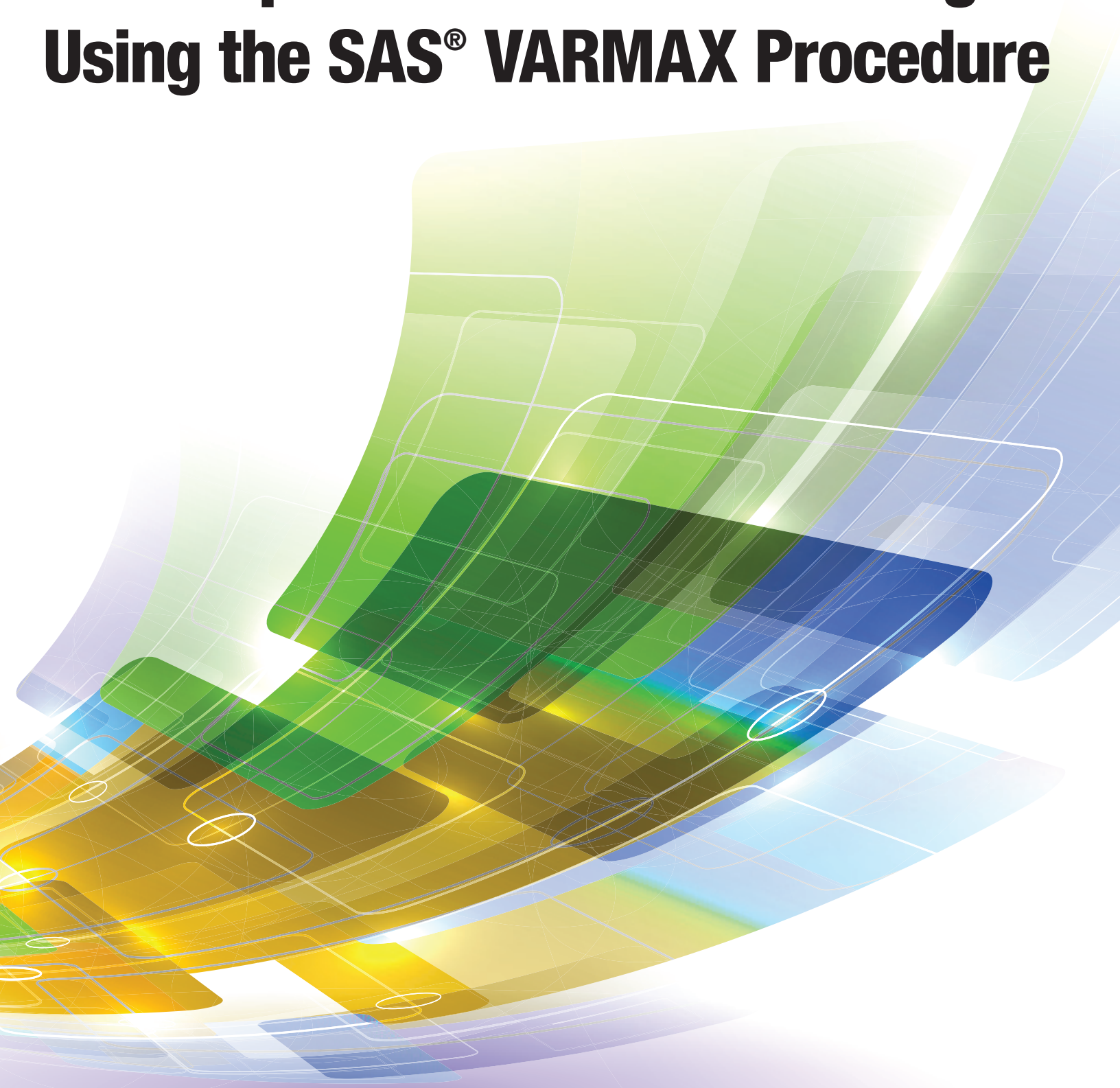
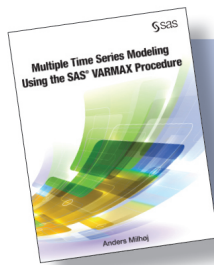


Multiple Time Series Modeling Using the SAS® VARMAX Procedure



Anders Milhøj



From *Multiple Time Series Modeling Using the SAS® VARMAX Procedure*. Full book available for purchase [here](#).

Contents

About This Book	ix
About the Author	xiii
Acknowledgment.....	xv
Chapter 1: Introduction	1
Introduction	1
Ordinary Regression Models	1
Regression Models in Time Series Analysis	2
Time Series Models	3
Which Time Series Features to Model	4
Parameterized Models for Time Series.....	4
Chapter 2: Regression Analysis for Time Series Data	7
Introduction	7
The Data Series	7
Durbin-Watson Test Using PROC REG.....	8
Definition of the Durbin-Watson Test Statistic.....	8
Procedure Output.....	9
Cochrane-Orcutt Estimation.....	10
Conclusion	12
Chapter 3: Regression Analysis with Autocorrelated Errors.....	13
Introduction	13
Correction of Standard Errors with PROC AUTOREG	13
Adjustment of Standard Deviations by the Newey-West Method	14
Cochrane-Orcutt Estimation Using PROC AUTOREG	15
Simultaneous Estimation Using PROC AUTOREG	16
Conclusion	18
Chapter 4: Regression Models for Differenced Series.....	19
Introduction	19
Regression Model for the Differenced Series	19
Regression Results	21
Inclusion of the Lagged Independent Variable.....	22
Reverted Regression	23
Inclusion of the Lagged Independent Variable in the Model	24
Two Lags of the Independent Variables	25
Inclusion of the Lagged Dependent Variable in the Regression.....	27
How to Interpret a Model with a Lagged Dependent Variable	28

Conclusions about the Models in Chapters 2, 3, and 4	28
Chapter 5: Tests for Differencing Time Series	29
Introduction	29
Stationarity.....	29
Unit Roots	30
Dickey-Fuller Tests for Unit Roots	30
Simple Applications of the Dickey-Fuller Test.....	32
Augmented Dickey-Fuller Tests for Milk Production	32
KPSS Unit Root Tests	33
An Application of the KPSS Unit Root Test.....	34
Seasonal Differencing	35
Conclusion	35
Chapter 6: Models for Univariate Time Series.....	37
Introduction	37
Autocorrelations.....	37
Autoregressive Models.....	38
Moving Average Models	39
ARIMA Models	40
Infinite-Order Representations	40
Multiplicative Seasonal ARIMA Models	41
Information Criteria.....	41
Use of SAS to Estimate Univariate ARIMA Models	42
Conclusion	42
Chapter 7: Use of the VARMAX Procedure to Model Univariate Series	43
Introduction	43
Wage-Price Time Series	43
PROC VARMAX Applied to the Wage Series.....	46
PROC VARMAX Applied to the Differenced Wage Series.....	46
Estimation of the AR(2) Model	47
Check of the Fit of the AR(2) Model	49
PROC VARMAX Applied to the Price Series	50
PROC VARMAX Applied to the Number of Cows Series	51
PROC VARMAX Applied to the Series of Milk Production.....	53
A Simple Moving Average Model of Order 1	54
Conclusion	56
Chapter 8: Models for Multivariate Time Series	57
Introduction	57
Multivariate Time Series	57
VARMAX Models.....	58
Infinite-Order Representations	59
Correlation Matrix at Lag 0	59
VARMAX Models	60
VARMAX Building in Practice	60

