t forms an *autoregressive moving average process* with lag p , and we denote ARMA(p, q), if there are coefficients $\phi_j \in \mathbb{R}$ which satisfy

$$X_t = \sum_{j=1}^p \phi_j X_{t-j} + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t \quad t \in \mathbb{Z}$$

where $\varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$. Furthermore, we require that X_t be covariance-stationary. Note that both MA and AR are special cases of ARMA.

ARIMA PROCESSES

Sometimes our data is non-stationary, which we must "remove" in order to generate an accurate approximation via an ARMA process. To do so, consider the *difference operator* ∇ :

$$\nabla X_t = X_t - X_{t-1} \implies \nabla^d X_t = \nabla^{d-1}(X_t - X_{t-1})$$

We call X_t an *ARIMA process*, and write ARIMA(p, d, q), if $\nabla^d X_t$ is an ARMA(p, q) process.

CAUSAL PROCESSES

We say that X_t is *causal* if there are coefficients ψ_i with

$$X_t = \sum_{i=0}^{\infty} \psi_i \varepsilon_{t-i} = \quad \text{with} \quad \sum_{i=0}^{\infty} |\psi_i| < \infty$$

with $\varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$.

DEF 2.27

DEF 2.28

DEF 2.30

PROP 2.5 If X_t is causal, then it is covariance-stationary with

$$\mathbb{E}[X_t] = 0 \quad \text{Var}(X_t) = \sum_{i=0}^{\infty} \psi_i^2 \sigma_{\varepsilon}^2 \quad \rho(h) = \frac{\sum_{i=0}^{\infty} \psi_i \psi_{i+|h|}}{\psi_i^2}$$

PROOF.

$$\mathbb{E}[\sum_{i=0}^{\infty} \psi_i \varepsilon_{t-i}] = \sum_{i=0}^{\infty} \psi_i \mathbb{E}[\varepsilon_{t-i}] = 0.$$

$$\text{Var}(X_t) = \sum_{i=0}^{\infty} \text{Var}(\psi_i \varepsilon_{t-i}) = \sum_{i=0}^{\infty} \psi_i^2 \sigma_{\varepsilon}^2.$$

Finally, recalling that covariance is bilinear, we compute:

$$\text{cov}(X_t, X_{t+h}) = \text{cov}\left(\sum_{i=0}^{\infty} \psi_i \varepsilon_{t-i}, \sum_{j=0}^{\infty} \psi_j \varepsilon_{t+h-j}\right) = \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} \psi_i \psi_j \text{cov}(\varepsilon_{t-i}, \varepsilon_{t+h-j})$$

but our innovations are white noise, and thus exhibit no autocovariance. Hence, $\text{cov}(\varepsilon_{t-i}, \varepsilon_{t+h-j}) = 0$ unless $j = i + h$, in which case it is σ_{ε}^2 . We rearrange, then,

$$\text{cov}(X_t, X_{t+h}) = \sum_{i=0}^{\infty} \psi_i \psi_{i+h} \sigma_{\varepsilon}^2 = \sum_{i=0}^{\infty} \psi_i \psi_{i+|h|} \sigma_{\varepsilon}^2$$

For the last equivalence, suppose $h < 0$ (in which case $h \neq |h|$). Then ϕ_{i+h} doesn't make sense for $i < |h|$. Thus:

$$\text{cov}(X_t, X_{t+h}) = \sum_{i=|h|}^{\infty} \psi_i \psi_{i+h} \sigma_{\varepsilon}^2 = \sum_{j=0}^{\infty} \psi_{j+|h|} \psi_j \sigma_{\varepsilon}^2 \text{ after re-indexing } j = i + |h|$$

Since our equation for $\gamma(t, t+h) = \text{cov}(X_t, X_{t+h})$ does not rely on t , we conclude that X_t is covariance-stationary, and write $\gamma(t, t+h) = \gamma(h)$. Dividing $\frac{\gamma(h)}{\gamma(0)} = \frac{\gamma(h)}{\text{Var}(X_t)} = \rho(h)$ gives the autocorrelation result. \square

