

Forecasting and Time Series Econometrics

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1 Introduction and Statistics Review

Definition 1.1. Given random variable X , the k^{th} **non-central moment** is defined as

$$\mathbb{E}[X^k] \tag{1.1}$$

Definition 1.2. Given random variable X , the k^{th} **central moment** is defined as

$$\mathbb{E}[(X - \mathbb{E}[X])^k] \tag{1.2}$$

Remark 1.1. Moments of order higher than a certain k may not exist for certain distribution.

Definition 1.3. Given the **joint density** $f(X, Y)$ of two *continuous* random variables, the **conditional density** of random Y conditioned on X is

$$f_{Y|X}(y|x) = \frac{f_{Y,X}(y,x)}{f_X(x)} \tag{1.3}$$

Definition 1.4. Given *discrete* random variables X and Y , the **conditional density** of Y conditioned on X is defined as

$$P(Y = y|X = x) = \frac{P(Y = y \wedge X = x)}{P(X = x)} \tag{1.4}$$

Assumption 1.1. Assumptions on linear regression on time series data:

(i) **Linearity**

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k + u \quad (1.5)$$

(ii) **Zero Conditional Mean**

$$\mathbb{E}[u|X_1, X_2, \dots, X_k] = 0 \quad (1.6)$$

(iii) **Homoscedasticity**

$$\mathbb{V}[u|X_1, X_2, \dots, X_k] = \sigma_u^2 \quad (1.7)$$

(iv) **No Serial Correlation**

$$\text{Cov}(u_t, u_s) = 0 \quad \forall t \neq s \in \mathbb{Z} \quad (1.8)$$

(v) **No Perfect Collinearity**

(vi) **Sample Variation in Regressors**

$$\mathbb{V}[X_j] > 0 \quad \forall j \quad (1.9)$$

Theorem 1.1 (Gauss-Markov Theorem). Under assumptions 1.1, the OLS estimators $\hat{\beta}_j$ are *best linear unbiased estimators* of the unknown population regression coefficients β_j .

Remark 1.2. The *no serial correlation* assumption is typically not satisfied for time series data. And the *linearity* assumption is also too restrictive for time series featuring complex dynamics. Hence, for time series data we typically use other models than linear regression with OLS.

2 Statistics and Time Series

2.1 Stochastic Processes

Definition 2.1. A **stochastic process** (or **time series process**) is a family (collection) random variables indexed by $t \in \mathcal{T}$ and defined on some given probability space (Ω, \mathcal{F}, P) .

$$\{Y_t\} = Y_1, \dots, Y_T \quad (2.1)$$

Definition 2.2. The function from \mathcal{T} to \mathbb{R} which assigns to each point in time $t \in \mathcal{T}$ the realization of the random variable Y_t , y_t is called a **realization** or a **trajectory** or an **outcome** of the stochastic process.

$$\{y_t\} = y_1, \dots, y_T \quad (2.2)$$

Such realization is called a **time series**.

Definition 2.3. A **time series model** or a **model** for the observations, $\{y_t\}$, is a specification of the *joint distribution* of $\{Y_t\}$ for which $\{y_t\}$ is a realization.

Assumption 2.1. The **ergodicity** assumption requires the observations cover in principle all possible events.

Definition 2.4. A stochastic process $\{Y_t\}$ is **first order strongly stationary** if all random variables $Y_t \in \{Y_t\}$ has the *same probability density function*.

Definition 2.5 (1.7). A stochastic process $\{Y_t\}$ is **strictly stationary** if for all $h, n \geq 1$, (Y_1, \dots, Y_n) and $(Y_{1+h}, \dots, Y_{n+h})$ have the same distribution.

Definition 2.6. A stochastic process $\{Y_t\}$ is **first order weakly stationary** if

$$\forall t \in \mathcal{T}, \mu_{Y_t} \equiv \mathbb{E}[Y_t] = \bar{\mu} \quad (2.3)$$

Definition 2.7. A stochastic process $\{Y_t\}$ is **second order weakly stationary**, or **covariance stationary** if all random variables $\{Y_t\}$ have the same mean and variance. And the covariances do not depend on t . That's, for all $t \in \mathcal{T}$,

- (i) $\mathbb{E}[Y_t] = \mu \forall t$
- (ii) $\mathbb{V}[Y_t] = \sigma^2 < \infty \forall t$
- (iii) $Cov(Y_t, Y_s) = Cov(Y_{t+r}, Y_{s+r}) \forall t, s, r \in \mathbb{Z}$

2.2 Auto-correlations

Definition 2.8. Let $\{Y_t\}$ be a stochastic process with $\mathbb{V}[Y_t] < \infty \forall t \in \mathcal{T}$, the **auto-covariance function** is defined as

$$\gamma_Y(t, s) \equiv Cov(Y_t, Y_s) \quad (2.4)$$

$$= \mathbb{E}[(Y_t - \mathbb{E}[Y_t])(Y_s - \mathbb{E}[Y_s])] \quad (2.5)$$

$$= \mathbb{E}[Y_t Y_s] - \mathbb{E}[Y_t] \mathbb{E}[Y_s] \quad (2.6)$$

Lemma 2.1. If $\{Y_t\}$ is stationary, then the auto-covariance function does not depend on specific time point t . We can write the $h \in \mathbb{Z}$ degree auto-covariance as

$$\gamma_Y(h) \equiv \gamma_X(t, t+h) \forall t \in \mathcal{T} \quad (2.7)$$

Proposition 2.1. By the symmetry of covariance,

$$\gamma_Y(h) = \gamma_Y(-h) \quad (2.8)$$

Definition 2.9. The **auto-correlation coefficient** of order k is given by

$$\rho_{Y_t, Y_{t-k}} = \frac{Cov(Y_t, Y_{t-k})}{\sqrt{\mathbb{V}[Y_t]} \sqrt{\mathbb{V}[Y_{t-k}]}} \quad (2.9)$$

Definition 2.10. Let $\{Y_t\}$ be a *covariance stationary process* and the **auto-correlation function** (ACF) is a mapping from *order* of auto-correlation coefficient to the coefficient $\rho_Y : k \rightarrow \rho_{Y_t, Y_{t-k}}$, defined as

$$\rho_Y(k) \equiv \frac{\gamma(k)}{\gamma(0)} = corr(Y_{t+k}, Y_t) \quad (2.10)$$

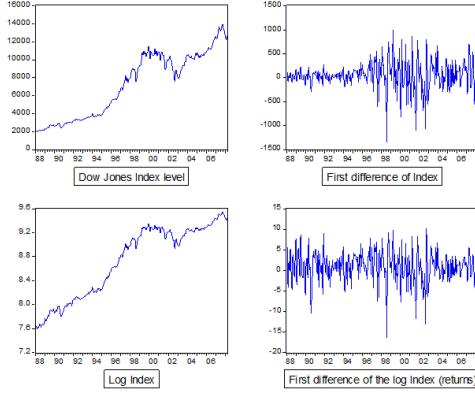
notice the choice of t does not matter, by definition of covariance stationary process.

