DYNAMIC FACTOR ANALYTIC MODEL ESTIMATION USING DYNFAC: A GUIDE FOR USERS*

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ABSTRACT

This is a user's guide for the DYNFAC package. A program written in GAUSS to estimate, by maximum likelihood in the time domain, DYNamic FACtor analytic models with one common factor (single-index models), by means of the Kalman filter.

The underlying theory and methods are briefly explained.

KEY WORDS: Dynamic Factor models, Kalman filter, software.

RESUMEN

Esta es la guía de usuario del programa DYNFAC. Un programa escrito en lenguaje matricial GAUSS para estimar, por máxima verosimilitud en el dominio temporal, modelos FACtoriales DYNámicos con un factor común no observable, por medio del filtro de Kalman.

La teoría y los métodos que forman la base del programa son explicados de forma concisa.

PALABRAS CLAVE: Modelos factoriales dinámicos, filtro de Kalman, software.

1. INTRODUCTION

DYNFAC is a program written in the GAUSS matrix programming language to estimate **Dynamic Factor Analytic Models** from a cross section of time series. At present the program is quite modest and it can only be used to estimate a very limited set of models that have been used successfully in business cycle analysis but it is planned to do further developments. Moreover with some knowledge of GAUSS it is possible to estimate variants of the implemented model at a little cost.

The program has been used and seems to be free of errors. However, the author does not assume responsibility for any remaining errors. In no event shall I be liable for any damages whatsoever arising out of the use of or inability to use this program package.

The guide is organized as follows. Section 2 describes how DYNFAC can be installed and how the data should be organized. Section 3 contains an account of the econometric models that can be estimated with DYNFAC, it contains some technical material and relevant references to the literature for the interested reader. It also stablises the limitation of the current version and the planning for further developments. Section 4 provides detailed instructions on how to use DYNFAC by means of the explanation of the command file DYNFAC.RUN, and section 5 contains an example.

No knowledge of GAUSS is required to use the program, nevertheless it is an advantage if you experience problems. Moreover by modifying the appropriate procedures it is possible to estimate a wider set of models than the ones contained in this guide.

2. INSTALLATION

DYNFAC is contained in 4 files: DYNFAC.RUN, DYNFAC.SRC, DYNFAC.ERR and DYNFAC.LIB, plus a set of general procedures, all of which have the SRC (*.SRC) extension, a DEClaration file (*.DEC) and an EXTernal file (*.EXT).[1] In addition DYNFAC.TXT contains the revisions of the program and information not contained in the manual. The DYNFAC.LIB file gives access to all of the procedures needed by the program. These were written using Version 3.1 of GAUSS.[2] In addition to the main program the MAXLIK module is required for DYNFAC to run. For speed reasons a 486 chip or higher is recommended, even if DYNFAC will still run on a lower machine. For the same reason the program should only be run from a hard disk.

The DYNFAC disk is organized in the same way as the GAUSS disks and an installation BATch file is supplied, DYNFAC.BAT. The program is located in the subdirectory DYNFAC of the root directory of the distribution disk, so Change Directory to DYNFAC to install the program.

Assume GAUSS has been fully installed (see chapter 1 of GAUSS' manual). The DYNFAC.BAT will copy the DYNFAC.LIB file to the LIBrary subdirectory of GAUSS (\GAUSS\LIB), all the files in the SRC subdirectory to the GAUSS SRC subdirectory (\GAUSS\SRC), the files in the EXAMPLES subdirectory to the GAUSS EXAMPLES subdirectory (\GAUSS\EXAMPLES), and the DYNFAC.RUN, DYNFAC.SRC, DYNFAC.ERR and DYNFAC.TXT files to the subdirectory where the GAUSS program is located (\GAUSS). If your prefer to keep separated the programs and data from the GAUSS files, which is probably the best option, just copy the DYNFAC.RUN, DYNFAC.SRC and DYNFAC.ERR files to your working directory. The program should work fine in this case as is supplied. Other configurations are however possible.

In addition a new directory will be created within the GAUSS structure (\GAUSS\MANUAL) which contains this guide, written in ChiWriter 4.10.

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[1] Naming convention follows GAUSS.

[2] In particular the GAUSSI Version 3.1.4 with virtual memory was used in the development of DYNFAC; if a non-i version of GAUSS is used some changes in the eigenvalue and eigenvector commands contained in the procedures may be needed.

2.1. Data

DYNFAC has been thought to work from a matrix in memory. As the command file is designed, the data will be loaded from an ASCII file containing a TxN matrix of data, where T is the number of observations, the time dimension, and N the number of variables, the cross section dimension.

3. ECONOMETRIC MODELS

In classical **Factor Analysis** it is assumed that a set of N observed variables $\mathbf{y}_t$ depends linearly on $Q < N$ unobserved common factors $\mathbf{c}_t$ and on individual factors $\mathbf{u}_t$,

$$\mathbf{y}_t = \beta + \Gamma\mathbf{c}_t + \mathbf{u}_t \tag{1}$$

where Γ is a NxQ matrix of **factor loadings**, the components of $\mathbf{c}_t$ are assumed to be uncorrelated with $\mathbf{u}_t$ and the components of $\mathbf{u}_t$ are assumed to be uncorrelated, that is, Var($\mathbf{u}_t$) is a diagonal matrix. Moreover serial correlation in either $\mathbf{c}_t$ or $\mathbf{u}_t$ is not allowed, which in turn implies the absence of serial correlation in $\mathbf{y}_t$. (Harman (1976), Srivastava y Carter (1983) y Magnus and Neudecker (1988)). The objective of factor analysis is, usually, to estimate the matrix of factor loadings, Γ, and/or the unobserved factors $\mathbf{c}_t$.

There are a number of programs that estimate models such as (1), among others the PRIN command of TSP and the PRIN procedure supplied with the DYNFAC package.[3]

[3] The PRIN procedure, which performs a PRINcipal components analysis, can be used independently of DYNFAC, see information in the PRIN.SRC file.

As is explained below, DYNFAC can also be used to estimate, by maximum likelihood, a static factor analytic model like (1) when Q = 1.

