THE USE OF ARIMA MODELS IN UNOBSERVED COMPONENTS ESTIMATION: AN APPLICATION TO SPANISH MONETARY CONTROL

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Time series analysts (often "econometricians") working in institutions involved with economic policy making or short-term economic analysis face two important professional demands: forecasting and unobserved components estimation (including seasonal adjustment). Estimation of unobserved components is overwhelmingly done in practice by using "ad hoc" filters; the most popular example is estimation of the seasonally adjusted series with the X11 or X11 ARIMA program.

Concerning forecasting, the decade of the seventies witnessed the proliferation of Autoregressive Integrated Moving Average (ARIMA) models (see Box and Jenkins, 1970), which seemed to capture well the evolution of many series. Since this evolution is related to the presence of trend, seasonal and noise variation, the possibility of using ARIMA models in the context of unobserved components was soon recognized. Since the early work of Grether and Nerlove (1970) on stationary series, several approaches have been suggested. I shall concentrate on one which is becoming, in my opinion, a powerful statistical tool in applied time series work (starting references are Cleveland and Tiao, 1976, and Box, Hillmer and Tiao, 1978; more recent references are Bell and Hillmer, 1984, and Maravall and Pierce, 1987.) In the context of an application, related to the control of the Spanish money supply, I shall address the issues of model specification, estimation of the components, diagnostic checking of the results and inference drawing.

1. MODEL SPECIFICATION

Let an observed series, z_t, be the sum of several independent components, as in

$$z_t = \Sigma_i \, z_{it} \, , \tag{1.1}$$

Let the i-th component and the overall observed series follow the ARIMA processes:

$$z_{it} = \psi_i(B)\, a_{it} , \quad \psi_i(B) = \theta_i(B)/\phi_i(B) , \quad (a_{it} \sim niid(0,\sigma_i^2)) \quad (1.2)$$

and

$$z_t = \psi(B)\, a_t , \quad \psi(B) = \theta(B)/\phi(B) , \quad (a_t \sim niid(0,\sigma_a^2)), \quad (1.3)$$

Although the approach can handle more general cases, I shall concentrate on the usual decomposition of a series z_t into trend (p_t), seasonal (s_t) and irregular (u_t) components, as in

$$z_t = p_t + s_t + u_t \quad , \quad (1.4)$$

where the three components are independent. Often, the two components p_t and u_t are considered jointly, so that z_t is decomposed as in

$$z_t = z_t^a + s_t , \quad (1.5)$$

where $z_t^a = p_t + u_t$ is the seasonally adjusted series. Since u_t may be such that erratic short-term movements render the seasonally adjusted series a poor indicator of the underlying evolution of the series, trend estimation has often been recommended as an alternative or complement to seasonal adjustment. I consider, thus, separate estimation of p_t and u_t. By comparing the properties of the estimators of p_t and of z_t^a, some light will be shed on the relative virtues of using either of the two components.

In practice, at institutions such as the Bank of Spain, many hundreds of series are routinely decomposed as in (1.4) or (1.5), and it is impossible to perform detailed univariate analysis of each series. There is, thus, a need for a standard model that approximates reasonably well a large number of series and hence that can be applied routinely.

Besides this practical reason, when dealing with a large collection of time series, there are also a priori theoretical reason for using some type of "common central model", perhaps letting just a few parameters differ across the series (see Sims, 1985).

An obviuos candidate among ARIMA models is the Airline model of Box and Jenkins (1970), given by

$$\nabla\nabla_{12}\, z_t = (1-\theta_1\, B)(1-\theta_{12}\, B^{12})a_t \ , \tag{1.6}$$

which has been found to approximate many series encountered in practice, characterized by the presence of trend and seasonal variation. The model (1.6) contains three parameters.Since $\theta_1=1$ implies a deterministic trend and $\theta_{12}=1$ implies a deterministic seasonal component, θ_1 and θ_{12} are related to the stability of the trend and seasonal components, respectively. The third parameter, σ_a^2, provides a measure of the size of the one-period ahead forecast error. When $-1<\theta_1<1$ and $0<\theta_{12}<1$, the model accepts a decomposition as in (1.4) (see Hillmer and Tiao, 1982).

The discussion will be clearer if we focus on a particular example. Consider the monetary aggregate targeted in Spanish monetary policy: the series of liquid assets in the hands of the public (the sum of currency, deposits in banks and savings institutions, and other liquid assets). Estimation of (1.6) for the log of the monthly series, using the period 1973-1985 (T=156), yields θ_1=-.1915 (SE=.080), θ_{12}=.6228 (SE=.069), and $\sigma_a^2=.138\text{x}10^{-4}$ (the standard error of the one-period-ahead forecast is aproximately equal to .37 percent of the level of the series.) The residual autocorrelation function (ACF) is relatively clean, and for example the Box-Pierce-Ljung statistic for the first 24 autocorrelations is equal to 20.6, well below the critical value $\chi^2_{22}(.05)=33.9$.