Proposition 2.2. Note that

$$\rho_k = \rho_{-k} = \rho_{|k|} \quad (2.11)$$

so the ACF for stationary process can be simplified to a mapping

$$\rho : k \rightarrow \rho_{|k|} \quad (2.12)$$



Remark 2.1. Strong stationarity is difficult to test so we will focus on weak(covariance) stationarity only.

Proposition 2.3. For a non-stationary stochastic process $\{Y_t\}$, $\{\Delta Y_t\}$ becomes *first order weakly stationary (mean stationary)* and $\{\Delta \log(Y_t)\}$ becomes *second order weakly stationary (covariance stationary)*.

Definition 2.11 (1.8). A stochastic process $\{Y_t\}$ is called a **Gaussian process** if all finite dimensional distribution from the process are multivariate normally distributed. That's

$$\forall n \in \mathbb{Z}_{>0}, \forall (t_1, \dots, t_n) \in \mathcal{T}^n, (Y_{t_1}, \dots, Y_{t_n}) \sim \mathcal{N}(\boldsymbol{\mu}, \Sigma) \quad (2.13)$$

Notation 2.1. Consider the problem of forecasting Y_{T+1} from observations $\{Y_t\}_{t=1}^T$, the *best linear predictor* is denoted as

$$\mathbb{P}_T Y_{T+1} = \sum_{i=1}^T a_i L^i Y_{T+1} \quad (2.14)$$

And Y_{T+1} can be expressed as

$$Y_{T+1} = \mathbb{P}_T Y_{T+1} + \varepsilon_{T+1} \quad (2.15)$$

where ε_{T+1} denotes the forecast error which is assumed to be *uncorrelated* with Y_T, \dots, Y_1 .

Definition 2.12 (3.3). The **partial auto-correlation function** (PACF) $r(h)$ with $h \in \mathbb{Z}_{\geq 0}$ of a *stationary* process is defined as

$$r(0) = 1 \quad (2.16)$$

$$r(1) = \text{corr}(Y_2, Y_1) = \rho(1) \quad (2.17)$$

$$r(h) = \text{corr}\left(Y_{h+1} - \mathbb{P}(Y_{h+1}|1, Y_2, \dots, Y_h), X_1 - \mathbb{P}(Y_1|1, Y_2, \dots, Y_h)\right) \quad (2.18)$$

Remark 2.2 (Interpretation of PACF). partial auto-correlation $r(k)$ only measures correlation between two variables Y_t and Y_{t+k} while *controlling intermediate variables* $(Y_{t+1}, \dots, Y_{t+k-1})$.

Remark 2.3. AR and MA signatures on ACF and PACF plot.

processes	ACF (ρ)	PACF (r)
AR(p)	Declines exponentially (monotonic or oscillating) to zero	$r(h) = 0 \forall h > p$
MA(q)	$\rho(h) = 0 \forall h > q$	Declines exponentially (monotonic or oscillating) to zero

2.3 Test for Auto-correlation

To test single auto-correlation with

$$H_0 : \rho_k = 0 \quad (2.19)$$

we can use usual t-statistic.

While testing the joint hypothesis

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_k = 0 \quad (2.20)$$

we are using the **Ljung-Box Q-statistic**:

$$Q_k = T(T+1) \sum_{j=1}^k \frac{\hat{\rho}_j^2}{T-j} \sim \chi_k^2 \quad (2.21)$$

2.4 Causality and Invertibility

2.4.1 Causality

Definition 2.13 (Causality). An ARMA(p, q) process $\{Y_t\}$ with

$$\Phi(L)Y_t = \Theta(L)\varepsilon_t \quad (2.22)$$

is called **causal with respect to $\{\varepsilon_t\}$** if there exists a sequence $\Psi \equiv \{\psi_j\}$ with the property $\sum_{j=0}^{\infty} |\psi_j| < \infty$ such that

$$Y_t = \Psi(L)\varepsilon_t \text{ with } \psi_0 = 1 \quad (2.23)$$

where $\Psi(L) \equiv \sum_{j=0}^{\infty} \psi_j L^j$. The above equation is referred to as the **causal representation** of $\{Y_t\}$ with respect to $\{\varepsilon_t\}$.

Proposition 2.4. By the definition of causality, a pure MA process (which is stationary) is naturally a causal representation with respect to its own error term $\{\varepsilon_t\}$.

Theorem 2.1. Let $\{Y_t\}$ be an ARMA(p, q) process with

$$\Phi(L)Y_t = \Theta(L)\varepsilon_t \quad (2.24)$$

such that polynomials $\Phi(z)$ and $\Theta(z)$ have no common roots.

Then $\{Y_t\}$ is causal with respect to $\{\varepsilon_t\}$ if and only if all roots of $\Phi(z)$ are outside the unit circle. The coefficients Ψ are then uniquely defined by identity

$$\Psi(z) = \sum_{j=0}^{\infty} \psi_j z^j = \frac{\Theta(z)}{\Phi(z)} \quad (2.25)$$

2.4.2 Invertibility

Definition 2.14 (Invertibility). An ARMA(p, q) process for $\{Y_t\}$ satisfying

$$\Phi(L)Y_t = \Theta(L)\varepsilon_t \quad (2.26)$$

is called **invertible** with respect to $\{\varepsilon_t\}$ if and only if there exists a sequence Π with the property $\sum_{j=0}^{\infty} |\pi_j| < \infty$ such that

$$\varepsilon_t = \sum_{j=0}^{\infty} \pi_j L^j Y_t \quad (2.27)$$

Proposition 2.5. By the definition of invertibility, a stationary auto-regressive process is naturally invertible with respect to its own error term $\{\varepsilon_t\}$.

Theorem 2.2. Let $\{Y_t\}$ be an ARMA(p, q) process with

$$\Phi(L)Y_t = \Theta(L)\varepsilon_t \quad (2.28)$$

Then $\{Y_t\}$ is invertible with respect to $\{\varepsilon_t\}$ if and only if all roots of $\Theta(z)$ are outside the unit circle. And the coefficients of $\Pi \equiv \{\pi_j\}$ are then uniquely determined by the relation

$$\Pi(z) = \sum_{j=0}^{\infty} \pi_j z^j = \frac{\Phi(z)}{\Theta(z)} \quad (2.29)$$

3 Forecasting Tools

3.1 Information Set

Definition 3.1. For stochastic process $\{Y_t\}$, the **information set** I_t is the *known time series* up to time t . It takes the form of a n -tuple $(y_{t_0}, y_{t_1}, \dots, y_{t_n})$ such that $t_n \leq t$ so the information set is certain at time t .

Definition 3.2. A **forecast** $f_{t,h}$ the image of a *time series model* g under given information set I_t . Specifically,

$$f_{t,h} = g(I_t) \in \mathbb{R} \quad (3.1)$$

3.2 Forecast Horizon

Remark 3.1. Covariance stationary processes are **short-memory processes**. More recent observation contains information far more relevant for the future than older information.

Remark 3.2. Non-stationary processes are **long-memory processes** and older information is as relevant for the forecast as more recent information.

3.2.1 Forecasting Environments: *Recursive*

- (i) Updating with *flexible* information set.
- (ii) Advantageous if model is *stable over time*.
- (iii) Not robust to *structural break*.