In a time series context serial correlation is the rule, rather than the exception, so it may be more sensible to assume that the factors and/or unobserved components are autocorrelated. For example, they may be generated by VAR o VARMA processes. Assuming a VAR process we have

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + \dots + \phi_p c_{t-p} + \eta_t \qquad (2)$$

or

$$\phi(L)c_t = \eta_t \qquad (2')$$

where L is the lag operator, and

$$\mathbf{u}_t = \mathbf{D}_1 \mathbf{u}_{t-1} + \mathbf{D}_2 \mathbf{u}_{t-2} + \dots + \mathbf{D}_k \mathbf{u}_{t-k} + \varepsilon_t \qquad (3)$$

or

$$\mathbf{D}(L)\mathbf{u}_t = \varepsilon_t \qquad (3')$$

where η_t and ε_t are white noise processes.

In this case we have what has been called a **Dynamic Factor Analytic Model.** These kind of models were introduced into economics by Sargent and Sims (1977), Geweke (1977) and Engle and Watson (1981).

Model (1)-(3) is the focus of the DYNFAC program, with some restrictions to make the model more easily interpretable from an economic point of view. In particular, we assume that the number of factors is equal to one, Q = 1, so we have what has been called a single-index model (Sargent and Sims (1977), Geweke (1977)).

In addition, some identifying assumptions are made. The main one expresses the core notion of the dynamic factor model that the co-movements of the multiple time series, $\mathbf{y}_t$, arise from a single source c_t. In statistical terms this implies assuming that $\mathbf{u}_t$ and c_t are mutually uncorrelated at all leads and lags, which in turn is achieved by assuming that $\mathbf{D}(L)$ is diagonal and that the N + 1 disturbances

$(\sigma^2_\eta, \sigma^2_{\varepsilon_1},...,\sigma^2_{\varepsilon_n})$ are mutually and serially uncorrelated[4].

$$D(L) = \mathrm{diag}(d_1(L), \; ... \; ,d_N(L))$$

and

$$E\begin{bmatrix}\eta_t\\ \varepsilon_t\end{bmatrix}.\begin{bmatrix}\eta_s & \varepsilon'_s\end{bmatrix} = \begin{cases}\Omega = \mathrm{diag}(\sigma^2_\eta, \sigma^2_{\varepsilon_1},...,\sigma^2_{\varepsilon_n}) & \text{if } s = t\\ \mathbf{0} & \text{if } s \neq t\end{cases}$$

Moreover, only the relative variances of disturbances are identified so we shall assume that $\mathrm{Var}(\eta_t) = \sigma^2_\eta = 1$, this is just a normalization restriction and fixes the scale of c_t.

In summary, the model we focus on is

$$\mathbf{y}_t = \beta + \gamma c_t + \mathbf{u}_t \qquad (4)$$

$$\phi(L).c_t = \eta_t \qquad (5)$$

$$\mathbf{D}(L).\mathbf{u}_t = \varepsilon_t \qquad (6)$$

where $\Gamma = \gamma$, $\phi(L)$ is an scalar polynomial in the lag operator of order p, $\mathbf{D}(L)$ is a diagonal matrix polynomial in the lag operator of order k, $\mathbf{D}(L) = \mathrm{diag}(d_1(L),...,d_N(L))$, η_t and ε_t are gaussian white noise processes with zero mean and variance given by $\mathrm{Var}(\eta_t) = 1$ and $\mathrm{Var}(\varepsilon_t) = \mathrm{diag}(\sigma^2_{\varepsilon_1},...,\sigma^2_{\varepsilon_n})$, and β allows for non-zero means in the elements of the y_t process, but since this vector can be concentrated out of the likelihood function it will be dropped in what

[4] It should be pointed out that when there are more than three uncorrelated series in the analysis or when the variables in y_t are serially correlated the dynamic factor formulation imposes testable overidentifying restrictions. This overidentification in the model allows us to interpret the single source specification as implying that there is a single causal source of common variation, or *shock*, among the variables y_t. But the econometrician should be careful not to read too much into the factor formulation, which is a purely statistical model (Stock and Watson (1989)).

follows without loss of generality.[5]

In addition, note that c_t is assumed to enter the model only contemporaneously. This could be generalized by considering a polynomial in the lag operator $\gamma(L)$ instead of γ, so (4) becomes

$$\mathbf{y}_t = \beta + \gamma(L)c_t + \mathbf{u}_t \tag{4'}$$

Imposing $\gamma(L) = \gamma$ further restricts the impulse response function from η_t to $\mathbf{y}_t$ to be proportional across the observable series.

The estimation of this model can be performed in the frequency domain, as has been suggested by Sargent and Sims (1977) and Geweke (1977), or in the time domain, as has been enfasized by Aigner et al (1984) and Stock and Watson (1989, 1991, 1992). DYNFAC focuses on the **time domain estimation**.

3.1. The state space representation

The first step towards estimating the model (4)-(6) is to cast it into a (linear) **state space** form so that the **Kalman filter** can be used to evaluate the **likelihood function**.

State space models are based on the idea that an observed multiple time series, $\mathbf{y}_t$, depends upon a possibly unobserved state, α_t, which is driven by a (linear) stochastic process. The state space system consists, then, if two equations, the **measurement equation**[6]

$$\mathbf{y}_t = \mathbf{Z}.\alpha_t + \xi_t \tag{7}$$

and the **transition equation**

[5] In practice this is achieved by standardizing variables prior to the analysis, this is also a common practice in static factor analysis.

[6] I follow the notation in Harvey (1989), suitable modified to the problem at hand, and assume that $\mathbf{y}_t$ is a zero mean vector of observations.

$$\alpha_t = \mathbf{T}.\alpha_{t-1} + \mathbf{R}.\zeta_t \tag{8}$$

that describes the transition of the state of nature from period t-1 to period t. In the simplest formulation ξ_t and ζ_t are assumed to be (gaussian) uncorrelated white noise sequences with variance matrices $Var(\xi_t) = \mathbf{H}$ and $Var(\zeta_t) = \mathbf{Q}$. The system (7)/(8) is one form of a **linear state space system.**

