

# ECO374 Winter 2019

## Forecasting and Time Series Econometrics

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## Contents

<b>1 Introduction and Statistics Review</b>	<b>2</b>
1.1 Definitions . . . . .	2
1.2 Multiple Linear Regression . . . . .	2
<b>2 Statistics and Time Series</b>	<b>3</b>
2.1 Stochastic Processes . . . . .	3
2.2 Auto-correlations . . . . .	3
2.3 Test for Auto-correlation . . . . .	5
2.4 Causality and Invertibility (Optional) . . . . .	5
2.4.1 Causality . . . . .	5
2.4.2 Invertibility . . . . .	6
<b>3 Forecasting Tools</b>	<b>6</b>
3.1 Information Set . . . . .	6
3.2 Forecast Horizon . . . . .	7
3.2.1 Forecasting Environments: <i>Recursive</i> . . . . .	7
3.2.2 Forecasting Environments: <i>Rolling</i> . . . . .	7
3.2.3 Forecasting Environments: <i>Fixed</i> . . . . .	8
3.3 Loss Function . . . . .	8
3.4 Optimal Forecast . . . . .	9
<b>4 Moving Average Process</b>	<b>10</b>
4.1 Wold Decomposition Theorem . . . . .	10
4.2 Moving Average Process . . . . .	10
4.3 Forecasting with MA(1) . . . . .	12
4.3.1 Forecasting with Horizon $h = 1$ . . . . .	12
4.3.2 Forecasting with Horizon $h = 2$ . . . . .	12
4.4 Properties of MA(2) Process . . . . .	12

<b>5 Auto-Regression Process and Seasonality</b>	<b>13</b>
5.1 AR Process . . . . .	13
5.1.1 Forecasting with AR(1) and $h = 1$ . . . . .	13
5.1.2 Forecasting with AR(1) and $h = s > 1$ . . . . .	14
5.1.3 Forecasting with AR(1) and $h \rightarrow \infty$ . . . . .	14
5.1.4 Forecasting with AR(2) process . . . . .	14
5.1.5 AP( $p$ ) process . . . . .	15
5.2 Procedures of Forecasting with Autoregressive Models . . . . .	16
5.3 Seasonality . . . . .	16
5.3.1 Deterministic Seasonality . . . . .	16
5.3.2 Stochastic Seasonality . . . . .	16
<b>6 Model Assessment and Asymmetric Loss</b>	<b>17</b>
6.1 Model Assessment . . . . .	17
6.2 Asymmetric Loss . . . . .	18
<b>7 Trends</b>	<b>19</b>
7.1 Deterministic Trend . . . . .	19
7.2 Model Selection . . . . .	20
7.3 Stochastic Trend . . . . .	20
7.4 Unit Root Test . . . . .	21
7.5 Optimal Forecast . . . . .	22
<b>8 Vector Auto-regression</b>	<b>23</b>
8.1 VAR Model . . . . .	23
8.2 Granger Causality . . . . .	23
8.3 Impulse-Response Function . . . . .	23
8.4 Forecasting . . . . .	24
<b>9 Vector Error Correction Model</b>	<b>24</b>
9.1 Cointegration . . . . .	24
9.2 Tests for Cointegrations . . . . .	24
9.3 Vector Error Correction for Short-term Dynamics . . . . .	24
9.4 Forecasting . . . . .	25
<b>10 Volatility I</b>	<b>25</b>
10.1 Higher-order Moments . . . . .	25
10.2 Moving Average on $\{r_t\}$ . . . . .	26
10.3 Simple Exponential Smoothing (SES) on $\{y_t\}$ . . . . .	26
10.4 Exponentially Weighted Moving Average (EWMA) . . . . .	27
<b>11 Volatility II</b>	<b>27</b>
11.1 Heteroskedasticity . . . . .	27
11.2 Autoregressive Conditional Heteroskedasticity (ARCH) . . . . .	27
11.3 Generalize Autoregressive Conditional Heteroskedasticity (GARCH) . . . . .	28

<b>12 Volatility III: Applications</b>	<b>29</b>
12.1 Risk Management . . . . .	29
12.2 Portfolio Allocation . . . . .	30
12.3 Asset Pricing: Classical Capital Asset Pricing Model . . . . .	30
<b>13 Nonlinear Models</b>	<b>31</b>
13.1 Threshold Auto-Regression (TAR) . . . . .	31
13.2 Test Significance of Regimes . . . . .	31
13.3 Smooth Transition Autoregressive Model (STAR) . . . . .	32
13.4 Markov Switching Model . . . . .	32
<b>14 Appendix</b>	<b>33</b>
14.1 A list of hypothesis tests in this course . . . . .	33

# 1 Introduction and Statistics Review

## 1.1 Definitions

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

$$\mathbb{E}[X^k] \quad (1.1)$$

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

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

**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

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

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

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

## 1.2 Multiple Linear Regression

**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) **Homoscedasitcity**

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

(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  $\beta_j$ .

**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  $(\Omega, \mathcal{F}, P)$ .

$$\{Y_t\}_{t \in \mathcal{T}} = Y_1, \dots, Y_T \quad (2.1)$$

so each  $Y_t$  in  $\{Y_t\}$  collection is associated with a density function, conditioned on time  $t$ .

**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**<sup>1</sup> of the stochastic process.

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

Such realization is called is 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 *exactly same probability density function*.

**Definition 2.5.** 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 2.6.** 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)  $\mathbb{E}[Y_t] = \mu \forall t$  constant;
- (ii)  $\mathbb{V}[Y_t] = \sigma^2 < \infty \forall t$  constant (lag 0 covariance);
- (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 2.7.** 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

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

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

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

---

<sup>1</sup>It's also called a **trajectory** or an **outcome**

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

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

**Proposition 2.1.** By the symmetry of covariance,

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

**Definition 2.8.** The **auto-correlation coefficient** of order  $k$  is given by

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

**Definition 2.9.** 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

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

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

**Proposition 2.2.** Note that

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

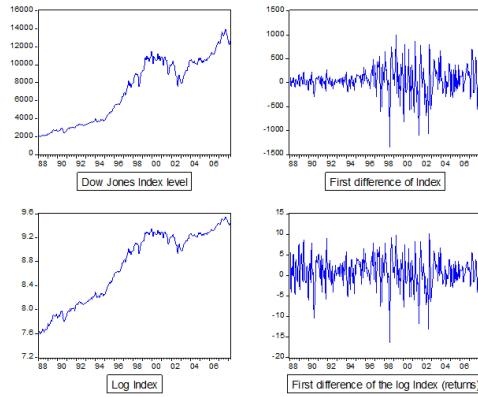
so the ACF for stationary process can be simplified to a mapping

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

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

**Proposition 2.3** (Transformations). For a non-stationary stochastic process  $\{Y_t\}$ ,

- $\{\Delta Y_t\}$  becomes *first order weakly stationary*;
- and  $\{\Delta \log(Y_t)\}$  becomes *second order weakly stationary (covariance stationary)*.



**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.** Partial auto-correlation can be interpreted as the estimated coefficients when regressing  $Y_t$  on its lagged values.

**Remark 2.4.** AR and MA signatures on ACF and PACF plot.<sup>2</sup>

processes	ACF ( $\rho$ )	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

**Multiple Auto-correlation Test** To test single auto-correlation with

$$H_0 : \rho_k = 0 \quad (2.13)$$

we can use usual t-statistic.

**Multiple Auto-correlation Test** While testing the joint hypothesis

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_k = 0 \quad (2.14)$$

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

$$Q_k = T(T+1) \sum_{j=1}^k \frac{\hat{\rho}_j^2}{T-j} \sim \chi_k^2 \quad (2.15)$$

## 2.4 Causality and Invertibility (Optional)

### 2.4.1 Causality

**Definition 2.10** (Causality). An ARMA( $p, q$ ) process  $\{Y_t\}$  with

$$\Phi(L)Y_t = \Theta(L)\varepsilon_t \quad (2.16)$$

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

$$Y_t = \Psi(L)\varepsilon_t \text{ with } \psi_0 = 1 \quad (2.17)$$

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  $\{\varepsilon_t\}$ .

---

<sup>2</sup>Zero here means statistically insignificant.