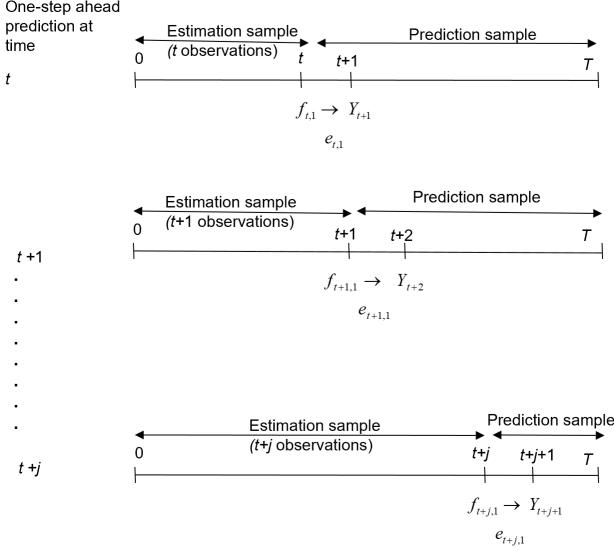


Figure 3.1: Recursive Forecasting Scheme

3.2.2 Forecasting Environments: *Rolling*

- (i) *Updating* with *fixed-size* information set.
- (ii) Robust against *structural breaks*.
- (iii) Not fully exploit information available.

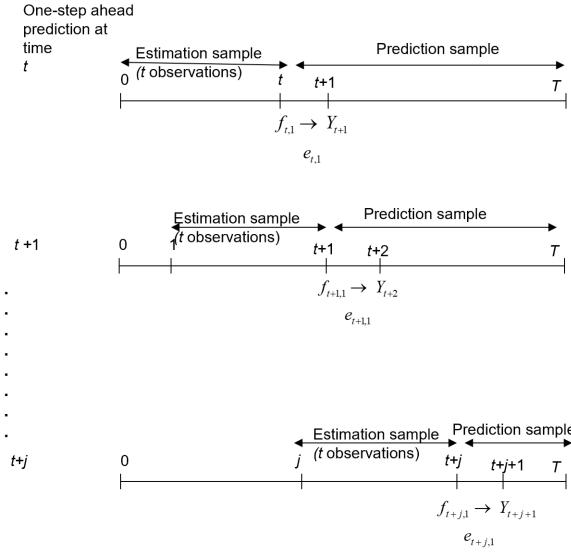


Figure 3.2: Rolling Forecasting Scheme

3.2.3 Forecasting Environments: *Fixed*

- (i) *One estimation* and forecast with *fixed-size* but *updated* information set.

(ii) Computationally cheap.

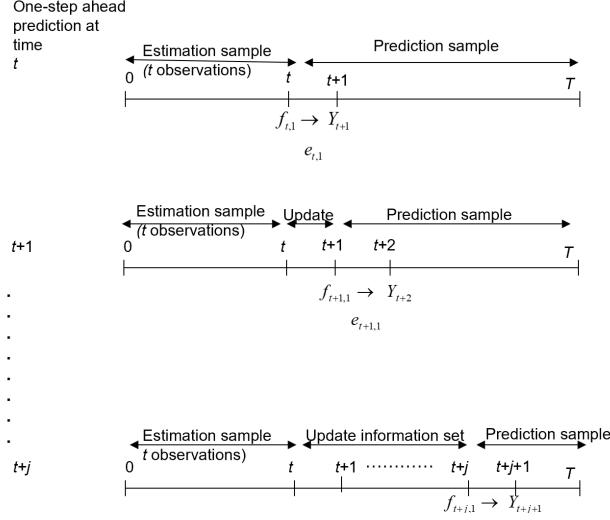


Figure 3.3: Fixed Forecasting Scheme

3.3 Loss Function

Definition 3.3. A loss function $L(e)$ is a real-valued function defined on the space of *forecast errors*, \mathcal{E} , and satisfies the following properties

- (i) $L(e) = 0 \iff \|e\| = 0$;
- (ii) $\forall e \in \mathcal{E}, L(e) \geq 0$ ¹;
- (iii) L is *monotonically increasing* in the norm of forecast error.

Example 3.1 (Symmetric Loss Functions with $\mathcal{E} = \mathbb{R}$).

$$L(e) = ae^2, \quad a > 0 \quad (3.2)$$

$$L(e) = a|e|, \quad a > 0 \quad (3.3)$$

Example 3.2 (Asymmetric Loss Functions with $\mathcal{E} = \mathbb{R}$).

$$L(e) = \exp(ae) - ae - 1, \quad a > 0 \quad \text{Linex Function} \quad (3.4)$$

$$L(e) = a|e| \mathbb{I}(e \geq 0) + b|e| \mathbb{I}(e < 0) \quad \text{Lin-lin Function} \quad (3.5)$$

3.4 Optimal Forecast

Definition 3.4. Based on information set I_t , the optimal forecast for future value y_{t+h} is the $f_{t,h}^*$ minimize the **expected loss function**

$$\mathbb{E}[L|I_t] = \int L(y_{t+h} - f_{t,h})f(y_{t+h}) dy_{t+h} \quad (3.6)$$

¹Since forecasting here can be considered as an optimization process, with L as the objective function. It's fine for L not satisfying the non-negativity condition. However, by convention, we assume L to be non-negative.

Assumption 3.1. Assuming the forecast $f(y_{t+h}|I_t)$ follows

$$f(y_{t+h}|I_t) \sim \mathcal{N}(\mathbb{E}[Y_{t+h}|I_t], \mathbb{V}[Y_{t+h}|I_t]) \quad (3.7)$$

Proposition 3.1. Given symmetric quadratic L , the optimal forecast $f_{t,h}^*$ is

$$\mu_{t+h|t} \equiv \mathbb{E}[Y_{t+h}|I_t] \quad (3.8)$$

Proof.

$$\min_{f_{t,h} \in \mathbb{R}} L \equiv \int (y_{t+h} - f_{t,h})^2 f(y_{t+h}|I_t) dy_{t+h} \quad (3.9)$$

$$\frac{\partial L}{\partial f_{t,h}} = -2 \int (y_{t+h} - f_{t,h}) f(y_{t+h}|I_t) dy_{t+h} = 0 \quad (3.10)$$

$$\implies \int (y_{t+h} - f_{t,h}) f(y_{t+h}|I_t) dy_{t+h} = 0 \quad (3.11)$$

$$\implies \int y_{t+h} f(y_{t+h}|I_t) dy_{t+h} = f_{t,h} \int f(y_{t+h}|I_t) dy_{t+h} \quad (3.12)$$

$$\implies f_{t,h} = \mathbb{E}[y_{t+h}|I_t] \equiv \mu_{t+h|t} \quad (3.13)$$

■

4 Moving Average Process

4.1 Wold Decomposition Theorem

Theorem 4.1 (Wold Decomposition Theorem). Every covariance stationary stochastic process $\{Y_t\}$ with mean zero and finite positive variance can be *uniquely* represented as

$$Y_t = V_t + \sum_{j=0}^{\infty} \psi_j L^j \varepsilon_t = V_t + \Psi(L) \varepsilon_t \quad (4.1)$$

where

- (i) $\{V_t\}$ is a *deterministic component* (e.g. trend or cycle);
- (ii) $\varepsilon_t \sim WN(0, \sigma^2)$ is the *stochastic component*;
- (iii) $\psi_0 = 1^2$ and $\sum_{j=0}^{\infty} \psi_j^2 < \infty$;
- (iv) $\mathbb{E}[\varepsilon_t, V_s] = 0 \ \forall t, s \in \mathcal{T}$.