Defining the state vector as

$$\alpha_t = \begin{bmatrix} c_t \\ \vdots \\ c_{t-p+1} \\ \mathbf{u}_t \\ \vdots \\ \mathbf{u}_{t-k+1} \end{bmatrix}_{(p+N.k)x1}$$

and choosing

$$T = \left[\begin{array}{cccc|cccc} \phi_1 & \dots & \phi_{p-1} & \phi_p & & & & \\ 1 & & 0 & 0 & & & & \\ \vdots & \ddots & \vdots & \vdots & & \mathbf{0} & & \\ 0 & \dots & 1 & 0 & & & & \\ \hline & & & & \mathbf{D}_1 & \dots & \mathbf{D}_{k-1} & \mathbf{D}_k \\ & & & & \mathbf{I}_N & & \mathbf{0} & \mathbf{0} \\ & \mathbf{0} & & & \vdots & \ddots & \vdots & \vdots \\ & & & & \mathbf{0} & \dots & \mathbf{I}_N & \mathbf{0} \end{array}\right]_{(p+N.k)x(p+N.k)},$$

$$\zeta_t = \begin{bmatrix} \eta_t \\ \varepsilon_t \end{bmatrix}_{(1+N)x1}$$

and

$$R = \left[\begin{array}{cc} 1 & \mathbf{0}' \\ 0 & \mathbf{0}' \\ \vdots & \vdots \\ 0 & \mathbf{0}' \\ \hline \mathbf{0} & \mathbf{I}_N \\ \mathbf{0} & \mathbf{0} \\ \vdots & \vdots \\ \mathbf{0} & \mathbf{0} \end{array}\right]_{(p+N.k)x(1+N)}$$

where $\mathbf{I}_N$ is the NxN identity matrix and $\mathbf{D}_i = \mathrm{diag}(d_{1i},...,d_{Ni})$, we can write the **transition equation** (8).

The corresponding **measurement equation** is obtained by defining

$$\mathbf{Z} = \left[\gamma\ \mathbf{0}\ ...\ \mathbf{0}\ \mathrm{I}_N\ \mathbf{0}\ ...\ \mathbf{0}\right]_{Nx(p+N.k)}$$

which allows us to write the **measurement equation** as

$$\mathrm{y}_t = \left[\gamma\ \mathbf{0}\ ...\ \mathbf{0}\ \mathrm{I}_N\ \mathbf{0}\ ...\ \mathbf{0}\right].\alpha_t = \mathbf{Z}.\alpha_t \tag{9}$$

Note that, in this formulation, the measurement noise, ξ_t, is set to zero.

As is usually the case, the state space representation given by the above equations is not unique. In practice, it is computationally more efficient to work with a lower dimensional state vector, since otherwise the dimension of the model may grow so fast that estimation becomes unfeasible because of memory constraints. This reduction in the dimensionality of the model can be achieved by filtering $\mathbf{y}_t$, $\gamma.\mathbf{c}_t$ and $\mathbf{u}_t$ in equation (4) by $\mathbf{D}(L)$ and treating ε_t as a measurement noise. The transformed model is then

$$\mathbf{D}(L).\mathbf{y}_t = \mathbf{D}(L).\gamma.\mathbf{c}_t + \varepsilon_t \tag{10}$$

$$\phi(L).c_t = \eta_t \tag{11}$$

The resulting state vector has then dimension max(p, k+1).

DYNFAC takes advantage of this transformation but, since this is not of interest to the user, discussion in what follows will proceed in terms of model (4)-(6), and the corresponding reparametrization in terms of the state space form given above.

3.2. Estimation

Once the model has been cast into the state space form, the **Kalman Filter** (Kalman (1960), Kalman and Bucy (1961)) is a well-known way to compute the Gaussian likelihood function for a given set of parameters (Schweppe (1965), Harvey (1981, 1989), Lütkepohl (1991)). The filter recursively constructs optimal estimators (in the sense of minimizing the mean square error) of the unobserved components in the state vector, given observations on y_t, the system matrices, **Z**, **T**, **R**, **H** and **Q**, and initial conditions. Under normality assumptions the optimal estimator produced by the Kalman Filter is the conditional expectation $E(\alpha_t | y_1,...,y_t)$. The Kalman Filter also provides the conditional covariance matrix $Var(\alpha_t | y_1,...,y_t)$, which may serve as a measure for estimation uncertainty.

The filter consists of two sets of equations, the **prediction and updating equations.** Letting $\alpha_{t|s} = E(\alpha_t | y_1,...,y_s)$ and $\Sigma_{t|s} = Var(\alpha_t | y_1,...,y_s)$ the **prediction equations** for the Kalman Filter for system (7)/(8) are[7]

$$\alpha_{t|t-1} = \mathbf{T}.\alpha_{t-1|t-1} \tag{12}$$

$$\Sigma_{t|t-1} = \mathbf{T}.\Sigma_{t-1|t-1}.\mathbf{T}' + \mathbf{RQR}' \tag{13}$$

Prediction for y_t given information up to and including t-1 is given by

$$y_{t|t-1} = \mathbf{Z}.\alpha_{t|t-1}$$

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[7] The Kalman Filter for more general systems can be found in Anderson and Moore (1979) or Harvey (1989).

And the **updating equations** for the Kalman Filter are

$$\alpha_{t|t} = \alpha_{t|t-1} + \Sigma_{t|t-1}.\mathbf{Z}'\mathbf{F}_t^{-1}.\upsilon_t \tag{14}$$

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1}.\mathbf{Z}'\mathbf{F}_t^{-1}\mathbf{Z}.\Sigma_{t|t-1} \tag{15}$$

where $\upsilon_t = \mathbf{y}_t - \mathbf{y}_{t|t-1}$ are the prediction errors, and $\mathbf{F}_t = E(\upsilon_t\upsilon_t' \,|\, \mathbf{y}_1,...,\mathbf{y}_t) = Z.\Sigma_{t|t-1}.Z' + \mathbf{H}$.

The filter needs to be initialized with $\alpha_{0|0}$ and $\Sigma_{0|0}$. Given the assumption that $\mathbf{y}_t$ is (covariance) stationary these initial values are taken from the unconditional distribution of the state vector, so $\alpha_{0|0} = \mathbf{0}$ and $\Sigma_{0|0} = \Sigma$, being Σ the unique solution of the Lyapunov equation

$$\Sigma = \mathbf{T}.\Sigma.\mathbf{T}' + \mathbf{RQR}' \tag{16}$$

Note that since the unconditional distribution of $\alpha_{1|1}$ is the same as the unconditional distribution of $a_{0|0}$, the Kalman Filter can also be initialized as $\alpha_{1|0} = \mathbf{0}$ and $\Sigma_{1|0} = \Sigma$. The covariance matrices $\Sigma_{0|0}$ and $\Sigma_{1|0}$ are consistent with each other, as can be seen by comparing (16) with the prediction equation (13).