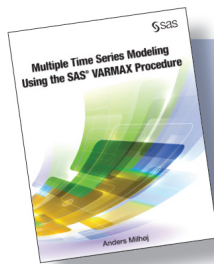
Conclusion	62
Chapter 9: Use of the VARMAX Procedure to Model Multivariate Series.....	63
Introduction	63
Use of PROC VARMAX to Model Multivariate Time Series	64
Dickey-Fuller Tests for Differenced Series	66
Selection of Model Orders.....	66
Fit of a Fourth-Order Autoregressive Model	67
Estimation for the Parameters	67
Restriction of Insignificant Model Parameters.....	68
Residual Autocorrelation in a VARMA(2,0) Model	70
Cross-Correlation Significance.....	70
Portmanteau Tests	70
Distribution of the Residuals in a VARMA(2,0) Model	71
Identification of Outliers	72
Use of a VARMA Model for Milk Production and the Number of Cows	74
Analysis of the Standardized Series	75
Correlation Matrix of the Error Terms.....	78
The Model Fit	78
Properties of the Fitted Model	79
Conclusion	80
Chapter 10: Exploration of the Output	81
Introduction	81
Roots of the Fitted Second-Order Autoregressive Model	81
Forecasts	82
Lag 0 Correlation of the Error Terms	83
The Infinite-Order Representations	84
Plots of the Impulse Response	85
Accumulated Effects.....	86
Effects of Orthogonal Shocks	88
Conclusion	90
Chapter 11: Causality Tests for the Danish Egg Market.....	91
Introduction	91
The Danish Egg Market	91
Formulation of the VARMA Model for the Egg Market Data	92
Estimation Results.....	93
Model Fit.....	94
Causality Tests of the Total Market Series	94
Granger Causality Tests in the VARMAX Procedure.....	95
Causality Tests of the Production Series	96
Causality Tests That Use Extended Information Sets.....	97
Estimation of a Final Causality Model.....	99

Fit of the Final Model	100
Conclusion	101
Chapter 12: Bayesian Vector Autoregressive Models	103
Introduction	103
The Prior Covariance of the Autoregressive Parameter Matrices.....	103
The Prior Distribution for the Diagonal Elements	104
The Prior Distribution for the Off-Diagonal Elements	104
The BVAR Model in PROC VARMAX	105
Specific Parameters in the Prior Distribution	106
Further Shrinkage toward Zero.....	107
Application of the BVAR(1) Model.....	108
BVAR Models for the Egg Market	108
Conclusion	110
Chapter 13: Vector Error Correction Models.....	111
Introduction	111
The Error Correction Model	112
The Matrix Formulation of the Error Correction Model.....	113
The Long-Run Relation	113
A Simple Example: The Price of Potatoes in Ohio and Pennsylvania.....	114
A Simple Regression	115
Estimation of an Error Correction Model by PROC VARMAX.....	116
Dickey-Fuller Test Results.....	116
Estimated Error Correction Parameters.....	117
The $\alpha\beta^T$ Matrix	118
Properties of the Estimated Model	119
The Autoregressive Terms in the Model	120
Theory for Testing Hypotheses on β Parameters	120
Tests of Hypotheses on the β Parameters Using PROC VARMAX	122
Tests for Two Restrictions on the β Parameters	123
Estimated α Parameters under the Restrictions	123
Tests of Hypotheses on the α Parameters by PROC VARMAX.....	124
The TEST Statement for Hypotheses on the α Parameters.....	126
The RESTRICT Statement for the β Parameters.....	126
Restrictions on Both α Parameters and β Parameters	127
Properties of the Final Model.....	128
Conclusion	129
Chapter 14: Cointegration	131
Introduction	131
Test for a Cointegration Relation in the Bivariate Case	132
Cointegration Test Using PROC VARMAX for Two Price Series	132
Cointegration Tests in a Five-Dimensional Series	133
Initial Estimates for the β Values.....	135
A Model with Rank 2	135

Use of the RESTRICT Statement to Determine the Form of the Model	138
Stock-Watson Test for Common Trends for Five Series	139
A Rank 4 Model for Five Series Specified with Restrictions	141
An Alternative Form of the Restrictions	142
Estimation of the Model Parameters by a RESTRICT Statement	143
Estimation with Restrictions on Both the α and β Parameters	144
Conclusion	145
Chapter 15: Univariate GARCH Models	147
Introduction	147
The GARCH Model	148
GARCH Models for a Univariate Financial Time Series	149
Use of PROC VARMAX to Fit a GARCH(1,1) Model	150
The Fitted Model	151
Use of PROC VARMAX to Fit an IGARCH Model	153
The Wage Series	155
Use of PROC VARMAX to Fit an AR(2)-GARCH(1,1) Model	157
The Conditional Variance Series	157
Other Forms of GARCH Models	158
The QGARCH Model	158
The TGARCH Model	159
The PGARCH Model	161
The EGARCH Model	162
Conclusion	164
Chapter 16: Multivariate GARCH Models	165
Introduction	165
Multivariate GARCH Models	165
The CCC Parameterization	165
The DCC Parameterization	166
The BEKK Parameterization	167
A Bivariate Example Using Two Quotations for Danish Stocks	168
Using the CCC Parameterization	169
Using the DCC Parameterization	170
Using the BEKK Parameterization	172
Using the CCC Bivariate Combination of Univariate TGARCH Models	172
Conclusion	173
Chapter 17: Multivariate VARMA-GARCH Models	175
Introduction	175
Multivariate VARMA-GARCH Models	175
The Wage-Price Time Series	176
A VARMA Model with a CCC-GARCH Model for the Residuals	176
A VARMA Model with a DCC-GARCH Model for the Residuals	178
Refinement of the Estimation Algorithm	178

The Final VARMA Model with DCC-GARCH Residuals.....	180
Conclusion	184
References.....	185
Index.....	187

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Chapter 8: Models for Multivariate Time Series

Introduction.....	57
Multivariate Time Series	57
VARMAX Models	58
Infinite-Order Representations.....	59
Correlation Matrix at Lag 0.....	59
VARMAX Models	60
VARMAX Building in Practice	60
Conclusion	62

Introduction

In this chapter, you will learn the basic theory for multivariate time series. The purpose is to introduce the simplest theoretical model behind the many tools offered by the VARMAX procedure, because most of them are extensions or refinements of this basic model. The idea is not to give a thorough introduction to the theory, for this subject is far too extensive to include in a book that is specific to SAS. For more information about multivariate time series analysis, consult ordinary textbooks like Lütkepohl (1993) or others listed in the references for SAS help for the VARMAX procedure.

In later chapters, the basic VARMAX model is extended in various ways. These chapters will introduce the theory of such extensions, together with the SAS coding for examples.