Definition 4.1. The stochastic component $\{\varepsilon_t\}$ in the decomposition is called **random shocks** or **innovations**.

Lemma 4.1. Given $\sum_{j=0}^{\infty} \psi_j^2 < \infty$, then for all $\varepsilon > 0$ there exists a natural number J such that

$$\sum_{j=J}^{\infty} \psi_j^2 < \varepsilon \quad (4.2)$$

²We can always normalize ψ_0 to 1.

Corollary 4.1. By above lemma, assuming $V_t = 0$, we can approximate the decomposition by a linear combination of finite innovations.

$$Y_t \approx \hat{Y}_t = \sum_{j=0}^n \psi_j L^j \varepsilon_t \quad (4.3)$$

and the approximation is *accurate in Euclidean norm*, that's,

$$\mathbb{E}[Y_t - \sum_{j=0}^n \psi_j L^j \varepsilon_t]^2 \rightarrow 0 \text{ as } n \rightarrow 0 \quad (4.4)$$

4.2 Moving Average Process

Definition 4.2. The **Moving Average** of order q with deterministic trend, $\text{MA}(q)$, process is defined by the following stochastic difference equation

$$Y_t = \mu + \Theta(L)\varepsilon_t = \mu + \theta_0\varepsilon_t + \theta_1\varepsilon_{t-1} + \cdots + \theta_q\varepsilon_{t-q} \text{ where } \theta_0 = 1, \theta_q \neq 0 \quad (4.5)$$

where $\{\varepsilon_t\}$ is innovations.

Lemma 4.2. The infinite lag polynomial in $\Psi(L)$ can be approximated by

$$\Psi(L) \approx \frac{\Theta_q(L)}{\Phi_p(L)} \quad (4.6)$$

Definition 4.3. $\text{MA}(1)$ process takes the form of

$$Y_t = \mu + \varepsilon_t + \theta\varepsilon_{t-1} \quad (4.7)$$

Unconditional Moments of $\text{MA}(1)$

$$\mathbb{E}[Y_t] = \mathbb{E}[\mu + \varepsilon_t + \theta\varepsilon_{t-1}] = \mu \quad (4.8)$$

$$\mathbb{V}[Y_t] = \mathbb{E}[(\varepsilon_t + \theta\varepsilon_{t-1})^2] \quad (4.9)$$

$$= \mathbb{V}[\varepsilon_t] + \theta^2\mathbb{V}[\varepsilon_{t-1}] \quad (4.10)$$

$$= (1 + \theta^2)\sigma_\varepsilon^2 \quad (4.11)$$

Auto-covariance

$$\gamma_0 = \mathbb{V}[Y_t] = (1 + \theta^2)\sigma_\varepsilon^2 \quad (4.12)$$

$$\gamma_1 = \mathbb{E}[(Y_t - \mu)(Y_{t-1} - \mu)] \quad (4.13)$$

$$= \mathbb{E}[(\varepsilon_t + \theta\varepsilon_{t-1})(\varepsilon_{t-1} + \theta\varepsilon_{t-2})] \quad (4.14)$$

$$= \theta\sigma_\varepsilon^2 \quad (4.15)$$

$$\gamma_k = 0 \quad \forall k > 1 \quad (4.16)$$

Auto-correlation

$$\rho_1 = \frac{\gamma_1}{\gamma_0} = \frac{\theta}{1 + \theta^2} \quad (4.17)$$

$$\rho_k = 0 \quad \forall k > 1 \quad (4.18)$$

Definition 4.4. A MA(1) process is **invertible** if $|\theta| < 1$, so that it can be written as an AR(∞) process.

Inverting. Let

$$Y_t = \mu + \varepsilon_t + \theta \varepsilon_{t+1} \quad (4.19)$$

where $|\theta| < 1$. Then,

$$Y_t = \mu + \varepsilon_t + \theta \varepsilon_{t+1} \quad (4.20)$$

$$\implies Y_t - \mu = (1 + \theta L) \varepsilon_t \quad (4.21)$$

$$\implies \frac{Y_t - \mu}{1 - (-\theta L)} = \varepsilon_t \quad (4.22)$$

$$\implies \varepsilon_t = (Y_t - \mu) \sum_{j=0}^{\infty} (-\theta L)^j \quad (4.23)$$

■

Equivalence note that for MA(1) process,

$$r_1 = \rho_1 = \frac{\theta}{1 + \theta^2} \quad (4.24)$$

and for any θ , $\frac{1}{\theta}$ will generate the same auto-correlation. We always choose the invertible MA representation with $|\theta| < 1$.

Proposition 4.1. For any process, $\rho_1 = r_1$.

Remark 4.1. If the MA process is invertible, we can always find an autoregressive representation in which the present is a function of the past.

4.3 Forecasting with MA(1)

4.3.1 Forecasting with Horizon $h = 1$

Point estimate

$$f_{t,1} = \mathbb{E}[Y_{t+1}|I_t] \quad (4.25)$$

$$= \mathbb{E}[\mu + \theta \varepsilon_t + \varepsilon_{t+1}|I_t] \quad (4.26)$$

$$= \mu + \theta \varepsilon_t \quad (4.27)$$

Forecasting error

$$e_{t,1} = Y_{t+1} - f_{t,1} = \varepsilon_{t+1} \quad (4.28)$$

Forecasting uncertainty

$$\sigma_{t+1|t}^2 = \mathbb{V}[Y_{t+1}|I_t] \quad (4.29)$$

$$= \mathbb{E}[\varepsilon_{t+1}^2|I_t] \quad (4.30)$$

$$= \sigma_\varepsilon^2 \quad (4.31)$$

Density forecast assuming *normality* of ε

$$\mathcal{F} \equiv \mathcal{N}(\mu_{t+1|t}, \sigma_{t+1|t}^2) \quad (4.32)$$

$$\mu_{t+1|t} = \mu + \theta\varepsilon_t \quad (4.33)$$

$$\sigma_{t+1|t}^2 = \sigma_\varepsilon^2 \quad (4.34)$$

4.3.2 Forecasting with Horizon $h = 2$

Point estimate

$$f_{t,2} = \mathbb{E}[Y_{t+2}|I_t] \quad (4.35)$$

$$= \mathbb{E}[\mu + \theta\varepsilon_{t+1} + \varepsilon_{t+2}|I_t] \quad (4.36)$$

$$= \mu \quad (4.37)$$

Forecasting Error

$$Y_{t+2} - f_{t,2} = \theta\varepsilon_{t+1} + \varepsilon_{t+2} \quad (4.38)$$

Forecasting Uncertainty

$$\sigma_{t+2|t}^2 \equiv \mathbb{V}[Y_{t+2}|I_t] \quad (4.39)$$

$$= (1 + \theta^2)\sigma_\varepsilon^2 \quad (4.40)$$

Density forecast

$$\mathcal{F} = \mathcal{N}(\mu, (1 + \theta^2)\sigma_\varepsilon^2) \quad (4.41)$$

Remark 4.2. Since for any $h > 1$, MA(1) only generates the unconditional mean μ as the point estimate, we say MA(1) process is **short memory**.