Theorem 2.1 Causality of an ARMA(p, q) Process

Consider a covariance-stationary series solution to the following equation

$$X_t = \sum_{j=1}^p \phi_j X_{t-j} + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t \quad t \in \mathbb{Z}, \varepsilon_t \sim \text{WN}(0, \sigma_{\varepsilon}^2)$$

i.e. $X_t \sim \text{ARMA}(p, q)$. Then X_t is causal if the complex polynomials

$$\phi(z) = 1 - \sum_{i=1}^p \phi_i z^i \quad \theta(z) = 1 + \sum_{i=1}^q \theta_i z^i$$

have no common factors, and if $\phi(z)$ has no complex roots in the unit circle. In this case, our coefficients are determined by solving $\sum_{i=0}^{\infty} \psi_i z^i = \frac{\theta(z)}{\phi(z)} : |z| \leq 1$.

Eg. 2.2 [Example 2.1](#) establishes that AR(1) is causal whenever $|\phi| < 1$. It's easy to see that any moving average process MA(q) is also causal. This allows us to compute their autocorrelations easily using the equations in [Prop 2.5](#).

Eg. 2.3 We know that MA(1) is causal. To compute its coefficients, we have

$$\phi(z) = 1 \quad \theta(z) = 1 + \theta z$$

Clearly $\phi(z)$ does not have roots. We have

$$\sum_{i=0}^{\infty} \psi_i z^i = \frac{\theta(z)}{\phi(z)} = 1 + \theta z$$

Eg. 2.4 Similarly, consider AR(1). We have

$$\phi(z) = 1 - \theta z \quad \theta(z) = 1$$

In order for $1 - \phi z$ to have no roots in the unit circle, we require that $|\frac{1}{\phi}| > 1 \implies |\phi| < 1$, as found before.

When X_t is causal and ARMA, with mean $\mathbb{E}[X_t] = \mu$, we can write

$$X_t = \underbrace{\mu \sum_{j=1}^p \phi_j (X_{t-j} - \mu) + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t}_{:= \mu_t} \quad t \in \mathbb{Z}, \varepsilon_t \sim \text{WN}(0, \sigma_\varepsilon^2)$$

Let X_t be a causal ARMA process, with mean μ . When ε_t are martingale differences, $\mathbb{E}[X_t | \mathcal{F}_{t-1}] = \mu_t$. When ε_t is SWN(0, σ_ε^2), then $\text{Var}(X_t | \mathcal{F}_{t-1}) = \sigma_\varepsilon^2$ as well.

♣ From now on, all ARMA processes are assumed to be causal ♠

Changing Volatility Models

Classical ARMA models, like those shown above, do not capture changing volatility, which markets generally exhibit (see stylized facts). GARCH processes aim to solve this problem.

GARCH PROCESSES

Let $X_t = \sigma_t Z_t$, where $Z_t \sim \text{SWN}(0, 1)$. Typically, $Z_t \sim \mathcal{N}(0, 1)$ or a scaled t_ν . Define

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i X_{t-i}^2 + \sum_{i=1}^q \beta_i \sigma_{t-i}^2 \quad \alpha_0, \alpha_p, \beta_q > 0 \quad \alpha_i, \beta_i \geq 0$$

If X_t is a strictly stationary solution to the equations above, we call X_t a [GARCH process](#) with parameters p and q , and write GARCH(p, q). We note GARCH($p, 0$) = ARCH(p).

DEF 2.31

PROP 2.8 Let $X_t \sim \text{GARCH}(p, q)$ process. Then, if $\mathbb{E}[X_t^2] < \infty$,

$$\mathbb{E}[X_t | \mathcal{F}_{t-1}] = 0 \quad \text{Var}(X_t | \mathcal{F}_{t-1}) = \sigma_t^2$$

In short, X_t is a martingale difference and white noise, with volatility σ_t .