Multivariate Time Series

A multivariate time series consists of many (in this chapter, k) univariate time series. The observation for the j th series at time t is denoted X_{jt} , $j = 1, \dots, k$ and $t = 1, \dots, T$. The length of the time series—that is, the number of observations—is, as in the chapters for the univariate models, denoted as T . In matrix notation, the k -dimensional observation is written as a column vector \mathbf{X}_t :

$$\mathbf{X}_t = \begin{pmatrix} X_{1t} \\ \vdots \\ X_{kt} \end{pmatrix}$$

The idea is to model these k series simultaneously because they can interact in a way that it is insufficient to establish by separate univariate models for each separate series.

A fundamental property of multivariate time series is that all series should be simultaneously stationary. This means that their joint distribution should be constant over time. This concept is a direct generalization from the univariate case. The extension of the definition of stationarity to more than just one time series states that a lagged dependence of one series to another series, if present, is constant for the whole data period. It also means that no trends should be present in the series.

If the series is not stationary, differencing often transforms the series into stationarity, just as for the univariate models. For instance, price indices for many countries might be trending due to inflation, but the series of year-

to-year changes in price levels might be rather constant, having a mean value that corresponds to the average annual inflation rate in the observed countries.

A time series (univariate or multivariate) that is stationary because of differencing is called integrated. This notation is the *I* in the name ARIMA models. In Chapters 13 and 14, this issue is considered in more detail because stationarity for two nonstationary series can be obtained in other ways, leading to the notion of cointegration for a stationary relationship between two nonstationary series.

VARMAX Models

If the multivariate series is stationary, then a Vector Autoregressive Moving Average (VARMA) is a direct generalization of the Autoregressive Moving Average (ARMA) models that were introduced in Chapter 6. The VARMA(p, q) model is defined as follows:

$$\mathbf{X}_t - \boldsymbol{\varphi}_1 \mathbf{X}_{t-1} - \dots - \boldsymbol{\varphi}_p \mathbf{X}_{t-p} = \mathbf{c} + \boldsymbol{\varepsilon}_t - \boldsymbol{\theta}_1 \boldsymbol{\varepsilon}_{t-1} - \dots - \boldsymbol{\theta}_q \boldsymbol{\varepsilon}_{t-q}$$

This formula just replicates the usual univariate definition of an ARMA model. The only difference is that all terms are now vectors or matrices, not just numbers. The model is for this reason well established and intuitively appealing for everybody familiar with univariate time series modeling. The arguments for the relevance of this class of model are direct replications of the arguments for the similar univariate time series. The interpretation of the multivariate model is also a straightforward generalization of the interpretation of the univariate model.

The parameter vector \mathbf{c} in this parameterization is a k -dimensional column vector. Only if $p = 0$ is it the mean value for each of the k series. If $p > 0$, then the mean vector $\boldsymbol{\mu}$ is given as follows:

$$\boldsymbol{\mu} = (\mathbf{I} - \boldsymbol{\varphi}_1 - \dots - \boldsymbol{\varphi}_p)^{-1} \mathbf{c}$$

The coefficients in the definition of a VARMA(p, q) model are $k \times k$ matrices, so they generally include k^2 parameters, as seen here:

$$\boldsymbol{\varphi}_m = \begin{pmatrix} \varphi_{m11} & \cdot & \cdot & \cdot & \varphi_{m1k} \\ \cdot & & & & \cdot \\ \cdot & & & & \cdot \\ \cdot & & \varphi_{mij} & & \cdot \\ \varphi_{mk1} & \cdot & \cdot & \cdot & \varphi_{mkk} \end{pmatrix}$$

The expression by the model formulation for a specific component X_{jt} is very involved even for small values of the model orders p and q . The expression involves lagged (up to lag p) values of all observed components of the time series X_{it} , $i = 1, \dots, k$ and, moreover, lagged (up to lag q) values of all error components ε_{jt} , $j = 1, \dots, k$.

In the syntax of PROC VARMAX, these coefficients in the code are denoted by ordinary Latin letters and symbols in plain text like “ar(m, i, j)” for the coefficient φ_{mij} for the entry (i, j) , $i, j = 1, \dots, k$ in the autoregressive parameter matrix $\boldsymbol{\varphi}_m$ for lag m , $m = 1, \dots, p$.

Similarly, the entry (i, j) in the moving average parameter matrix $\boldsymbol{\theta}_m$ for Lag m , $m = 1, \dots, q$ is denoted as “ma(m, i, j)” for the coefficient θ_{mij} for the entry (i, j) , $i, j = 1, \dots, k$ in the moving average parameter matrix $\boldsymbol{\theta}_m$.

The models often include many parameters that could easily lead to over-parameterization. Many of the refinements are invented merely to reduce the number of parameters. For this reason, various ways of interpreting the model emerge.

The dependencies among different series with lagged effects are described by the off-diagonal elements of the coefficient matrices $\boldsymbol{\phi}_m$ and $\boldsymbol{\theta}_m$. The diagonal elements of the coefficient matrices $\boldsymbol{\phi}_m$ and $\boldsymbol{\theta}_m$ correspond to univariate ARMA models for the individual series.

Infinite-Order Representations

In the theory of stationary processes, it is proved that a stationary time series under some assumptions can be represented both as an autoregression of infinite order and as a moving average of infinite order:

$$\mathbf{X}_t = \boldsymbol{\pi}_1 \mathbf{X}_{t-1} + \boldsymbol{\pi}_2 \mathbf{X}_{t-2} + \dots + \boldsymbol{\varepsilon}_t$$

and

$$\mathbf{X}_t = \boldsymbol{\varepsilon}_t + \boldsymbol{\psi}_1 \boldsymbol{\varepsilon}_{t-1} + \boldsymbol{\psi}_2 \boldsymbol{\varepsilon}_{t-2} + \dots$$

All VARMA models can be written in this way if the roots of the corresponding models are larger than 1 in absolute value.

In this parameterization, the (i, j) entry of $\boldsymbol{\pi}_m$ (the parameter π_{mij}) directly gives the effect of the j th component of \mathbf{X}_{t-m} to the i th component of \mathbf{X}_t in the same way as it would as an input variable in an ordinary regression model. Similarly, the parameter ψ_{mij} represents the effect of a sudden shock ε_{jt-m} for the j th series at time $t - m$ to \mathbf{X}_{it} the i th series m time periods later at time t .

These representations are used to elucidate the meaning of the fitted models; see, for example, Chapter 10.

Correlation Matrix at Lag 0

The error series (see below) are assumed to be a white noise series in the sense that all entries of $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\varepsilon}_{t-m}$ at two different points in time are supposed to be independent for all integers $m \neq 0$.

$$\boldsymbol{\varepsilon}_t = \begin{pmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{kt} \end{pmatrix}$$

But for lag 0 the entries are not necessarily independent. The $k \times k$ dimensional covariance matrix of the vector $\boldsymbol{\varepsilon}_t$ has this form:

$$\text{var}(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Sigma} = \begin{pmatrix} \sigma_{11} & \cdot & \cdot & \sigma_{1k} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \sigma_{k1} & \cdot & \cdot & \sigma_{kk} \end{pmatrix}$$

The diagonal elements of this matrix are the error variances for the series in the model. The off-diagonal elements are the covariances between two components of the error series. Normalized, these covariances are considered as correlations that tell us about the degree of dependence between the two series at the same point in time.