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

$$\Phi(L)Y_t = \Theta(L)\varepsilon_t \quad (2.18)$$

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  $\Psi$  are then uniquely defined by identity

$$\Psi(z) = \sum_{j=0}^{\infty} \psi_j z^j = \frac{\Theta(z)}{\Phi(z)} \quad (2.19)$$

## 2.4.2 Invertibility

**Definition 2.11** (Invertibility). An ARMA( $p, q$ ) process for  $\{Y_t\}$  satisfying

$$\Phi(L)Y_t = \Theta(L)\varepsilon_t \quad (2.20)$$

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

$$\varepsilon_t = \sum_{j=0}^{\infty} \pi_j L^j Y_t \quad (2.21)$$

**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

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

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

$$\Pi(z) = \sum_{j=0}^{\infty} \pi_j z^j = \frac{\Phi(z)}{\Theta(z)} \quad (2.23)$$

## 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  $(y_{t_1}, y_{t_2}, \dots, y_{t_n})$  such that  $t_n \leq t$  so the information set is *certain* at time  $t$ .

**Definition 3.2.** A **forecast**  $f_{t,h}$  is 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. Therefore, as a result, the forecast  $f_{t,h}$  converges when  $h \rightarrow \infty$ .

**Remark 3.2.** Non-stationary processes are **long-memory processes** and older information is as relevant for the forecast as more recent information (e.g., including trends).

### 3.2.1 Forecasting Environments: *Recursive*

- (i) Re-train and predict with *updated* information set;
- (ii) Advantageous if model is *stable over time*;
- (iii) Not robust to *structural break*.

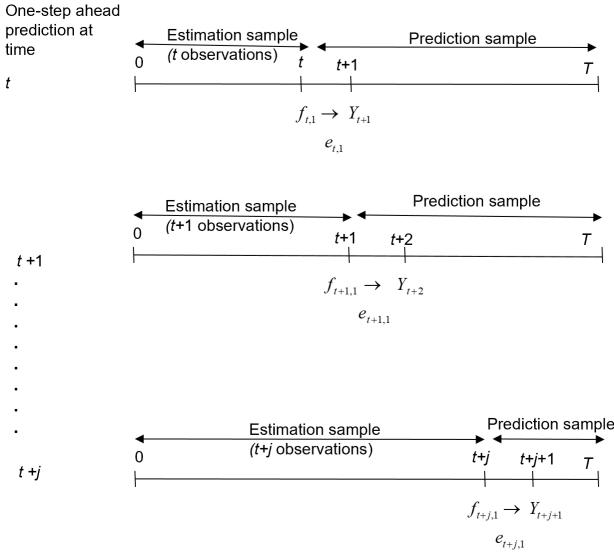


Figure 3.1: Recursive Forecasting Scheme

### 3.2.2 Forecasting Environments: *Rolling*

- (i) Re-train and predict with *updated but fixed-size* information set;
- (ii) Robust against *structural breaks*;
- (iii) Not fully exploit information available.

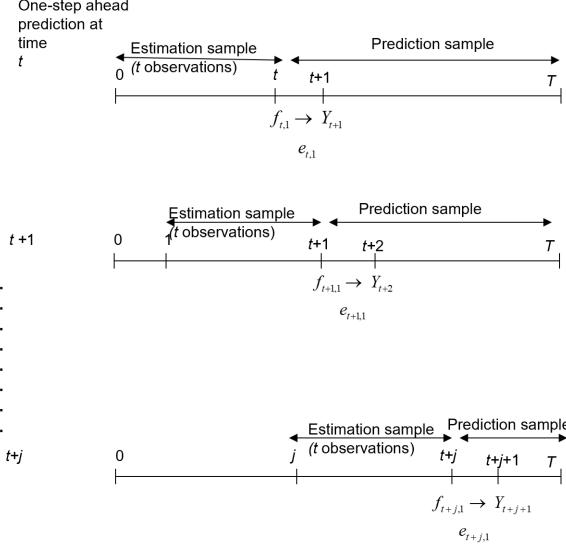


Figure 3.2: Rolling Forecasting Scheme

### 3.2.3 Forecasting Environments: *Fixed*

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

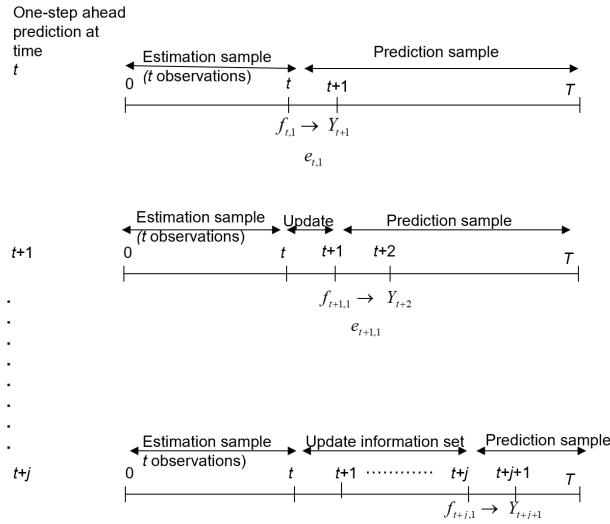


Figure 3.3: Fixed Forecasting Scheme

## 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)  $\forall e \in \mathbb{R}, L(e) \geq 0$ <sup>3</sup>;
- (iii)  $L$  is monotonically increasing in the norm of forecast error.

**Example 3.1** (Symmetric Loss Functions).

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

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

**Example 3.2** (Asymmetric Loss Functions).

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

$$L(e) = a|e|\mathbb{1}\{e \geq 0\} + b|e|\mathbb{1}\{e < 0\} \quad \text{Lin-lin Function} \quad (3.5)$$

### 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**

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

**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

$$f_{t,h}^* := \mu_{t+h|t} = \mathbb{E}[Y_{t+h}|I_t] \quad (3.8)$$

*Proof.*

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

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

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

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

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

■

**Remark 3.3.** Above proof for optimal forecasting does not depends on the specific distribution of  $Y_t$ .

---

<sup>3</sup>Since 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.

## 4 Moving Average Process

### 4.1 Wold Decomposition Theorem

**Theorem 4.1** (Wold Decomposition Theorem). Every covariance stationary stochastic process  $\{Y_t\}$  with finite positive variance has an unique linear representation.

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

where

- (i)  $\{V_t\}$  is a *deterministic component* (e.g. trend or cycle);
- (ii)  $\varepsilon_t \sim \text{WN}(0, \sigma^2)$  is the *stochastic component*;
- (iii)  $\psi_0 = 1^4$  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

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

**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,

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

**Corollary 4.2.** The Wold decomposition guarantees that there always exists a *finite linear model* that can represent the dynamics of a covariance stationary process.

### 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 the series of innovations.

---

<sup>4</sup>We can always normalize  $\psi_0$  to 1.

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

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

*Proof Idea.* Taylor's Series. ■

**Remark 4.1.** MA process is always *causal* by definition.

**Definition 4.3.** MA(1) process takes the form of

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

**Unconditional Moments of MA(1)** where  $\mu :=$  unconditional mean.

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

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

### Auto-covariance

$$\gamma_0 = \mathbb{V}[Y_t] = (1 + \theta^2) \sigma_\varepsilon^2 \quad (4.10)$$

$$\gamma_1 = \mathbb{E}[(Y_t - \mu)(Y_{t-1} - \mu)] = \mathbb{E}[(\varepsilon_t + \theta \varepsilon_{t-1})(\varepsilon_{t-1} + \theta \varepsilon_{t-2})] = \theta \sigma_\varepsilon^2 \gamma_k = 0 \quad \forall k > 1 \quad (4.11)$$

### Auto-correlation

$$\rho_1 = \frac{\gamma_1}{\gamma_0} = \frac{\theta}{1 + \theta^2} \quad (4.12)$$

$$\rho_k = 0 \quad \forall k > 1 \quad (4.13)$$

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

*Inverting.* Let

$$Y_t = \mu + \varepsilon_t + \theta \varepsilon_{t-1} \quad (4.14)$$

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

$$Y_t = \mu + \varepsilon_t + \theta \varepsilon_{t-1} \implies Y_t - \mu = (1 + \theta L) \varepsilon_t \quad (4.15)$$

$$\implies \frac{Y_t - \mu}{1 - (-\theta L)} = \varepsilon_t \implies \varepsilon_t = (Y_t - \mu) \sum_{j=0}^{\infty} (-\theta L)^j \quad (4.16)$$
■

**Equivalence** note that for MA(1) process,

$$r_1 = \rho_1 = \frac{\theta}{1 + \theta^2} \quad (4.17)$$

and for any  $\theta$ ,  $\frac{1}{\theta}$  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 4.2.** If the MA process is invertible, we can always find an autoregressive representation in which the present is a function of the past innovations.