The spectrum of the estimated model for z_t is given in Figure 1, part a). It displays peaks for the frequencies $\omega=0$, associated with the trend, and $\omega=j\pi/6$, $j=1,\dots,6$, associated with the 1 to 6 times a year seasonal frequencies. Writing $\nabla\nabla_{12}=\nabla^2 S$, where $S=1+B+\dots+B^{11}$, the peak for $\omega=0$ is induced by the factor ∇^2, while the peaks for $\omega=j\pi/6$, $j=1,\dots,6$, are induced by the unit roots of S. Therefore, the models for the trend, seasonal and irregular components will be of the type $\nabla^2 p_t=\alpha(B)b_t$, $S s_t=\beta(B)c_t$ and u_t white noise, where $\alpha(B)$ and $\beta(B)$ are polynomials in B of finite order. From (1.4) and (1.6), consistency with the overall model implies

$$\theta(B)\, a_t = S\alpha(B)\, b_t + \nabla^2\beta(B)c_t + \nabla\nabla_{12}\, u_t \,, \qquad (1.7)$$

where $\theta(B) = (1-\theta_1\, B)(1-\theta_{12}\, B^{12})$. Since the l.h.s. of (2.4) is a moving average of order 13, we can set $\alpha(B)$ to be of order 2 and $\beta(B)$ to be of order 11, so that the three terms in the r.h.s. are also of order 13. Therefore, the models for the components are of the type:

$$\nabla^2\, p_t = (1-\alpha_1\, B - \alpha_2\, B^2)b_t \qquad (1.8a)$$

$$S\, s_t = (1-\beta_1\, B - \dots - \beta_{11}\, B^{11})c_t \qquad (1.8b)$$

$$u_t \sim \text{white noise} \qquad (1.8c)$$

and for the seasonally adjusted series, the identity $z_t^a=p_t+u_t$ implies that z_t^a is an IMA(2,2) model, say

$$\nabla^2 z_t^a = (1-\lambda_1 B-\lambda_2 B^2)d_t \qquad (1.8d)$$

where λ_1, λ_2 and σ_d^2 can be obtained from the models for p_t and u_t.

Equating the variance and autocovariances of the l.h.s. and r.h.s. of (1.7), a system of 14 equations is obtained. These equations express the relationship between the parameters of the overall model and the unknown parameters in the components models. Since the number of the latter is 16 (α_1, α_2, $\beta_1,\ldots,\beta_{11}$, σ_b^2, σ_c^2, and σ_u^2), there is an infinite number of structures of the type (1.8) that are compatible with the same model (1.6). The identification problem is similar to the one that appears in standard econometric models. The model for the observed series is the reduced form, while the models for the components represent the associated structural form. For a particular reduced form, there are an infinite number of structures from which it can be generated. In order to select one, additional information has to be incorporated. The traditional approach in econometrics has been to set a priori some parameters in the structural model equal to zero, rationalized as reflecting a priori economic theory information. In the case of our unobserved-components model, such a priori information is not available. We follow instead an alternative approach, originally suggested by Box, Hillmer and Tiao (1978) and Pierce (1978). The additional information will be the requirement that separable white noise should not be a part of either the trend or the seasonal component, and should go to the irregular. The variance of the irregular is thus maximized and the resulting decomposition has been termed "canonical" by Hillmer and Tiao (1982). These two authors and Burman (1980) have developed methods for estimating the canonical components. For the case of the Airline model, both methods imply the same decomposition.

Without loss of generality, let $\sigma_a^2=1$. All variances will be expressed then in units of σ_a^2. For $\theta_1=-.1915$, $\theta_{12}=.6228$, the models obtained for the components are:

$$\begin{aligned} \nabla^2 p_t &= (1+.039\ B-.961\ B^2)\ b_t \\ &= (1+B)(1-.961\ B)\ b_t \quad , \end{aligned} \tag{1.9a}$$

$$\begin{aligned} \nabla^2 z_t^a &= (1-.779\ B-.175\ B^2)\ d_t \\ &= (1+.182\ B)(1-.961\ B)\ d_t \end{aligned} \tag{1.9b}$$

and

$$S\,s_t = (1+2.019\,B+2.487\,B^2+2.619\,B^3+2.481\,B^4+ \\ +2.182\,B^5+1.800\,B^6+1.365\,B^7+.972\,B^8+ \\ +.568\,B^9+.310\,B^{10}-.032\,B^{11})\,c_t\,. \qquad (1.9c)$$

Futhermore the innovation variances are given by

$$\sigma_b^2 = .234\ ;\quad \sigma_c^2 = .053\ ;\quad \sigma_u^2 = .108\ ;\quad \sigma_d^2 = .670\ . \qquad (1.10)$$

Thus, for example, the irregular component variance is approximately 10% of the one-step-ahead forecast error variance and hence the random character of the trend and seasonal components contributes heavily to the error in forecasting the overall series z_t.