In a VARMA model, the immediate dependence between two of the components in \mathbf{X}_t is parameterized only by the correlation between the two components in $\boldsymbol{\varepsilon}_t$. As a correlation, this dependence is of no specific direction; in other words, it does not say anything about causality as such. But it is possible to derive the conditional distribution of one component conditioned on another component of the series. This means that if, for some

reason, the i th component X_{it} is observed or assumed known, it is possible to calculate the conditional expectation of another component X_{jt} , which could be applied as a forecast.

VARMAX Models

The letter X in the procedure name VARMAX comes from the word exogenous. An exogenous variable is a variable that enters the model but in no way is modeled by the model. A typical example is seasonal factors, such as monthly dummy variables in a model for monthly sales. The weather and the holiday season are not at all determined by the sales, but they have great impact on sales.

For example, a VARMAX model with monthly dummy variables is written as follows:

$$\mathbf{X}_t - \boldsymbol{\phi}_1 \mathbf{X}_{t-1} - \dots - \boldsymbol{\phi}_p \mathbf{X}_{t-p} = \mathbf{c} + \mathbf{D}_{Jan} \boldsymbol{\delta}_{Jan} + \dots + \mathbf{D}_{Nov} \boldsymbol{\delta}_{Nov} + \boldsymbol{\varepsilon}_t - \boldsymbol{\theta}_1 \boldsymbol{\varepsilon}_{t-1} - \dots - \boldsymbol{\theta}_q \boldsymbol{\varepsilon}_{t-q}$$

The dummy variables are the $k \times k$ matrices, with all entries equaling 0 unless the month t is correct. If the month t is January, the matrix \mathbf{D}_{Jan} is the identity matrix; otherwise, it is just a $\mathbf{0}$ matrix. The parameter vector \mathbf{c} in this parameterization corresponds to the December level. The parameters $\boldsymbol{\delta}_{Nov}$ are k -dimensional column vectors including the monthly effect δ_{iNov} for the i th series, $i = 1, \dots, k$. The November effect, δ_{iNov} , is in fact equal to the difference between the December and the November level, so that the actual November level is $\mathbf{c} + \boldsymbol{\delta}_{Nov}$.

In econometrics, the concept of exogeneity is important. The question is whether a variable can be treated as exogenous or not. In some cases, it is rather obvious. An example is the economy of a small country like Denmark. The Danish economy cannot have any impact on the price of oil, so the price of oil can be treated as exogenous in a model for the Danish economy. In Chapter 12, this subject of testing exogeneity with multivariate time series models and PROC VARMAX in SAS is discussed with an example.

VARMAX Building in Practice

PROC VARMAX in SAS makes the selection of the precise orders, p and q , for a VARMA(p, q) model easy. The assumption of stationarity is tested by means of the Dickey-Fuller test and similar tests for differencing as opposed to stationarity. Then, PROC VARMAX offers an automatic model-selection algorithm that fits many possible candidate models' orders and selects the best according to a relevant criterion.

The model parameters are estimated by the method of maximum likelihood, which assumes that the error terms are Gaussian. The estimation is rather complicated because models for multivariate time series often include many parameters. So numerical algorithms have to be chosen with care. This is, however, not usually a problem that the user encounters frequently. PROC VARMAX includes modern algorithms. But, nevertheless, it happens now and then that the estimation algorithm fails. In such cases, the estimating procedure can be fine-tuned by detailed options for the numerical iterative process. In this book, however, the point is that an estimation process that fails is a sign of a poorly specified model. So the user should preferably alleviate the problem rather than insist on estimating the parameters of an incorrectly formulated model.

The parameters can, alternatively, be estimated by the method of least squares. This method is more robust, but it has a tendency of bias toward 0. The numerical value of, for instance, an autoregressive parameter is typically reduced.

The criterion for model selection is defined as a term that rewards model fit. It is given by a formula that includes the maximum likelihood value in this form:

$$-2 \log(\hat{L})$$

The maximum likelihood value is minimized; note that this value of the likelihood function in the univariate case is related to the residual variance as follows:

$$-2 \log(\hat{L}) \approx T \log(\hat{\sigma}^2)$$

See Chapter 6.

But the criterion also includes a term that rewards parameter parsimony. The number of estimated parameters is here denoted r . In a VARMA(p, q) model, it is $r = (p + q)k^2$.

The Akaike Information Criterion (AIC) is defined as follows:

$$\text{AIC} = 2r - 2 \log(\hat{L})$$

Another criterion is Schwarz's Bayesian Criterion (SBC), which also depends on the number of observations, T :

$$\text{SBC} = \log(T)r - 2 \log(\hat{L})$$

SBC has a more severe penalty for the number of parameters, which leads to models with fewer parameters because $\log(T) > 2$.

The default method in PROC VARMAX is the corrected Akaike Criterion (AICc), which is defined by adding a further punishment to the AIC:

$$\text{AICc} = \text{AIC} + \frac{2rT}{T - r - 1}$$

With this model-selection procedure, it is easy to at least find a good order for the model as a starting point. But usually the selected model includes too many parameters because all elements in the autoregressive and moving average coefficient matrices are estimated. These matrices, however, include many entries and therefore many parameters. Many of these parameters in practice turn out to be insignificant. They must be omitted from the model in order to gain precision in terms of degrees of freedom. This increase in precision is accomplished by tests for the significance of the individual parameters. It is also possible to test a hypothesis that more than one parameter could be left out of the model.

The fit of a model is tested in different ways. A VARMA model is specified in order to end up with an error series ϵ_t , which has no autocorrelation or cross-correlations other than correlations among the entries of ϵ_t at lag 0. The model is tested by way of the hypotheses that all these correlations equal 0.

This hypothesis can be tested for each individual autocorrelation or cross-correlation. This possibility is relevant for lags of special interest, like lag 1 or lag 12 for monthly observations. The estimated correlations can all be considered as approximately normally distributed, having mean 0 and variance equal the inverse, T^{-1} , to the number of observations, T . For small lags, the variance is a bit smaller. The tests are easily performed by a quick glance at a plot of estimated correlations with confidence bounds as produced by PROC VARMAX.

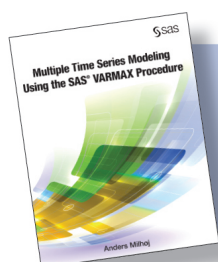
If many such hypotheses tested at a 5% test level, the tests would lead to rejection of the model fit despite the model's being perfect. This situation is precisely the definition of the 5% test level, which means that the probability of rejection of the hypothesis is 5% even if the hypothesis is true. In this multivariate context, with many possible dimensions for lack of fit in VARMA models, this problem is more apparent than in other contexts.