4.4 Properties of MA(2) Process

Model

$$Y_t = \mu + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} \quad (4.42)$$

Unconditional Moments

$$\mathbb{E}[Y_t] = \mu \quad (4.43)$$

$$\mathbb{V}[Y_t] = (1 + \theta_1^2 + \theta_2^2)\sigma_\varepsilon^2 \quad (4.44)$$

Auto-covariance

$$\gamma_0 = \mathbb{V}[Y_t] = (1 + \theta_1^2 + \theta_2^2)\sigma_\varepsilon^2 \quad (4.45)$$

$$\gamma_1 = (\theta_1 + \theta_1\theta_2)\sigma_\varepsilon^2 \quad (4.46)$$

$$\gamma_2 = \theta_2\sigma_\varepsilon^2 \quad (4.47)$$

Auto-correlation

$$\rho_1 \equiv \frac{\gamma_1}{\gamma_0} = \frac{\theta_1 + \theta_1 \theta_2}{1 + \theta_1^2 + \theta_2^2} \quad (4.48)$$

$$\rho_2 \equiv \frac{\gamma_2}{\gamma_0} = \frac{\theta_2}{1 + \theta_1^2 + \theta_2^2} \quad (4.49)$$

Optimal Forecasting

$$f_{t,1} = \mu + \theta_1 \varepsilon_t + \theta_2 \varepsilon_{t-1} \quad (4.50)$$

$$f_{t,2} = \mu + \theta_2 \varepsilon_t \quad (4.51)$$

$$f_{t,h} = \mu \quad \forall h > 2 \quad (4.52)$$

4.5 MA Forecasting Procedure

Remark 4.3. Assuming the MA process used is invertible, we use its inverting representation to recover $\hat{\varepsilon}_t$.

5 Auto-Regression Process and Seasonality

5.1 AR Process

Definition 5.1. An **auto-regressive** model of order p is taken in the form of

$$Y_t = c + \sum_{j=1}^p \phi_j L^j Y_t + \varepsilon_t \quad (5.1)$$

or equivalently

$$\Phi_p(L)Y_t = c + \varepsilon_t \quad (5.2)$$

Definition 5.2. An **auto-regressive** process of order 1 takes the form of stochastic difference equation

$$Y_t = c + \phi Y_{t-1} + \varepsilon_t \quad (5.3)$$

where ϕ is called the **persistence parameter**.

Proposition 5.1. AR(1) process is stationary if and only if $|\phi| < 1$.

ACF and PACF

$$\rho_1 = r_1 = \phi \quad (5.4)$$

$$r_k = 0 \quad \forall k > 1 \quad (5.5)$$

5.1.1 Forecasting with AR(1) and $h = 1$

³ Point Estimate

$$f_{t,1} = \mathbb{E}[Y_{t+1}|I_t] \quad (5.6)$$

$$= c + \phi Y_t \quad (5.7)$$

³While examining the optimal forecast in this section, we are assuming the loss function is *symmetric*.

Forecast Variance(Uncertainty)

$$\mathbb{V}[Y_{t+1}|I_t] = \mathbb{V}[c + \phi Y_t + \varepsilon_{t+1}|I_t] = \sigma_\varepsilon^2 \quad (5.8)$$

Density Forecast

$$\mathcal{F} = \mathcal{N}(c + \phi Y_t, \sigma_\varepsilon^2) \quad (5.9)$$

5.1.2 Forecasting with AR(1) and $h = s > 1$

Point Estimate

$$f_{t,s} = \mathbb{E}[Y_{t+s}|I_t] \quad (5.10)$$

$$= c + \mathbb{E}[\phi Y_{t+s-1}|I_t] \quad (5.11)$$

$$= (1 + \phi + \cdots + \phi^{s-1})c + \phi^s Y_t \quad (5.12)$$

Forecasting Uncertainty

$$\mathbb{V}[Y_{t+s}|I_t] = \mathbb{V}[\varepsilon_{t+s} + \phi \varepsilon_{t+s-1} + \cdots + \phi^{s-1} \varepsilon_{t+1}|I_t] \quad (5.13)$$

$$= \sum_{j=0}^{s-1} \phi^{2j} \sigma_\varepsilon^2 \quad (5.14)$$

Remark 5.1. ACF and PACF are estimated functions subject to sampling error, so the estimated ACF and PACF from sample might be different from their theoretical values.

5.1.3 Forecasting with AR(1) and $h \rightarrow \infty$

Assumption 5.1. For this subsection, assuming the AR(1) process is **stationary**, that's, $|\phi| < 1$.

Point Estimate

$$\lim_{h \rightarrow \infty} f_{t,h} = \frac{c}{1 - \phi} \quad (5.15)$$

Forecasting Uncertainty

$$\lim_{h \rightarrow \infty} \mathbb{V}[Y_{t+h}|I_t] = \frac{\sigma_\varepsilon^2}{1 - \phi^2} \quad (5.16)$$

Remark 5.2. The convergences demonstrated above suggest auto-regressive process is still a **short memory** process.

5.1.4 Forecasting with AR(2) process

Definition 5.3. AR(2) process

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \varepsilon_t \quad (5.17)$$

Unconditional Moments

$$\mathbb{E}[Y_t] = c + \phi_1 \mathbb{E}[Y_{t-1}] + \phi_2 \mathbb{E}[Y_{t-2}] \quad (5.18)$$

$$\implies \mu_Y = \frac{c}{1 - \phi_1 - \phi_2} \quad (5.19)$$

Auto-covariance and Auto-correlation

$$\rho_1 = r_1 \quad (5.20)$$

$$r_2 = \phi_2 + \text{ sampling error} \quad (5.21)$$

Optimal Forecasts $h = 1$

$$f_{t,1} = \mathbb{E}[Y_{t+1}|I_t] \quad (5.22)$$

$$= \mathbb{E}[c + \phi_1 Y_t + \phi_2 Y_{t-1} + \varepsilon_{t+1}|I_t] \quad (5.23)$$

$$= c + \phi_1 Y_t + \phi_2 Y_{t-1} \quad (5.24)$$

$$e_{t,1} = \varepsilon_{t+1} \quad (5.25)$$

$$\sigma_{t+1|t}^2 = \mathbb{V}[Y_{t+1}|I_t] = \sigma_\varepsilon^2 \quad (5.26)$$

