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EMPIRICAL ANALYSIS of TIME SERIES: ILLUSTRATIONS with SIMULATED DATA

by

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Abstract

Simulated data are used to illustrate the properties of the major types of time series process. This knowledge helps in the choice of data–admissible model classes when modelling time series variables. Knowledge of the DGP for simulated data enables the calculation of the properties of estimators and other statistics of interest such as indicators of misspecification in particular models of the data. The analogous role of the congruent general model in a modelling strategy which seeks to develop simple, economically interpretable models, which parsimoniously encompass the general model (and hence are congruent and encompass all rival models nested within the general model), is also illustrated.

This paper is based on material used in lectures presented to the meeting of the Network on Quantitative Economics held in Leiden, The Netherlands, February 1989. **PC GIVE** (see Hendry [1989]) was used for the econometric analysis of data, and the simulated data were generated using **PC NAIVE** (see Hendry, Neale, and Ericsson [1990]), which was also used for the Monte Carlo analysis reported. The financial support of the ESRC under grant B01250024 is gratefully acknowledged.

I. Introduction

The theme of the lectures, on which this paper draws, was practical econometric modelling with time series data. The aim was to use a mixture of real and simulated data to illustrate some of the difficult problems that face the applied econometrician, and to indicate methods by which they might be overcome. The approach adopted has been made possible by availability of powerful personal computers, and the development of sophisticated econometric software packages such as **PC GIVE**, **PC FIML**, **PC ASYMP** and **PC NAIVE**. The same approach is adopted in this paper, and in addition emphasis is placed on the value of simulated data for analyzing the relationship between data generation processes (DGP's) and particular models of the data. In particular, knowledge of the DGP enables the derivation of the properties of statistics of interest, such as estimators, and test statistics for specification and misspecification hypotheses (see Mizon [1977]), for any model of the generated data. This argument is then extended to show that a congruent general model of the data available for modelling has an analogous role to that of the unknown DGP. This has implications for the choice of modelling strategy, and in particular indicates the importance of congruence and encompassing as critical properties for models to possess. This analysis using simulated data is an illustration of the huge potential value in teaching Monte Carlo simulation programs like **PC NAIVE** have.

The next section discusses model congruence, concentrating on the development of models that are data admissible, and in particular consistent with the time series properties of the data. Section III uses examples to illustrate that it is possible for a model to be congruent with its own information set, but nonetheless statistically inadequate, in that it cannot encompass rival models. Section IV contains conclusions.

II. Congruence and the Time Series Properties of Data: Data Admissibility

The importance in econometric modelling of developing models that are congruent with **all** the available information is now well documented (see *inter alia* Hendry and Richard [1982,1983], Hendry [1987], Hendry and Mizon [1990], Mizon [1989, 1991], and Spanos [1989]), and so will not be discussed at length here. Briefly, models that are not congruent are by definition failing to exploit available information which would improve their performance, whether this be in their goodness of fit, forecasting ability, *a priori* theory consistency, or policy analysis. Hence, a non–congruent model can be improved from information already available, and a scientific approach to modelling suggests that it should be so improved rather than left in its present inadequate state. In fact, the value of seeking to develop congruent models has been indicated in many empirical pieces in recent years (e.g. Åhumada [1992], Bårdsen [1992], Clements and Mizon [1991], Hendry and Ericsson [1991a, 1991b], Johansen and Juselius [1990], Nyomen [1992], and Spanos [1990]).

One source of information with which it is important to have models coherent is the measurement system, and in particular the properties of the sample data being used. To use a well known example, the linear regression model $y_t = \beta x_t + u_t$ with u_t assumed to be symmetrically distributed around zero (e.g. $u_t \sim NI(0,\sigma^2)$) is not congruent with a known property of the data when y_t is a probability and thus satisfies $0 \leq y_t \leq 1$, in that fitted and predicted values of y_t from this model can lie outside this range. Note that the problem arises from specifying the statistical properties of the model via the unknown and unobservable error u_t, rather specifying an appropriate distribution for the observed regressand y_t. Similar examples arise if the same linear regression model is used for modelling aggregate consumption expenditure ($0 \leq y_t$), or the rate of unemployment ($0\% \leq y_t \leq 100\%$). In the modelling of financial data it is equally important to use models that are capable of capturing the "stylized facts" of such data, namely unimodal densities with fat tails, and usually a higher mode than that of an ARCH process – see Pagan [1991]. When modelling time series variables it is equally important that the class of model chosen for the analysis is capable of being congruent with the time series properties of the data. For example, the above linear regression model would again be non–congruent if y_t was temporally dependent but x_t was not, for in such a case u_t will be serially correlated and this implies that it contains valuable information for the modelling of y_t (namely y_{t-1}, y_{t-2},....) which is being unexploited. Note that in this example even if the parameter of interest is $\partial y_t/\partial x_t = dy_t/dx_t$ in the distribution of y_t conditional only on x_t, OLS estimation of this parameter will be inefficient since it ignores the fact that the variance and autocovariances of u_t depend on this same parameter!

Table 1:Results Using Simulated Data from Replication 1000

(na = not applicable)

	DGP VALUE	INEFFICIENT OLS ESTIMATE	EFFICIENT OLS ESTIMATE	RALS
β	0.9	1.0245	0.9520	0.7413
$SE(\hat{\beta}_1)$	0.072	0.0811	na	na
$SE(\hat{\beta}_2)$	0.044	na	0.0456	0.0533
α	0.5	0.0	0.5174	0.7069
$SE(\hat{\alpha})$	0.038	na	0.0350	0.0732
DW_1	1.0	0.915	na	na
DW_2	2.0	na	1.80	na
R^2_1	0.6075	0.619	na	na
R^2_2	0.8575	na	0.884	na
σ_u	0.723	0.794	na	na
σ_ν	0.436	na	0.444	na
σ_ξ	0.627	na	na	0.6045

To argue in this case that since the OLS estimator is consistent there is no serious problem arising from ignoring the serial correlation in u_t seems inappropriate as the results above (which are explained in detail later in the section) using simulated data show. The OLS estimate of β using this simulated data, at 1.0245, is larger than might be expected for an unbiased estimator of the population parameter value of 0.9. However, its standard error at 0.0811 is 84% larger than that associated with the efficient OLS estimator which regresses y_t on x_t and y_{t-1}, and slightly larger than its population value for a sample of size 100 (namely 0.072). Note that in this case reacting to the low Durbin Watson test statistic when y_t is regressed on x_t alone (DW = 0.915), by re–estimating using autoregressive least squares (RALS), is also inappropriate since it yields an inconsistent ($\hat{\beta} = 0.7413$) and imprecise ($SE(\hat{\beta}) = 0.0533$) estimate of β. Hence although the noncongruent (u_t is serially correlated) model which regresses y_t on x_t alone yields an unbiased estimator of β (though it is 13.8% above the population value for this particular replication), there is a strong case for correctly identifying the cause of the serial correlation, so that β can be estimated consistently and efficiently by exploiting all the available relevant information. Note that introducing the assumption that $u_t = \alpha u_{t-1} + \xi_t$ does not yield a congruent model or a good estimator of β, for although ξ_t is white noise it is not an innovation with respect to the information set containing x_t, x_{t-1}, and y_{t-1}. These empirical results using the simulated data from replication 1000, which illustrate the importance of developing models that are congruent with the properties of the data, are shown at the end of this section to be reliable and expected by analyzing the results of all 1000 replications in a Monte Carlo study. Mizon [1992] contains more detailed analysis of this example.