The simultaneous hypothesis of many autocorrelations and cross-correlations being 0 is tested by means of portmanteau tests. A portmanteau test is basically defined as the summed squares of many correlations, but with some minor corrections to meet the approximating distribution. It gives statistics that are approximately chi-square distributed, with the number of terms in the sum of squares adjusted for the number of estimated parameters as degrees of freedom.

Conclusion

In this chapter, univariate time series models are generalized to multivariate series. This extension is straightforward because coefficients, which are simply numbers in the univariate case, are replaced by matrices in the multivariate model. The resulting models, the VARMAX models, give the name to the procedure PROC VARMAX, which is the main subject of this book.

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Index

A

accumulated effects 86–87
ACE (autocorrelations) 5, 37–38, 100–101
ACF (residual autocorrelation function) 71
ADF (Augmented Dickey-Fuller) test 31, 32–33
Akaike information criteria (AIC) 41, 61, 66–67
 $\alpha\beta^T$ matrix 118–119
 α parameters
 estimated under restrictions 123–124, 144–145
 restrictions on 127–128
 TEST statement for hypotheses on 126
 testing hypotheses by VARMAX procedure 124–125
ARCH (Autoregressive Conditional Heteroscedasticity)
 effects 49, 101, 176
ARCH-effect testing 73
ARIMA models
 See Autoregressive Integrated Moving Average (ARIMA) models
ARIMA procedure
 Dickey-Fuller test and 35
 estimating univariate ARIMA models 42
ARMA models
 See Autoregressive Moving Average (ARMA) models
AR(p) models 38–39, 47–48, 49–50, 51–53, 74, 75, 104, 157
Augmented Dickey-Fuller (ADF) test 31, 32–33
autocorrelated errors, regression analysis with 13–18
autocorrelations (ACE) 5, 37–38, 100–101
AUTOREG procedure
 Cochrane-Orcutt Estimation using 15–16
 correction of standard errors with 13–14
 Dickey-Fuller test and 35
 GARCH models and 149, 158
 inclusion of lagged dependent variable in regression 27
 reverted regression 23–24
 simultaneous estimation using 16–18
Autoregressive Conditional Heteroscedasticity (ARCH)
 effects 49, 101, 176
Autoregressive Integrated Moving Average (ARIMA) models
 about 33, 37, 40, 43
 infinite-order representations 40–41
 multiplicative seasonal 41
autoregressive models 38–39

Autoregressive Moving Average (ARMA) models
 about 33, 37, 40
 infinite-order representations 40–41
autoregressive parameter matrices, prior covariance of 103–105
autoregressive terms, in models 120

B

Bayesian Vector Autoregressive (BVAR(p)) models
 about 103
 application of 108
 for egg market 108–110
 prior covariance of autoregressive parameter matrices 103–105
 VARMAX procedure 105–106
BEKK parameterization 167–168, 172
 β parameters
 estimation with restrictions on 144–145
 RESTRICT statement for 126–127
 restrictions on 127–128
 testing hypotheses on 120–124
 testing hypotheses on using VARMAX procedure 122–124
 tests for two restrictions on 123
 β values, estimates for 135
bivariate case, tests for cointegration relation in 132
BOUND statement 77, 163
Box-Jenkins procedure 33, 35, 37–38
Brocklebank, J.C. 41, 42
BVAR(p) models
 See Bayesian Vector Autoregressive (BVAR(p)) models

C

CAUSAL statement 95, 109
causality tests
 for Danish egg market 91–101
 estimation of final causality model 99–100
 of production series 96–97
 that use extended information sets 97–98
 of total market series 94–95
CCC (Constant Conditional Correlation)
 parameterization 165–166, 169–170, 172–173, 176–177
Cochrane-Orcutt Estimation 10–12, 15–16
COINTEG statement 125, 135–136
 ECTREND option 116, 122, 126
 NORMALIZE=OHIO option 117–118, 122

- cointegration
 - about 131–132
 - rank 4 model for five series specified with restrictions 141–145
 - Stock-Watson test for common trends for five series 139–141
 - using RESTRICT statement to determine form of models 138–139
- cointegration rank 132
- cointegration relations 131–132
- cointegration tests
 - in five-dimensional series 133–134
 - using VARMAX procedure for two price series 132–133
- COINTEST=(JOHANSEN) option, MODEL statement 133
- conditional variance series 157–158
- Constant Conditional Correlation (CCC)
 - parameterization 165–166, 169–170, 172–173, 176–177
- CORRCONSTANT=EXPECT option, GARCH statement 169
- correlation matrix
 - of error terms 78
 - at lag 0 59–60
- COWEST=NEWKEYWEST option, MODEL statement 14
- cross-correlation significance 70
- D**
- DATALABEL=YEAR option 115
- DCC (Dynamic Conditional Correlation)
 - parameterization 166–167, 170–171, 178, 180–183
- DFTEST option 46
- diagonal elements, prior distribution for 104
- Dickey, D.A. 41, 42
- Dickey-Fuller tests
 - about 133–134
 - applying VARMAX procedure to wage series 46
 - for differenced series 66
 - simple applications of 32
 - for stationarity 63
 - for unit roots 30–32
 - in VARMAX procedure 46
 - vector error correction models and 116–117
- DIF option 64, 92
- differenced series
 - applying VARMAX procedure to 46–47
 - Dickey-Fuller tests for 66
 - regression models for 19–28
- differencing
 - seasonal 35
 - time series 29–35
- distribution, of residuals in VARMA(2,0) model 71–72
- Durbin-Watson test 8–10, 49, 73, 116
- DWPROB option, MODEL statement 9
- Dynamic Conditional Correlation (DCC)
 - parameterization 166–167, 170–171, 178, 180–183
- E**
- ECM option, MODEL statement 116, 122
- ECTREND option, COINTEG statement 116, 122, 126
- effects
 - accumulated 86–87
 - of orthogonal shocks 88–89
- EGARCH model 162–164
- Engle, R.F. 96
- error terms
 - correlation matrix of 78
 - lag 0 correlation of 83–84
- estimated models, properties of 119
- estimation
 - of error correction models with VARMAX procedure 116
 - of model parameters by RESTRICT statement 143–144
 - with restrictions on α and β parameters 144–145
 - for β values 135
- estimation algorithm 178–180
- F**
- fit
 - of final model 100–101
 - of fourth-order autoregressive model 67–70
- fitted model 78–79, 151–153
- fitted second-order autoregressive model, roots of 81–82
- five series
 - rank 4 model for 141–145
 - Stock-Watson test for common trends for 139–141
- five-dimensional series, cointegration tests in 133–134
- forecasts 82–83
- FORM option 172
- FORM=CCC option 151, 158
- fourth-order autoregressive model, fit of 67–70
- G**
- Gammelgaard, S. 43
- GARCH models
 - about 30
 - forms of 158–164
 - for univariate financial time series 149–155
- GARCH statement
 - CORRCONSTANT=EXPECT option 169
 - OUTHT=CONDITIONAL option 151–153, 182
 - SUBFORM option 158, 172–173
- Gaussian residuals, test for hypothesis of 49
- Granger causality tests 63, 95–96
- "gray zone" 9
- H**
- HAC (heteroscedasticity and autocorrelation consistent)