**Remark 4.3.** The value of  $\varepsilon_t$  is retrieved from dataset  $\{y_t\} \subset I_t$  using the AR representation from the invertibility of MA process.

### 4.3 Forecasting with MA(1)

#### 4.3.1 Forecasting with Horizon $h = 1$

**Point estimate**

$$f_{t,1} = \mathbb{E}[Y_{t+1}|I_t] = \mathbb{E}[\mu + \theta\varepsilon_t + \varepsilon_{t+1}|I_t] = \mu + \theta\varepsilon_t \quad (4.18)$$

**Forecasting error**

$$e_{t,1} = Y_{t+1} - f_{t,1} = \varepsilon_{t+1} \quad (4.19)$$

**Forecasting uncertainty**

$$\sigma_{t+1|t}^2 = \mathbb{V}[Y_{t+1}|I_t] = \mathbb{E}[\varepsilon_{t+1}^2|I_t] = \sigma_\varepsilon^2 \quad (4.20)$$

**Density forecast** assuming *normality* of  $\varepsilon$ . Confidence interval can be computed using the density forecast.

$$\mathcal{F} \equiv \mathcal{N}(\mu_{t+1|t}, \sigma_{t+1|t}^2) \mu_{t+1|t} = \mu + \theta\varepsilon_t \sigma_{t+1|t}^2 = \sigma_\varepsilon^2 \quad (4.21)$$

#### 4.3.2 Forecasting with Horizon $h = 2$

**Point estimate**

$$f_{t,2} = \mathbb{E}[Y_{t+2}|I_t] = \mathbb{E}[\mu + \theta\varepsilon_{t+1} + \varepsilon_{t+2}|I_t] = \mu \quad (4.22)$$

**Forecasting error**

$$Y_{t+2} - f_{t,2} = \theta\varepsilon_{t+1} + \varepsilon_{t+2} \quad (4.23)$$

**Forecasting Uncertainty**

$$\sigma_{t+2|t}^2 \equiv \mathbb{V}[Y_{t+2}|I_t] = (1 + \theta^2)\sigma_\varepsilon^2 \quad (4.24)$$

**Density forecast**

$$\mathcal{F} = \mathcal{N}(\mu, (1 + \theta^2)\sigma_\varepsilon^2) \quad (4.25)$$

**Remark 4.4.** Since for any  $h > 1$ , MA(1) only generates the unconditional mean  $\mu$  as the point estimate, we say MA(1) process is **short memory**.

### 4.4 Properties of MA(2) Process

**Model**

$$Y_t = \mu + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} \quad (4.26)$$

**Unconditional Moments**

$$\mathbb{E}[Y_t] = \mu \mathbb{V}[Y_t] = (1 + \theta_1^2 + \theta_2^2)\sigma_\varepsilon^2 \quad (4.27)$$

## Auto-covariance

$$\gamma_0 = \mathbb{V}[Y_t] = (1 + \theta_1^2 + \theta_2^2)\sigma_\varepsilon^2 \quad (4.28)$$

$$\gamma_1 = (\theta_1 + \theta_1\theta_2) \quad (4.29)$$

$$\sigma_\varepsilon^2\gamma_2 = \theta_2\sigma_\varepsilon^2 \quad (4.30)$$

## Auto-correlation

$$\rho_1 \equiv \frac{\gamma_1}{\gamma_0} = \frac{\theta_1 + \theta_1\theta_2}{1 + \theta_1^2 + \theta_2^2} \quad (4.31)$$

$$\rho_2 \equiv \frac{\gamma_2}{\gamma_0} = \frac{\theta_2}{1 + \theta_1^2 + \theta_2^2} \quad (4.32)$$

## Optimal Forecasting

$$f_{t,1} = \mu + \theta_1\varepsilon_t + \theta_2\varepsilon_{t-1} \quad (4.33)$$

$$f_{t,2} = \mu + \theta_2\varepsilon_t \quad (4.34)$$

$$f_{t,h} = \mu \quad \forall h > 2 \quad (4.35)$$

# 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

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

**Remark 5.1.** In AR(1) process, ACF decays exponentially to zero, faster for smaller  $\phi$ .

**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  $\phi$  is called the **persistence parameter**.

**Proposition 5.1.** AR(1) process is stationary if and only if  $|\phi| < 1$  (*all roots outside the unit circle*).

## 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 $h = 1$

**Assumption 5.1.** While examining the optimal forecast in this section, we are assuming the loss function is *symmetric*.

**Point estimate**

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

**Forecast variance(uncertainty)**

$$\mathbb{V}[Y_{t+1}|I_t] = \mathbb{V}[c + \phi Y_t + \varepsilon_{t+1}|I_t] = \sigma_\varepsilon^2 \quad (5.7)$$

**Density forecast**

$$\mathcal{F} = \mathcal{N}(c + \phi Y_t, \sigma_\varepsilon^2) \quad (5.8)$$

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

**Point estimate**

$$f_{t,s} = \mathbb{E}[Y_{t+s}|I_t] = c + \mathbb{E}[\phi Y_{t+s-1}|I_t] = (1 + \phi + \dots + \phi^{s-1})c + \phi^s Y_t \quad (5.9)$$

**Forecasting uncertainty**

$$\mathbb{V}[Y_{t+s}|I_t] = \mathbb{V}[\varepsilon_{t+s} + \phi \varepsilon_{t+s-1} + \dots + \phi^{s-1} \varepsilon_{t+1}|I_t] = \sum_{j=0}^{s-1} \phi^{2j} \sigma_\varepsilon^2 \quad (5.10)$$

**Remark 5.2.** 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 5.2.** For this subsection, assuming the AR(1) process is stationary, that's,  $|\phi| < 1$ .

**Point Estimate**

$$\lim_{h \rightarrow \infty} f_{t,h} = \frac{c}{1 - \phi} \quad (5.11)$$

**Forecasting Uncertainty**

$$\lim_{h \rightarrow \infty} \mathbb{V}[Y_{t+h}|I_t] = \frac{\sigma_\varepsilon^2}{1 - \phi^2} \quad (5.12)$$

**Remark 5.3.** 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

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \varepsilon_t \quad (5.13)$$

**Unconditional Moments**

$$\mathbb{E}[Y_t] = c + \phi_1 \mathbb{E}[Y_{t-1}] + \phi_2 \mathbb{E}[Y_{t-2}] \quad (5.14)$$

$$\implies \mu_Y = \frac{c}{1 - \phi_1 - \phi_2} \quad (5.15)$$

## Auto-covariance and Auto-correlation

$$\rho_1 = r_1 \quad (5.16)$$

$$r_2 = \phi_2 + \text{ sampling error} \quad (5.17)$$

**Optimal Forecasts**  $h = 1$

$$f_{t,1} = \mathbb{E}[Y_{t+1}|I_t] = \mathbb{E}[c + \phi_1 Y_t + \phi_2 Y_{t-1} + \varepsilon_{t+1}|I_t] \quad (5.18)$$

$$= c + \phi_1 Y_t + \phi_2 Y_{t-1} \quad (5.19)$$

$$e_{t,1} = \varepsilon_{t+1} \quad (5.20)$$

$$\sigma_{t+1|t}^2 = \mathbb{V}[Y_{t+1}|I_t] = \sigma_\varepsilon^2 \quad (5.21)$$

**Optimal Forecasts**  $h = 2$

$$f_{t,2} = \mathbb{E}[Y_{t+2}|I_t] = \mathbb{E}[c + \phi_1 Y_{t+1} + \phi_2 Y_t + \varepsilon_{t+2}|I_t] = c + \phi_1 \textcolor{red}{f}_{t,1} + \phi_2 Y_t \quad (5.22)$$

$$e_{t,2} = Y_{t+2} - f_{t,2} = \phi_1(Y_{t+1} - f_{t,1}) + \varepsilon_{t+2} = \phi_1 e_{t,1} + \varepsilon_{t+2} \quad (5.23)$$

$$\sigma_{t+2|t}^2 = \mathbb{V}[Y_{t+2}|I+t] = \phi_1^2 \sigma_{t+1|t}^2 + \sigma_\varepsilon^2 = (1 + \phi_1^2) \sigma_\varepsilon^2 \quad (5.24)$$