If it is important to develop models that are congruent with the properties of the data (data admissible), it is equally important to be able to determine what these properties are. One obvious way to identify the essential characteristics of a time series variable is to inspect its time plot or graph. Figure 1 gives the time plots of 200 realizations, generated by **PC NAIVE**, from nine of the basic time series processes. The first three are stationary processes: white noise ($\epsilon_t \sim NI(0,1)$, with each of the following ϵ_{it} being independent white noise variables), a first order moving average ($x_t = \epsilon_{1t} + \theta\, \epsilon_{1t-1}$, $\theta = 0.9$), a stationary first order autoregression ($y_t = \rho\, y_{t-1} + \epsilon_{2t}$, $\rho = 0.9$). The remaining five are nonstationary processes: a random walk ($\Delta w_t = \epsilon_{3t}$), a random walk with drift ($\Delta d_t = \delta_1 + \epsilon_{4t}$, $\delta_1 = 0.1$), a trend stationary process ($z_t = \delta_2 t + \epsilon_{5t}$, $\delta_2 = 0.1$), a second order autoregressive conditional heteroskedastic process ($a_t | \epsilon_{6t-1}, \epsilon_{6t-2} \sim N(0, h_t^2)$ with $h_t^2 = (1-\alpha)/\sigma + 0.33\,(2\alpha\, \epsilon_{6t-1}^2 + \alpha\, \epsilon_{6t-2}^2)$ when $\alpha = 0.5$ and $\sigma = 1$), and two random walks with trend ($\Delta\tau_{1t} = \delta_3 t + \epsilon_{7t}$, with $\delta_3 = 0.1$ and $\Delta\tau_{2t} = \delta_3 t + \epsilon_{8t}$, with $\delta_3 = 0.01$) respectively. The distinguishing feature of a stationary process is the constancy of its first and second moments over time (weak or wide sense stationarity), whereas nonstationary processes have time dependent moments. The three stationary processes have zero means and bounded variances, though inspection of the ordinates of the first three graphs in figure 1 shows that the variability increases from white noise ($V(\epsilon_t) = 1.0$ so that approximately 95% of the realizations will be within $[-1.96, +1.96]$)), to moving average ($V(x_t) = V(\epsilon_{1t})\times(1 + \theta^2) = 1.81$ so that approximately 95% of the realizations will be within $[-2.64, +2.64]$), and finally the first order autoregression ($V(y_t) = V(\epsilon_{2t})/(1 - \rho^2) = 5.263$ so that approximately 95% of the realizations will be within $[-4.50, +4.50]$). This is information that the frequency plot option in **PC GIVE** will reveal, as well as indicating the normal kurtosis (i.e. without fat tails or excess concentration of values around the mean) and the symmetrical distribution of each of these variables around their means of zero. The other feature which distinguishes these three stationary processes is their correlograms. Defining the k^{th} order serial correlation coefficient for a stationary random variable η_t as $\rho_k(\eta_t) = \gamma_k(\eta_t)/\gamma_0(\eta_t)$ with $\gamma_k(\eta_t) = E\{(\eta_t - \mu)(\eta_{t-k} - \mu)\}$ and $\mu = E(\eta_t) = E(\eta_{t-k})$, it follows that $\rho_k(\epsilon_t) = 0\ \forall\ k$, $\rho_1(x_t) = \theta/(1+\theta^2) = 0.497$, $\rho_k(x_t) = 0$ for $k > 1$, and $\rho_k(y_t) = \rho^k = 0.9^k\ \forall\ k$. Hence, inspection of correlograms is a good way to assess whether a stationary time series variable is dependent or not, and if it is dependent whether it is of the moving average or autoregressive type, or combines features of both (ARMA). The Data Description option in **PC GIVE** can be used to inspect the correlograms of the series being analyzed in practice.

The moments of nonstationary processes can vary deterministically (e.g. as a function of trend or other deterministic shift variables), or can vary stochastically as in integrated processes which can be differenced to become stationary. Graphs 4, 5, 8 and 9 of figure 1 are of variables that have unit roots, and so have "stochastic trend" or "trend in variance" which is evident in their time plots. In fact, graph 4 gives the time plot of the random walk $w_t = w_0 + \Sigma_{i=1}^{t} \epsilon_{3i}$ which is dominated by the partial sum $\Sigma_{i=1}^{t} \epsilon_{3i}$ that has mean of zero but unconditional variance of $\sigma^2_{\epsilon_3} t$ thus giving rise to the "erratic" behaviour of w_t. Graph 5 provides the time plot of the random walk with drift variable $d_t = d_0 + \delta_1 t + \Sigma_{i=1}^{t} \epsilon_{4i}$, which for small enough $\delta_1/\sigma_{\epsilon_4}$ will behave like the random walk w_t, but when $\delta_1/\sigma_{\epsilon_4}$ is large enough d_t will be dominated by the deterministic trend $\delta_1 t$ and so behave like a trend stationary variable, an example of which is given by the time plot of z_t in graph 6. The importance of the magnitude of $\delta_1/\sigma_{\epsilon_4}$ in determining the distribution of least squares estimators involving variables like d_t is emphasized in Hylleberg and Mizon [1989b]. In particular, whilst the limiting distribution of OLS estimators involving variables like d_t is normal (see West [1988]), in small samples the empirical distribution of the OLS estimator can be closer to the Dickey–Fuller distribution than the normal. Each of w_t, d_t, and z_t is I(0) when differenced once, though the non–stationarity in z_t derives from $\delta_1 t$ and so de–trending, rather than differencing, is the appropriate transformation of z_t to achieve stationarity. In fact, $\Delta z_t = \delta_2 + \Delta\epsilon_{5t}$ so that the transformed error is a first order moving average with a unit root, which implies that it cannot be inverted into a finite order autoregression (non–invertible), and that its serial correlation coefficient (which is also that of Δz_t) is $\theta/(1+\theta^2) = -0.5$ for the redundant unit root $\theta = -1$. Hence, one way to spot over–differencing is to inspect the correlogram of a variable for a first order serial correlation coefficient of –0.5 and a flat correlogram otherwise. This latter comment however should not be interpreted as implying that it is easy to distinguish between deterministically nonstationary variables (e.g. z_t) and stochastically non–stationary variables (e.g. w_t and d_t) – see Hendry and Neale [1991], Perron [1989], and Rappaport and Reichlin [1989] for more discussion of this point.