The spectra of the components, p_t, s_t and u_t are displayed in Figure 1. (The spectrum of z_t^a is that of p_t plus a constant.) The ACF of $\nabla^2 p_t$, and Ss_t are given by the continuous line in Figure 2. Looking at the factorization of $\alpha(B)$ in (1.9a), the root (1+B) induces the zero in the spectrum for $\omega=\pi$. The second root, (1-.961 B), is close to (1-B) and hence nearly cancels out with one of the ∇'s in the r.h.s. of (1.9a). Therefore, the model for the trend can be rewriten as

$$\nabla\, p_t = (1+B)\, b_t + \delta\ ,$$

where δ is a slowly changing parameter. Similarly, the seasonally adjusted series follows the model

$$\nabla\, z_t^a = (1+.182\ B)\, d_t + \delta'\ ,$$

close to that of a random walk with a slowly changing drift. The model for the seasonal component is a relatively complicated expression. The zero in the spectrum is attained at the frequency $\omega=.9175\pi$, between the 5 and the 6 times a year frequencies; the stationary component Ss_t displays a slowly decaying ACF.

Although the model for the trend depends on 3 parameters, the model for the seasonal component on 12, and the model for the irregular on 1, all those parameters are simply functions of θ_1 and θ_{12}. It can be seen that different values of θ_1 and θ_{12} have very little effect on the α-parameters of the trend component model, and a moderate effect on the β-parameters of the model for the seasonal component. Different values of θ_1 and θ_{12}, however have a strong effect on the variance of the component model innovations: more stable trends (i.e. larger values of θ_1) yield smaller values of σ_b^2, and more stable seasonal components (i.e., larger values of θ_{12}) yield smaller values of σ_c^2. Therefore, in terms of the structural parameters, different reduced form parameters (θ_1 and θ_{12}) translate mostly into differences in the variances of the component model innovations, leaving the rest of the structure relatively unchanged. In general, the more random a component is, the larger will be its innovation variance.

2. ESTIMATION OF THE COMPONENTS

2.1 Minimum Mean Squared Error Estimators

Back to the equations (1.2) and (1.3), when the information consists of a complete realization of z_t, denoted by $[z_t]$, the minimum mean squared error (MMSE) estimator of the component z_{it} is given by

$$\hat{z}_{it} = k_i \frac{\psi_i(B)\ \psi_i(F)}{\psi(B)\ \ \psi(F)} z_t = \nu_i(B,F)\ z_t \qquad (2.1)$$

where $k_i = \sigma_i^2/\sigma_a^2$ and $F=B^{-1}$. Under our assumptions, this expression also yields the conditional mean $E(z_{it} | [z_t])$. The derivation of (2.1) for the stationary case can be found in Whittle (1962), and the extension to nonstationary series in Cleveland and Tiao (1976) and Bell, (1984).

For the Airline model (1.6) and components models of the type (1.8), writing for notational simplicity:

$$\theta = (1-\theta_1 B)(1-\theta_{12} B^{12})$$

$$\alpha = 1-\alpha_1 B-\alpha_2 B^2$$

$$\beta = 1-\beta_1 B-\ldots-\beta_{11} B^{11} ,$$

$$\lambda = 1-\lambda_1 B-\lambda_2 B^2 ,$$

and letting a bar denote the same polynomial with B replaced by F, the filter $\nu_i(B,F)$ in (2.1) becomes

$$\nu_p(B,F) = k_b \frac{\alpha\bar{\alpha}\, S\bar{S}}{\theta\, \bar{\theta}} \tag{2.2a}$$

for the trend component, and

$$\nu_s(B,F) = k_c \frac{\alpha\bar{\alpha}\, \nabla^2\bar{\nabla}^2}{\theta\, \bar{\theta}} \tag{2.2b}$$

for the seasonal component. In the example we are analysing, from (1.9) and (1.10) the two filters are easily obtained. They are centered and symmetric, and invertibility of the overall model guarantees its convergence. The two filters are displayed in Figure 3.