**Optimal Forecasts**  $h = s > 2$

$$f_{t,s} = \mathbb{E}[Y_{t+s}|I_t] = c + \phi_1 f_{t,s-1} + \phi_2 f_{t,s-2} \quad (5.25)$$

$$e_{t,s} = \phi_1(Y_{t+s-1} - f_{t,s-1}) + \phi_2(Y_{t+s-2} - f_{t,s-2}) + \varepsilon_{t+s} \quad (5.26)$$

$$= \phi_1 e_{t,s-1} + \phi_2 e_{t,s-2} + \varepsilon_{t+s} \quad (5.27)$$

$$\sigma_{t+s|t}^2 = \mathbb{V}[Y_{t+s}|I_t] = \mathbb{V}[e_{t,s}|I_t] = \phi_1 \sigma_{t+s-1|t}^2 + \phi_2 \sigma_{t+s-2|t}^2 + \sigma_\varepsilon^2 \quad (5.28)$$

**Remark 5.4.** AR(2) is still classified as *short memory processes* as

$$\lim_{s \rightarrow \infty} f_{t,s} = \mu \quad (5.29)$$

$$\lim_{s \rightarrow \infty} \sigma_{t+2|t}^2 = \sigma_Y^2 \quad (5.30)$$

### 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).

$$\textcolor{red}{f}_{t,1} = c + \sum_{j=1}^p \phi_j L^j Y_{t+1} \quad (5.31)$$

$$\textcolor{orange}{f}_{t,2} = c + \phi_1 \textcolor{red}{f}_{t,1} + \sum_{j=2}^p \phi_j L^j Y_{t+2} \quad (5.32)$$

$$\textcolor{blue}{f}_{t,3} = c + \phi_1 \textcolor{orange}{f}_{t,2} + \phi_2 \textcolor{red}{f}_{t,1} + \sum_{j=3}^p \phi_j L^j Y_{t+3} \quad (5.33)$$

$$f_{t,s} = c + \sum_{j=1}^p \phi_j f_{t,s-j} \quad \forall s > p \quad (5.34)$$

## 5.2 Procedures of Forecasting with Autoregressive Models

(i) Estimate  $\hat{\Phi}$  and  $\hat{\sigma}_\varepsilon^2$  and  $\hat{\mu}$  (unconditional mean).

(ii) Calculate  $\hat{c}$  (intercept) from  $\hat{\Phi}$  and  $\hat{\mu}$ .

$$\hat{c} = \hat{\mu}(1 - \sum_{j=1}^p \hat{\phi}_j) \quad (5.35)$$

(iii) Construct forecast  $f_{t,h}$  with **chain rule of forecasting**.

(iv) **Density forecast**, under normality assumption of  $\varepsilon$  is

$$\mathcal{N}(f_{t,h}, \hat{\sigma}_{t+h|t}^2) \quad (5.36)$$

(v) 95% confidence interval of forecasting is

$$(f_{t,h} \pm 1.96 \times \hat{\sigma}_{t+h|t}) \quad (5.37)$$

## 5.3 Seasonality

### 5.3.1 Deterministic Seasonality

**Definition 5.5.** The seasonality is **deterministic** if the seasonal component regressors are always exactly predictable.

**Remark 5.5.** To handle deterministic seasonality, just add those indicator terms into the regression.

### 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

$$Y_t = c + \phi_s Y_{t-s} + \phi_2 s + Y_{t-2s} + \cdots + \phi_{ps} Y_{t-ps} + \varepsilon_t \quad (5.38)$$

$$\Phi_p(L^s)Y_t = c + \varepsilon_t \quad (5.39)$$

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

$$Y_t = \mu + \Theta_q(L^s)\varepsilon_t \quad (5.40)$$

**Remark 5.6.** 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** (Combing ARMA and S-ARMA). Given ARMA

$$\Phi_p(L)Y_t = c + \Theta_q(L)\varepsilon_t \quad (5.41)$$

and S-ARMA

$$\Phi'_p(L^{s_1})Y_t = c + \Theta'_q(L^{s_2})\varepsilon_t \quad (5.42)$$

The combined model is given by **multiplying the lag polynomials**

$$\Phi_p(L)\Phi'_p(L^{s_1})Y_t = c + \Theta_q(L)\Theta'_q(L^{s_2})\varepsilon_t \quad (5.43)$$

## 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

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

**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

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

**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  $\mu$  and variance  $\sigma^2$ . 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.

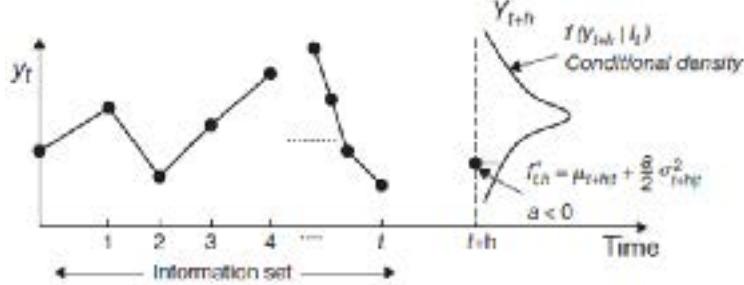


Figure 6.1: Illustration of the Optimal Forecast with Lin-Ex loss and  $a < 0$

**Forecasting** Assuming AR(1) process.

**Error with  $h = 1$**

$$e_{t+1,t} = c + \phi Y_t + \varepsilon_{t+1} - f_{t,1} = \varepsilon_{t+1} - \frac{a\sigma_{t+1|t}^2}{2} \quad (6.23)$$

$$\mathbb{E}[e_{t+1,t}] = -\frac{a\sigma_{t+1|t}^2}{2} \quad (6.24)$$

$$\mathbb{V}[e_{t+1,t}|I_t] = \sigma_\varepsilon^2 \quad (6.25)$$

**Error with  $h = 2$**

$$e_{t+2,t} = Y_{t+2} - f_{t,2} \quad (6.26)$$

$$= c + \phi(Y_{t+1}) + \varepsilon_{t+2} - f_{t,2} \quad (6.27)$$

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

$$= c + \phi c + \phi \varepsilon_{t+1} + \phi Y_t + \varepsilon_{t+2} - \mathbb{E}[Y_{t+2}|I_t] - \frac{a\sigma_{t+2|t}^2}{2} \quad (6.29)$$

$$= \underbrace{\phi \varepsilon_{t+1} + \varepsilon_{t+2} - \frac{a\sigma_{t+2|t}^2}{2}}_{\text{forecasting error is not mean-zero}} \quad (6.30)$$

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

$$\mathbb{E}[e_{t+2,t}|I_t] = -\frac{a\sigma_{t+2|t}^2}{2} \quad (6.31)$$

$$\mathbb{V}[e_{t+2,t}|I_t] = (1 + \phi^2)\sigma_\varepsilon^2 \quad (6.32)$$

## 7 Trends

**Definition 7.1.** Time series is called **non-stationary** if it contains a **trend**.

### 7.1 Deterministic Trend

**Definition 7.2.** Deterministic trends take form of

$$Y_t = g(t) + \varepsilon_t \quad (7.1)$$

where  $f$  is a function capturing the *shape of trend*.

**Remark 7.1.** The error term in trend modelling is always additive.

**Example 7.1.** Common deterministic trends

$$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \cdots + \varepsilon_t \text{ (polynomial)} \quad (7.2)$$

$$Y_t = e^{\beta_0 + \beta_1 t + \beta_2 t^2 + \cdots} + \varepsilon_t \text{ (exponential)} \quad (7.3)$$

$$Y_t = \frac{1}{\beta_0 + \beta_1 t + \beta_2 t^2 + \cdots} + \varepsilon_t \text{ (logistic/inverse-polynomial)} \quad (7.4)$$

**Remark 7.2.** With trend in mean, the unconditional mean depends on time  $t$ , and thus the process is not covariance stationary, we call such stochastic process **trend-stationary**. For such process, the first order

- Unconditional mean  $= \mathbb{E}[Y_t] \equiv g(t)$
- Variance  $\mathbb{V}[Y_t] = \sigma_\varepsilon^2$
- Auto-covariance  $\gamma_k = 0 \forall k \neq 0$
- Auto-correlation  $\rho_k = 0 \forall k \neq 0$
- Optimal forecast  $f_{t,h} = g(t+h) \forall h$
- Forecast error  $e_{t,h} = \varepsilon_{t+h} \forall h$
- Density forecast  $f_{t,h} \sim \mathcal{N}(g(t+h), \sigma_\varepsilon^2) \forall h$

**Remark 7.3.** After accounting for the non-stationary trend, the remainder of the model is stationary and we could replace  $\varepsilon_t$  with any ARMA model specification.