Another case in which it can be difficult to distinguish between a stochastically non–stationary variable and a deterministically non–stationary variable is illustrated by the random walks with trend τ_{1t} and τ_{2t} which have the form $\tau_t = \tau_0 + 0.5\ \delta_3 t(t+1) + \Sigma_{i=1}^{t} \epsilon_i$ so that they are dominated by quadratic trend when δ_3/σ_ϵ is sufficiently large. Graph 8 shows τ_{1t} dominated by quadratic trend when $\delta_3/\sigma_\epsilon = 0.1$, whereas graph 9 shows τ_{2t} to reflect both the stochastic non–stationarity in the partial sum $\Sigma_{i=1}^{t} \epsilon_{8i}$ and the deterministic non–stationarity in $\delta_3 t(t+1)$ when $\delta_3/\sigma_\epsilon = 0.005$. Note that both $\Delta\tau_{1t}$ and $\Delta\tau_{2t}$ are still non–stationary, but that $\Delta^2\tau_{1t}$ and $\Delta^2\tau_{2t}$ although being stationary have been overdifferenced so that they are non–invertible first order moving averages.

Each of the non–stationary variables that have been considered above have empirical correlograms which reveal the failure of $\rho_k(\eta_t)$ to approach zero as k increases (when $\rho_k(\eta_t) = \gamma_k(\eta_t)/\gamma_0(\eta_t)$ with $\gamma_k(\eta_t) = E\{(\eta_t - E(\eta_t))(\eta_{t-k} - E(\eta_{t-k}))\}$). Indeed, $\rho_k(\eta_t)^2 \simeq (t-k)^2/t(t-k)$ which is close to unity for t large relative to k. Hence the correlogram is useful for distinguishing stationary from non–stationary variables, but other means will have to be used to attempt to distinguish between the different forms of non–stationary process, such as inspection of the correlograms for different orders of differencing applied to the variables, remembering that over–differencing results in a variable with a first order serial correlation coefficient of –0.5.

Despite the difficulty of distinguishing between deterministic and stochastic non–stationarity, a popular and important way to attempt to determine whether a variable is non–stationary is to use unit root test statistics. Table 2 provides values of some of the commonly used test statistics for the nine "typical" time series variables and differences of some of them. For the generic time series variable ϕ_t the particular test statistics reported are:

(i) DW = $\Sigma_{t=2}^{T}(\Delta\phi_t)^2/\Sigma_{t=1}^{T}(\phi_t - \overline{\phi})^2$ which was proposed by Sargan and Bhargava [1983] as a test for a unit root in the $\{\phi_t\}$ process, and takes values close to zero when there is a unit root;

(ii) DF which is the "t" statistic for the hypothesis $\delta = 0$ in the regression $\Delta\phi_t = c_0 + \delta\phi_{t-1} + \zeta_t$ which was shown by Dickey and Fuller [1979,1981] to have a non–standard distribution when $\delta = 0$, critical values for which they tabulated using simulation. In testing the unit root hypothesis against stationary alternatives $\delta = 0$ is rejected when the "t" statistic is significantly negative;

(iii)ADF which is an augmented version of the test statistic in (ii), with the augmentation being the inclusion of $\Delta\phi_{t-1}$ in the regression;

(iv) DF + t which is an augmentation of (ii) including a linear trend, and so is based on the regression $\Delta\phi_t = c_0^* + \delta\phi_{t-1} + \lambda t + \zeta_t^*$;

(v) ADF + t which is an augmentation of (iii) to include a linear trend, thus being based on the regression $\Delta\phi_t = c_0^{**} + \delta\phi_{t-1} + \lambda t + \psi\,\Delta\phi_{t-1} + \zeta_t^{**}$.

The use of these unit root test statistics is intended to be illustrative, and it is noted that there are other test statistics which allow for more general heterogeneous and dependent error processes – see for example Phillips [1987]. It is also the case that test statistics for the hypotheses that there is no intercept and/or linear trend in the ADF regressions can reveal important information, and so are potentially of value. However, these test statistics are not reported in order not to unnecessarily complicate the presentation. For more detailed discussion of these and other tests see for example Banerjee *et al* [1992].

Table 2: Unit Root Test Statistics

(nc = not calculated, and * indicates rejection of the unit root hypothesis)

Variable	DW	DF	ADF	DF + t	ADF + t
ϵ_t	1.874*	–13.179*	–9.176*	nc	nc
x_t	0.908*	–7.613*	–9.768*	nc	nc
y_t	0.194	–3.009	–2.733	nc	nc
Δy_t	2.193*	–15.430*	–10.877*	nc	nc
w_t	0.023	–0.143	–0.055	–2.651	–2.548
Δw_t	2.080*	–14.644*	–10.877*	nc	nc
d_t	0.018	–0.586	–0.595	–2.191	–2.229
Δd_t	1.982*	–13.844*	–10.424*	nc	nc
z_t	0.058	–1.630	–0.832	–14.246*	–9.567*
Δz_t	3.054*	–25.145*	–15.838*	–25.080*	–15.798*
τ_{1t}	0.0004	52.290	6.669	0.211	0.212
$\Delta\tau_{1t}$	0.051	–1.650	–1.117	–13.526*	–10.056*
$\Delta^2\tau_{1t}$	2.912*	–23.189*	–17.235*	–23.126*	–17.187*
τ_{2t}	0.0013	3.347	2.887	–0.671	–0.830
$\Delta\tau_{2t}$	1.681*	–12.050*	–12.206*	–12.726*	–9.285*
a_t	1.660*	–11.805*	7.732*	nc	nc

For the three variables ϵ_t, x_t, and a_t the test statistics correctly reject the unit root hypothesis. However, the performance of the test statistics for y_t, which is generated by a first order autoregressive process with a serial correlation coefficient of 0.9, illustrates the difficulty in discriminating between roots close to unity and unit roots. The hypothesis that y_t has two unit roots reassuringly is rejected decisively by the tests on Δy_t. The results of the DW, DF, and ADF tests for the random walk w_t and the random walk with drift d_t confirm the ability of these unit root tests to work well in situations for which they were designed. For these two variables the trend augmented DF and ADF statistics correctly fail to reject the unit root hypothesis, and correctly reject the presence of a deterministic trend, with the mirror image property "$t_{\lambda=0} = -t_{\delta=0}$" holding approximately for d_t (the DF $t_{\lambda=0} = 2.1597$ and the ADF $t_{\lambda=0} = 2.202$) but not for w_t (the DF $t_{\lambda=0} = -2.848$ and the ADF $t_{\lambda=0} = -2.772$), in accord with the results in Haldrup [1991]. The performance of the DW, DF, and ADF test statistics for the trend stationary variable z_t illustrates the difficulty these tests can have in distinguishing between unit roots and deterministic trends, and further highlights the importance of using the trend augmented ADF test statistics which correctly reject the unit root hypothesis. Note also that the inclusion of the linear trend in DF + t and ADF + t test statistics applied to Δz_t does not adversely affect their performance – they correctly reject the unit root hypothesis and have values almost identical to the corresponding test statistics without trend. It is also worth noting that in the ADF regression for z_t the estimated coefficient of Δz_{t-1} is –0.522 (with "t" value of –8.55) and the estimated coefficient of z_{t-1} is –0.0123 (with a "t" value of –0.832), thus indicating that the differencing of z_t was inappropriate since the transformed variable Δz_t behaves like a non–invertible moving average process with a first serial correlation coefficient of –0.5 (N.B. $\Delta z_t = \delta_2 + \Delta\epsilon_{5t}$). The results of the tests for τ_{1t} and τ_{2t} illustrate the importance of the magnitude of δ_3/σ_ϵ in determining whether deterministic or stochastic non–stationarity dominate. For the less extreme variable τ_{2t}, for which $\delta_3/\sigma_\epsilon = 0.005$, the set of unit root test statistics reported in Table 2 correctly indicate the presence of one unit root, whether or not a linear trend is included in DF and ADF regressions. In the case of τ_{1t}, which has $\delta_3/\sigma_\epsilon = 0.1$, it is only the DF + t and ADF + t test statistics that correctly indicate the presence of one unit root and a linear trend. Without the inclusion of the linear trend the DF and ADF statistics suggest that τ_{1t} has two unit roots. All the test statistics clearly reject the hypothesis of three unit roots in τ_{1t}, as the test statistics for $\Delta^2\tau_{1t}$ show.