When the system matrices, **Z**, **T**, **R**, **H** and **Q**, contain unknown time invariant parameters, as is the case in the present context, they should be estimated, and the Kalman Filter is a useful tool in computing the **likelihood function** for a trial set of parameters. Assuming

$$\mathbf{y}_t \,|\, \mathbf{y}_1,...,\mathbf{y}_{t-1} \sim N(\mathbf{y}_{t|t-1}, \mathbf{F}_t) \tag{17}$$

the log-likelihood function is given by

$$\ln L(\theta) = -\frac{NT}{2}\ln(2\pi) - \frac{1}{2}.\sum_{t=1}^{T}\left[\ln(\det(\mathbf{F}_t)) + \upsilon_t'\mathbf{F}_t^{-1}\upsilon_t\right] \tag{18}$$

where θ is a vector that picks up all the time invariant parameters that have to be estimated. Note that υ_t and $\mathbf{F}_t$ are both functions of θ.

If a specific vector θ is assumed all the quantities in the log-likelihood function can be computed with the Kalman Filter recursions. Thus, in this way the Kalman Filter is seen to be a useful tool for evaluating the log-likelihood function. Given initial values, θ_0, equation (18) can be maximized over the parameter space with standard numerical optimization algorithms.

3.3. Computational remarks about the Kalman Filter

Some computational aspects of the Kalman Filter need to be taken into account.

(1) **Numerical accuracy.**

From the computational point of view, using the Kalman Filter recursions as written in equations (12)-(15) is not necessarily the best way to proceed. Computational inaccuracies may accumulate in such a way that the actually computed covariance matrices are not positive semidefinite. Numerical modifications of the recursions are suggested in the literature, such as the **information** or **square root filters**, to overcome these difficulties. (Anderson and Moore (1979, Chap.-6), Schneider (1990)).

However even if the use of **square root filters** are generally regarded as being the most numerically stable algorithms, they have not been extensively used outside engineering given that they require more programming and involve a higher computational burden. The fact that economic time series are typically much shorter than engineering series perhaps makes them less necessary. See however an exception in Kitagawa (1981).

DYNFAC uses the Kalman Filter in the way equations (12)-(15) have been written above. No computational problems have been detected even if the positive semidefinite of the covariance matrices are not guaranteed by construction.

(2) **Normality.**

It is possible to justify the Kalman Filter even if the disturbances in the state space model are not normally distributed. In this case the quantities obtained by the recursions are no longer moments of conditional normal distributions but if attention is restricted to estimators that are linear combinations of the observations, then $\alpha_{t|t}$ is the **Minimum Mean Square Linear Estimator (MMSLE)** of α_t based on observations up to and including time t. (Duncan and Horn (1972), Anderson and Moore (1979), Harvey (1981, Chap.-4, 1989), Schneider (1988)).

However, the normality assumption is necessary to justify maximum likelihood estimation.

(3) **Initial conditions.**

DYNFAC assumes that $\mathbf{y}_t$ is stationary so the Kalman Filter is initialized with the mean and variance of the unconditional distribution of the state vector. DYNFAC offers two algorithms for solving for Σ in equation (16).

(i) One is based on the observation that

$$\mathrm{Vec}(\Sigma) = \left[\mathbf{I} - \mathbf{T} \otimes \mathbf{T}' \right]^{-1} . \mathrm{Vec}(\mathbf{RQR}')$$

(ii) The other is an **iterative doubling algorithm.**

The default algorithm is (ii) which works in all situations. When the state vector is reasonably small both should work well, but as the state vector grows the use of algorithm (i) may be binding because of memory or computing time restrictions.[8]

In both algorithms the symmetry of Σ is checked before exiting the procedure.

When the transition equation is non-stationary, the unconditional distribution of the state vector is not defined and the above initial values are not correct. DYNFAC, however, does not take into account this case. See de Jong (1988, 1991), Harvey (1989) and Gómez and Maravall (1993) for a discussion about

[8] Algorithm (ii) is faster for very large models. In an example it was found that the computation time could be reduced from 20 to about 3 hours by using algorithm (ii) instead of (i).

this point.

Given the model (4)-(6) an interesting case arises when $\mathbf{y}_t$ is non-stationary so it can be characterized as integrated of order 1, I(1), and the only source of non-stationarity enter the model through c_t. In this case each element of $\mathbf{y}_t$ would contain a stochastic trend, but this trend would be common to each element of $\mathbf{y}_t$. Thus $\mathbf{y}_t$ would be cointegrated of order (1,1) in the sense of Engle and Granger (1987). The current version of DYNFAC is not suitable to estimate this class of models. Harvey, Fernández-Macho and Stock (1987) and King, Plosser, Stock and Watson (1991) discuss modeling strategies of vector autoregressions with unobserved components and cointegrated variables.

(4) **Initial conditions and convergence.**

For our model the covariance matrix $\Sigma_{t|t-1}$ has a steady state solution, so $\mathbf{F}_t$ also converges to a steady state. It can be shown that, given some regularity conditions that are satisfied in our case, convergence to the steady state is monotonic in the sense that the variance matrix of $\alpha_{t|t-1}$ exceeds the variance matrix of $\alpha_{t+1|t}$ by a positive semidefinite matrix, that is $\Sigma_{t|t-1} \geq \Sigma_{t+1|t}$ for some t onwards. Intuitively this follows because there is no information at time 0 and so the estimator at t is based on more information than the estimator at t-1, and its precision, $\Sigma_{t|t-1}$, does not depend on the actual observations.

The knowledge that a state space model has a **steady state Kalman filter** can be exploited in computational algorithms, since the most time-consuming part of the filter is the updating of $\mathbf{F}_t$, the covariance matrix of the innovations. Thus once it is known that $\Sigma_{t+1|t}$ has converged to $\bar{\Sigma}$ the equations (13) and (15) become redundant, as the covariance matrix of the innovations is time invariant. In practice it is necessary to monitor the progress of the filter in order to determine when $\Sigma_{t+1|t}$ is sufficiently close to $\bar{\Sigma}$ to deem it to have converged. This may be carried out indirectly by examining the sequence of prediction error covariance matrix since by a similar argument $\mathbf{F}_t \geq \mathbf{F}_{t+1}$, so $\mathbf{F}_t \geq \mathbf{F}_{t+1} \geq \bar{\mathbf{F}}$, where $\bar{\mathbf{F}}$ is the steady state of $\mathbf{F}_t$ given by

$$\lim_{t\to\infty} \mathbf{F}_t = \bar{\mathbf{F}} = \mathbf{Z}.\bar{\Sigma}.\mathbf{Z}' + \mathbf{H}$$

In fact, this is simply a consequence of the above condition, since $\mathbf{F}_t = \mathbf{Z}.\Sigma_{t|t-1}.\mathbf{Z}' + \mathbf{H}$ and $\mathbf{Z}$ is of rank N, while $\mathbf{H}$ is a positive semidefinite matrix.