## 7.2 Model Selection

**Remark 7.4.** The specification for the deterministic trend is selected based on minimization of the AIC/BIC.

## 7.3 Stochastic Trend

**Definition 7.3.** A **stochastic trend** is the result of *accumulation over time of random shocks/innovations* of the form

$$Y_t = \sum_{j=0}^{t-1} \varepsilon_{t-j} \quad (7.5)$$

where  $\varepsilon_{t-j} \sim \mathcal{N}(0, \sigma_\varepsilon^2) \forall j$ . Note that such model is equivalent to an AR(1) model with  $\phi_0 = 0, \phi_1 = 1$ .

**Example 7.2** (Random walk without a drift).

$$Y_t = Y_{t-1} + \varepsilon_t = \sum_{\tau=0}^t \varepsilon_\tau + Y_0 \quad (7.6)$$

$$\mu = 0 \quad (7.7)$$

$$\sigma_Y^2 = t\sigma_\varepsilon^2 \quad (7.8)$$

$$\gamma_k = (t - k)\sigma_\varepsilon^2 \quad (7.9)$$

$$\rho_k = \frac{t - k}{\sqrt{t(t - k)}} = \sqrt{\frac{t - k}{t}} \rightarrow 1 \text{ as } t \rightarrow \infty \quad (7.10)$$

**Remark 7.5.** AR(2) model with  $\phi_1 + \phi_2 = 1$  can also generate a random walk. This can be generalized to AR( $p$ ) for any order  $p$ . Moreover, any non-stationary AR( $p$ ) process generates a random walk.

**Example 7.3** (Random walk without a drift).

$$Y_t = c + Y_{t-1} + \varepsilon_t = ct + \sum_{\tau=0}^t \varepsilon_\tau + Y_0 \quad (7.11)$$

$$\mu = ct \quad (7.12)$$

$$\sigma_Y^2 = t\sigma_\varepsilon^2 \quad (7.13)$$

$$\gamma_k = (t - k)\sigma_\varepsilon^2 \quad (7.14)$$

$$\rho_k = \frac{t - k}{\sqrt{t(t - k)}} = \sqrt{\frac{t - k}{t}} \rightarrow 1 \text{ as } t \rightarrow \infty \quad (7.15)$$

**Remark 7.6.** Difference between deterministic trend model and random walk.

model	deterministic trend	random walk
mean	changing	constant
variance	constant	changing

## 7.4 Unit Root Test

### Dickey-Fuller test for AR(1)

$$H_0 : \phi = 1 \text{ non-stationary} \quad (7.16)$$

$$H_1 : \phi < 1 \text{ stationary} \quad (7.17)$$

and the test statistic

$$z = \frac{\hat{\phi} - 1}{\sigma_{\hat{\phi}}} \quad (7.18)$$

follows **Dickey-Fuller distribution**.

**Remark 7.7.** Dickey-Fuller test is most useful in small samples ( $T < 100$ ).

- Type I: if non-stationary.

$$H_0 : Y_t = Y_{t-1} + \varepsilon_t \quad (7.19)$$

$$H_1 : Y_t = \phi Y_{t-1} + \varepsilon_t \quad (7.20)$$

- Type II: if *unconditional mean* presents.

$$H_0 : Y_t = Y_{t-1} + \varepsilon_t \quad (7.21)$$

$$H_1 : Y_t = \textcolor{red}{c} + \phi Y_{t-1} + \varepsilon_t \quad (7.22)$$

- Type III: if *linear trend* presents.

$$H_0 : Y_t = c + Y_{t-1} + \varepsilon_t \quad (7.23)$$

$$H_1 : Y_t = c + \textcolor{red}{at} + \phi Y_{t-1} + \varepsilon_t \quad (7.24)$$

## 7.5 Optimal Forecast

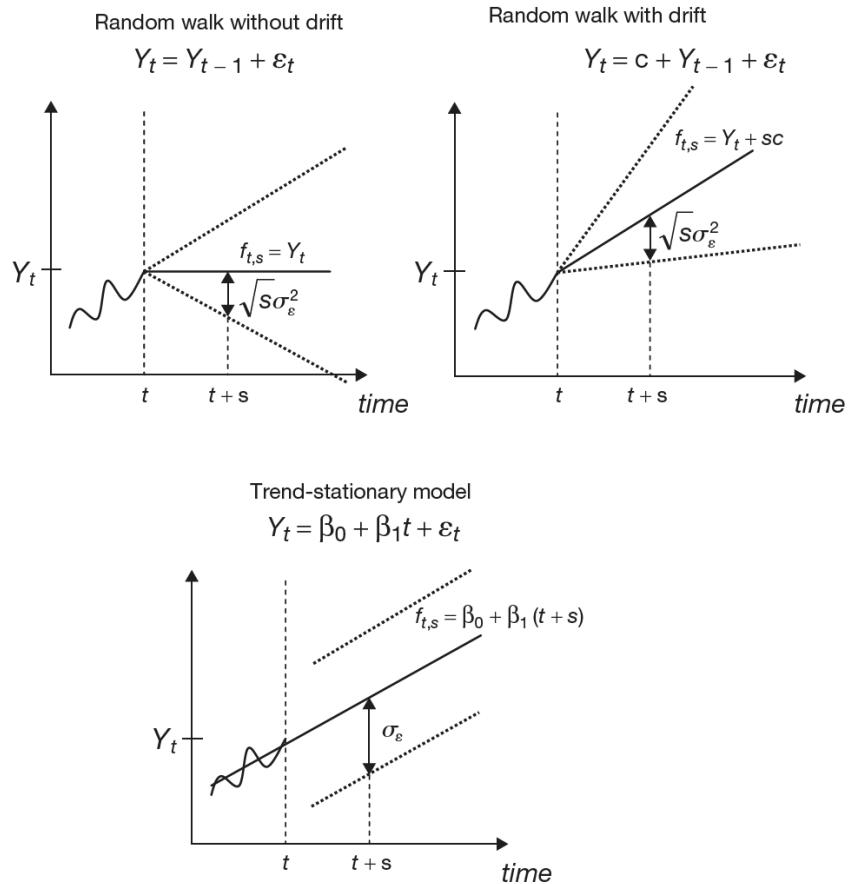


Figure 7.1: Optimal forecast for different trends

## 8 Vector Auto-regression

### 8.1 VAR Model

**Definition 8.1.**

$$\mathbf{V}_t := \begin{pmatrix} Y_t \\ X_t \end{pmatrix} \quad (8.1)$$

$$\mathbf{V}_t = \boldsymbol{\gamma}_0 + \Gamma_1 \mathbf{V}_{t-1} + \dots + \Gamma_p \mathbf{V}_{t-p} + \boldsymbol{\varepsilon}_t \quad (8.2)$$

where  $\Gamma_j$  are  $2 \times 2$  matrices, and  $\boldsymbol{\gamma}_0$  and  $\boldsymbol{\varepsilon}_t$  are vectors.

**Remark 8.1.** Note that the error terms (components in  $\boldsymbol{\varepsilon}_t$ ) can be correlated.

**Remark 8.2.** We assume the error terms follows multivariate Gaussian distribution

$$\boldsymbol{\varepsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}) \quad (8.3)$$

**Remark 8.3.** Model selection based on ACF and PACF can become quite cumbersome in the multivariate environment. Therefore we will not consider the MA component, and use information criteria (AIC) to select  $p$  in the VAR model specification.

### 8.2 Granger Causality

**Definition 8.2.** The process  $\{X_t\}$  is said to **Granger cause** the process  $\{Y_t\}$  if lagged values of  $X_t$  help predicting  $Y_t$  beyond the information contained in the lagged values of  $Y_t$ .