A number of these illustrations of the use and performance of unit root tests suggest that in practice a sensible strategy will be to include a linear trend in the Dickey–Fuller regressions, since this enables the identification of deterministic trend when it is present, and does not adversely affect the performance of the tests otherwise. Another practical suggestion for alleviating an additional problem that can arise in the use of unit root tests, is to compute DF and ADF statistics recursively, in order to check for sensitivity in the results to changes in the sample period. This can be particularly important when the series to be analyzed has been affected by regime shifts or structural breaks, as is the case for many macroeconomic time series. Hendry and Mizon [1992] in analyzing a small system containing money, inflation, total final expenditure, and an interest rate for the UK during the turbulent 1970's and 1980's demonstrate the value of this suggestion.

The final example of a non–stationary process is a_t which has a constant conditional mean of zero, but has autoregressive conditional heteroskedasticity. Such processes have become very popular in the modelling of volatile data such as stock prices and other financial data which have fat tailed distributions. Note that the results in Table 2 show that the unit root hypothesis is rejected for a_t, which is appropriate for a variable generated by an ARCH process, for although it is non–stationary, it is not integrated. These results demonstrate the power of the unit root tests to discriminate in such cases. The graph of a_t shows a number of outliers which will lie in the tails of the empirical frequency distribution, with an especially large one around 1978. In fact, one way of checking for non–constant conditional second moments is to graph the recursive standard deviation (or variance) which should be constant for a stationary series. Mizon [1991a] illustrates the use of recursive means and variances in determining the essential characteristics of data, and Pagan and Schwert [1990a, 1990b] provide more detailed discussion including the proposal of a test for the hypothesis of no change in the conditional variance. Figure 2 provides a graph of the recursive standard deviation of a_t with an initial sample of size 50, from which it is clear that the second moment of a_t is not constant over time with a particularly big change around 1978. However, great care needs to be exercised in interpreting such graphs since even for stationary series there can appear to be "clear" changes or breaks in the graph. Hence the computation of the bounds test proposed by Pagan and Schwert [1990a] is advisable. It is interesting to note that whilst a_t has a fat tailed distribution it does not have the height of mode relative to the range that is typical of financial data – see Pagan [1991]. A transformation of a_t that yields a leptokurtic distribution, but at the expense of introducing a positive skew, is a_t^2. These features of a variable (namely skewness, kurtosis, and the possibility of multimodality) can be examined via its empirical frequency distribution and nonparametric kernel estimates of its density. Figure 3 shows the empirical frequency distribution of a_t^2 together with a nonparametric estimate of its density using a routine of Silverman [1982, 1986]. Multimodality in the frequency distribution and density estimate for a variable can result from changes in the unconditional mean, such as regime shifts or seasonality. The importance of, and practical difficulty in, distinguishing between stochastic and deterministic shifts in a variable was emphasized above. The fact that many economic time series exhibit seasonal characteristics is also important, and there are many models of seasonality that an investigator needs to be aware of, so that an appropriate choice can be made in the development of an overall congruent model of the variables being analyzed. Hylleberg [1992] contains many seminal papers in the analysis of seasonality, and discussion of deterministic models of constant seasonality as well as stochastic seasonality such as seasonal integration and cointegration.

More detailed analysis of the properties of time series processes can be found in texts such as Granger and Newbold [1986], Fuller [1976], and Harvey [1990]. Attention here has been concentrated on the use of practical ways to determine the characteristics of time series variables, since such information plays a critical role in the development of models that are congruent with available information.

As a final illustration of the importance of determining the characteristics of data to be modelled and then ensuring that the chosen class of model is capable of representing these characteristics, consider again the modelling of y_t when the relevant data set consists of x_t and the history of both variables. The behaviour of alternative estimators of β can be assessed via a Monte Carlo study which generates y_t and x_t with the appropriate characteristics, and then computes descriptive statistics for the simulated distributions of these estimators. In fact, the sample means and sample standard deviations of the simulated distributions can be used as estimators of the corresponding population parameters. For example, the simulation sample mean of an econometric estimator of interest (calculated by averaging the value the econometric estimator takes across the Monte Carlo replications), describes the central tendency of the simulated distribution of the estimator, and also provides an estimate of the population mean of the estimator from which its population bias can be calculated. In order that y_t be temporally dependent, but x_t not, the DGP takes the form:

$$y_t = \alpha\, y_{t-1} + \epsilon_t \quad \text{with} \quad \begin{pmatrix}\epsilon_t\\ \eta_t\end{pmatrix} \sim \mathrm{NI}\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma_\epsilon^2 & \rho\\ \rho & \sigma_\eta^2\end{pmatrix}\right)$$
$$x_t = \eta_t$$

when $\sigma_\epsilon^2 = \sigma_\eta^2 = 1$, $\alpha = 0.5$, $\rho = 0.9$, and the econometric sample size T =100.

This DGP was set up in **PC NAIVE**, and then in three separate runs of **PC NAIVE** (one for each of M_1, M_2 and M_3, with the same seed for the random number generator and 1000 replications) the results given in Table 3 were obtained. The alternative estimators considered are the OLS estimators of β in the following regression models:

M_1: $y_t = \beta_1 x_t + u_t$

M_2: $y_t = \beta_2 x_t + \alpha_2 y_{t-1} + \nu_t$

M_3: $y_t = \beta_3 x_t + \alpha_3 y_{t-1} + \gamma_3 x_{t-1} + \omega_t$

Model M_1 is noncongruent in that though y_t and x_t are related to each other, x_t (which is serially uncorrelated) cannot explain the temporal dependence in y_t, and as a result the error u_t is serially correlated. In fact, $u_t = \alpha\, u_{t-1} + \xi_t$ with $V(\xi_t) = \sigma_\epsilon^2 - \beta^2\sigma_\eta^2(1-\alpha^2)$, and although $E(u_t\eta_t) = 0$ there is feedback from x to y in this model since $E(u_t\eta_{t-k}) = \alpha^k\beta\sigma_\eta^2$ for $k > 0$. Hence despite being unbiased, the OLS estimator of β in M_1 is inefficient, and can result in misleading inferences about β. Note in particular, that although there is essentially no bias in the estimators of β from M_1, M_2 or M_3, there is a big difference between the standard errors of the alternative estimators of β. Note also the magnitude of the Durbin Watson test statistics, and the 100% rejection frequency for the null hypothesis of no serial correlation in the errors of the noncongruent model M_1.

