

# Stochastic processes: generating functions and identification \*

Jean-Marie Dufour †  
McGill University

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† William Dow Professor of Economics, McGill University, Centre interuniversitaire de recherche en analyse des organisations (CIRANO), and Centre interuniversitaire de recherche en économie quantitative (CIREQ). Mailing address: Department of Economics, McGill University, Leacock Building, Room 414, 855 Sherbrooke Street West, Montréal, Québec H3A 2T7, Canada. TEL: (1) 514 398 4400 ext. 09156; FAX: (1) 514 398 4800; e-mail: [jean-marie.dufour@mcgill.ca](mailto:jean-marie.dufour@mcgill.ca). Web page: <http://www.jeanmariedulfour.com>

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# List of Definitions, Assumptions, Propositions and Theorems

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## 1. Generating functions and spectral density

Generating functions constitute a convenient technique for representing and determining the autocovariance structure of a stationary process.

**Definition 1.1** GENERATING FUNCTION. *Let  $(a_k : k = 0, 1, 2, \dots)$  and  $(b_k : k = \dots, -1, 0, 1, \dots)$  two sequences of complex numbers. Let  $D(a) \subseteq \mathbf{C}$  the set of points  $z \in \mathbf{C}$  at which the series  $\sum_{k=0}^{\infty} a_k z^k$  converges, and  $D(b) \subseteq \mathbf{C}$  the set of points  $z$  for which where the series  $\sum_{k=-\infty}^{\infty} b_k z^k$  converges. Then the functions*

$$a(z) = \sum_{k=0}^{\infty} a_k z^k, z \in D(a) \quad (1.1)$$

and

$$b(z) = \sum_{k=-\infty}^{\infty} b_k z^k, z \in D(b) \quad (1.2)$$

are called the generating functions of the sequences  $a_k$  and  $b_k$  respectively.

**Proposition 1.1** CONVERGENCE ANNULUS OF A GENERATING FUNCTION. *Let  $(a_k : k \in \mathbb{Z})$  be a sequence of complex numbers. Then the generating function*

$$a(z) = \sum_{k=-\infty}^{\infty} a_k z^k \quad (1.3)$$

*converges for  $R_1 < |z| < R_2$  where*

$$R_1 = \limsup_{k \rightarrow \infty} |a_{-k}|^{1/k}, \quad (1.4)$$

$$R_2 = 1 / \left[ \limsup_{k \rightarrow \infty} |a_k|^{1/k} \right], \quad (1.5)$$

*and diverges for  $|z| < R_1$  or  $|z| > R_2$ . If  $R_2 < R_1$ ,  $a(z)$  converges nowhere and, if  $R_1 = R_2$ ,  $a(z)$  diverges everywhere except possibly, for  $|z| = R_1 = R_2$ . Further, when  $R_1 < R_2$ , the coefficients  $a_k$  are uniquely defined, and*

$$a_k = \frac{1}{2\pi i} \int_C \frac{a(z) dz}{(z - z_0)^{k+1}}, \quad k = 0, \pm 1, \pm 2, \dots \quad (1.6)$$

*where  $C = \{z \in \mathbf{C} : |z - z_0| = R\}$  and  $R_1 < R < R_2$ .*

**Proposition 1.2** SUMS AND PRODUCTS OF GENERATING FUNCTIONS. *Let  $(a_k : k \in \mathbb{Z})$  and  $(b_k \in \mathbb{Z})$  two sequences of complex numbers such that the generating functions  $a(z)$  and  $b(z)$  converge for  $R_1 < |z| < R_2$ , where  $0 \leq R_1 < R_2 \leq \infty$ . Then,*

1. *the generating function of the sum  $c_k = a_k + b_k$  is  $c(z) = a(z) + b(z)$ ;*
2. *if the product sequence*

$$d_k = \sum_{j=-\infty}^{\infty} a_j b_{k-j} \tag{1.7}$$

*converges for any  $k$ , the generating function of the sequence  $d_k$  is*

$$d(z) = a(z)b(z). \tag{1.8}$$

*Further, the series  $c(z)$  and  $d(z)$  converge for  $R_1 < |z| < R_2$ .*

We will be especially interested by generating functions of autocovariances  $\gamma_k$  and autocorrelations  $\rho_k$  of a second-order stationary process  $X_t$ :

$$\gamma_x(z) = \sum_{k=-\infty}^{\infty} \gamma_k z^k, \tag{1.9}$$

$$\rho_x(z) = \sum_{k=-\infty}^{\infty} \rho_k z^k = \gamma_x(z) / \gamma_0. \tag{1.10}$$