**Remark 8.4.** Granger causality measures predictive power (statistical association) and has nothing to do with the concept of causality

**Remark 8.5** (Granger Causality Test). partial  $F$ -test for the VAR( $p$ ) model

$$Y_t = c_1 + \alpha_{11} Y_{t-1} + \dots + \alpha_{1p} Y_{t-p} \quad (8.4)$$

$$+ \beta_{11} X_{t-1} + \dots + \beta_{t-p} X_{t-p} + \varepsilon_{1t} \quad (8.5)$$

$$X_t = c_2 + \alpha_{21} Y_{t-1} + \dots + \alpha_{2p} Y_{t-p} \quad (8.6)$$

$$+ \beta_{21} X_{t-1} + \dots + \beta_{2p} X_{t-p} \quad (8.7)$$

- $X_t$  does not Granger cause  $Y_t$ :

$$H_0 := \beta_{11} = \beta_{12} = \dots = \beta_{1p} = 0 \quad (8.8)$$

- $Y_t$  does not Granger cause  $X_t$ :

$$H_0 := \alpha_{21} = \alpha_{22} = \dots = \alpha_{2p} = 0 \quad (8.9)$$

### 8.3 Impulse-Response Function

**Definition 8.3.** The **Impulse-Response Function**(IRF) quantifies the progression of the unit-sized shock through the VAR system.

$$\begin{array}{c|cc|cc} & & \varepsilon_{1t} & & \varepsilon_{2t} \\ \hline Y_{t+s} & \frac{\partial Y_{t+s}}{\partial \varepsilon_{1t}} \approx \frac{\Delta Y_{t+s}}{\Delta \varepsilon_{1t}} & & \frac{\partial Y_{t+s}}{\partial \varepsilon_{2t}} \approx \frac{\Delta Y_{t+s}}{\Delta \varepsilon_{2t}} \\ X_{t+s} & \frac{\partial X_{t+s}}{\partial \varepsilon_{1t}} \approx \frac{\Delta X_{t+s}}{\Delta \varepsilon_{1t}} & & \frac{\partial X_{t+s}}{\partial \varepsilon_{2t}} \approx \frac{\Delta X_{t+s}}{\Delta \varepsilon_{2t}} \end{array}$$

**Remark 8.6** (Compute IRF). Given  $\varepsilon_{11} = 1$  (initial impulse), and  $\varepsilon_{21} = 0$ , with

$$\varepsilon_{1t} = \varepsilon_{2t} = 0 \quad \forall t > 1 \quad (8.10)$$

## 8.4 Forecasting

Use chain rule of forecasting.

- Optimal forecast;
- Forecast errors;
- Forecast error variance.

$$\sigma_{Y,t+2|t}^2 = (1 + \alpha_{11}^2)\sigma_{\varepsilon_1}^2 + \beta_{11}^2\sigma_{\varepsilon_2}^2 + 2\alpha_{11}\beta_{11}Cov(\varepsilon_1, \varepsilon_2) \quad (8.11)$$

# 9 Vector Error Correction Model

## 9.1 Cointegration

**Definition 9.1.** For any two unit-root process  $\{x_t\}$  and  $\{y_t\}$ , we say they are **cointegrated** if there is a linear combination  $z_t = y_t - \alpha_0 - \alpha x_t$  that is stationary. The process  $\{z_t\}$  is called the **disequilibrium error**. If  $y_t$  and  $x_t$  are cointegrated, then they share the same stochastic trend (common long-run information).

**Remark 9.1.** The notion of cointegration only applies to unit-root processes.

## 9.2 Tests for Cointegrations

**Remark 9.2. Johansen Cointegration Test**

$$\mathbf{Y}_t := \begin{pmatrix} x_t \\ y_t \end{pmatrix} \quad (9.1)$$

- $\hat{z}_t$  is constructed using OLS of  $y_t$  on  $x_t$  and taking the residual;
- if  $r = 0$  then there is no cointegrating relationship in  $\mathbf{Y}_t$ ;
- if  $r = 1$  then there is one cointegrating relationship in  $\mathbf{Y}_t$ .

Reject  $H_0$  when test statistic exceeds the critical value given in the test output.

## 9.3 Vector Error Correction for Short-term Dynamics

**Definition 9.2.**

$$z_t = \log Y_t - \alpha_0 - \alpha \log X_t \quad (9.2)$$

$$\Delta x_t = \gamma_1 z_{t-1} + \varepsilon_{1,t} \quad (9.3)$$

$$\Delta y_t = \gamma_2 z_{t-1} + \varepsilon_{2,t} \quad (9.4)$$

where  $\gamma_1, \gamma_2$  are called the **adjustments coefficients**, and  $\varepsilon_{1,t}, \varepsilon_{2,t}$  are white noise components.

**Definition 9.3.** VEC model can be extended to include **temporal dependence** and **cross-correlation**

$$\Delta x_t = \gamma_1 z_{t-1} + \beta_{11} \Delta x_{t-1} + \beta_{12} \Delta x_{t-2} + \dots \quad (9.5)$$

$$+ \phi_{11} \Delta y_{t-1} + \phi_{12} \Delta y_{t-2} + \dots + \varepsilon_{1,t} \quad (9.6)$$

$$\Delta y_t = \gamma_2 z_{t-1} + \underbrace{\beta_{21} \Delta x_{t-1} + \beta_{22} \Delta x_{t-2} + \dots}_{\text{cross correlation}} \quad (9.7)$$

$$+ \underbrace{\phi_{21} \Delta y_{t-1} + \phi_{22} \Delta y_{t-2} + \dots + \varepsilon_{2,t}}_{\text{temporal dependence}} \quad (9.8)$$

**Remark 9.3.** Note that the VEC model has the same form as the VAR model plus the error correction terms  $\gamma_1 z_{t-1}$  and  $\gamma_2 z_{t-1}$ . The number of lags in the model can be selected by information criteria.

**Theorem 9.1** (Granger Representation Theorem). Consider two stochastic processes,  $\{x_t\}$  and  $\{y_t\}$ , each containing a unit root (i.e. non-stationary). If  $\{x_t\}$  and  $\{y_t\}$  are cointegrated, then:

- (i) There exists a linear combination of  $y_t$  and  $x_t$  such as  $z_t = y_t - \alpha_0 - \alpha x_t$  that is a stationary process.
- (ii) There exists an error correction representation given

$$\Delta x_t = \gamma_1 z_{t-1} + \beta_{11} \Delta x_{t-1} + \beta_{12} \Delta x_{t-2} + \dots \quad (9.9)$$

$$+ \phi_{11} \Delta y_{t-1} + \phi_{12} \Delta y_{t-2} + \dots + \varepsilon_{1,t} \quad (9.10)$$

$$\Delta y_t = \gamma_2 z_{t-1} + \beta_{21} \Delta x_{t-1} + \beta_{22} \Delta x_{t-2} + \dots \quad (9.11)$$

$$+ \phi_{21} \Delta y_{t-1} + \phi_{22} \Delta y_{t-2} + \dots + \varepsilon_{2,t} \quad (9.12)$$

## 9.4 Forecasting

**Example 9.1.**

$$\Delta x_t = \gamma_1 z_{t-1} + \varepsilon_{1,t} \quad (9.13)$$

$$\Delta y_t = \gamma_2 z_{t-1} + \varepsilon_{2,t} \quad (9.14)$$

$$z_{t-1} = y_{t-1} - \alpha_0 - \alpha x_{t-1} \quad (9.15)$$

$$\Rightarrow x_t - x_{t-1} = \gamma_1 (y_{t-1} - \alpha_0 - \alpha x_{t-1}) + \varepsilon_{1,t} \quad (9.16)$$

$$\Rightarrow x_t = \gamma_1 y_{t-1} + (1 - \gamma_1 \alpha) x_{t-1} - \gamma_1 \alpha_0 + \varepsilon_{1,t} \quad (9.17)$$

$$\Rightarrow f_{t,1}^X = \gamma_1 y_t + (1 - \gamma_1 \alpha) x_t - \gamma_1 \alpha_0 \quad (9.18)$$

$$f_{t,2}^X = \underbrace{\gamma_1 f_{t,1}^Y + (1 - \gamma_1 \alpha) f_{t,1}^X - \gamma_1 \alpha_0}_{\text{Chain rule of forecasting}} \quad (9.19)$$

# 10 Volatility I

## 10.1 Higher-order Moments

**Definition 10.1.** The third order moment, **Skewness**, of  $X$  is defined as

$$k_3 := \mathbb{E}[(X - \mathbb{E}[X])^3] \quad (10.1)$$

**Definition 10.2.** The **excess Kurtosis** of defined as

$$k_4 := \underbrace{\mathbb{E}[(X - \mathbb{E}[X])^4]}_{\text{Kurtosis}} - \underbrace{3\mathbb{V}[X]^2}_{\text{Kurtosis of Gaussian}} \quad (10.2)$$

Kurtosis measures the thickness of the tails of the density of  $X$ , and consequently the peakedness of the middle, relative to the Normal distribution with  $k_4 = 0$ .