Table 3:Monte Carlo estimates with 1000 replications
(seed = 980, econometric sample size T = 100)

	DGP VALUE	M_1	M_2	M_3
$\beta_{1,2,3}$	0.9	0.8996	0.8986	0.8985
$SE(\hat{\beta}_1)$	0.072	0.0723	na	na
$SE(\hat{\beta}_{2,3})$	0.044	na	0.0441	0.0443
$\alpha_{2,3}$	0.5	0.0	0.5015	0.4971
$SE(\hat{\alpha}_2)$	0.038	na	0.0385	na
$SE(\hat{\alpha}_3)$	0.060	na	na	0.0616
γ	0.0	na	na	0.0024
$SE(\hat{\gamma})$	0.070	na	na	0.0709
DW_1	1.0	1.0100	na	na
reject freq		100%	na	na
$DW_{2,3}$	2.0	na	1.9789	1.9771
reject freq		na	5.4%	2.2%
R^2_1	0.6075	0.6097	na	na
$R^2_{2,3}$	0.8575	na	0.8556	0.8570
σ_μ	0.723	0.7228	na	na
σ_ν	0.436	na	0.4366	na
σ_ω	0.436	na	na	0.4365

It is straightforward in this case to calculate analytically the population parameter values for the three models, by deriving the alternative parameterizations of the DGP which relate directly to the three models:

for M_1

$$y_t = \beta x_t + u_t \text{ with } u_t = \alpha u_{t-1} + \xi_t, \quad \begin{pmatrix}\xi_t\\ \eta_t\end{pmatrix} \sim NI\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma^2_\xi & 0\\ 0 & \sigma^2_\eta\end{pmatrix}\right)$$
$$x_t = \eta_t$$

when $\beta = \rho/\sigma^2_\eta$, $\sigma^2_\xi = \sigma^2_\epsilon - \beta^2\sigma^2_\eta(1-\alpha^2)$ and $E(u_t\eta_{t-k}) = \alpha^k\beta\sigma^2_\eta$ for $k > 0$;

for M_2

$$y_t = \beta x_t + \alpha y_{t-1} + \nu_t \quad \text{with} \quad \begin{pmatrix}\nu_t\\ \eta_t\end{pmatrix} \sim NI\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma^2_\nu & 0\\ 0 & \sigma^2_\eta\end{pmatrix}\right)$$
$$x_t = \eta_t$$

when $\beta = \rho/\sigma^2_\eta$, and $\sigma^2_\nu = \sigma^2_\epsilon - \beta^2\sigma^2_\eta$;

for M_3

$$y_t = \beta x_t + \alpha y_{t-1} + \gamma x_{t-1} + \omega_t \quad \text{with} \quad \begin{pmatrix}\omega_t\\ \eta_t\end{pmatrix} \sim \mathrm{NI}\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma^2_\omega & 0\\ 0 & \sigma^2_\eta\end{pmatrix}\right)$$
$$x_t = \eta_t$$

when $\beta = \rho/\sigma^2_\eta$, $\gamma = 0$, and $\sigma^2_\omega = \sigma^2_\epsilon - \beta^2\sigma^2_\eta$.

However, since the DGP is linear and stationary it is possible to use **PC ASYMP** (a companion program to **PC NAIVE** for calculating the asymptotic moments and population parameters for regression models estimated by OLS or instrumental variables IV) to calculate the values of model parameters implied by the DGP. There was agreement between the analytical derivations and the calculations performed by **PC ASYMP** for these models. Note that all the Monte Carlo estimates, which are averages across the 1000 replications for each statistic, are extremely close to the population parameter values in all cases.

III. Congruence and Encompassing

It has been argued in the previous section that it is important to develop models that are congruent with available information, otherwise misleading and/or inefficient inferences may be drawn. Of necessity though the available information, and especially the sample information, will be determined by choices made by the investigator. As a consequence, a model developed by a particular investigator, even if it is congruent with the information considered by the investigator, may be revealed to be inadequate relative to a larger information set that includes the data of rival models. If this is the case then the investigator's model will not be able to account for, or explain, the results of rival models, and so it will not encompass the rival models. Hence the investigator's model lacks what is an essential property of a good model, namely the ability to explain why previous models were found to perform well, and why they now are inadequate relative it. That a model can be congruent with respect to a particular information set, and non–congruent when evaluated relative to a larger information set, is not surprising and may be thought to pose no problems since each investigator carefully chooses a relevant information set and thus does not need to consider a larger one. However, this ignores the importance of developing models that encompass rival models, and falls fowl of a fundamental flaw in the approach to modelling which uses empirical evidence to confirm or corroborate theories – more than one congruent model can be developed for the same phenomenon when the congruence of each is with respect to its own information set. The disturbing implication of this result for traditional econometric modelling is, that the development of a theory consistent and data admissible model, which has been subjected to, and passed, a battery of diagnostic tests, does not guarantee that it is the best model currently available. Further, it makes it abundantly clear that to demonstrate that a model is theory consistent, data admissible, and has revealed no evidence of misspecification in diagnostic testing, is not sufficient to establish it's credentials, and in particular does not raise the issue of inter–model comparison. Ericsson and Hendry [1989] present an analysis of this issue, and Mizon [1989] illustrates the nature of the problem, and demonstrates that it could occur widely in practice, by generating data so that both a monetarist and a Keynesian model of inflation (which could have very different policy implications) reveal no evidence of misspecification. It is only when each model is evaluated in the context of a larger information set which incorporates the separate information sets supporting each model, that their mutual inadequacy is found. Note also, the fact that both models are inadequate relative to wider information set needed to support their statistical comparison, implies that the use of a selection criterion to choose one of the models (e.g. minimum mean squared error, Hannan–Quinn [1979], or Schwarz [1978]) is not a sensible way to resolve the problem of having to advise on, or implement, a policy.