Optimal Forecasts $h = 2$

$$f_{t,2} = \mathbb{E}[Y_{t+2}|I_t] \quad (5.27)$$

$$= \mathbb{E}[c + \phi_1 Y_{t+1} + \phi_2 Y_t + \varepsilon_{t+2}|I_t] \quad (5.28)$$

$$= c + \phi_1 \textcolor{red}{f}_{t,1} + \phi_2 Y_t \quad (5.29)$$

$$e_{t,2} = Y_{t+2} - f_{t,2} \quad (5.30)$$

$$= \phi_1(Y_{t+1} - f_{t,1}) + \varepsilon_{t+2} \quad (5.31)$$

$$= \phi_1 e_{t,1} + \varepsilon_{t+2} \quad (5.32)$$

$$\sigma_{t+2|t}^2 = \mathbb{V}[Y_{t+2}|I+t] \quad (5.33)$$

$$= \phi_1^2 \sigma_{t+1|t}^2 + \sigma_\varepsilon^2 \quad (5.34)$$

$$= (1 + \phi_1^2) \sigma_\varepsilon^2 \quad (5.35)$$

Optimal Forecasts $h = s > 2$

$$f_{t,s} = \mathbb{E}[Y_{t+s}|I_t] \quad (5.36)$$

$$= c + \phi_1 f_{t,s-1} + \phi_2 f_{t,s-2} \quad (5.37)$$

$$e_{t,s} = \phi_1 e_{t,s-1} + \phi_2 e_{t,s-2} + \varepsilon_{t+s} \quad (5.38)$$

$$\sigma_{t+s|t}^2 = \mathbb{V}[Y_{t+s}|I_t] \quad (5.39)$$

$$= \mathbb{V}[e_{t,s}|I_t] \quad (5.40)$$

$$= \phi_1 \sigma_{t+s-1|t}^2 + \phi_2 \sigma_{t+s-2|t}^2 + \sigma_\varepsilon^2 \quad (5.41)$$

Remark 5.3. AR(2) is still classified as *short memory processes* as

$$\lim_{s \rightarrow \infty} f_{t,s} = \mu \quad (5.42)$$

$$\lim_{s \rightarrow \infty} \sigma_{t+2|t}^2 = \sigma_Y^2 \quad (5.43)$$

5.1.5 AP(p) process

Definition 5.4. Let $\Phi(L)Y_t = c + \varepsilon_t$ be an AR(p) process with trend c , then $\Phi(\cdot)$ is called the **characteristic polynomial** of this stochastic process.

Theorem 5.1. An autoregressive process is stationary if and only if all roots of its characteristic polynomial are **outside** the unit circle on \mathbb{C} .

Forecasting with AR(p) Process we apply a **recursive** scheme, or **chain rule of forecasting**, in which we use the *forecasted* values to make prediction on even further values.

Example 5.1 (AP(p) chain rule of forecasting).

$$\textcolor{red}{f}_{t,1} = c + \sum_{j=1}^p \phi_j L^j Y_{t+1} \quad (5.44)$$

$$\textcolor{brown}{f}_{t,2} = c + \phi_1 \textcolor{red}{f}_{t,1} + \sum_{j=2}^p \phi_j L^j Y_{t+2} \quad (5.45)$$

$$\textcolor{blue}{f}_{t,3} = c + \phi_1 \textcolor{brown}{f}_{t,2} + \phi_2 \textcolor{red}{f}_{t,1} + \sum_{j=3}^p \phi_j L^j Y_{t+3} \quad (5.46)$$

$$f_{t,s} = c + \sum_{j=1}^p \phi_j f_{t,s-j} \quad \forall s > p \quad (5.47)$$

5.2 AR Forecasting Procedures

- (i) **Estimate** $\hat{\Phi}$ and $\hat{\sigma}_\varepsilon^2$ and $\hat{\mu}$ (unconditional mean).
- (ii) Calculate \hat{c} (intercept) from $\hat{\Phi}$ and $\hat{\mu}$.
- (iii) Construct forecast $f_{t,h}$ with **chain rule of forecasting**.
- (iv) **Density forecast**, under normality assumption of ε is

$$\mathcal{N}(f_{t,h}, \hat{\sigma}_{t+h|t}^2) \quad (5.48)$$

- (v) 95% confidence interval of forecasting is

$$(f_{t,h} \pm 1.96 \times \hat{\sigma}_{t+h|t}) \quad (5.49)$$

5.3 Seasonality

5.3.1 Deterministic Seasonality

Definition 5.5. The seasonality is **deterministic** if the regressors indicating seasons are always exactly predictable.

5.3.2 Stochastic Seasonality

Definition 5.6. The seasonality is **stochastic** if the seasonal component is driven by random variables.

Definition 5.7. A seasonal AP(p) model, S-AR(p), is defined by

$$Y_t = c + \phi_s Y_{t-s} + \phi_{2s} Y_{t-2s} + \cdots + \phi_{ps} Y_{t-ps} + \varepsilon_t \quad (5.50)$$

$$\Phi_p(L^s)Y_t = c + \varepsilon_t \quad (5.51)$$

where s refers to the **data frequency**. Such model seeks to explain the **dynamics across seasons**.

Definition 5.8. Characteristics of realizations from S-AR(p) process:

- (i) ACF decays slowly with spikes at multiples of s .
- (ii) PACF **only** spikes at multiples of s .

Definition 5.9. A seasonal MA(q) model, S-MA(q), is given by

$$Y_t = \mu + \Theta_q(L^s)\varepsilon_t \quad (5.52)$$

Remark 5.4. Characteristics of realizations from S-MA(q) process:

- (i) ACF **only** spikes at multiples of s .
- (ii) PACF decays slowly with spikes at multiples of s .

Proposition 5.2 (Combining ARMA and S-ARMA). Given ARMA

$$\Phi_p(L)Y_t = c + \Theta_q(L)\varepsilon_t \quad (5.53)$$

and S-ARMA

$$\Phi'_p(L^{s_1})Y_t = c + \Theta'_q(L^{s_2})\varepsilon_t \quad (5.54)$$

The combined model is given by multiplying the lag polynomials

$$\Phi_p(L)\Phi'_p(L^{s_1})Y_t = c + \Theta_q(L)\Theta'_q(L^{s_2})\varepsilon_t \quad (5.55)$$

6 Model Assessment and Asymmetric Loss

6.1 Model Assessment

Definition 6.1. Akaike information criterion(AIC) of a model with k parameters is defined as

$$AIC \equiv -2 \ln(\mathcal{L}) + 2k \quad (6.1)$$

Definition 6.2. Bayes information criterion(BIC)/Schwarz information criterion(SIC) of a model with k parameters and fitted on the sample with size N is defined as

$$BIC \equiv -2 \ln(\mathcal{L}) + 2 \ln(N)k \quad (6.2)$$

Definition 6.3. Given time series data sample with size T , and use the *recursive scheme* starting from $t < T$, with forecasting horizon h , given sequence of *ground truth*

$$\mathcal{Y} = (y_j)_{j=t+h}^T \quad (6.3)$$

we can construct a sequence of forecast

$$\mathcal{F} = (f_{t,h}, f_{t+1,h}, f_{t+2,h}, \dots, f_{T-h,h}) \quad (6.4)$$

and a sequence of forecasting errors

$$\mathcal{E} = (e_{j,t})_{j=t+h}^T \quad (6.5)$$

then,

$$\text{MSE} \equiv \frac{1}{|\mathcal{F}|} \sum_{e \in \mathcal{E}} e^2 \quad (6.6)$$

$$\text{MAE} \equiv \frac{1}{|\mathcal{F}|} \sum_{e \in \mathcal{E}} ||e|| \quad (6.7)$$

$$\text{MAPE} \equiv \frac{1}{|\mathcal{F}|} \sum_{(y,e) \in (\mathcal{Y}, \mathcal{E})} \left| \frac{e}{y} \right| \quad (6.8)$$