DYNFAC exploits this result in the implementation of the Kalman filter, switching to a time invariant Kalman Filter once a suitable converge criterion is satisfied.[9]

(5) **Filtering and smoothing.**

Sometimes reconstruction of the state vector given all sample information $y_1,...,y_T$ is of interest.[10] Recursions are also available to compute $\alpha_{t|T}$ and $\Sigma_{t|T}$ for $t < T$. The evaluation of $\alpha_{t|T}$ for $t < T$ is known as **smoothing**.

DYNFAC only performs the statistical estimation of θ and uses the Kalman filter to construct the log-likelihood function (18). Filtering and/or smoothing for known (or assumed) values of the system matrices, **Z**, **T**, **R**, **H** and **Q**, can be done with the additional procedures KFILTER and KSMOOTH supplied with the program.[11]

4. USER INPUT INFORMATION: THE DYNFAC.RUN FILE

This section provides detailed instructions on how to use DYNFAC by means of the command file DYNFAC.RUN.

The DYNFAC.RUN file is organized into several sections, but only the section between USER and END USER should be changed by the user. Most of the information

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[9] The convergence criterion is given by $\max(\text{abs}(\mathbf{F}_{t+1} - \mathbf{F}_t)) < \varepsilon$, where ε is a global variable with default value 10^{-12} and max($\bullet$) refers to the maximum element in the matrix.

[10] In business cycle analysis an estimate of the unobserved common factor c_t given all sample information can be used to date business cycles turning points.

[11] See the information in the KFILTER.SRC and KSMOOTH.SRC files.

the program needs is self-explanatory since comments provide "on-line" assistance, but a brief description follows. Don't change the name of the variables (left hand side references), since they are used in other parts of the program.

DYNFAC is controlled with the following parameters:[12]

Input/output information

Parameter	Meaning
outf = "."	File name for the results. This file will be located on the directory from which you run the program, unless a path is specified, and will be reset each time you run the program
data = "."	File name for the data set. Data are assumed to be organized in a TxN matrix. This file should be located on the directory from which you run the program, unless a path is specified.
nvar = N	Number of variables, N.
nobs = T	Number of observations, T.

Transformations

Parameter	Meaning
logs = 0	Don't take logs of data.
= 1	Take logs of data.
diff = 0	Don't take differences of the data.
= 1	Take differences of the data.
lags = scalar	If **diff** is set to 1 set **lags** to the order of the difference.

Note that if both, **logs** and **diff**, are set to 1 logarithms are taken first so you are performing logarithmic differences, i.e. calculating growth rates.

Transformations are applied to all variables in y_t. Other kind of transformations should be performed prior to the analysis.

[12] Vectors are assumed to be column vectors, unless otherwise is specified.

Analysis to perform

Parameter	Meaning
ident = 0	Don't perform identification analysis.
= 1	Perform identification analysis.
	Identification is based on the correlogram and preliminary autoregression analysis of the estimates of c_t and $\mathbf{u}_t$ from the static ML estimation of (1). The order of the autoregression comes determined by **plag** and **klag** below.
estim = 0	Don't perform estimation.
= 1	Perform estimation.
	After estimation a likelihood ratio test of the static factor analysis model (1) against the specified dynamic factor analysis model is automatically performed.
varde = 0	Don't perform variance decomposition analysis after estimation.
= 1	Perform variance decomposition analysis after estimation.
	In this case the variance decompositions are stored in a matrix with rows equal to the number of elements in the vector **horizon** plus one (see below) and columns equal to 2xN, the first N columns are the percentage of variance of the forecast error that, for each variable, can be attributed to c_t and the last N columns are the percentaje of variance that, for each variable, can be attributed to $\mathbf{u}_t$.
	The horizons at which the variance decomposition are calculated are given by the vector horizon, but the last row gives the unconditional (steady state) decomposition of variance.
irf = 0	Don't perform impulse response function analysis.
= 1	Perform impulse response function analysis.
	In this case the impulse response functions are stored in a matrix with rows equal to the maximum element the vector **horizon** plus one (see below) and columns equal to 2xN, the first N columns are the impulse response functions of each variable to a one standar deviation in η_t and the last N columns are the impulse response functions of each variable to a one standar deviation in ε_t. The horizon at which the impulse response functions are calculated are given by the maximum element in the

	vector horizon.
mar = 0	Don't obtain the moving average responses.
= 1	Obtain the moving average responses. In this case the moving average responses are stored in a matrix with rows equal to the maximum element the vector **horizon** plus one (see below) and columns equal to N+1, the first column is the moving average response corresponding to the AR polynomial $\phi(L)$ and the last N columns are the moving average responses corresponding to the AR polynomials **D**(L). The horizon at which the moving average responses are calculated are given by the maximum element in the vector horizon.
horizon = vector	Horizons at which the variance decomposition is calculated. The maximum element of this vector determines the maximum horizon in the calculations of impulse response functions and/or moving average responses. It is not necessary that the elements in horizon are in increasing order.

After estimation the **one step ahead prediction errors** (innovations) of the estimated model are stored in the matrix OSAPE. The innovations are obtained from the filtered model, so is a $(T\text{-}k)_x N$ matrix, and can be used for diagnostic testing of the estimated model since they should be random, in particular they should be unpredictable from lagged information, this is, lagged innovations or lagged variables in the system.

After estimation, the vector of parameters and its covariance matrix is in memory under the names **b** and **cov**, respectively. These can be used for further analysis, like calculation of bootstrap confidence interval of variance decomposition or impulse responses to shocks in the system.

State Space Information

Parameter	Meaning
plag = vector	Elements in the $\phi(L)$ polynomial that are nonzero.
klag = vector	Elements in the **D**(L) polynomial that are nonzero.

Note that the same restrictions apply to all equations in **D(L)**.

Example: Assume p in $\phi(L)$ is 3 but $\phi_2 = 0$, then set plag = {1, 2}. If $\phi_2 \neq 0$, then set plag = {1, 2, 3} or using the GAUSS function seqa(#,#,#), plag = seqa(1,1,3). The same convention applies to k and klag.

It is no necessary that the elements in plag/klag are in increasing order.