The estimator of the irregular component is obtained as the residual, after the trend and seasonal component estimators have been removed. Hence

$$\hat{u}_t = z_t - \hat{p}_t - \hat{s}_t = [1 - \nu_p(B,F) - \nu_s(B,F)] z_t \ , \tag{2.3}$$

which eventually yields:

$$\hat{u}_t = k_u \frac{\nabla \bar{\nabla} \nabla_{12} \bar{\nabla}_{12}}{\theta \bar{\theta}} z_t = k_u [\psi(B) \ \psi(F)]^{-1} z_t . \tag{2.4}$$

Therefore, $\hat{u}_t$ estimated as the residual is the same as what would result from direct estimation using (2.1). More generally, it is irrelevant which two of the three components on the r.h.s. of (1.4) are estimated directly, leaving the third as the residual.

Returning to the Spanish Money Supply, estimates of the components were computed with a program developed by Burman and are displayed in Figure 4. (Notice that, once the spectra of the components are known, the autocovariance functions are easily derived, and nothing more is needed to find the filters ν_p and ν_s. In particular, estimation of the components does not require the derivation of their ARIMA expressions.)

2.2 The Models for the Estimators

Having derived expressions for the component models and for their MMSE estimators, by comparing the two it is seen that, as noticed by Grether and Nerlove (1970), the model for a component is different from the model for its estimator. It is of interest to look at the differences between the two.

An easy way to derive the theoretical model for the estimator is the following: Setting $z_t = \psi(B)\ a_t$ in (2.1), the estimator $\hat{z}_{it}$ can be expressed as a function of the innovations $[a_t]$ in the observed series. After simplifying, it is obtained that

$$\hat{z}_{it} = \psi_i(B)\ \eta_i(F)\ a_t\ , \tag{2.5}$$

where

$$\eta_i(F) = k_i[\psi_i(F)/\psi(F)]a_t \tag{2.6}$$

Comparing (1.2) and (2.5), the ACF and the spectrum of the component will differ from those of the estimator because of the presence of $\eta_i(F)$ in (2.5), a filter in F which is always convergent. It is worth noticing that the component and the estimator require the same stationarity transformation and that estimation preserves the canonical property of a component.

For the case of the Airline model, the expressions for the seasonal and trend estimators become

$$\nabla^2\ \hat{p}_t = \alpha(B)\ \eta_p(F)\ a_t\ , \tag{2.7a}$$

$$S\hat{s}_t = \beta(B)\ \eta_s(F)\ a_t\ , \tag{2.7b}$$

where

$$\eta_p(F) = k_b\ \frac{\bar{\alpha}\ \bar{S}}{\bar{\theta}}\ ; \quad \eta_s(F) = k_c\ \frac{\bar{\beta}\ \bar{\nabla}^2}{\bar{\theta}}\ , \tag{2.8}$$

For the irregular component estimator

$$\hat{u}_t = \eta_u(F)\ a_t\ , \tag{2.9}$$

where

$$\eta_u(F) = k_u\ \frac{\bar{\nabla}\ \bar{\nabla}_{12}}{\bar{\theta}}\ , \tag{2.10}$$

and hence $\hat{u}_t$ follows the "inverse" process of the observed series. The estimator $\hat{u}_t$ is a linear function of innovations a_{t+j}, $j \geq 0$, so that although autocorrelated, at any time t, its forecast will be zero. The estimator $\hat{u}_t$ is seen to be stationary, with finite variance; this variance is always smaller than that of the theoretical u_t.

From expressions (2.7) to (2.10), ACFs and spectra of the theoretical estimators can be easily computed. For the example of the monetary aggregate series they are displayed in Figures 2 and 5, where they are compared to those of the theoretical components. Looking at the ACFs, it is seen that, for the seasonally adjusted series, MMSE estimation leaves practically unchanged the low order autocorrelations, while it induces some negative autocorrelation at lag 12. In the case of the trend, estimation lowers the value of ρ_1 and induces some negative autocorrelation at lag 12. For the seasonal component, the slow decay of the component ACF is replaced by a cycle of period 12 for the ACF of the estimator. In the case of the irregular component, the two ACFs differ markedly, with the estimator displaying negative autocorrelation at both low-order and seasonal lags. Finally, the negative autocorrelations at lag 12 induced in the seasonally adjusted series, trend, and irregular components are seen to be all equal to -.19.