Eg. 2.5 A GARCH(1, 1) process has

$$X_t = \sigma_t Z_t \quad \sigma_t^2 = \alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 \sigma_{t-1}^2 = \alpha_0 + \sigma_{t-1}^2 (\alpha_1 Z_{t-1}^2 + \beta_1)$$

Set $Y_t = \sigma_t^2$ and $B_t = \alpha_0$ (a constant variable) and $A_t = \alpha_1 Z_{t-1}^2$. Then, σ_t^2 satisfies the stochastic recurrence equation

$$Y_t = A_t Y_{t-1} + B_t : t \in \mathbb{Z}$$

The theory of stochastic processes provides that there is a unique strictly stationary solution Y_t if $\mathbb{E}[\max(0, \log |B_t|)] < \infty$ and $\mathbb{E}[\log |A_t|] < 0$. The first condition holds trivially. The second provides the basis for the theorem below.

Theorem 2.2 Nelson

A stationary solution for GARCH(1, 1) exists if and only if

$$\mathbb{E}[\log(\alpha_1 Z_t^2 + \beta_1)] < 0$$

Moreover, the solution X_t is unique, and will satisfy

$$X_t = Z_t \sqrt{\alpha_0 \left(1 + \sum_{i=1}^{\infty} \prod_{j=1}^i (\alpha_1 Z_{t-j}^2 + \beta_1) \right)}$$

PROOF.

The first statement is taken as black-box from the theory of stochastic recurrences. Let X_t be a stationary solution. Then

$$\begin{aligned} \sigma_t^2 &= \alpha_0 + \sigma_{t-1}^2 (\alpha_1 Z_{t-1}^2 + \beta_1) \\ &= \alpha_0 + (\alpha_0 + \sigma_{t-2}^2 (\alpha_1 Z_{t-2}^2 + \beta_1)) (\alpha_1 Z_{t-1}^2 + \beta_1) \\ &\vdots \\ &= \alpha_0 + \sum_{i=1}^{\infty} \alpha_0 \prod_{j=0}^{i-1} (\alpha_1 Z_{t-j-1}^2 + \beta_1) = \alpha_0 + \sum_{i=1}^{\infty} \alpha_0 \prod_{j=1}^i (\alpha_1 Z_{t-j-1}^2 + \beta_1) \\ &= \alpha_0 \left[1 + \sum_{i=1}^{\infty} \prod_{j=0}^{i-1} (\alpha_1 Z_{t-j-1}^2 + \beta_1) \right] \end{aligned}$$

Recalling $X_t = \sigma_t Z_t$ gives the result. □

Theorem 2.3 Bollerslev

A GARCH(1, 1) process has a covariance-stationary solution if and only if

$$\alpha_1 + \beta_1 < 1$$

In this case, the unconditional variance of X_t is given by

$$\text{Var}(X_t) = \frac{\alpha_0}{1 - \alpha_1 - \beta_1}$$

Generally, a GARCH(p, q) process is covariance-stationary if and only if $\sum_{i=1}^p \alpha_i + \sum_{j=1}^q \beta_j < 1$, in which case $\text{Var}(X_t) = \frac{\alpha_0}{1 - \sum_{i=1}^p \alpha_i - \sum_{j=1}^q \beta_j}$.

We'll give a treatment of the GARCH(1, 1) case, and leave the generalization to the reader.

PROOF.

(\implies) Suppose X_t is a covariance-stationary solution. We have

$$\infty > \mathbb{E}[X_t^2] = \mathbb{E}[\sigma_t^2 Z_t^2] = \mathbb{E}[\sigma_t^2] \mathbb{E}[Z_t^2] = \mathbb{E}[\sigma_t^2]$$

We compute $\mathbb{E}[\sigma_t^2]$:

$$\begin{aligned} \mathbb{E}[\sigma_t^2] &= \mathbb{E}[\alpha_0 + \sigma_{t-1}^2(\alpha_1 Z_{t-1}^2 + \beta_1)] \\ &= \mathbb{E}[\alpha_0 + (\alpha_0 + \sigma_{t-2}^2(\alpha_1 Z_{t-2}^2 + \beta_1))(\alpha_1 Z_{t-1}^2 + \beta_1)] \\ &= \alpha_0 + \mathbb{E}[\sigma_{t-1}^2](\alpha_1 + \beta_1) \end{aligned}$$