Hendry, D.F. 96
 heteroscedasticity and autocorrelation consistent (HAC) 14
 hypotheses
 null 33
 TEST statement for on α parameters 126
 testing on α parameters by VARMAX procedure 124–125
 testing on β parameters 120–124
 testing on β parameters using VARMAX procedure 122–124

I

IAC (inverse autocorrelations) 71
 IACF (inverse autocorrelations) 100–101
 ID statement 48
 IGARCH model, using VARMAX procedure to fit 153–155
 impulse response, plots of 85–86
 independent variables, two lags of 25–26
 infinite-order representations 59, 84–89
 information criteria 41–42
 INITIAL statement 127, 171
 INTERVAL option 48
 inverse autocorrelations (IAC) 71
 inverse autocorrelations (IACF) 100–101

J

Jarque-Bera test 63, 73
 Johansen, S. 112, 132
 JOHANSEN option 134
 Johansen rank tests 63
 Juselius, K. 112, 132

K

Koyck lag 28
 KPSS unit root tests
 about 33
 application of 34
 k th-order autocorrelation 38
 Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) 33

L

lag 0, correlation matrix at 59–60
 lag correlation, of error terms 83–84
 LAG function 11
 lagged dependent variable
 inclusion of in regression 27
 interpreting models with 28
 lagged independent variable
 inclusion of 22, 24–25
 two lags 25–26
 LAGMAX=25 option, MODEL statement 93
 Litterman, R.B. 103
 Ljung-Box test 38, 49
 long-run relation 113–114
 Lütkepohl, H. 4, 57

M

MA(q) model 39–40, 50, 51, 53–54, 54–56, 74, 77
 matrix formulation, of vector error correction model 113
 METHOD=ML option 16, 47, 67
 Milhøj, A. 4
 MINIC option, MODEL statement 66
 minus sign (–) 105
 model fit 78–79, 94
 MODEL statement 89, 92, 122
 COINTEST=(JOHANSEN) option 133
 COWEST=NEWKEYWEST option 14
 DWPROB option 9
 ECM option 116, 122
 LAGMAX=25 option 93
 MINIC option 66
 NOINT option 151
 NSEASON=4 option 53
 NSEASON=12 option 93, 108
 PRIOR option 105, 106–108
 SW option 140
 models
 See also specific types
 autoregressive terms in 120
 interpreting with lagged dependent variables 28
 moving average 39–40
 multiplicative seasonal ARIMA 41
 for multivariate time series 57–61
 with rank 2 135–137
 selecting 66–67
 for univariate time series 37–42
 using RESTRICT statement to determine form of 138–139
 VARMAX 58–59, 60–61
 Morgan, D.P. 4
 moving average models 39–40
 multiplicative seasonal ARIMA models 41
 multivariate GARCH models
 about 165
 BEKK parameterization 167–168, 172
 bivariate example using two quotations for Danish stocks 168–173
 CCC (Constant Conditional Correlation)
 parameterization 165–166, 169–170, 172–173, 176–177
 DCC (Dynamic Conditional Correlation)
 parameterization 166–167, 170–171, 178, 180–183
 multivariate series, modeling with VARMAX procedure 63–79
 multivariate time series
 about 57–58
 modeling with VARMAX procedure 64–67
 models for 57–61
 multivariate VARMA-GARCH models
 about 175–176
 estimation algorithm 178–180

multivariate VARMA-GARCH models (*continued*)
 for residuals 176–177, 178, 180–183
 wage-price time series 176

N

Newey-West method, adjusting standard deviations with
 14–15
 NLAG=1 option 16
 NLOPTIONS statement, PALL option 178–179
 NOINT option, MODEL statement 151
 NORMALIZE option 133–134
 NORMALIZE=OHIO option, COINTEG statement
 117–118, 122, 126
 NSEASON=4 option, MODEL statement 53
 NSEASON=12 option, MODEL statement 93, 108
 null hypothesis 33

O

ODS (SAS Output Delivery System) 1–2
 off-diagonal elements, prior distribution for 104–105
 options
 See specific options
 ordinary least squares (OLS) 8
 ordinary regression models 1–2
 orthogonal shocks, effects of 88–89
 OUTHT=CONDITIONAL option, GARCH statement
 151–153, 182
 outliers, identification of 72–74
 output
 about 81
 forecasts 82–83
 infinite-order representations 84–89
 lag 0 correlation of error terms 83–84
 roots of fitted second-order autoregressive model
 81–82

P

PACF (partial autocorrelations) 100–101
 PALL option, NLOPTIONS statement 178–179
 parameterized models, for time series 4–5
 parameters
 See also specific types
 estimated for vector error correction models 117–
 120
 estimating 67–68
 estimation of by RESTRICT statement 143–144
 in prior distribution 106–108
 restriction of insignificant model 68–70
 partial autocorrelations (PACF) 100–101
 periods (.) 105
 PGARCH model 161–162
 plots, of impulse response 85–86
 PLOTS=ALL option 46, 64, 70
 plus sign (+) 105
 portmanteau tests 61, 70–71, 94
 price series
 applying VARMAX procedure to 50–51
 cointegration test for two using VARMAX
 procedure 132–133

PRINTALL option 46, 47, 64, 70, 156
 PRINT=(DIAGNOSE) option 156
 prior covariance, of autoregressive parameter matrices
 103–105

prior distribution

 for diagonal elements 104
 for off-diagonal elements 104–105
 parameters in 106–108

PRIOR option, MODEL statement 105, 106–108

PROC statement 13

procedures

See specific procedures

production series, causality tests of 96–97

properties

 of estimated model 119
 of final model 128–129
 of fitted model 79

p-test 31

p-value 9

Q

QGARCH model 158–159

R

rank 2 model 135–137

rank 4 model 141–145

REG procedure 1–2, 8–10, 19–20, 22, 23–24, 27, 30–
 32, 116

regression, inclusion of lagged dependent variable in
 27

regression analysis

 with autocorrelated errors 13–18
 reverted 23–24
 for time series data 7–12

regression models

 for differenced series 19–28
 ordinary 1–2
 in time series analysis 2–3

residual autocorrelation, in VARMA(2,0) model 70–71

residual autocorrelation function (ACF) 71

residuals

 distribution of in VARMA(2,0) model 71–72
 multivariate VARMA-GARCH models for 176–
 177, 178, 180–183

RESTRICT statement 68, 76, 126–127, 138–139, 143–
 144, 154, 164, 172, 176–177, 180

restrictions

 alternative form of 142
 estimated α parameters under 123–124
 estimation with on α and β parameters 144–145
 of insignificant model parameters 68–70
 rank 4 model for five series specified with 141–
 145
 tests for two on β parameters 123
 on α and β parameters 127–128

reverted regression 23–24

Richard, J.F. 96

roots, of fitted second-order autoregressive model 81–
 82

S

SAS Output Delivery System (ODS) 1–2
 Schwarz Bayesian criterion (SBC) 41, 61
 seasonal differencing 35
 SGPLOT procedure 19–20, 44, 92, 114, 115, 153
 shrinkage, toward zero 107
 simple regression 115–116
 simultaneous estimation, using AUTOREG procedure 16–18
 standard deviations, adjusting with Newey-West method 14–15
 standard errors, correction of with AUTOREG procedure 13–14
 STANDARD procedure 75
 standardized series, analysis of 75–77
 statements
 See specific statements
 stationarity 5, 29–30
 STATIONARITY=(ADF) option 32
 Stock-Watson test, for common trends for five series 139–141
 SUBFORM option, GARCH statement 158, 172–173
 SW option, MODEL statement 140