The spectra of the estimators display additional zeroes that are implied by the unit roots in the denominators of the η_i filters. Let $\hat{g}_p(\omega)$, $\hat{g}_s(\omega)$ and $\hat{g}_u(\omega)$ denote the spectra of the trend, seasonal and irregular component estimators, respectively. The zeroes in $\hat{g}_p(\omega)$ and $\hat{g}_u(\omega)$ for the seasonal frequencies reflect the fact that, for these frequencies, the ratio of the variance of the trend and of the irregular component to that of the seasonal component is zero. Therefore, these frequencies will be ignored when estimating the trend or the irregular component. Similarly, the zero in $\hat{g}_s(\omega)$ and $\hat{g}_u(\omega)$ for $\omega=0$ is explained by the fact that, for $\omega=0$, the ratio of the variance of the seasonal or the irregular to that of the trend is zero.

In relative terms, the difference between the two spectra is particularly noticeable for the case of the irregular component estimator, which is far from white noise. Its upward shape reflects the predominance of the trend component variance as the frequency becomes lower.

In all cases, the spect...n of the estimator lies below the spectrum of the component. Accordingly, the variance of the (stationary transformation of the) estimator is smaller than that of the component, as seen in Table 1. Since the sum of the three components is equal to the sum of the three estimators, the difference in the sum of the variances reflects covariances among the estimators. While the theoretical components are uncorrelated, the estimators $\nabla^2\hat{p}_t$, $S\hat{s}_t$ and $\hat{u}_t$, in view of (2.7) and (2.9), will be correlated in general. These correlations can easily be computed and they are also displayed in Table 1. Although nonzero, the correlations between the estimators are nevertheless small.

3. DIAGNOSIS AND INFERENCE

3.1 Diagnosis

An important virtue of a model-based approach to unobserved component estimation is that it provides the grounds for diagnostic checks by comparing theoretical models with the obtained estimates. As we have seen, the theoretical model to use in the comparison should be that of the estimator, which can be quite different from that of the theoretical component.

Figure 6 exhibits the ACF of the stationary transformations of the theoretical estimators, derived from (2.7) and (2.9), and compares them with the empirical ACF of the component estimates for the monetary aggregate series. For the seasonally adjusted series and the trend and irregular components, the empirical and theoretical ACFS are in close agreement. In the case of the seasonal component, the shapes are also similar, although the empirical ACF dies off faster that the theoretical one.

In order for the comparison of the two ACF to be meaningful, we need to have an idea of how close we can expect to get to the theoretical autocorrelations in a particular realization. To answer that question, three hundred independent series were generated with the Airline model with $\theta_1=-.1915$ and $\theta_{12}=.6228$. Each series consisted of 156 observations. The trend, seasonal and irregular components were estimated and the variance and ACF were computed for their stationary transformations. As shall be discussed in Section 3.2, the series of estimates obtained are contaminated at both ends by the replacement of starting and future observations by expectations. It was found, however, that the results changed very little when years were removed from both ends of the series, and the results reported are for the complete series of estimates.

The biases were found to be small, practically nonexistent for ρ_1 and for the variance, and slowly increasing for ρ_k as k gets larger. Table 2 reports the results for the estimators of ρ_1, ρ_{12} and the standard deviation (σ) of the stationary transformation of the component estimators. Table 2 displays also their theoretical values and the empirical estimates obtained for the monetary aggregate series. The comparison between the last two rows in a), b) and c) of Table 3 provides an overall check of the validity of the decomposition obtained. Considering the simulation results, the estimates obtained for the seasonally adjusted series, trend and irregular components are comfortably in agreement with the theoretical estimators. For the seasonal component, however, both $\hat{\rho}_{12}$ and $\hat{\sigma}$ are borderline acceptable.

A similar simulation was carried out for a series half the length of the one considered in our example. The estimators had small biases and were reasonably precise. Comparison of the theoretical and empirical second moments of the stationary component estimators seems to provide a convenient, easy to compute, check on the results. In the example we are considering, the check leads to (nonenthusiastic) acceptance of the results.

3.2. Inferences

An important issue of applied concern (see for example, Bach et al., 1976, and Moore et al, 1981) is the error incurred in estimating the components. In the example we are considering of the Spanish monetary aggregate, since targets are set for the seasonally adjusted series, in order to judge whether targets are being met or not it is important to know how accurately the seasonally adjusted series can be measured. Furthermore, the measurement error in the adjusted series should imply a range of tolerance for future targets. The model-based approach offers a convenient framework to address the issue (see, for example, Pierce, 1979 and 1980, Hillmer, 1985, and Burridge and Wallis, 1985).