We see immediately that the generating function with a white noise  $\{u_t : t \in \mathbb{Z}\} \sim WN(0, \sigma^2)$  is constant::

$$\gamma_u(z) = \sigma^2, \rho_u(z) = 1. \tag{1.11}$$

**Proposition 1.3** CONVERGENCE OF AUTOCOVARIANCE GENERATING FUNCTIONS. *Let  $\gamma_k, k \in \mathbb{Z}$ , the autocovariances of a second-order stationary process  $X_t$ , and  $\rho_k, k \in \mathbb{Z}$ , the corresponding autocorrelations.*

1. *If  $R \equiv \limsup_{k \rightarrow \infty} |\rho_k|^{1/k} < 1$ , the generating functions  $\gamma_x(z)$  and  $\rho_x(z)$  converge for  $R < |z| < 1/R$ .*
2. *If  $R = 1$ , the functions  $\gamma_x(z)$  and  $\rho_x(z)$  diverge everywhere, except possibly on the circle  $|z| = 1$ .*
3. *If  $\sum_{k=0}^{\infty} |\rho_k| < \infty$ , the functions  $\gamma_x(z)$  and  $\rho_x(z)$  converge absolutely and uniformly on the circle  $|z| = 1$ .*

**Proposition 1.4** IDENTIFIABILITY OF AUTOCOVARIANCES AND AUTOCORRELATIONS BY GENERATING FUNCTIONS. *Let  $\gamma_k$  and  $\rho_k, k \in \mathbb{Z}$ , autocovariance and autocorrelation sequences such that*

$$\gamma(z) = \sum_{k=-\infty}^{\infty} \gamma_k z^k = \sum_{k=-\infty}^{\infty} \gamma'_k z^k, \quad (1.12)$$

$$\rho(z) = \sum_{k=-\infty}^{\infty} \rho_k z^k = \sum_{k=-\infty}^{\infty} \rho'_k z^k \quad (1.13)$$

*where the series considered converge for  $R < |z| < 1/R$ , where  $R \geq 0$ . Then  $\gamma_k = \gamma'_k$  and  $\rho_k = \rho'_k$  for any  $k \in \mathbb{Z}$ .*

**Proposition 1.5** GENERATING FUNCTION OF THE AUTOCOVARIANCES OF A MA( $\infty$ ) PROCESS. *Let  $\{X_t : t \in \mathbb{Z}\}$  a second-order stationary process such that*

$$X_t = \sum_{j=-\infty}^{\infty} \psi_j u_{t-j} \quad (1.14)$$

where  $\{u_t : t \in \mathbb{Z}\} \sim WN(0, \sigma^2)$ . *If the series*

$$\psi(z) = \sum_{j=-\infty}^{\infty} \psi_j z^j \quad (1.15)$$

and  $\psi(z^{-1})$  converge absolutely, then

$$\gamma_x(z) = \sigma^2 \psi(z) \psi(z^{-1}). \quad (1.16)$$



**Corollary 1.6** GENERATING FUNCTION OF THE AUTOCOVARIANCES OF AN ARMA PROCESS. *Let  $\{X_t : t \in \mathbb{Z}\}$  a second-order stationary and causal ARMA( $p, q$ ) process, such that*

$$\varphi(B)X_t = \bar{\mu} + \theta(B)u_t \quad (1.17)$$

*where  $\{u_t : t \in \mathbb{Z}\} \sim WN(0, \sigma^2)$ ,  $\varphi(z) = 1 - \varphi_1 z - \dots - \varphi_p z^p$  and  $\theta(z) = 1 - \theta_1 z - \dots - \theta_q z^q$ . Then the generating function of the autocovariances of  $X_t$  is*

$$\gamma_x(z) = \sigma^2 \frac{\theta(z) \theta(z^{-1})}{\varphi(z) \varphi(z^{-1})} \quad (1.18)$$

*for  $R < |z| < 1/R$ , where*

$$0 < R = \max\{|G_1|, |G_2|, \dots, |G_p|\} < 1 \quad (1.19)$$

*and  $G_1^{-1}, G_2^{-1}, \dots, G_p^{-1}$  are the roots of the polynomial  $\varphi(z)$ .*