- (i) **Leptokurtic**,  $k_4 > 0$ , *Heavy Tails*;
- (ii) **Platykurtic**,  $k_4 < 0$ , *Thin Tails*.

## 10.2 Moving Average on $\{r_t\}$

**Definition 10.3.** Modelling conditional variance

$$\hat{\sigma}_{t|t-1}^2 = \frac{1}{n} \sum_{i=1}^n (r_{t-i} - \mu)^2 \quad (10.3)$$

Higher  $n$  will yield a smoother estimate.

## 10.3 Simple Exponential Smoothing (SES) on $\{y_t\}$

**Model** for the mean  $\mu$

$$\mu_T = \alpha y_T + (1 - \alpha)\mu_{T-1} \quad (\text{smooth equation}) \quad (10.4)$$

$$\iff \mu_T = \mu_{T-1} + \underbrace{\alpha(y_T - \mu_{T-1})}_{\text{error}} \quad (\text{error correction form}) \quad (10.5)$$

where  $\alpha \in (0, 1)$  is a **smoothing constant**.

**Choosing Parameter  $\alpha$**  using *numerical methods*(e.g. grid search) to minimize the *in-sample prediction error*:

$$\alpha^* = \underset{\alpha \in (0, 1)}{\operatorname{argmin}} \sum_{t=1}^T \underbrace{(y_t - \mu_{t-1})^2}_{SSE} \quad (10.6)$$

### Recursive Expansion

$$\mu_T = \alpha y_T + (1 - \alpha)\mu_{T-1} \quad (10.7)$$

$$= \alpha y_T + (1 - \alpha)[\alpha y_{T-1} + (1 - \alpha)\mu_{T-2}] \quad (10.8)$$

$$= \alpha \sum_{k=0}^{T-1} (1 - \alpha)^k y_{T-k} + \underbrace{(1 - \alpha)^{T-1}\mu_0}_{=0} \quad (10.9)$$

$$(10.10)$$

and in general  $\mu_0$  is initialized to zero.

## 10.4 Exponentially Weighted Moving Average (EWMA)

**Remark 10.1.** By replacing the objective of prediction in SES ( $\mu$ ) with the variance of series, we can build a EWMA model.

**Model for the variance**  $(r_t - \mu)^2$

$$\hat{\sigma}_{t|t-1}^2 = (1 - \lambda) \sum_{k=0}^{t-1} \lambda^k (r_{t-k} - \mu)^2 \quad (10.11)$$

### Error Correction Form (Recursive Definition)

$$\hat{\sigma}_{t|t-1}^2 = \hat{\sigma}_{t-1|t-2}^2 + (1 - \lambda)((r_{t-1} - \mu)^2 - \hat{\sigma}_{t-1|t-2}^2) \quad (10.12)$$

## 11 Volatility II

### 11.1 Heteroskedasticity

**Definition 11.1.** Given model

$$r_t = \mu_{t|t-1} + \varepsilon_t \quad (11.1)$$

where  $\mu_{t|t-1}$  can be modelled using an ARMA model, and

$$\varepsilon_t = \sigma_{t|t-1} z_t \quad (11.2)$$

and  $z_t$  satisfies  $\mathbb{E}[z_t] = 0$  and  $\mathbb{V}[z_t] = 1$  and *i.i.d.*

**Remark 11.1.**

$$\sigma_{t|t-1}^2 = \mathbb{E}[\varepsilon_t^2 | I_t] \quad (11.3)$$

where  $\varepsilon_t$  is **heteroskedastic**, which means it has non-constant conditional variance.

**Remark 11.2.** Note here only the *conditional* variance is heteroskedastic, but the *unconditional* variance is constant  $\mathbb{E}[\mathbb{E}[\varepsilon_t^2 | I_t]] = \sigma_\varepsilon^2$ . This is similar to the unconditional mean ( $\mu$ ) of stochastic process  $\{y_t\}$  in ARMA, which is constant, and the conditional mean of  $\{y_t\}$  ( $\mu_{t|t-1}$ ), which is non-constant.

### 11.2 Autoregressive Conditional Heteroskedasticity (ARCH)

**Definition 11.2.** ARCH( $p$ ) model

$$\sigma_{t|t-1}^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \quad (11.4)$$

**Remark 11.3.** In contrast to AR models, here the dependent variable is not  $\varepsilon_t^2$  but instead its **conditional expectation** (since we already assumed the white noise distribution of  $\varepsilon_t$ ).

**Remark 11.4.** Sufficient conditions for  $\sigma_{t|t-1}^2 > 0$  are

$$\begin{cases} \omega > 0 \\ \alpha_i \geq 0 \quad \forall i \in \{1, \dots, p\} \end{cases} \quad (11.5)$$

**Remark 11.5.** ARCH(1) forecasting (*apply the chain rule of forecasting*)

$$\sigma_{t+h|t}^2 = \omega + \alpha \sigma_{t+h-1|t}^2 \quad (11.6)$$

$$= \omega + \alpha \omega + \alpha^2 \sigma_{t+h-2|t}^2 \quad (11.7)$$

$$= \omega(1 + \alpha + \cdots + \alpha^{h-2}) + \alpha^{h-1} \sigma_{t+1|t}^2 \quad (11.8)$$

$$\rightarrow \frac{\omega}{1 - \alpha} \text{ as } h \rightarrow \infty \quad (11.9)$$

### 11.3 Generalize Autoregressive Conditional Heteroskedasticity (GARCH)

**Definition 11.3.** GARCH( $p, q$ )

$$\sigma_{t|t-1}^2 = \underbrace{\omega + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2}_{\text{ARCH}(p) \text{ Part}} \quad (11.10)$$

$$+ \underbrace{\beta_1 \sigma_{t-1|t-2}^2 + \cdots + \beta_q \sigma_{t-q|t-q-1}^2}_{\text{Generalized Past Conditional Part}} \quad (11.11)$$

Generalized Past Conditional Part

**Remark 11.6.** GARCH( $p, q$ ) typically needs smaller total number of parameters  $(\alpha_i, \beta_j)_{i=1, \dots, p; j=1, \dots, q}$  than the number of ARCH( $\tilde{p}$ ) parameters  $(\alpha_i)_{i=1, \dots, \tilde{p}}$  required for a comparable model fit.

**Proposition 11.1.** GARCH(1,1) is equivalent to an ARCH( $\infty$ ).

*Proof.*

$$\sigma_{t|t-1}^2 = \underbrace{\omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1|t-2}^2}_{\text{GARCH}(1,1)} \quad (11.12)$$

$$= \omega + \alpha \varepsilon_{t-1}^2 + \beta \omega + \beta \alpha \varepsilon_{t-2}^2 + \beta^2 \sigma_{t-1|t-2}^2 \quad (11.13)$$

$$= \underbrace{\omega(1 + \beta + \beta^2 + \cdots)}_{\text{Expand Recursively to } (t - \infty) \text{ Period}} + \alpha \sum_{i=1}^{\infty} \beta^{i-1} \varepsilon_{t-i}^2 \quad (11.14)$$

$$= \frac{\omega}{1 - \beta} + \alpha \underbrace{\sum_{i=1}^{\infty} \beta^{i-1} \varepsilon_{t-i}^2}_{\text{Persistence}} \quad (11.15)$$

■

**Definition 11.4.** The **persistence** of GARCH(1,1) process is defined as

$$\alpha \sum_{i=1}^{\infty} \beta^{i-1} = \frac{\alpha}{1 - \beta} \quad (11.16)$$

measures how permanent the innovations  $\varepsilon_t^2$  are in the conditional variance. When  $\frac{\alpha}{1 - \beta} = 1$ , the process is an **integrated GARCH** process, its *unconditional* variance does not exist (equals  $\infty$ ).