If both plag = 0 and klag = 0 then we have the static factor analytic model (1). In this case DYNFAC generates two sets of results: (i) a PRINcipal components analysis using the PRIN procedure, and (ii) a maximum likelihood (ML) estimation of the static factor model using the Kalman Filter algorithm described above. The ML estimation of the static model is always printed. If in addition plag = 0 and klag = 0 the results from the PRIN procedure are also printed.

Starting values for the Kalman Filter

Parameter	Meaning
kf0 = 1	Direct method for solving for Σ in equation (16).
= 2	Iterative **doubling algorithm** for solving for Σ.
	For globals used in this case see the UNCONDD.SRC file.

Starting values

Because (18) is nonlinear in θ estimation should be performed by a nonlinear optimization algorithm, which implies that a starting point, θ_0, should be specified. There are no general methods for computing starting values and it may be necessary to attempt the estimation from a variety of starting values. Good starting values are crucial in reducing computing time.

The user may choose between to supply their own starting values, in which case a vector of dimension **[p + N*(k + 2)]x1** should be given in **x0**, where p or k should be understood as the nonzero elements of the $\phi(L)$ and **D(L)** polynomials, or to allow DYNFAC to calculate their own starting values. Starting values provided by DYNFAC exploit the fact that there are well known algorithms for the static version of our problem.[13] They have been found to work well. In any case these are printed before the results on estimation.

Parameter	Meaning
x0 = 0	Starting values for γ and Ω will be found and the elements of $\phi(L)$ and **D**(L) will be set to zero.
= 1	Starting values for γ and Ω will be found from static factor analysis and the elements of $\phi(L)$ and **D**(L) will be obtained from preliminary regression analysis. This is probably the best choice.
= vector	Vector of dimension **[p + N*(k + 2)]x1** of starting values. Note again that p or k should be understood as the nonzero elements of the $\phi(L)$ and **D**(L) polynomials. If starting values are supplied it is important to know the order of the parameters in θ, first the elements in $\phi(L)$, second the elements in **D**(L) equation by equation, third the elements in γ and eventually the standard errors of ε_t, $\sigma_{\varepsilon_1},\ldots,\sigma_{\varepsilon_n}$. Please note that what is estimated are the standard errors, not the variances.

Optimization information

Eventually you can supply information about the optimization. At present optimization is carried out by the MAXLIK module of GAUSS, so consult the MAXLIK manual or the MAXLIK.DOC file for details, but please don't change the **__row = 0** global variable since this is used in the procedure that calculates the log-likelihood function. By default MAXLIK uses the Broyden, Fletcher, Goldfarb and Shanno method (Luenberger (1984)) with numerical derivatives and covariance matrix of parameters obtained from the inverse of the Hessian.

There are currently under development two other optimization algorithms, the EM and the scoring algorithm with analytical derivatives (Watson and Engle (1983),

[13] In particular DYNFAC uses the PRINcipal components analysis (PRIN procedure) in first instance, these estimates are used as starting values for ML estimation of the static factor analysis, plag = klag = 0. The estimates from this procedure are used to construct the initial starting values for final estimation.

Harvey (1989, Chap.-3)).

Three global variables are included in the DYNFAC.RUN file, but see the MAXLIK manual for a complete reference list.

Parameter	Meaning
__title = "."	Title to be printed.
__row = 0	**DON'T CHANGE THIS** parameter.
__output = 0	Determines printing of intermediate results. Nothing is written.
= 1	Serial ASCII output format suitable for disk files or printers.
= 2	Output is suitable for screen only. ANSI.SYS must be active. See DOS manual for details.

Once DYNFAC.RUN has been edited the program is ready to run. It can be run from the dos prompt by typing GAUSSI DYNFAC.RUN or within GAUSS in command mode by typing RUN DYNFAC.RUN. The output file is self explanatory, and an example is included in the next section.

5. AN EXAMPLE

In this section I present an example file together with the output file that it produces. The example data set is in file VAB80.ASC and is supplied with DYNFAC in the EXAMPLES subdirectory under the name DYNFAC1.RUN. The VAB80.ASC contains the gross value added sectorial series at constant prices of García, Goerlich and Orts (1994), the data set includes 14 series for the period 1964-1989, and is organized accordingly in a 26x14 matrix.

The example DYNFAC1.RUN specifies an AR(1) for both c_t and $\mathbf{u}_t$ in the growth rates of the variables. The output from the example, which follows next, is send to the file DYNFAC1.OUT. A more complex example that uses data from the Industrial Production Index (IPI.ASC) is in DYNFAC2.RUN in the EXAMPLES subdirectory of the distribution disk.

DYNFAC is supplied with some other procedures that are used by the DYNFAC program but that can be used independently. Information on the syntax of these procedures are in the corresponding files.

```
*************************************************************************
*                        COMMAND FILE: DYNFAC.RUN                      *
*************************************************************************
/*
**   DYNFAC.RUN                                              20/6/95
**                                          Version:  1.2 - 21/4/97
**
**   This is a command file to estimate a DYNAMIC FACTOR model.
**   See Goerlich (1997) "Dynamic Factor Analytic Models using DYNFAC.
**      - A user guide - Version 1.2" Working Paper 97-06. IVIE.
**
**   Below is provided an example.
**
**   The user only has to change information under the headings USER.
*/

/*   Starting   */
new;
library dynfac,maxlik;
#include maxlik.ext;
fjgset;
maxset;

/***********************************************************************/
/*                                USER                                 */
/***********************************************************************/

/*   Input/output information   */
outf = "DYNFAC1.OUT";                 /* File name for output      */
data = "VAB80.ASC";                   /* File name for data        */
nvar = 14;                            /* Number of variables       */
nobs = 26;                            /* Number of observations    */

/*   Transformations 1 = yes, 0 = no. Applied to all variables   */
logs = 1;                             /* Take logs                 */
diff = 1;                             /* Take differences          */
lags = 1;                             /* Order of lags in diff     */

/*   Analysis to perform   */
ident = 1;                            /* Identification             */
estim = 1;                            /* Estimation                 */
varde = 1;                            /* Variance decomposition     */
irf   = 1;                            /* Impulse response analysis  */
mar   = 1;                            /* Moving average responses   */
horizon = {1, 5, 10};                 /* Horizon for varde & irf    */

/*   State Space information   */
plag = 1;                               /* AR poly in c(t)   */
klag = 1;                               /* AR poly in u(t)   */

/*   Starting values for Kalman filter   */
kf0  = 2;

/*   Starting values: If x0 scalar they will be calculated   */
x0 = 1;

/*   MAXLIK global variables: See MAXLIK.DOC for details   */
__title = "Dynamic Factor Model: VAB example";
```

```
__row = 0;                              /* Do not change this !!! */
__output = 2;

/**********************************************************************/
/*                              END USER                             */
/**********************************************************************/

***********************************************************************
*                               OUTPUT                                *
***********************************************************************
```