**Proposition 1.7** GENERATING FUNCTION OF THE AUTOCOVARIANCES OF A FILTERED PROCESS. *Let  $\{X_t : t \in \mathbb{Z}\}$  a second-order stationary process and*

$$Y_t = \sum_{j=-\infty}^{\infty} c_j X_{t-j}, t \in \mathbb{Z}, \quad (1.20)$$

where  $(c_j : j \in \mathbb{Z})$  is a sequence of real constants such that  $\sum_{j=-\infty}^{\infty} |c_j| < \infty$ . If the series  $\gamma_x(z)$  and  $c(z) = \sum_{j=-\infty}^{\infty} c_j z^j$  converge absolutely, then

$$\gamma_y(z) = c(z)c(z^{-1})\gamma_x(z). \quad (1.21)$$

**Definition 1.2** SPECTRAL DENSITY. *Let  $X_t$  a second-order stationary process such that the generating function of the autocovariances  $\gamma_x(z)$  converge for  $|z| = 1$ . The spectral density of the process  $X_t$  is the function*

$$\begin{aligned} f_x(\omega) &= \frac{1}{2\pi} \left[ \gamma_0 + 2 \sum_{k=1}^{\infty} \gamma_k \cos(\omega k) \right] \\ &= \frac{\gamma_0}{2\pi} + \frac{1}{\pi} \sum_{k=1}^{\infty} \gamma_k \cos(\omega k) \end{aligned} \quad (1.22)$$

where the coefficients  $\gamma_k$  are the autocovariances of the process  $X_t$ . The function  $f_x(\omega)$  is defined for all the values of  $\omega$  such that the series  $\sum_{k=1}^{\infty} \gamma_k \cos(\omega k)$  converges.

**Remark 1.1** If the series  $\sum_{k=1}^{\infty} \gamma_k \cos(\omega k)$  converges, it is immediate that  $\gamma_x(e^{-i\omega})$  converge and

$$f_x(\omega) = \frac{1}{2\pi} \gamma_x(e^{-i\omega}) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_k e^{-i\omega k} \quad (1.23)$$

where  $i = \sqrt{-1}$ .

**Proposition 1.8** CONVERGENCE AND PROPERTIES OF THE SPECTRAL DENSITY. *Let  $\gamma_k, k \in \mathbb{Z}$ , be an autocovariance function such that  $\sum_{k=0}^{\infty} |\gamma_k| < \infty$ . Then*

1. *the series*

$$f_x(\omega) = \frac{\gamma_0}{2\pi} + \frac{1}{\pi} \sum_{k=1}^{\infty} \gamma_k \cos(\omega k) \quad (1.24)$$

*converges absolutely and uniformly in  $\omega$  ;*

2. *the function  $f_x(\omega)$  is continuous ;*

3.  *$f_x(\omega + 2\pi) = f_x(\omega)$  and  $f_x(-\omega) = f_x(\omega), \forall \omega$  ;*

4.  *$\gamma_k = \int_{-\pi}^{\pi} f_x(\omega) \cos(\omega k) d\omega, \forall k$  ;*

5.  *$f_x(\omega) \geq 0$  ;*

6. (6)  *$\gamma_0 = \int_{-\pi}^{\pi} f_x(\omega) d\omega$  .*

**Proposition 1.9** SPECTRAL DENSITIES OF SPECIAL PROCESSES. *Let  $\{X_t : t \in \mathbb{Z}\}$  be a second-order stationary process with autocovariances  $\gamma_k$ ,  $k \in \mathbb{Z}$ .*

1. *If  $X_t = \mu + \sum_{j=-\infty}^{\infty} \psi_j u_{t-j}$  where  $\{u_t : t \in \mathbb{Z}\} \sim WN(0, \sigma^2)$  and  $\sum_{j=-\infty}^{\infty} |\psi_j| < \infty$ , then*

$$f_x(\omega) = \frac{\sigma^2}{2\pi} \psi(e^{i\omega}) \psi(e^{-i\omega}) = \frac{\sigma^2}{2\pi} |\psi(e^{i\omega})|^2. \quad (1.25)$$