## 12 Volatility III: Applications

### 12.1 Risk Management

**Definition 12.1.** The  **$\alpha$ -Value at Risk (VaR)**,  $r_t^{VaR(\alpha)}$ , is the  $\alpha$ -quantile of  $r_t$ . Let  $F$  be the cumulative density function of returns, then

$$r_t^{VaR(\alpha)} := F^{-1}(\alpha) \quad (12.1)$$

**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  $\alpha\%$ .*

$$\mathbb{P}[r_t \leq r_t^{VaR(\alpha)}] = \alpha \quad (12.2)$$

#### Model Setup

$$r_t = \mu_{t|t-1} + \sigma_{t|t-1} z_t \quad (12.3)$$

$$z_t \sim \mathcal{N}(0, 1) \quad (12.4)$$

$$\mu_{t|t-1} \sim \text{ARMA} \quad (12.5)$$

$$\sigma_{t|t-1} \sim \text{GARCH} \quad (12.6)$$

$$\implies r_t \sim \mathcal{N}(\mu_{t|t-1}, \sigma_{t|t-1}^2) \quad (12.7)$$

$$\implies r_t^{VaR(\alpha)} = \mu_{t|t-1} + \Phi^{-1}(\alpha) \sigma_{t|t-1} \quad (12.8)$$

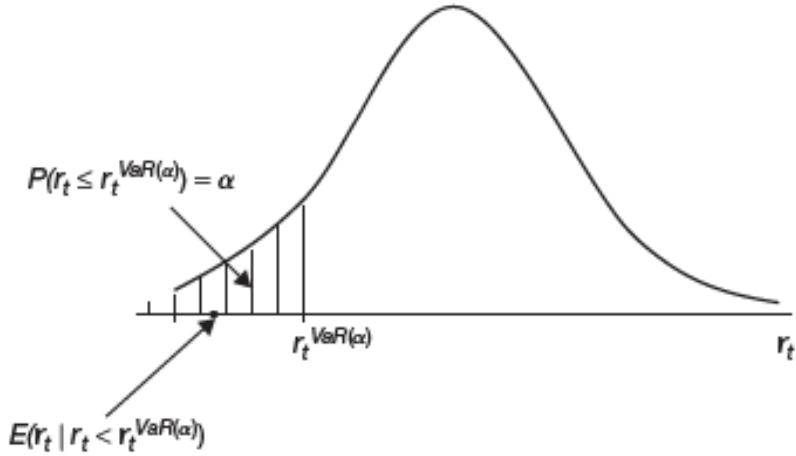


Figure 12.1: VaR and Expected Shortfall

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

$$ES(\alpha) := \mathbb{E}[r_t | r_t < r_t^{VaR(\alpha)}] \quad (12.9)$$

**Lemma 12.1** (Expected of Truncated Normal Distribution).

$$X \sim \mathcal{N}(\mu, \sigma^2) \quad (12.10)$$

$$\implies \mathbb{E}[X|a < X < b] = \mu + \sigma \frac{\phi(\frac{a-\mu}{\sigma}) - \phi(\frac{b-\mu}{\sigma})}{\Phi(\frac{b-\mu}{\sigma}) - \Phi(\frac{a-\mu}{\sigma})} \quad (12.11)$$

$$= \mu + \sigma \frac{\phi(\alpha) - \phi(\beta)}{\Phi(\beta) - \Phi(\alpha)} \quad (12.12)$$

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

$$r_t \sim \mathcal{N}(\mu_{t|t-1}, \sigma_{t|t-1}^2) \quad (12.13)$$

$$\implies \mathbb{E}[r_t | r_t < r_t^{VaR(\alpha)}] = \mu_{t|t-1} + \sigma_{t|t-1} \frac{-\phi\left(\frac{r_t^{VaR(\alpha)} - \mu_{t|t-1}}{\sigma_{t|t-1}}\right)}{\Phi\left(\frac{r_t^{VaR(\alpha)} - \mu_{t|t-1}}{\sigma_{t|t-1}}\right)} \quad (12.14)$$

$$= \mu_{t|t-1} - \sigma_{t|t-1} \frac{\phi(\Phi^{-1}(\alpha))}{\alpha} \quad (12.15)$$

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  $\mu_i$  and variance  $\sigma_i^2$  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,  $\sigma_p^2$ , is minimized.

**Assumption 12.1.**

$$\text{Cov}(r_i, r_j) = 0 \quad \forall i \neq j \in N \quad (12.16)$$

**Solution**

$$\min_{(w_i)_{i \in N}} \sigma_p^2 \equiv \sum_{i \in N} w_i^2 \sigma_i^2 \quad (12.17)$$

$$\text{s.t. } \bar{\mu}_p = \sum_{i \in N} w_i \mu_i \quad (12.18)$$

$$\implies w_i^* = \frac{\mu_i / \sigma_i^2}{\sum_{j \in N} \mu_j^2 / \sigma_j^2} \bar{\mu}_p \quad (12.19)$$

**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.**

$$\mathbb{E}[r_i] = r_f + \beta_i \mathbb{E}[r_m - r_f] \quad (12.20)$$

$$\beta_i := \frac{\text{Cov}(r_i, r_m)}{\text{Var}(r_m)} \equiv \frac{\rho_{im}\sigma_i\sigma_m}{\sigma_m^2} \quad (12.21)$$

and if  $\beta_i > 1$ , the asset  $i$  is more *risky* than the market risk. In practice,  $\beta_i$  is estimated with  $\rho_{im}$  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

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

**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

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

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

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

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

And test the hypothesis (equivalently, test the joint significance of coefficients of  $D_t$  and  $D_t Y_{t-1}$  (**partial F test**))

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

$$H_1 := \neg H_0 \text{ model is non-linear} \quad (13.9)$$

### 13.3 Smooth Transition Autoregressive Model (STAR)

**Definition 13.3.** A **smooth transition autoregressive model**(STAR) is defined by two autoregression regimes and a *bounded and continuous* (activation function)  $\mathcal{G}(s_t, \gamma, c)$ . Where

- (i)  $\gamma$  denotes the **speed parameter**;
- (ii)  $c$  denotes **threshold**;
- (iii)  $\mathcal{G}$  is bounded and continuous in **threshold variables**  $s_t$ .

$$Y_t = \underbrace{\left( \phi_0 + \sum_{j=1}^p \phi_j L^j Y_t \right)}_{\text{base model}} + \underbrace{\left( \phi'_0 + \sum_{j=1}^p \phi'_j L^j Y_t \right) \mathcal{G}(s_t, \gamma, c)}_{\text{activation}} + \varepsilon_t \quad (13.10)$$

**Example 13.2** (STAR(1) without intercept).

$$Y_t = \phi_0 Y_{t-1} + \phi_1 Y_{t-1} \mathcal{G}(s_t, \gamma, c) + \varepsilon_t \quad (13.11)$$

**Example 13.3** (Logistic STAR).

$$\mathcal{G}(s_t, \gamma, c) = \frac{1}{1 + \exp(-\gamma(s_t - c))} \quad (13.12)$$

**Example 13.4** (Exponential STAR).

$$\mathcal{G}(s_t, \gamma, c) = 1 - \exp(-\gamma(s_t - c)^2) \quad (13.13)$$

**Remark 13.2.** STAR is effectively a TAR with infinitely many regimes.

### 13.4 Markov Switching Model

**Definition 13.4.** MS models the *probability of various regimes to happen*. A Markov switching model consists both

- (i) **State space**  $\Omega := \{\omega_i\}_{i=1}^n$ ;
- (ii) **Outcome** functions depend on state realized at time  $t$ ,  $s_t$ ;

$$Y_t \sim \mathcal{N}(\mu_i, \sigma^2) \text{ if } s_t = \omega_i \quad (13.14)$$

- (iii) A  $n \times n$  **transition matrix**  $T$  defined as

$$T_{i,j} := \mathbb{P}[s_t = \omega_j | s_{t-1} = \omega_i] \quad (13.15)$$

## 14 Appendix

### 14.1 A list of hypothesis tests in this course

- (i)  $t$  test for auto-correlation  $H_0 : \rho_k = 0$ .
- (ii) Ljung-Box test for auto-correlations  $H_0 : \rho_1 = \rho_2 = \dots = \rho_k = 0$ .
- (iii) ADF for unit root,  $z = \frac{\hat{\phi}-1}{\sigma_{\hat{\phi}}}$ ,  $H_0$  : non-stationary/unit root exists in any of three types of trendings.
- (iv) Partial  $F$  test for testing Ganger causality.
- (v) Johansen co-integration test
  - Construct  $\hat{z}$  from OLS procedure (residual);
  - $r = 0$  no integrating relationship;
  - $r = 1$  one integrating relationship.
- (vi) TAR model specification: partial  $F$  test with dummy variables.