Since X_t is covariance-stationary, $\mathbb{E}[X_t]$, and hence, $\mathbb{E}[X_t^2] = \mathbb{E}[\sigma_t^2]$, takes on one value. The above then shows that

$$\mathbb{E}[\sigma_t^2] = \frac{\alpha_0}{1 - \alpha_1 - \beta_1} \geq 0 \implies \alpha_1 + \beta_1 < 1$$

(\impliedby) On the other hand, suppose $\alpha_1 + \beta_1 < 1$. Then,

$$0 > \log(\alpha_1 + \beta_1) = \log(\mathbb{E}[\alpha_1 Z_t^2 + \beta_1]) \geq \mathbb{E}[\log(\alpha_1 Z_t^2 + \beta_1)]$$

by Jensen's inequality. It follows by the previous theorem that some strictly stationary solution exists. It remains to show $\mathbb{E}[X_t^2] = \mathbb{E}[\sigma_t^2] < \infty$. One writes

$$\mathbb{E}[\sigma_t^2] = \mathbb{E}\left[\alpha_0 + \sum_{i=1}^{\infty} \alpha_0 \prod_{j=1}^i (\alpha_1 Z_{t-j}^2 + \beta_1)\right] = \alpha_0 + \sum_{i=1}^{\infty} \alpha_0 \mathbb{E}\left[\prod_{j=1}^i (\alpha_1 Z_{t-j}^2 + \beta_1)\right]$$

By independence of the Z_t 's, we get

$$\mathbb{E}[\sigma_t^2] = \alpha_0 + \sum_{i=1}^{\infty} \alpha_0 \prod_{j=1}^i (\alpha_1 + \beta_1) = \alpha_0 + \alpha_0 \sum_{i=1}^{\infty} (\alpha_1 + \beta_1)^i = \frac{\alpha_0}{1 - \alpha_1 - \beta_1} < \infty$$

as desired. By [Prop 2.2](#), X_t is a white noise process, and so $\text{Var}(X_t) = \mathbb{E}[X_t^2] = \mathbb{E}[\sigma_t^2]$. \square

PROP 2.9 A GARCH(p, q) process is heavy-tailed.

Forecasting

We assume an ARMA(p_1, q_1)-GARCH(p_2, q_2) model. Then, we write

$$X_t = \mu_t + \varepsilon_t \quad \varepsilon_t = \sigma_t Z_t \quad \mu_t = \mu + \sum_{i=1}^{p_1} \phi_i (X_{t-i} - \mu) + \sum_{j=1}^{q_1} \theta_j \varepsilon_{t-j}$$

where ε_t follows a GARCH(p_2, q_2) process. We rewrite μ_t as follows:

$$\begin{aligned} \mu_t &= \mu + \sum_{i=1}^p \phi_i (X_{t-i} - \mu) + \sum_{j=1}^q \theta_j \varepsilon_{t-j} \\ &= \mu + \sum_{i=1}^p \phi_i (X_{t-i} - \mu) + \sum_{i=1}^q \theta_j (X_{t-j} - \mu_{t-j}) \end{aligned}$$

Similarly, we compute σ_t^2 :

$$\begin{aligned} \sigma_t^2 &= \alpha_0 + \sum_{i=1}^{p_2} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q_2} \beta_j \sigma_{t-j}^2 \\ &= \alpha_0 + \sum_{i=1}^{p_2} \alpha_i (X_{t-i} - \mu_{t-i})^2 + \sum_{j=1}^{q_2} \beta_j \sigma_{t-j}^2 \end{aligned}$$

If Z_t has a CDF F_Z and density f_Z , then the conditional distribution $X_t | \mathcal{F}_{t-1}$ has CDF $F_Z\left(\frac{x-\mu}{\sigma_t}\right)$ and density $f_Z\left(\frac{x-\mu_t}{\sigma_t}\right)\frac{1}{\sigma_t}$

Eg. 2.6 Consider ARCH(1), with no ARMA part. Then $\mu_t = 0$, $X_t = \varepsilon_t$, and

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 = \alpha_0 + \alpha_1 X_{t-1}^2$$

Hence, the distribution of $(X_t | \mathcal{F}_{t-1})$ is the same as that of $(X_t | X_{t-1})$.