2. *If  $\varphi(B)X_t = \bar{\mu} + \theta(B)u_t$ , where  $\varphi(B) = 1 - \varphi_1 B - \dots - \varphi_p B^p$ ,  $\theta(B) = 1 - \theta_1 B - \dots - \theta_q B^q$  and  $\{u_t : t \in \mathbb{Z}\} \sim WN(0, \sigma^2)$ , then*

$$f_x(\omega) = \frac{\sigma^2}{2\pi} \left| \frac{\theta(e^{i\omega})}{\varphi(e^{i\omega})} \right|^2 \quad (1.26)$$

3. *If  $Y_t = \sum_{j=-\infty}^{\infty} c_j X_{t-j}$  where  $(c_j : j \in \mathbb{Z})$  is a sequence of real constants such that  $\sum_{j=-\infty}^{\infty} |c_j| < \infty$ , and if*

*$\sum_{k=0}^{\infty} |\gamma_k| < \infty$ , then*

$$f_y(\omega) = |c(e^{i\omega})|^2 f_x(\omega). \quad (1.27)$$

## 2. Inverse autocorrelations

**Definition 2.1** INVERSE AUTOCORRELATIONS. *Let  $f_x(\omega)$  the spectral density of a second-order stationary process  $\{X_t : t \in \mathbb{Z}\}$ . If the function  $1/f_x(\omega)$  is also a spectral density, the autocovariances  $\gamma_x^{(I)}(k)$ ,  $k \in \mathbb{Z}$ , associated with the inverse spectrum inverse  $1/f_x(\omega)$  are called the inverse autocovariances of the process  $X_t$ , i.e.*

$$\gamma_x^{(I)}(k) = \int_{-\pi}^{\pi} \frac{1}{f_x(\omega)} \cos(\omega k) d\omega, k \in \mathbb{Z}. \quad (2.1)$$

The inverse autocovariances satisfy the equation

$$\frac{1}{f_x(\omega)} = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_x^{(I)}(k) \cos(\omega k) = \frac{1}{2\pi} \gamma_x^{(I)}(0) + \frac{1}{\pi} \sum_{k=1}^{\infty} \gamma_x^{(I)}(k) \cos(\omega k). \quad (2.2)$$

The inverse autocorrelations are

$$\rho_x^{(I)}(k) = \gamma_x^{(I)}(k) / \gamma_x^{(I)}(0), k \in \mathbb{Z}. \quad (2.3)$$

A sufficient condition for the function  $1/f_x(\omega)$  to be a spectral density is that the function  $1/f_x(\omega)$  be continuous on the interval  $-\pi \leq \omega \leq \pi$ , which entails that  $f_x(\omega) > 0, \forall \omega$ .

If the process  $X_t$  is a second-order stationary  $ARMA(p, q)$  process such that

$$\varphi_p(B)X_t = \bar{\mu} + \theta_q(B)u_t \quad (2.4)$$

where  $\varphi_p(B) = 1 - \varphi_1B - \dots - \varphi_pB^p$  and  $\theta_q(B) = 1 - \theta_1B - \dots - \theta_qB^q$  are polynomials whose roots are all outside the unit circle and  $\{u_t : t \in \mathbb{Z}\} \sim WN(0, \sigma^2)$ , then

$$f_x(\omega) = \frac{\sigma^2}{2\pi} \left| \frac{\theta_q(e^{i\omega})}{\varphi_p(e^{i\omega})} \right|^2, \quad (2.5)$$

$$\frac{1}{f_x(\omega)} = \frac{2\pi}{\sigma^2} \left| \frac{\varphi_p(e^{i\omega})}{\theta_q(e^{i\omega})} \right|^2. \quad (2.6)$$

The inverse autocovariances  $\gamma_x^{(I)}(k)$  are the autocovariances associated with the model

$$\theta_q(B)X_t = \bar{\bar{\mu}} + \varphi_p(B)v_t \quad (2.7)$$

where  $\{v_t : t \in \mathbb{Z}\} \sim WN(0, 1/\sigma^2)$  and  $\bar{\bar{\mu}}$  is some constant. Consequently, the inverse autocorrelations of an  $ARMA(p, q)$  process behave like the autocorrelations of an  $ARMA(q, p)$ . For an process  $AR(p)$  process,

$$\rho_x^{(I)}(k) = 0, \text{ for } k > p. \quad (2.8)$$

For a  $MA(q)$  process, the inverse partial autocorrelations (*i.e.* the partial autocorrelations associated with the inverse autocorrelations) are equal to zero for  $k > q$ . These properties can be used for identifying the order of a process.