To illustrate this point consider a situation in which a large national food supplier wishes to learn more about the major determinants of the demand for its product. A consultant to the company has provided a model that is based on the premise the demand D_t is best explained in terms of the product's price P_t, and advertising expenditure A_t. The model was estimated using quarterly data on these variables for the period 1960(1) to 1989(4), with the following results:

M_1: Modelling D_t by OLS

Variable	Coefficient	SE	HCSE	t
A_t	0.76163	.13388	.14799	5.6887
P_t	−1.05029	.15577	.13823	−6.7424
Constant	−0.05279	.13514	.14082	−0.3906

$R^2 = .4242$ $\hat{\sigma}_1 = 1.4551$ F(2,117) = 43.10 [.0000] DW = 2.015
RSS = 247.7158 for 3 Variables and 120 Observations
Information Criteria: SC = .844478; HQ = .803091; FPE = 2.17

Serial Correlation tests: $\chi^2(12)$= 9.0261; F(12,105) = .712 [.7371]

ARCH Test: F(1,115) = 1.07 [.3036] Normality Test: $\chi^2(2)$ = .918
Heteroskedastic Errors Test: F(4, 112) = 1.0892 [.3654]

RESET F–Test for adding $\hat{y}_t^2$: F(1,116) = .713 [.4001]

On the basis of these results, which have estimated coefficients the signs expected from economic theory ($\partial D_t/\partial A_t > 0$ and $\partial D_t/\partial P_t < 0$), and have none of the diagnostic test statistics indicating any misspecification (for definitions of the test statistics see Hendry [1989]), this model appears to be congruent and to form an adequate basis for the company to analyze the demand for its product. However, a second consultant has argued that D_t is best explained in terms of P_t, and Total Final Expenditure E_t as a measure of the strength of demand in the economy. The estimates for this model were:

M_2: Modelling D_t by OLS

Variable	Coefficient	SE	HCSE	t
E_t	0.98213	.12075	.11440	8.1333
P_t	−1.07294	.14021	.13524	−7.6521
Constant	−0.11475	.12036	.12066	−0.9534

$R^2 = .5304$ $\hat{\sigma}_2 = 1.31401$ F(2,117) = 66.09 [.0000] DW = 1.961
RSS = 202.0145 for 3 Variables and 120 Observations
Information Criteria: SC = .640535; HQ = .59948; FPE = 1.77

Serial Correlation tests: $\chi^2(12)$= 10.691; F(12,105) = .8413 [.6081]

ARCH Test: F(1,115) = 4.99 [.0274] Normality Test: $\chi^2(2)$ = .886
Heteroskedastic Errors Test: F(4, 112) = .4766 [.7529]

RESET F–Test for adding $\hat{y}_t^2$: F(1,116) = .250 [.6183]

Again these results have estimated coefficients that are significantly different from zero, and accord with the predictions of economic theory ($\partial D_t/\partial E_t > 0$ and $\partial D_t/\partial P_t < 0$), with only the ARCH diagnostic test statistic indicating the possibility of misspecification. In fact, though not shown, when both of these models are estimated by recursive least squares there is no evidence of parameter non–constancy, and so both models appear to be reasonably congruent with their respective information sets. In this situation it may seem appropriate to use a selection criterion, and on the basis of R^2, the Schwarz criterion SC, the Hannan–Quinn criterion HQ, and the final prediction error FPE, the second model is unanimously "selected" (the model with the smallest value of the criterion function is chosen) despite the apparent ARCH effects in its residuals. However, to use a selection criterion, even when it is to select amongst models that are congruent with respect the their own information sets, ignores the possibility that there may be a better model than any of those amongst which the selection is being made, which incorporates features of some, or all, of the competing models. One of the properties of encompassing tests, since they require a common statistical distribution within which to compare the rival models, is that they have power against such alternatives. The table below provides the values of the Cox (see Cox [1961,1962], and Pesaran [1974]) and complete parametric encompassing CPE (see Mizon and Richard [1986]) test statistics, from which it is seen that neither M_1 nor M_2 can encompass the other model. Further, note that although $\hat{\sigma}_2 < \hat{\sigma}_1$, there is strong rejection of the hypothesis that $M_2 \mathcal{E} M_1$, thus illustrating directly that variance dominance is necessary but not sufficient for encompassing.

ENCOMPASSING TEST STATISTICS

$M_1 \mathcal{E} M_2$	Null	Test	Null	$M_2 \mathcal{E} M_1$
–81.377	N(0,1)	Cox	N(0,1)	–37.799
81.458	F(1,116)	CPE	F(1,116)	45.029
[.0000]				[.0000]

Hence the use of a selection criterion would result in M_2 being preferred to M_1, whereas the encompassing tests reveal that both models are inadequate, in that though they each capture something of value in explaining the variation in D_t, neither dominates the other in this explanation. Despite the fact that both M_1 and M_2 were congruent with respect to their own information sets, the encompassing comparisons revealed their failure to fully exploit all the available information.

Rather than attempt to modify M_1 and M_2 until the resulting (more general) model is both congruent (with respect to a larger information set implied by the modifications), and can encompass rival models (including M_1 and M_2), it is preferable to start the modelling of D_t again from a general model that nests M_1 and M_2 and includes other potentially relevant variables. This has the advantage of avoiding the dangers of specific–to–general modelling (see for example Hendry [1987] and Mizon [1989,1991b] for amplification of this point), and enables a congruent encompassing model to be found as a series of reductions from a congruent general model. In the present context it seems appropriate to consider linear models for the explanation of D_t which include A_t, E_t, P_t, and a variable C_t which measures the availability of credit, with $\partial D_t / \partial C_t > 0$ expected. The results from estimating this general model M_g are:

M_g: Modelling D_t by OLS

Variable	Coefficient	SE	HCSE	t
E_t	.9376	.1028	.0928	9.118
A_t	.6969	.1029	.1149	6.773
P_t	–.9988	.1195	.1174	–8.357
C_t	.1376	.0959	.1140	1.434
Constant	.0072	.1038	.1082	0.070

R^2 = .6677 $\hat{\sigma}_g$ = 1.1149 F(4,115) = 57.77 [.0000] DW = 2.00
RSS = 142.9667 for 5 Variables and 120 Observations
Information Criteria: SC = .3746; HQ = .3056; FPE = 1.29

Serial Correlation tests: $\chi^2(12)$= 6.943; F(12,103) = .53 [.8928]

ARCH Test: F(1,113) = 1.29 [.2589] Normality Test: $\chi^2(2)$ = .589
Heteroskedastic Errors Test: F(8,106) = 1.2096 [.3005]

RESET F–Test for adding $\hat{y}_t^2$: F(1,114) = .701 [.4044]

These results for M_g indicate that each of A_t, E_t, and P_t have important roles to play in the explanation of D_t, and their estimated regression coefficients have the theoretically expected signs. Though the estimated coefficient of C_t has the expected sign, it is poorly determined and small. The model as a whole reveals no evidence of misspecification. In view of these results it is appropriate to test for simplifications or reductions of M_g, and bearing in mind the previous interest in M_1 and M_2, an obvious reduction to consider is from M_g to M_c, a completing model which nests both M_1 and M_2, but does not include C_t. When this model was estimated the following results were obtained:

M_c: Modelling D_t by OLS

Variable	Coefficient	SE	HCSE	t
E_t	.9315	.1032	.0900	9.025
A_t	.6934	.1033	.1111	6.710
P_t	–.9969	.1201	.1102	–8.304
Constant	.0099	.1043	.1055	.095

$R^2 = .6618$ $\hat{\sigma}_c = 1.1201$ $F(3,116) = 75.646$ [.0000] DW = 2.04
RSS = 145.5247 for 4 Variables and 120 Observations
Information Criteria: SC = .352437; HQ = .297254; FPE = 1.296