6.2 Asymmetric Loss

Definition 6.4 (Log-Normal Distribution). Let X be a Gaussian random variable with mean μ and variance σ^2 . Define $Y \equiv \exp(X)$, then Y follows **log-normal distribution**, with

$$\mathbb{E}[Y] = \exp(\mu + \frac{\sigma^2}{2}) \quad (6.9)$$

Example 6.1. Consider the Lin-ex loss function

$$L(e) = \exp(ae) - ae - 1 \quad (6.10)$$

then the expected loss for h step forecasting made at t is

$$\mathbb{E}[L(e_{t,h})|I_t] \quad (6.11)$$

$$= \mathbb{E}[\exp(a(y_{t+h} - f_{t,h})) - a(y_{t+h} - f_{t,h}) - 1 | I_t] \quad (6.12)$$

$$= \mathbb{E}[\exp(ay_{t+h}) \exp(-af_{t,h}) | I_t] - \mathbb{E}[ay_{t+h} | I_t] + af_{t,h} - 1 \quad (6.13)$$

$$= \exp(-af_{t,h}) \mathbb{E}[\exp(ay_{t+h}) | I_t] - a\mathbb{E}[y_{t+h} | I_t] + af_{t,h} - 1 \quad (6.14)$$

$$(6.15)$$

To find the optimal forecasting, take the FOC

$$\frac{\partial \mathbb{E}[L(e_{t,h})|I_t]}{\partial f_{t,h}} = 0 \quad (6.16)$$

$$\implies -a \exp(-af_{t,h}) \mathbb{E}[\exp(ay_{t+h}) | I_t] + a = 0 \quad (6.17)$$

$$\implies \exp(-af_{t,h}) \mathbb{E}[\exp(ay_{t+h}) | I_t] = 1 \quad (6.18)$$

$$\implies -af_{t,h} + \log(\mathbb{E}[\exp(ay_{t+h}) | I_t]) = 0 \quad (6.19)$$

$$\implies f_{t,h} = \frac{1}{a} \log(\mathbb{E}[\exp(ay_{t+h}) | I_t]) \quad (6.20)$$

Assuming $y_{t+h} \sim \mathcal{N}(\mu_{t+h|t}, \sigma_{t+h|t}^2)$,

$$\implies f_{t,h} = \frac{1}{a} \log(\exp(a\mathbb{E}[y_{t+h}|I_t] + \frac{a^2\sigma_{t+h|t}^2}{2})) \quad (6.21)$$

$$\implies f_{t,h} = \mathbb{E}[y_{t+h}|I_t] + \frac{a\sigma_{t+h|t}^2}{2} \quad (6.22)$$

So if $a < 0$, the penalty on making negative error is higher than positive error, and the optimal forecast would be *pushed down* to less than the conditional mean.

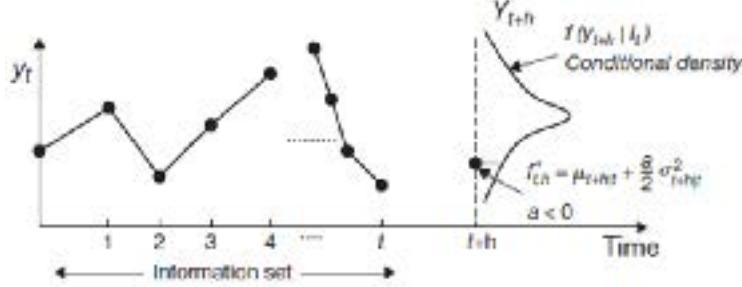


Figure 6.1: Illustration of the Optimal Forecast with Lin-Ex loss and $a < 0$

Forecasting Assuming AR(1) process.

Error with $h = 1$

$$e_{t+1,t} = c + \phi Y_t + \varepsilon_{t+1} - f_{t,1} \quad (6.23)$$

$$= \varepsilon_{t+1} - \frac{a\sigma_{t+1|t}^2}{2} \quad (6.24)$$

$$\mathbb{E}[e_{t+1,t}] = -\frac{a\sigma_{t+1|t}^2}{2} \quad (6.25)$$

$$\mathbb{V}[e_{t+1,t}|I_t] = \sigma_\varepsilon^2 \quad (6.26)$$

Error with $h = 2$

$$e_{t+2,t} = Y_{t+2} - f_{t,2} \quad (6.27)$$

$$= c + \phi(Y_{t+1}) + \varepsilon_{t+2} - f_{t,2} \quad (6.28)$$

$$= c + \phi c + \phi \varepsilon_{t+1} + \phi Y_t + \varepsilon_{t+2} - f_{t,2} \quad (6.29)$$

$$= c + \phi c + \phi \varepsilon_{t+1} + \phi Y_t + \varepsilon_{t+2} - \mathbb{E}[Y_{t+2}|I_t] - \frac{a\sigma_{t+2|t}^2}{2} \quad (6.30)$$

$$= \phi \varepsilon_{t+1} + \varepsilon_{t+2} - \frac{a\sigma_{t+2|t}^2}{2} \quad (6.31)$$

Note that for every $h > 0$, the term $\sigma_{t+h|t}$ is constant conditioned on I_t .

$$\mathbb{E}[e_{t+2,t}|I_t] = -\frac{a\sigma_{t+2|t}^2}{2} \quad (6.32)$$

$$\mathbb{V}[e_{t+2,t}|I_t] = (1 + \phi^2)\sigma_\varepsilon^2 \quad (6.33)$$

7 Trends

8 Vector Auto-regression Model

9 Vector Error Correction Model

10 Volatility I

11 Volatility II

12 Volatility III: Applications

12.1 Risk Management

Definition 12.1. The **α -Value at Risk (VaR)**, $r_t^{VaR(\alpha)}$, is the α -quantile of r_t .

Remark 12.1 (Interpretation). $r_t^{VaR(\alpha)}$ is the value in the domain of r_t such that *the possibility of obtaining an equal or smaller value than r_t is $\alpha\%$* .

$$\mathbb{P}[r_t \leq r_t^{VaR(\alpha)}] = \alpha \quad (12.1)$$

Model Setup

$$r_t = \mu_{t|t-1} + \sigma_{t|t-1} z_t \quad (12.2)$$

$$z_t \sim \mathcal{N}(0, 1) \quad (12.3)$$

$$\mu_{t|t-1} \sim \text{ARMA} \quad (12.4)$$

$$\sigma_{t|t-1} \sim \text{GARCH} \quad (12.5)$$

$$\implies r_t \sim \mathcal{N}(\mu_{t|t-1}, \sigma_{t|t-1}^2) \quad (12.6)$$

$$\implies r_t^{VaR(\alpha)} = \mu_{t|t-1} + \Phi^{-1}(\alpha) \sigma_{t|t-1} \quad (12.7)$$

Definition 12.2. The **expected shortfall** measures the average value of such loss,

$$ES(\alpha) := \mathbb{E}[r_t | r_t < r_t^{VaR(\alpha)}] \quad (12.8)$$

Lemma 12.1 (Expected of Truncated Normal Distribution).