### 3. Multiplicity of representations

#### 3.1. Backward representation ARMA models

By the backward Wold theorem, we know that any strictly indeterministic second-order stationary process  $X_t : t \in \mathbb{Z}$  can be written in the form

$$X_t = \mu + \sum_{j=0}^{\infty} \bar{\psi}_j \bar{u}_{t+j} \quad (3.1)$$

where  $\bar{u}_t$  is a white noise such that  $E(X_{t-j}\bar{u}_t) = 0$ ,  $\forall j \geq 1$ . In particular, if

$$\varphi_p(B)(X_t - \mu) = \theta_q(B)u_t \quad (3.2)$$

where the polynomials  $\varphi_p(B) = 1 - \varphi_1 B - \dots - \varphi_p B^p$  and  $\theta_q(B) = 1 - \theta_1 B - \dots - \theta_q B^q$  have all their roots outside the unit circle and  $\{u_t : t \in \mathbb{Z}\} \sim WN(0, \sigma^2)$ , the spectral density of  $X_t$  is

$$f_x(\omega) = \frac{\sigma^2}{2\pi} \left| \frac{\theta_q(e^{i\omega})}{\varphi_p(e^{i\omega})} \right|^2. \quad (3.3)$$



Consider the process

$$Y_t = \frac{\varphi_p(B^{-1})}{\theta_q(B^{-1})} (X_t - \mu) = \sum_{j=0}^{\infty} c_j (X_{t+j} - \mu). \quad (3.4)$$

By Proposition 1.9, the spectral density of  $Y_t$  is

$$f_y(\omega) = \left| \frac{\varphi_p(e^{i\omega})}{\theta_q(e^{i\omega})} \right|^2 f_x(\omega) = \frac{\sigma^2}{2\pi} \quad (3.5)$$

and thus  $\{Y_t : t \in \mathbb{Z}\} \sim WN(0, \sigma^2)$ . If we define  $\bar{u}_t = Y_t$ , we see that

$$\frac{\varphi_p(B^{-1})}{\theta_q(B^{-1})} (X_t - \mu) = \bar{u}_t \quad (3.6)$$

or

$$\varphi_p(B^{-1})X_t = \bar{\mu} + \theta_q(B^{-1})\bar{u}_t, \quad (3.7)$$

and

$$X_t - \varphi_1 X_{t+1} - \cdots - \varphi_p X_{t+p} = \bar{\mu} + \bar{u}_t - \theta_1 \bar{u}_{t+1} - \cdots - \theta_q \bar{u}_{t+q} \quad (3.8)$$

where  $(1 - \varphi_1 - \cdots - \varphi_p)\mu = \bar{\mu}$ . We call (3.6) or (3.8) the backward representation of the  $X_t$  process.

### 3.2. Multiple moving-average representations

Let  $\{X_t\} \sim \text{ARIMA}(p, d, q)$ . Then

$$W_t = (1 - B)^d X_t \sim \text{ARMA}(p, q). \quad (3.9)$$

If we suppose that  $E(W_t) = 0$ ,  $W_t$  satisfies an equation of the form

$$\varphi_p(B)W_t = \theta_q(B)u_t \quad (3.10)$$

or

$$W_t = \frac{\theta_q(B)}{\varphi_p(B)} u_t = \psi(B)u_t. \quad (3.11)$$

To determine an appropriate *ARMA* model, one typically estimates the autocorrelations  $\rho_k$ . The latter are uniquely determined by the generating function of the autocovariances:

$$\gamma_x(z) = \sigma^2 \psi(z) \psi(z^{-1}) = \sigma^2 \frac{\theta_q(z)}{\varphi_p(z)} \frac{\theta_q(z^{-1})}{\varphi_p(z^{-1})}. \quad (3.12)$$

If

$$\theta_q(z) = 1 - \theta_1 z - \dots - \theta_q z^q = (1 - H_1 z) \dots (1 - H_q z) = \prod_{j=1}^q (1 - H_j z), \quad (3.13)$$

then

$$\gamma_x(z) = \frac{\sigma^2}{\varphi_p(z) \varphi_p(z^{-1})} \prod_{j=1}^q (1 - H_j z)(1 - H_j z^{-1}). \quad (3.14)$$