Eg. 2.7 Consider GARCH(1, 1), again with no ARMA part. Then $\mu_t = 0$ and $X_t = \varepsilon_t$, as before. We compute

$$\begin{aligned} \sigma_t^2 &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \\ &= \alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \end{aligned}$$

Hence, the distribution of $(X_t | \mathcal{F}_{t-1})$ is the same as that of $(X_t | X_{t-1}, \sigma_{t-1})$.

Eg. 2.8 Consider ARMA(1, 1) – GARCH(1, 1). Then

$$\begin{aligned}\mu_t &= \mu + \phi_1(X_{t-1} - \mu) + \theta_1 \varepsilon_{t-1} \\ &= \mu + \phi_1(X_{t-1} - \mu) + \theta_1(X_{t-1} - \mu_{t-1})\end{aligned}$$

Similarly, we compute σ_t^2 :

$$\begin{aligned}\sigma_t^2 &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \\ &= \alpha_0 + \alpha_1 (X_{t-1} - \mu_{t-1})^2 + \beta_1 \sigma_{t-1}^2\end{aligned}$$

Hence, the conditional distribution of $(X_t | \mathcal{F}_{t-1})$ is the same as that of $(X_t | X_{t-1}, \sigma_{t-1})$, similar to before.

We wish to use ARMA-GARCH models to forecast. In particular, we need to find parameters to fit to our data. MLE is sufficient for this purpose.

We remind ourselves $\mathcal{L}_\theta(y_1, \dots, y_n) = \prod_{i=1}^n f_\theta(y_i)$, with $\log(\mathcal{L}_\theta) = \sum_{i=1}^n \log(f_\theta(y_i))$. But this only holds when our observations are independent, which returns are not. In general,

$$\mathcal{L}_\theta(y_1, \dots, y_n) = f_\theta(y_1, \dots, y_n)$$

is our *likelihood function* using the joint density of our parameter θ . DEF 2.32

Using conditional densities, PROP 2.10

$$f(y_1, \dots, y_n) = f_{Y_1}(y_1) \cdot f_{Y_2|Y_1}(y_2) \cdot \dots \cdot f_{Y_n|Y_1, \dots, Y_{n-1}}(y_n)$$

For us, our observations are returns over the past n days, X_1, \dots, X_n . Unfortunately, the joint density of ARMA-GARCH over X_1, \dots, X_n is not tractable. However $(X_1, \dots, X_n | \mathcal{F}_0)$ is tractable. In particular,

$$f(X_1, \dots, X_n | \mathcal{F}_0) = f(X_1 | \mathcal{F}_0) f(X_2 | X_1, \mathcal{F}_0) \cdot \dots \cdot f(X_n | X_1, \dots, X_{n-1}, \mathcal{F}_0)$$

Eg. 2.9 Consider ARCH(1). We have two parameters, α_0, α_2 , with

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 = \alpha_0 + \alpha_1 X_{t-1}^2$$

Suppose we have a training sample X_0, \dots, X_n . Then, for $t \in [n]$,

$$f(x_t | x_{t-1}, \dots, x_0) = f(x_t | x_{t-1}) = \frac{1}{\sigma_t} f_Z\left(\frac{x_t}{\sigma_t}\right)$$

with $\sigma_t = \sqrt{\alpha_0 + \alpha_1 x_{t-1}^2}$. From this, we build the conditional likelihood:

$$\mathcal{L}_{\alpha_0, \alpha_1 | X_0} = f(x_1, \dots, x_n | x_0) = \prod_{i=1}^n \frac{1}{\sigma_t} f_Z \left(\frac{x_t}{\sigma_t} \right)$$

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