Serial Correlation tests: $\chi^2(12)=$ 8.2072; $F(12,104) = .6363$ [.8069]

ARCH Test: $F(1,114) = 1.388$ [.2412] Normality Test: $\chi^2(2) = .845$
Heteroskedastic Errors Test: $F(6,109) = .9713$ [.4482]

RESET F–Test for adding $\hat{y}_t^2$: $F(1,115) = .713$ [.4002]

On the basis of these results M_c is also congruent with respect to an information set which incorporates the information for both M_1 and M_2 and the extra variable C_t. The F test for the reduction from M_g to M_c is given by $F(1,115) = 2.06$ [0.1542], and so the hypothesis that $M_c \; \mathcal{E}_p \; M_g$ having a p–value of 15.4%, appears to be consistent with the evidence. On the other hand the F test statistics for the reductions from M_g to M_1 ($F(2,115) = 42.13$ [.0000]) and M_g to M_2 ($F(2,115) = 23.75$ [.0000]) mean that neither M_1 nor M_2 can parsimoniously encompass the congruent general model M_g. Indeed, the same conclusion is reached if the testing is done incrementally, that is M_c cannot be parsimoniously encompassed by either M_1 or M_2 (N.B. the relevant test statistics are the CPE F test statistics reported above). In fact, the data for this example were also generated using **PC NAIVE** (the seed was 282 and the data saved from replication 5), and the DGP defined by:

$$D_t = 0.5A_t + 0.9E_t - 1.0P_t + \epsilon_{1t} \qquad \text{for } t = 1,\ldots.120$$
$$A_t = \epsilon_{2t}$$
$$E_t = \epsilon_{3t} \qquad \text{with } \underline{\epsilon}_t \sim NI(0, I_5)$$
$$P_t = \epsilon_{4t} \qquad \text{when } \underline{\epsilon}_t' = (\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t}, \epsilon_{4t}, \epsilon_{5t})$$
$$C_t = \epsilon_{5t}$$

Hence M_c corresponds to the DGP for D_t so that in the population M_c has the following properties: (i) it is congruent with respect to the information set that includes all the variables in the DGP (i.e. D_t, A_t, E_t, P_t, and C_t, and their lags); (ii) M_c is a valid reduction of M_g and so $M_c \; \mathcal{E}_p \; M_g$; and (iii) M_c automatically encompasses M_1 and M_2 and in particular can explain their misspecifications, since in this case $M_i \; \mathcal{E}_p \; M_c$ does NOT hold for i = 1,2. Although these are population properties of M_c, note that in the sample of size 120 obtained from replication 5, none of these three properties was rejected. Further, these properties remained intact on average across 1000 replications of the simulation experiment – e.g. the hypothesis $M_c \; \mathcal{E}_p \; M_g$ was rejected in only 6.5% of the replications when a nominal 5% critical value was used for the test. Also note that since (i) and (ii) are characteristics of the population, the test of (ii) is statistically valid. A further important point is that the Monte Carlo experiment was designed so that C_t, which is redundant for the modelling of D_t, is generated as a temporally independent standard normal variate since M_g could not otherwise have been a congruent model. As argued in the previous section, potential regressors in a linear time series regression model must have time series properties (in isolation or in combination with other regressors) which are coherent with those of the regressand.

The example above provides a demonstration (albeit in a simple case) of the use of Monte Carlo simulation to illustrate the properties of the DGP namely: its congruence; its ability to detect and explain the misspecifications of models nested within it that are not valid reductions of it (i.e. models that cannot parsimoniously encompass the DGP); its ability to parsimoniously encompass overspecified models which are nonetheless congruent. Knowledge of the DGP, were it available, would endow a modeller with olympian powers for model evaluation and comparison. Indeed, the DGP is a powerful metric against which to assess the performance of alternative models. Though modellers do not in practice know the DGP, they can by seeking models that are congruent and encompass rival models, hope to develop models that mimic the powerful properties of the DGP. Finally, note that whilst the DGP of a Monte Carlo simulation is fixed once chosen, the process generating observed data in the economy may change. Though this can make it more difficult for the econometrician to develop congruent (particularly ones with constant parameters) and encompassing models, it also can provide sufficient variability in the data for the econometrician to be able to discriminate between alternative models. For further discussion of the impact of structural change on, and the role of parameter constancy tests in, econometric modelling see *inter alia* Anderson and Mizon [1989], Engle and Hendry [1989], and Favero and Hendry [1989].

IV. Conclusions

Unless a model is congruent with available information (from all sources), the result is likely to be, at worst, that investigators who use it will make invalid or misleading inferences, poor forecasts, and consequently give inappropriate policy advice, and at least the extant potential to improve the quality and performance of the model remains unexploited. It has been argued in this paper that it is important in modelling to develop models that are congruent and encompass rival models of the same phenomena. In modelling with time series data an essential requirement is that models are congruent with the temporal characteristics of the data, as well as other properties of the measurement system. In section II advantage has been taken of the powerful personal computers and sophisticated econometric software (particularly **PC GIVE**, **PC NAIVE**, and **PC ASYMP**) to illustrate ways in which the properties of time series data can be determined. Though this is much better done in live demonstrations in the lecture hall or class room where interaction is also possible, it is hoped that this text captures some of the essence of the live performance.

By using simulated data, generated by known processes, it was possible to demonstrate the use, and assess the performance, of these methods. The methods used ranged from graphical analysis to the application of unit root tests, and all were seen to have a valuable role as well as weaknesses. It was also possible using simulated data to illustrate the fundamental flaw in using empirical evidence to confirm theories, namely that more than one congruent model can be found. Even if models are subjected to rigorous diagnostic checking **with respect to their own information set**, they may be unable to account for the behaviour of alternative congruent models of the same phenomena. Hence by requiring a model to be congruent and encompass rival models, ensures that the model is congruent with respect to an information set larger than the minimum needed to sustain itself, that is with respect to a general model that nests the competing or rival models. Another advantage accruing from the use of simulated data is that it enables a demonstration of the relationship between the DGP and models involving the generated data. In particular, the DGP is by definition congruent, it can be used to detect and explain the deficiencies in misspecified models nested within it, and it can parsimoniously encompass models more general than itself which contain redundant information. Although these are population properties of the DGP, they will also hold with sample data subject to caveats associated with sampling variability and probabilities of Type I error in hypothesis testing. Indeed, provided that the general, model which nests the rival models under consideration, is congruent, it will be able to mimic these powerful properties of the DGP. Therefore, a modelling strategy that aims to develop data admissible and coherent models, that are simple and economically interpretable, as well as being able to encompass rival models, has much to recommend it. At the very least it should result in the development of a partial ordering for a set of models relevant for the study of the phenomena of interest, and that are not profligate in their use of information.