There are several types of errors involved in the estimation of the components. Consider the estimator $\hat{z}_{it}$ given by (2.1). This is the final estimator of z_{it}, obtainable when a complete realization of z_t is available. The error

$$\delta_{it} = z_{it} - \hat{z}_{it} \tag{3.1}$$

will be called the "final estimation error". The second type of error is related to the distortion induced at both ends of the component estimator series by the fact that, starting and future values of the series are unknown. Direct inspection of the filters ν_p and ν_s in Figure 3 shows that the weight assigned to the observation z_T in the estimation of a component, s_t or p_t, is negligible when T and t are separated by more than five years (this is also evident from the results in Hillmer, 1985.) Considering the series length, the unknown starting values will only affect the early, distant years. We focus on the error induced by the lack of future observations, which shall be termed "revision error". As shown in Pierce (1980), the final estimation and the revision errors are independent of each other, therefore I shall analyze the two separately.

a) Final Estimation Error

For notational simplicity, consider estimation of the first component. Equation (1.1) can be rewriten as

$$z_t = z_{1t} + Z_{1t} ,$$

where $Z_{1t} = \Sigma_{j\geq 2} z_{jt}$. Since all components follow ARIMA models, Z_{1t} will also be an ARIMA and its expression will be of the type

$$\phi_1^* Z_{1t} = \theta_1^* g_t ,$$

where g_t is white noise with variance σ_g^2, ϕ_1^* is the product of the AR polynomials of the components included in Z_{1t} and θ_1^* is a moving average that can be obtained from the models for the components. Then it can be seen that (3.1) simplifies into

$$\delta_{1t} = \frac{\theta_1 \theta_1^*}{\theta} \varepsilon_t , \qquad (3.2)$$

where ε_t is white noise, with $\sigma_\varepsilon^2 = \sigma_1^2 \sigma_g^2 / \sigma_a^2$ (see Pierce, 1979). Notice that the final estimation error for all components is an ARMA process, with the autoregressive polynomial always the same and equal to the moving average polynomial of the model for the observed series. Since this model is invertible, the error will always be stationary.

For the Airline model and the three component decomposition (1.4), since it has to be that $\Sigma_i \; \delta_{it} = 0$, we need to consider only two out of the three components' final estimation errors.

According to of (3.2), the model for the final estimation error in the seasonally adjusted series can be expressed as

$$\theta \; \delta_{at} = \beta \; \lambda \; \varepsilon_t \; .$$

Therefore δ_{at} follows a stationary ARMA (13, 13) model with autoregressive polynomial $(1-\theta_1 B)(1-\theta_{12} B^{12})$; its ACF is displayed in the first column of Table 3, part a.

To obtain the model for the trend final estimation error, we need the MA polynomial θ^* in the ARIMA representation of $Z_t = s_t + u_t$, which can be obtained by solving the system of covariance equations associated with $\theta^* \; g_t = \beta \; b_t + S \; u_t$. From (3.2), δ_{pt} follows then the model

$$\theta \; \delta_{pt} = \alpha \; \theta^* \; \varepsilon_t \; ,$$

again a stationary ARMA (13,13) model. The ACF of δ_{pt} is displayed in the fist column, part b, of Table 3 and is remarkably close to that of δ_{at}. These ACF's will be needed when computing the estimation error for alternative measures of the rate of change of a component.

Table 4 shows the variances of the final estimation error of the trend and of the seasonally adjusted series. They are similar and, in both cases, the standard deviation of the error is close to one half of the standard deviation of the one-period-ahead forecast error of the overall series. In our example, the error in the final estimator of the seasonally adjusted series is of considerable size; no improvement however in precision can be expected from using, alternatively, the trend.

b) Revision Error

When estimating a component, in order to obtain $\hat{z}_{it}$ by means of (2.1), a complete realization $[z_t]$ is needed. From (2.2), the filter ν in convergent in B and in F, hence it can be truncated. Still, at time T, when the last observation available is z_T, estimation of z_{it} for t close enough to T requires unknown future observations. As shown by Cleveland and Tiao (1976), a preliminary estimator can be obtained by applying (2.1) to the extended series: $z_1, \ldots, z_T, \hat{z}_T(1), \hat{z}_T(2) \ldots,$ where $\hat{z}_T(j)$ denotes the forecast of z_{T+j} with origin T. Accordingly, the preliminary estimator will be subject to revisions since, as new observations become available, forecasts will be updated and eventually replaced with observations. The difference between the preliminary and final estimator represents a measurement error in the former and will be called the revision error.