T

TEST statement 10, 68, 76, 99, 126, 153
 tests
 See also specific tests
 for cointegration relation in bivariate case 132
 for differencing time series 29–35
 for two restrictions on β parameters 123
 TGARCH model 159–161, 172–173
 time series
 about 3–4
 differencing 29–35
 model features 4
 parameterized models for 4–5
 regression analysis for data 7–12
 regression models in analysis of 2–3
 wage-price 43–45
 total market series, causality tests of 94–95

U

unit roots
 about 30
 Dickey-Fuller tests for 30–32
 KPSS unit root tests 33
 univariate ARIMA models, estimating 42
 univariate financial time series, GARCH models for 149–155
 univariate GARCH models
 about 147–149
 wage series 155–158
 univariate series, modeling with VARMAX procedure 43–56
 univariate time series, models for 37–42

V

VARMA model
 See Vector Autoregressive Moving Average (VARMA) model
 VARMAX models
 about 58–59, 60
 building 60–61
 VARMAX procedure
 See also Bayesian Vector Autoregressive (BVAR(p)) models; causality tests; output; vector error correction models
 about 4, 57, 63
 AICc and 42
 applying to differenced wage series 46–47
 applying to number of cows series 51–53
 applying to price series 50–51
 applying to series of milk production 53–54
 applying to wage series 46
 Bayesian Vector Autoregressive (BVAR(p)) models and 105–106
 BEKK parameterization and 167, 172
 CCC models and 166
 cointegration test for two price series using 132–133
 cointegration tests in five-dimensional series 133–134
 DCC models and 167
 Dickey-Fuller tests and 35, 46, 66
 estimates for β values 135
 estimating AR(2) model 47–48
 estimating parameters 68
 estimating univariate ARIMA models 42
 estimating vector error correction models with 116
 GARCH models and 149, 158–161
 Granger causality tests in 95–96
 modeling multivariate series with 63–79
 modeling multivariate time series with 64–67
 modeling univariate series with 43–56
 multiplicative seasonal ARIMA models and 41
 Stock-Watson test for common trends 140
 testing hypotheses on α parameters by 124–125
 testing hypotheses on β parameters using 122–124
 using to fit AR(2)-GARCH(1,1) models 157
 using to fit GARCH(1,1) model 150–151
 using to fit IGARCH model 153–155
 using VARMA model for milk production and number of cows 74–79
 wage series 155–158
 Vector Autoregressive Moving Average (VARMA) model
 about 58–59
 for Danish egg market 92–94
 Danish egg market and 91
 distribution of residuals in 71–72
 residual autocorrelation in 70–71
 using for milk production and number of cows 74–79

vector error correction models

- about 111–113
- Dickey-Fuller tests and 116–117
- estimated parameters 117–120
- estimating with VARMAX procedure 116
- example 114–117
- matrix formulation of 113
- properties of final model 128–129
- RESTRICT statement for β parameters 126–127
- restrictions on α and β parameters 127–128
- TEST statement for hypotheses on α parameters 126
- testing hypotheses on α parameters by VARMAX procedure 124–125
- testing hypotheses on β parameters 120–122
- testing hypotheses on β parameters using VARMAX procedure 122–124

W

- wage series 46, 155–158
- wage-price time series 43–45, 176
- Wiener processes 132

X

- X12 procedure 4
- XLAG=3 option 93

Z

- zero, shrinkage toward 107

About This Book

Purpose

The purpose of this book is to show how broadly the VARMAX procedure supports modern time series econometrics. The VARMAX procedure includes modern facilities like automatic model selection and GARCH models for univariate series. But the main focus is on multivariate time series, for which automatic VARMA model selection and GARCH are of course supported. Moreover, BVAR models, together with subjects like Granger Causality and cointegration, are supported. All these featured are illustrated mainly by examples using real data.

Is This Book for You?

This book is useful for readers who are analyzing a time series for the first time. They will find PROC VARMAX easy to use. But PROC VARMAX also includes many advanced features; therefore, readers who know more advanced theoretical time series models will find this book useful as a guide for applying PROC VARMAX for advanced model building.

Prerequisites

The book is aimed at econometricians who have completed at least one course in time series modeling.

Scope of This Book

Chapters 2 through 4 give the background for time series models as a special case of regression analysis. In these chapters, you will learn how ordinary regression fails; for example, see Figure 1.2. Chapters 2 through 4 also demonstrate how these failures to some extent can be accounted for. These methods are, however, not sufficient to establish reliable statistical models for many common data problems.

The models focused on are models for multivariate time series—that is, models for the interdependence of two or more univariate time series. Such models can be seen as generalizations of the usual regression model to the case of multivariate, left side, response variables. Relationships among time series are not necessarily immediate but can happen with some time delay. In order to model such delays, both wages and prices have to be right side variables in a regression model with both wages and prices as right side variables. In time series, a system like this one is said to “have feedback.” A major part of the book is devoted to describing such models and to showing by example how you can do the analysis by means of the VARMAX procedure (Chapters 7 through 12).

Another assumption underlying the usual regression model is often violated. The variance in many situations is nonconstant, so that the residuals cannot be identically distributed. One simple example is that the variance often increases as the level increases. In many situations, this problem is rather easily solved by a logarithmic transformation. In more detailed analysis, this transformation can be refined by a Box-Cox transformation. This topic is, however, beyond the scope of this book.

For time series, the variance can vary in a seemingly random manner even if the variance is constant in a broad sense. A typical example is a stock rate that for some days is very volatile but in other periods is nearly constant. For such series, the variance can be considered as a time series in itself, which can be modeled by the so-called GARCH models. These methods are also covered by PROC VARMAX. See Chapters 15 through 17.

In modern econometric analysis of time series data, cointegration and error correction models play a major role. The basic idea is that, even if two or more time series seem to be unstable individually, some stable relationship exists among them. This stable relationship can be considered as an economic equilibrium. In this case, the series are said to be cointegrated. If the series for some reason are away from this stable relationship, an error correction mechanism can describe how they find their way back to equilibrium. So dynamics of economic data can be modeled in a way that is closely related to economic theory. Similar models are useful for time series from branches other than economics. These topics are covered by Chapters 13 through 14.

About the Examples

Software Used to Develop the Book's Content

The software used to develop the content of this book is as follows:

- SAS/STAT 14.1
- SAS/ETS 14.1

But most of the content is also available in SAS ETS 13.1.