Dynamic Factor Model: VAB example - Static Analysis

===

MAXLIK: Version 3.1.3 4/21/97 5:21 pm

===

return code = 0
normal convergence

Mean log-likelihood -3.33576
Number of cases 25

Covariance matrix of the parameters computed by the following method:
Inverse of computed Hessian

Parameters	Estimates	Std. err.	Est./s.e.	Prob.	Gradient
01G	0.2110	0.1996	1.057	0.1452	0.0000
02G	0.8354	0.1594	5.241	0.0000	0.0000
03G	0.8713	0.1549	5.626	0.0000	-0.0000
04G	0.6413	0.1780	3.603	0.0002	-0.0000
05G	0.7930	0.1636	4.849	0.0000	-0.0000
06G	0.4536	0.1897	2.390	0.0084	0.0000
07G	0.1607	0.2001	0.803	0.2109	0.0000
08G	0.6800	0.1747	3.892	0.0000	0.0000
09G	0.7099	0.1725	4.114	0.0000	0.0000
10G	0.1596	0.2016	0.792	0.2143	-0.0000
11G	0.7030	0.1722	4.082	0.0000	-0.0000
12G	0.6191	0.1795	3.448	0.0003	-0.0000
13G	0.8852	0.1529	5.788	0.0000	-0.0000
14G	0.6442	0.1791	3.596	0.0002	-0.0000
01S	0.9568	0.1357	7.049	0.0000	0.0000
02S	0.5120	0.0888	5.767	0.0000	0.0000
03S	0.4481	0.0842	5.322	0.0000	-0.0000
04S	0.7407	0.1102	6.723	0.0000	0.0000
05S	0.5754	0.0919	6.264	0.0000	0.0000
06S	0.8685	0.1248	6.961	0.0000	-0.0000
07S	0.9665	0.1369	7.059	0.0000	0.0000
08S	0.7054	0.1061	6.647	0.0000	-0.0000
09S	0.6753	0.1037	6.512	0.0000	-0.0000
10S	0.9667	0.1370	7.057	0.0000	0.0000
11S	0.6825	0.1027	6.643	0.0000	-0.0000
12S	0.7595	0.1120	6.780	0.0000	0.0000
13S	0.4201	0.0814	5.161	0.0000	-0.0000
14S	0.7382	0.1116	6.616	0.0000	0.0000

Correlation matrix of the parameters

1.000	0.090	0.126	0.099	0.083	0.057	0.022	0.077	0.077
0.005	0.070	0.089	0.124	0.091	-0.019	0.055	-0.033	-0.034
0.043	-0.006	-0.002	0.005	0.015	0.003	0.025	-0.024	-0.016
-0.023								
.								
.								
.								
-0.023	0.034	-0.032	-0.033	-0.011	0.017	-0.032	-0.016	0.032
-0.021	0.018	-0.020	0.037	-0.089	0.008	-0.098	0.117	0.046
0.026	-0.013	0.008	0.025	-0.056	0.005	-0.031	0.026	-0.147
1.000								

Number of iterations 14
Minutes to convergence 0.25083

IDENTIFICATION

Asymptotic standar errors for autocorrelations 0.2000

Autocorrelation of common factor

	C1
R01	1.0000
R02	0.7193
R03	0.5201
R04	0.4985
R05	0.3514
R06	0.1824
R07	0.0781
R08	-0.0077
R09	-0.1355
R10	-0.2759

Autocorrelation of individual factors

	C01	C02	C03	C04	C05	C06	C07
R01	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
R02	0.0492	0.4341	-0.2660	0.3334	0.0360	-0.2841	-0.1140
R03	0.0244	0.0464	0.0051	-0.1842	0.0327	0.0512	-0.3137
R04	-0.0883	-0.2177	0.0677	-0.2027	-0.3197	-0.0651	0.1154
R05	-0.0995	-0.4027	-0.0263	-0.3700	-0.0663	-0.0733	0.0105
R06	-0.0363	-0.3684	0.0410	-0.3973	-0.0199	-0.0159	-0.3233
R07	-0.0824	-0.2224	-0.2348	-0.1514	-0.2250	-0.1177	0.2810
R08	0.0665	-0.0602	0.0634	-0.0144	0.1720	-0.0709	0.1286
R09	0.0800	0.2515	0.0706	0.3265	0.1484	0.0478	-0.3321
R10	-0.0020	0.3454	-0.1579	0.3752	0.1389	-0.0144	-0.2004

Autocorrelation of individual factors (cont)

	C08	C09	C10	C11	C12	C13	C14
R01	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
R02	0.2583	-0.1354	-0.0393	-0.0999	0.0323	0.4284	-0.1053
R03	0.4732	-0.0750	0.1911	-0.3854	-0.1661	0.1870	0.0077
R04	0.0799	-0.1438	-0.2310	-0.2670	-0.0903	0.0632	0.0126
R05	0.0159	-0.1456	-0.0105	0.1899	-0.2060	-0.1212	-0.0880
R06	0.0905	0.3267	-0.2180	0.3318	0.1500	-0.3140	0.0123
R07	-0.2716	-0.2209	-0.2977	-0.0446	0.1525	-0.4552	-0.1314

R08	-0.1717	0.0181	-0.0515	-0.1976	0.1110	-0.3296	-0.0292
R09	-0.5164	0.1695	-0.1366	-0.0844	-0.2015	-0.1959	-0.2897
R10	-0.3417	-0.0638	0.0697	0.1746	-0.0299	-0.1959	-0.0342

Autoregression for common factor:

Lag	Estimate	S.E.	T-stat
1	0.7209	0.1303	5.5325

Autoregression for individual factors

Factor: 1

Lag	Estimate	S.E.	T-stat
1	0.0492	0.2077	0.2370

Factor: 2

Lag	Estimate	S.E.	T-stat
1	0.4347	0.1875	2.3177

Factor: 3

Lag	Estimate	S.E.	T-stat
1	-0.2669	0.1961	-1.3609

Factor: 4

Lag	Estimate	S.E.	T-stat
1	0.3440	0.1992	1.7265

Factor: 5

Lag	Estimate	S.E.	T-stat
1	0.0360	0.2041	0.1765

Factor: 6

Lag	Estimate	S.E.	T-stat
1	-0.2954	0.1721	-1.7165

Factor: 7

Lag	Estimate	S.E.	T-stat
1	-0.1143	0.2061	-0.5547

Factor: 8

Lag	Estimate	S.E.	T-stat
1	0.2584	0.2014	1.2832

Factor: 9

Lag	Estimate	S.E.	T-stat
1	-0.1360	0.2034	-0.6687

Factor: 10

Lag	Estimate	S.E.	T-stat
1	-0.0398	0.2081	-0.1913

Factor: 11

Lag	Estimate	S.E.	T-stat
1	-0.1000	0.2057	-0.4863

Factor: 12

Lag	Estimate	S.E.	T-stat
1	0.0326	0.2090	0.1560

Factor: 13

Lag	Estimate	S.E.	T-stat
1	0.4344	0.1882	2.3083

Factor: 14

Lag	Estimate	S.E.	T-stat
1	-0.1078	0.2082	-0.5178

Starting values

0.72085216	0.049229162	0.43466964	-0.26692729
0.34400441	0.036016723	-0.29542326	-0.11430116
0.25837328	-0.13603328	-0.039803578	-0.10002056
0.032615121	0.43438948	-0.10779523	0.14625468
0.57899264	0.60391776	0.44450062	0.54963166
0.31435957	0.11140795	0.47131986	0.49202091

0.11060719	0.48725907	0.42905735	0.61349292
0.44651407	0.95564947	0.46109676	0.43180275
0.69552643	0.57504456	0.82973610	0.96019903
0.68143681	0.66904094	0.96594325	0.67903233
0.75905143	0.37840002	0.73390683	

Dynamic Factor Model: VAB example

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return code = 0
normal convergence

Mean log-likelihood -2.39937
Number of cases 25

Covariance matrix of the parameters computed by the following method:
Inverse of computed Hessian

Parameters	Estimates	Std. err.	Est./s.e.	Prob.	Gradient
P1	0.8130	0.1247	6.518	0.0000	0.0000
01D1	0.0361	0.2079	0.174	0.4311	-0.0000
02D1	0.5456	0.2390	2.283	0.0112	-0.0000
03D1	-0.4328	0.2034	-2.128	0.0167	0.0000
04D1	0.3127	0.2099	1.490	0.0681	-0.0000
05D1	0.0453	0.2184	0.207	0.4179	0.0000
06D1	-0.3118	0.1663	-1.875	0.0304	-0.0000
07D1	-0.1185	0.2092	-0.566	0.2856	-0.0000
08D1	0.2939	0.2065	1.423	0.0773	-0.0000
09D1	-0.0710	0.2074	-0.342	0.3660	-0.0000
10D1	-0.0548	0.2050	-0.267	0.3947	0.0000
11D1	-0.1281	0.2040	-0.628	0.2649	0.0000
12D1	0.0074	0.2285	0.032	0.4871	-0.0000
13D1	0.4523	0.3913	1.156	0.1239	-0.0000
14D1	-0.1927	0.2092	-0.921	0.1786	-0.0000
01G	0.1057	0.1346	0.785	0.2161	-0.0000
02G	0.6000	0.1714	3.500	0.0002	0.0000
03G	0.5690	0.1049	5.423	0.0000	-0.0000
04G	0.3786	0.1378	2.748	0.0030	0.0000
05G	0.4671	0.1106	4.225	0.0000	-0.0000
06G	0.2190	0.0800	2.737	0.0031	0.0000
07G	0.1181	0.1190	0.992	0.1605	0.0000
08G	0.4346	0.1404	3.096	0.0010	0.0000
09G	0.3999	0.1120	3.572	0.0002	0.0000
10G	0.0886	0.1220	0.726	0.2338	0.0000
11G	0.4547	0.1117	4.069	0.0000	-0.0000
12G	0.3655	0.1200	3.045	0.0012	0.0000
13G	0.6009	0.1948	3.084	0.0010	0.0000
14G	0.4527	0.1095	4.136	0.0000	-0.0000
01S	0.9757	0.1410	6.920	0.0000	0.0000
02S	0.4878	0.0920	5.303	0.0000	0.0000
03S	0.3538	0.0738	4.795	0.0000	0.0000
04S	0.6923	0.1029	6.725	0.0000	0.0000
05S	0.5605	0.0870	6.443	0.0000	0.0000

06S	0.6869	0.1008	6.814	0.0000	-0.0000
07S	0.9678	0.1399	6.916	0.0000	0.0000
08S	0.6869	0.1039	6.611	0.0000	0.0000
09S	0.6874	0.1037	6.627	0.0000	-0.0000
10S	0.9744	0.1408	6.922	0.0000	0.0000
11S	0.6646	0.1008	6.596	0.0000	-0.0000
12S	0.7771	0.1146	6.780	0.0000	0.0000
13S	0.4243	0.0889	4.774	0.0000	-0.0000
14S	0.7060	0.1078	6.548	0.0000	-0.0000

Correlation matrix of the parameters

1.000	0.003	0.069	-0.045	0.002	0.003	0.001	-0.000	0.016
0.012	-0.006	-0.044	-0.002	-0.125	0.019	-0.044	-0.039	-0.223
-0.064	-0.149	-0.123	-0.015	-0.101	-0.156	-0.022	-0.160	-0.115
-0.187	-0.145	0.004	0.026	-0.074	-0.016	-0.015	0.010	-0.008
0.016	0.031	-0.001	-0.009	0.001	0.174	-0.057		
.								
.								
.								
-0.057	-0.001	0.037	0.001	0.016	0.005	0.003	0.010	0.020
0.012	0.002	0.021	0.001	0.048	0.039	0.002	0.079	0.104
0.014	0.070	0.056	-0.012	0.044	0.080	0.004	0.090	0.042
0.096	0.026	0.003	-0.088	0.029	0.023	0.012	-0.003	0.009
0.003	-0.024	0.002	-0.029	0.016	-0.128	1.000		

Number of iterations 23
Minutes to convergence 3.34683

LR tests of Static Model against Dynamic Model
Chi-square statistic 26.218928
Degrees of freedom 15
p-value 0.035784

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