Consider first (concurrent) estimation of z_{it} at time t, the case of most applied interest. The revision in the concurrent estimator, $\hat{z}^o_{it}$, is

$$r^o_{it} = \hat{z}_{it} - \hat{z}^o_{it} = \Sigma^{\infty}_{j=1} \, \nu_j (z_{t+j} - \hat{z}_t(j)) = \Sigma^{\infty}_{j=1} \, \nu_j \, e_t(j) \quad , \tag{3.3}$$

where $e_t(j)$ denotes the j-th period-ahead forecast error of z_t. From (1.3),

$$e_t(j) = a_{t+j} + \Sigma^{j-1}_{k=1} \, \psi_k \, a_{t+j-k} \quad ,$$

and hence expression (3.3) can be rewriten as a moving average of future innovations $a_{t+1}, a_{t+2}, \ldots$ However, a more direct way of obtaining this moving average representation is through the model derived for the estimators given by (2.5). Let $\zeta(B,F) = \psi_i(B) \, \eta_i(F)$. Then

$$\hat{z}_{it} = \zeta_i(B,F) \, a_t = \Sigma^{\infty}_{j=-\infty} \, \zeta_{ij} \, a_{t+j} \quad , \tag{3.4}$$

Since $E_t a_{t-j} = a_{t-j}$ for $j \geq 0$, and $E_t a_{t+j} = 0$ for $j>0$, it follows that

$$\hat{z}^{o}_{it} = E_t \hat{z}_{it} = \Sigma^{o}_{j=-\infty} \zeta_{ij} a_{t+j} , \tag{3.5}$$

and substracting (3.5) from (3.4), the revision is equal to

$$r^{o}_{it} = \Sigma^{\infty}_{j=1} \zeta_{ij} a_{t+j} = \zeta_i(F) a_{t+1} . \tag{3.6}$$

From expression (3.6) it is possible to derive properties of the revisions (see Maravall, 1986).

In a similar way, (3.4) can be used to derive the revision in any preliminary estimator. If $\hat{z}^{n}_{it}$ denotes the estimator of z_{it} obtained at time t+n ($n \gtrless 0$), then

$$\hat{z}^{n}_{it} = E_{t+n} \hat{z}_{it} = \Sigma^{n}_{j=-\infty} \zeta_{ij} a_{t+j} .$$

and the revision in the preliminary estimator becomes

$$r^{n}_{it} = \hat{z}_{it} - \hat{z}^{n}_{it} = \Sigma^{\infty}_{j=n+1} \zeta_{ij} a_{t+j} . \tag{3.7}$$

Given that the filter $\zeta_i(B,F)$ is convergent in F, the revision is a stationary process. Notice that (3.7) implies that the change in the revision when the estimation period moves from T to T+n is a moving average of order (n-1) (see Pierce, 1980), and that updating an estimator when a new observation becomes available is equivalent to adding the last innovation multiplied by the corresponding ζ_i-weight.

In the case of the Airline model, from (2.7),

$$\zeta_p(B,F) = \frac{\alpha(B)\ \eta_p(F)}{\nabla^2} \ ; \quad \zeta_s(B,F) = \frac{\beta(B)\ \eta_s(F)}{S} , \tag{3.8}$$

where $\eta_p(F)$ and $\eta_s(F)$ are given in (2.8). For the particular example we are considering, Table 5 displays the variance of the revision in the concurrent estimator and of the revision after one, two, three, four and five years of additional data have become available. It is seen that, after five years, the revision in the trend and in the seasonally adjusted series are negligible, so that the filter can be truncated safely. (In fact, more than 95% of the variance of the revision in the concurrent estimator of both components is explained by the first three years.)

Looking at Table 4, the revision error in the concurrent estimator of the trend is seen to be slightly larger than the revision in the concurrent estimator of the seasonal. For both components, the variance of the final estimation error is slightly smaller than that of the revision error. Approximately, the two types of error in the estimators of the two components are all in the same order of magnitude: the standard deviation of the error is close to 50% of the standard deviation of the innovations in the observed series.

One implication of the previous results is the following. In connection with the conduct of short term monetary policy, Maravall and Pierce (1986) recently concluded "... why so much emphasis on seasonal adjustment? Perhaps attention should shift to estimation of a smoother signal less affected by revisions (possibly some type of trend)." For the case of the Spanish monetary aggregate the trend certainly provides a smoother signal, but it is not subject to smaller revisions, nor is it estimated with more precision. The trend estimator, in fact, performs slightly worse on both accounts.

Finally, seasonal adjustment of the Spanish monetary aggregate series has been done traditionally once a year instead of concurrently. This implies the use of the concurrent seasonal estimator for January and the projected seasonal components for the next 11 months. The variances of the revision error in the projected components are reported in Table 6. There is some gain from using concurrent adjustment: averaging over the year, the improvement represents roughly a 15% reduction in the variance of the total estimation error.