Data Sets Used in the Book

All series are downloaded by the author at some specific point in time, so subsequent revisions of the series are, of course, not incorporated in the examples. The focus is on applications and not on specific conclusions about the series and their impact. Intuitive arguments for understanding the models based on the nature of the series are, of course, used. Otherwise, the series are analyzed without any political or economic viewpoints, to ensure that the presentation is neutral and purely technical.

Time series examples, by their very nature, soon become obsolete. Even forecasting experiments, in which more recent observations are compared with forecasts, begin to seem like historical exercises after a while. Keeping this in mind, know that forecasts in this book are in no way suggested to be the future realizations of the time series.

You can access the data, as well as example code, for this book by linking to its author's page at <http://support.sas.com/publishing/authors>. Select the name of the author. Then look for the cover thumbnail of this book, and select Example Code and Data to display the SAS programs that are included in this book.

If you are unable to access the code through the Web site, send e-mail to saspress@sas.com.

WAGEPRICE

This data set includes yearly index numbers for the wage and the prices in Denmark for the years 1818–1981. It gives a total of 164 observations. The observations are taken from a small book on historical data for Denmark (Gammelgaard 1985), but originally they were published in many historical sources.

EGG

The data set includes 144 monthly observations of index numbers for the Danish-produced quantity of eggs and the price to the farmers for eggs. The data is rather old, 1965–1976, but at that time the Danish market was rather closed to foreign competition. So the relation between produced quantity and the price can be modeled without corrections for other variables. The data is published by Statistics Denmark.

QUARTERLY_MILK

The data set includes quarterly observations of the number of cows and the milk production in the United States. The data set includes observations from 1998 to 2012, a total of 60 observations. The series is quoted from an Excel data sheet found on the U.S. Department of Agriculture's Economic Research Service website.

QUOTES

The data set includes daily observations of quotes for two stocks at the Danish stock exchange from March 21, 2002, to March 19, 2003. One firm is a bank, and the other operates in the field of biotech. Both companies have changed since the time of the observations, so firm-specific information is of no longer of interest. The series has 248 observations of the quotes, the log-transformed quotes, and the daily change in the notation for both companies expressed as a percentage.

POTATOES_YEAR

This data set includes yearly observations of the average price of potatoes in states in the United States: Delaware, Maryland, Ohio, Virginia, and Pennsylvania. The observation period is 1866 and up to 2013, giving a total of 148 observations.

The original price is the total value of the production of potatoes within the state divided by the produced quantity. The unit of the price is US Dollar per CWT (approximately 45 kg), but the precise unit of measurement is of no importance because of the transformation by logarithms.

The time series are published by United States Department of Agriculture, National Agricultural Statistics Service.

SAS University Edition

If you are using SAS University Edition to access data and run your programs, then please check the SAS University Edition page to ensure that the software contains the product or products that you need to run the code: <http://support.sas.com/software/products/university-edition/index.html>.

PROC VARMAX is not supported by SAS University Edition in the version available in autumn 2015, when this book was produced.

Output and Graphics Used in This Book

The output tables and the output graphics are mainly created by PROC VARMAX, which produces a huge amount of graphical output. A few figures are, however, created by PROC SGLOT. The actual code for the displayed output is included in the text and in the code at <http://support.sas.com/publishing/authors/milhoj.html>.

Additional Help

Although this book illustrates many analyses regularly performed in businesses across industries, questions specific to your aims and issues may arise. To fully support you, SAS Institute and SAS Press offer you the following help resources:

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- For questions about topics in or beyond the scope of this book, post queries to the relevant SAS Support Communities at <https://communities.sas.com/welcome>.
- SAS Institute maintains a comprehensive Web site with up-to-date information. One page that is particularly useful to both the novice and the seasoned SAS user is its Knowledge Base. Search for relevant notes in the "Samples and SAS Notes" section of the Knowledge Base at <http://support.sas.com/resources>.
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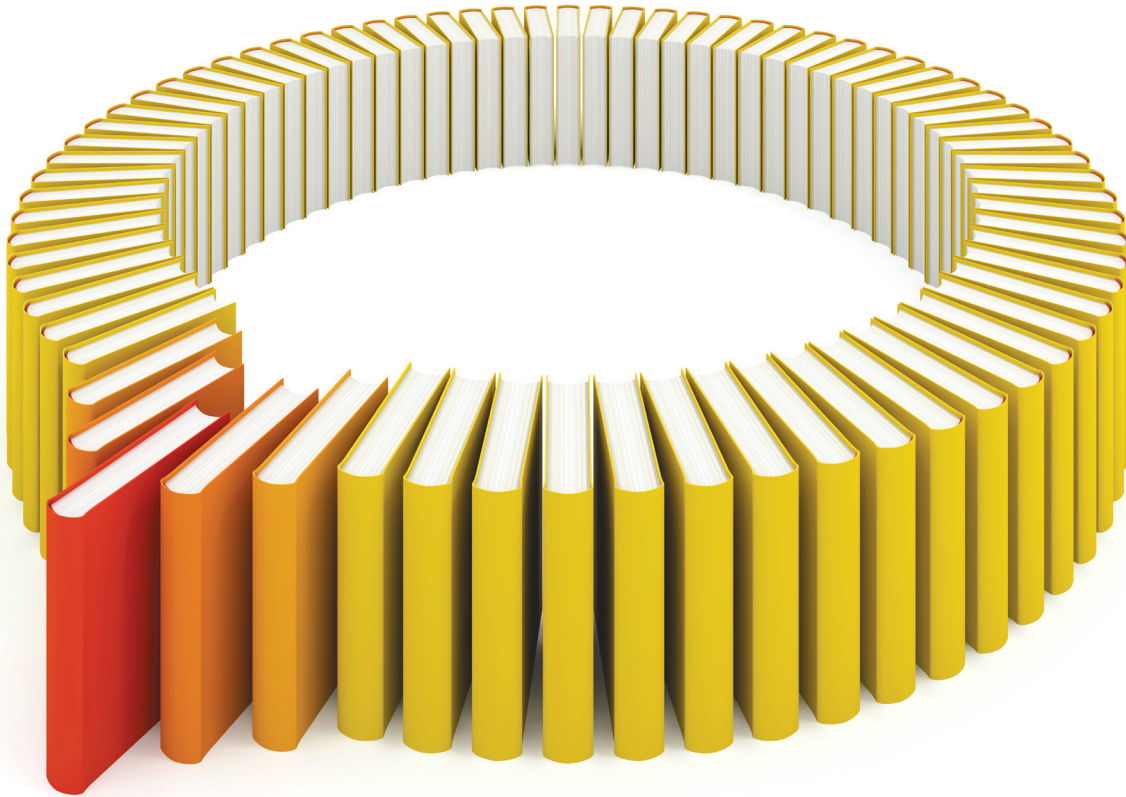
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Anders Milhøj is associate professor in the Department of Economics at the University of Copenhagen, where he conducts research and lectures on applied statistics topics including survey sampling, regression analysis, time series analysis, and factor analysis. A SAS user since 1984, he employs a variety of SAS procedures in his work, such as SAS/STAT, SAS/IML, SAS/ETS, and SAS/OR. He holds university degrees in statistics and mathematics, as well as a Ph.D. in statistics, all from the University of Copenhagen.

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