$$X \sim \mathcal{N}(\mu, \sigma^2) \quad (12.9)$$

$$\implies \mathbb{E}[X | a < X < b] = \mu + \sigma \frac{\phi(\frac{a-\mu}{\sigma}) - \phi(\frac{b-\mu}{\sigma})}{\Phi(\frac{b-\mu}{\sigma}) - \Phi(\frac{a-\mu}{\sigma})} \quad (12.10)$$

$$= \mu + \sigma \frac{\phi(\alpha) - \phi(\beta)}{\Phi(\beta) - \Phi(\alpha)} \quad (12.11)$$

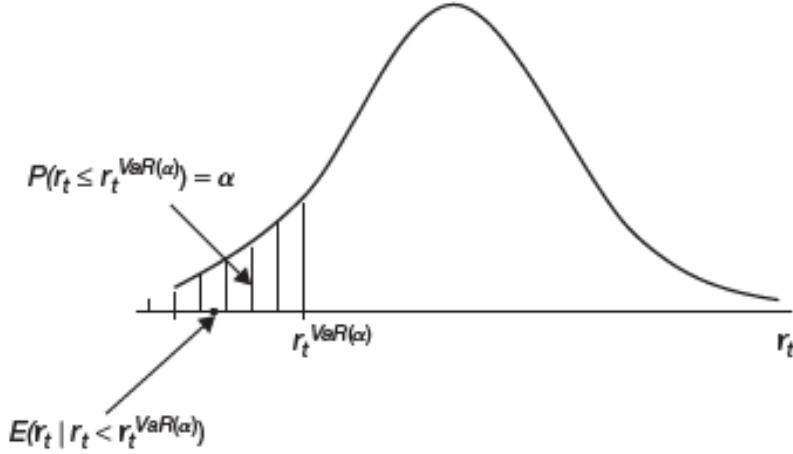


Figure 12.1: VaR and Expected Shortfall

Proposition 12.1. Computing the *expected shortfall* with normality assumption.

$$r_t \sim \mathcal{N}(\mu_{t|t-1}, \sigma_{t|t-1}^2) \quad (12.12)$$

$$\implies \mathbb{E}[r_t | r_t < r_t^{VaR(\alpha)}] = \mu_{t|t-1} + \sigma_{t|t-1} \frac{-\phi\left(\frac{r_t^{VaR(\alpha)} - \mu_{t|t-1}}{\sigma_{t|t-1}}\right)}{\Phi\left(\frac{r_t^{VaR(\alpha)} - \mu_{t|t-1}}{\sigma_{t|t-1}}\right)} \quad (\text{by equation (7.7)}) \quad (12.13)$$

$$= \mu_{t|t-1} - \sigma_{t|t-1} \frac{\phi(\Phi^{-1}(\alpha))}{\alpha} \quad (12.14)$$

with R-code `coef <- dnorm(pnorm(alpha))/alpha.`

12.2 Portfolio Allocation

The Problem Suppose there are two assets (can be easily extend to the general case, let N denote the set of assets). Returns associated with those assets have mean μ_i and variance σ_i^2 for each $i \in N$. For given level of $\bar{\mu}_p$, one has to choose $(w_i)_{i \in N}$ such that the risk, σ_p^2 , is minimized.

Assumption 12.1.

$$\text{Cov}(r_i, r_j) = 0 \quad \forall i \neq j \in N \quad (12.15)$$

Solution

$$\min_{(w_i)_{i \in N}} \sigma_p^2 \equiv \sum_{i \in N} w_i^2 \sigma_i^2 \quad (12.16)$$

$$\text{s.t. } \bar{\mu}_p = \sum_{i \in N} w_i \mu_i \quad (12.17)$$

$$\implies w_i^* = \frac{\mu_i / \sigma_i^2}{\sum_{j \in N} \mu_j / \sigma_j^2} \bar{\mu}_p \quad (12.18)$$

Remark 12.2. The means and variances of assets can be estimated *conditionally on t* using the hybrid ARMA – GARCH model.

12.3 Asset Pricing: Classical Capital Asset Pricing Model

Definition 12.3. A **market portfolio** is a theoretical bundle of investments that includes every type of asset available in the world financial market, with each asset weighted in proportion to its total presence in the market.

Proposition 12.2.

$$\mathbb{E}[r_i] = r_f + \beta_i \mathbb{E}[r_m - r_f] \quad (12.19)$$

$$\beta_i := \frac{\text{Cov}(r_i, r_m)}{\text{Var}(r_m)} \equiv \frac{\rho_{im}\sigma_i\sigma_m}{\sigma_m^2} \quad (12.20)$$

and if $\beta_i > 1$, the asset i is more *risky* than the market risk. In practice, β_i is estimated with ρ_{im} estimated directly from samples and $\sigma_{i,t|t-1}^2, \sigma_{mz,t|t-1}^2$ estimated using *GARCH*.

13 Nonlinear Models

13.1 Threshold Auto-Regression (TAR)

Definition 13.1. Given data structure containing **main/target series**

$$\{y_t\} \quad (13.1)$$

and **threshold/activation variable series**

$$\{x_t\} \quad (13.2)$$

To construct a $TAR(p)$ model with r regimes,

- (i) Partitioning the range of X_t (typically \mathbb{R}) into r disjoint sets $\{R_i\}_{i=1}^r$.
- (ii) Construct model using indicator functions

$$Y_t = \sum_{i=1}^r \mathbf{1}\{x_{\textcolor{red}{t}} \in R_i\} \underbrace{\left(\phi_{i0} + \sum_{j=1}^p \phi_{ij} Y_{t-j} + \varepsilon_{it} \right)}_{\text{Regim } i \text{ AR}(p) \text{ Model}} \quad (13.3)$$

Definition 13.2. If the threshold/activation variable in a TAR model is any *lagged variation of the main/target series*, then the TAR model is called **self-exciting**.

13.2 Test Significance of Regimes

Remark 13.1. To test the significance of multiple regimes, we use conventional hypothesis testing for significance of coefficients in multiple regression models.

Example 13.1. To test the significance (whether it is necessary to include it) of two regimes (but with same error term) here

$$Y_t = \mathbf{1}\{Y_{t-1} \geq 0\} (\phi_0 + \phi_1 Y_{t-1}) + \mathbf{1}\{Y_{t-1} < 0\} (\phi'_0 + \phi'_1 Y_{t-1}) + \varepsilon_t \quad (13.4)$$

$$D_t := \mathbf{1}\{Y_{t-1} \geq 0\} \quad (13.5)$$

$$\implies Y_t = D_t (\phi_0 + \phi_1 Y_{t-1}) + (1 - D_t) (\phi'_0 + \phi'_1 Y_{t-1}) + \varepsilon_t \quad (13.6)$$

$$\implies Y_t = \phi'_0 + \phi'_1 Y_{t-1} + (\underbrace{\phi_0 - \phi'_0}_{\Delta\phi_0}) D_t + (\underbrace{\phi_1 - \phi'_1}_{\Delta\phi_1}) D_t Y_{t-1} + \varepsilon_t \quad (13.7)$$

And test the hypothesis

$$H_0 := \Delta\phi_0 = 0 \wedge \Delta\phi_1 = 0 \text{ model is linear} \quad (13.8)$$

$$H_1 := \neg H_0 \quad (13.9)$$