However

$$\begin{aligned}(1 - H_j z)(1 - H_j z^{-1}) &= 1 - H_j z - H_j z^{-1} + H_j^2 = H_j^2(1 - H_j^{-1} z - H_j^{-1} z^{-1} + H_j^{-2}) \\ &= H_j^2(1 - H_j^{-1} z)(1 - H_j^{-1} z^{-1})\end{aligned}\quad (3.15)$$

hence

$$\gamma_x(z) = \frac{\left[ \sigma^2 \prod_{j=1}^q H_j^2 \right]}{\varphi_p(z) \varphi_p(z^{-1})} \prod_{j=1}^q (1 - H_j^{-1} z) (1 - H_j^{-1} z^{-1}) = \bar{\sigma}^2 \frac{\theta'_q(z) \theta'_q(z^{-1})}{\varphi_p(z) \varphi_p(z^{-1})}\quad (3.16)$$

where

$$\bar{\sigma}^2 = \sigma^2 \prod_{j=1}^q H_j^2, \quad \theta'_q(z) = \prod_{j=1}^q (1 - H_j^{-1} z).\quad (3.17)$$

$\gamma_x(z)$  in (3.16) can be viewed as the generating function of a process of the form

$$\varphi_p(B)W_t = \theta'_q(B)\bar{u}_t = \left[ \prod_{j=1}^q (1 - H_j^{-1} B) \right] \bar{u}_t\quad (3.18)$$

while  $\gamma_x(z)$  in (3.14) is the generating function of

$$\varphi_p(B)W_t = \theta_q(B)u_t = \left[ \prod_{j=1}^q (1 - H_j B) \right] u_t.\quad (3.19)$$

The processes (3.18) and (3.19) have the same autocovariance function and thus cannot be distinguished by looking at their seconds moments.

**Example 3.1** Identification of an ARMA(1, 1) model

$$(1 - 0.5B)W_t = (1 - 0.2B)(1 + 0.1B)u_t \quad (3.20)$$

$$(1 - 0.5B)W_t = (1 - 5B)(1 + 10B)\bar{u}_t \quad (3.21)$$

have the same autocorrelation function.

In general, the models

$$\phi_p(B)W_t = \left[ \prod_{j=1}^q (1 - H_j^{\pm 1} B) \right] \bar{u}_t \quad (3.22)$$

all have the same autocovariance function (and are thus indistinguishable). Since it is easier with an invertible model, we select

$$H_j^* = \begin{cases} H_j & \text{if } H_j < 1 \\ H_j^{-1} & \text{if } H_j > 1 \end{cases} \quad (3.23)$$

where  $|H_j| \leq 1$ , in order to have an invertible model.

### 3.3. Redundant parameters

Suppose  $\varphi_p(B)$  and  $\theta_q(B)$  have a common factor, say  $G(B)$ :

$$\varphi_p(B) = G(B)\varphi_{p_1}(B), \quad \theta_q(B) = G(B)\theta_{q_1}(B). \quad (3.24)$$

Consider the models

$$\varphi_p(B)W_t = \theta_q(B)u_t \quad (3.25)$$

$$\varphi_{p_1}(B)W_t = \theta_{q_1}(B)u_t. \quad (3.26)$$

The MA( $\infty$ ) representations of these two models are

$$W_t = \psi(B)u_t, \quad (3.27)$$

where

$$\psi(B) = \frac{\theta_q(B)}{\varphi_p(B)} = \frac{\theta_{q_1}(B)G(B)}{\varphi_{p_1}(B)G(B)} = \frac{\theta_{q_1}(B)}{\varphi_{p_1}(B)} \equiv \psi_1(B), \quad (3.28)$$

$$W_t = \psi_1(B)u_t. \quad (3.29)$$

(3.25) and (3.26) have the same MA( $\infty$ ) representation, hence the same autocovariance generating functions:

$$\gamma_x(z) = \sigma^2 \psi(z)\psi(z^{-1}) = \sigma^2 \psi_1(z)\psi_1(z^{-1}). \quad (3.30)$$

It is not possible to distinguish a series generated by (3.25) from one produced with (3.26). Among these two models, we will select the simpler one, *i.e.* (3.26). Further, if we tried to estimate (3.25) rather than (3.26), we would meet singularity problems (in the covariance matrix of the estimators).

#### **4. Proofs and references**

A general overview of the technique of generating functions is available in Wilf (1994).

## References

WILF, H. S. (1994): *Generatingfunctionology*. Academic Press, New York, second edn.