Finally, it is important to realize that although the emphasis in this paper has been on the demonstration of particular properties and results for univariate time series and single equation econometric analysis, most of the analysis extends to multivariate modelling with suitable modification. For example, the discussion of Dickey–Fuller unit root test statistics has its parallel, for multivariate analysis, in the literature on cointegration such as the maximum likelihood analysis of Johansen [1988] and Johansen and Juselius [1990] (see also Phillips and Loretan [1991]). Similarly, the arguments about congruence and encompassing have been extended to systems of non–stationary cointegrated variables by Hendry and Mizon [1989]. In addition, although all (or almost all) the properties illustrated in this paper by using simulation and simulated data can be derived analytically, the purpose of the paper has been to provide additional insight and understanding of these analytical results.

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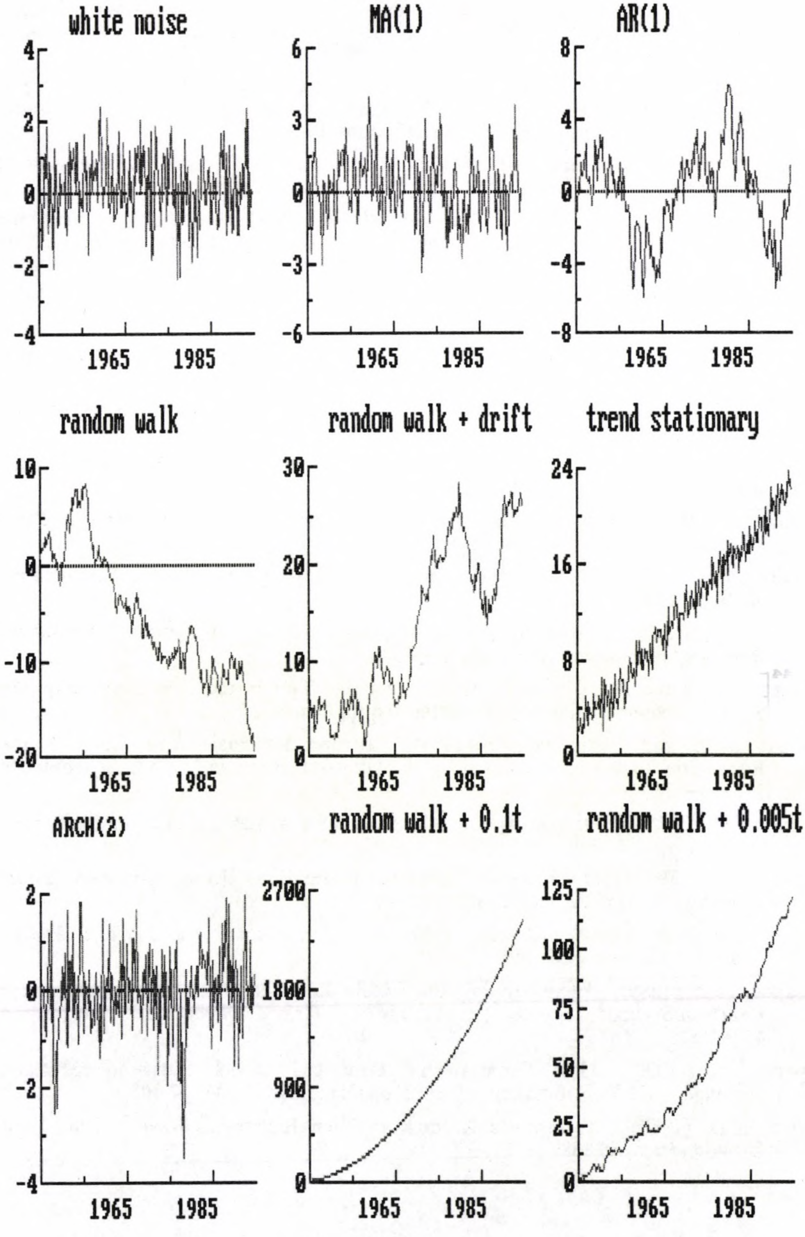

white noise
MA(1)
AR(1)
random walk
random walk + drift
trend stationary
ARCH(2)
random walk + 0.1t
random walk + 0.005t
1965
1985

Figure 2: Recursive standard deviation of ARCH(2)

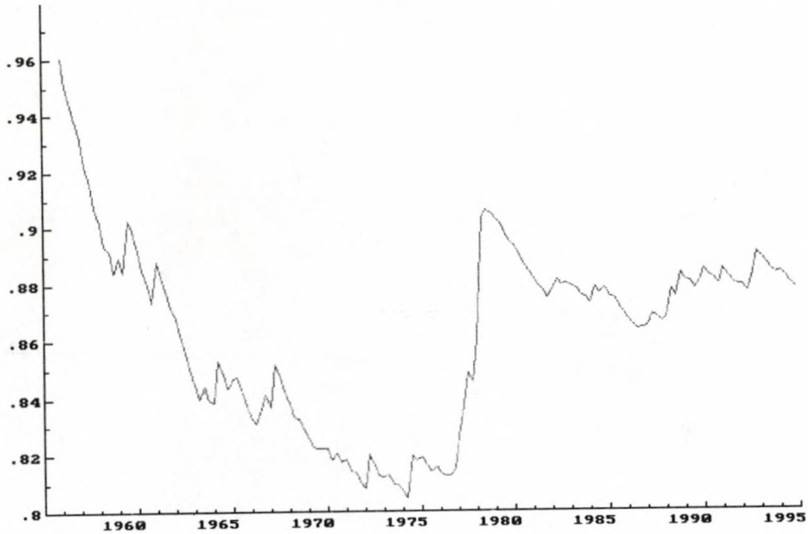
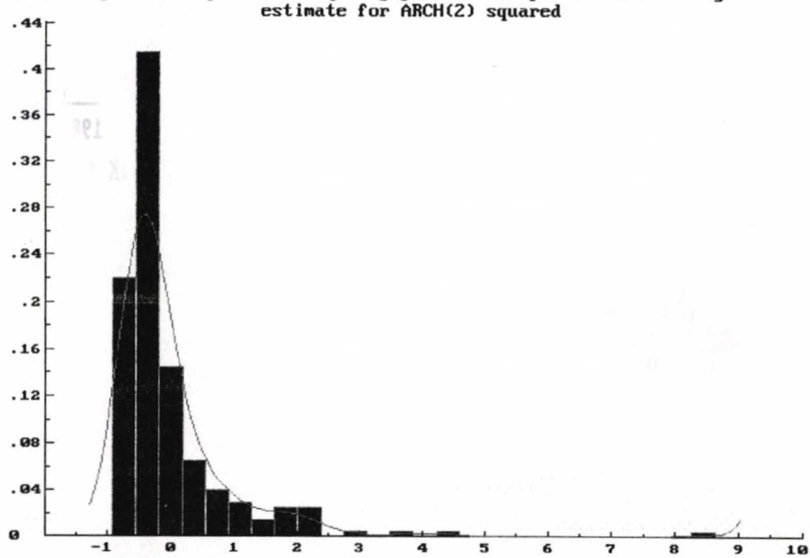


Figure 3: Empirical frequency plot and nonparametric density estimate for ARCH(2) squared



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