4. A FINAL REMARK: CONFIDENCE INTERVALS AND RATES OF GROWTH

I have analysed the additive decomposition of the log of the series. The seasonal component obtained in this way is the log of the seasonal factor, used in practice. Table 7 displays the confidence intervals (C.I.), at the 95% and 67% levels, for a seasonal factor estimated as 100. It is seen that the width of the 95% C.I. for the concurrent estimator represents .9% of the level of the series; for the 67% C.I. around the final estimator, the interval shortens to .32%.

Since targets are set for the rates of growth and not for the levels, it is of interest to see the effect of measurement error on the rates. The rate most widely used is the monthly rate of growth of the monthly series (annualized and expressed in percentage points); this rate is denoted T11. Linearizing T11 and using Tables 3 and 4, the variances of the different measurement errors can be easily computed and Table 9 presents the 95% C.I. for the concurrent and final estimator of the rate T11 for the seasonally adjusted series and for the trend. Roughly, the interval associated with the concurrent estimator is in the order of ± 5 percentage points, which narrows to ± 3 points when the final estimator becomes available. If, for example, the T11 measured for the last month is 12%, the associated error implies that this measurement could be compatible with a true underlying growth between 7% and 17%, approximately. In other words, if the target for the present month growth is 12%, a measured growth between 7% and 17% could be taken as acceptable. The width of these intervals is unquestionably larger than the tolerance ranges typically used in practice. Obviously, lowering the confidence level decreases the width of the interval: for example, the 67% C.I.'s would be approximately one half of those reported in Table 8.

Since the rate T11 of either the seasonally adjusted series or the trend is subject to large measurement errors, there is interest in attenuating its unreliability. One way to do it is to average consecutive T11 measures. For the seasonally adjusted series, Figure 7 shows the number of months needed to conclude that the target is not being met, as a function of the average deviation with respect to the target. Thus, for example, if the average deviation is 1.5%, with a 67% confidence, it should have occurred over a period of at least two months in order to conclude that growth is being significantly different from the targeted one. At the 95% level, at least five months would be needed.

Alternatively, rates different from T11 are also used. Of these, the most important one is the monthly rate of growth of a three month moving average, annualized and expressed in percentage points. This rate is denoted T31 and, again, linearizing the rate and using Tables 3 and 4, it is possible to estimate the associated measurement errors. Table 9 exhibits the 95% C.I. for the estimators of the T31 rate of the seasonally adjusted series and of the trend. The width of these intervals represents between 55% and 60% of the width of the intervals for the T11 rate.

Finally, I have emphasized the problems that estimation errors cause to the conduct of monetary policy. In terms of historical series, it is worth noticing that the standard deviation of the error in the final estimator of either component (seasonally adjusted series or trend), available with a 5-year delay, represents (approximately) an annual growth of one percent, a small, yet not negligible, amount.

REFERENCES

Bach, G.L., Cagan, P.D., Friedman, M., Hildreth, C.G., Modigliani, F. and Okun, A. (1976), Improving the Monetary Aggregates: Report of the Advisory Committee on Monetary Statistics, Washington, D.C.: Board of Governors of the Federal Reserve System.

Bell, W.R. (1984), "Signal Extraction for Nonstationary Time Series", The Annals of Statistics, 12, 2, 646-664.

Bell, W.R. and Hillmer, S.C. (1984), "Issues Involved with the Seasonal Adjustment of Economic Time Series", Journal of Business and Economic Statistics, 2, 4, 291-320.

Box, G.E.P., Hillmer, S.C. and Tiao, G.C. (1978), "Analysis and Modeling of Seasonal Time Series" in Seasonal Analysis of Economic Time Series, ed. A. Zellner, Washington, D.C.: U.S. Dept. of Commerce - Bureau of the Census, 309-334.

Box, G.E.P., and Jenkins, G.M. (1970), Time Series Analysis: Forecasting and Control, Holden Day, San Francisco.

Burman, J.P. (1980), "Seasonal Adjustment by Signal Extraction", Journal of the Royal Statistical Society, A, 143, 321-337.

Burridge, P. and Wallis, K.F. (1985) "Calculating the Variance of Seasonally Adjusted Series", Journal of the American Statistical Association, 80, 391, 541-552.

Cleveland, W.P. and Tiao, G.C. (1976), "Decomposition of Seasonal Time Series: A Model for the X-11 Program", Journal of the American Statistical Association, 71, 581-587.

Grether, D.M. and Nerlove, M. (1970), "Some Properties of 'Optimal' Seasonal Adjustment", Econometrica, 38, 682-703.

Hillmer, S.C. (1985) "Measures of Variability for Model-based Seasonal Adjustment Procedures", Journal of Business and Economic Statistics, 3, 1, 60-68.

Hillmer, S.C and G.C. Tiao (1982), "An ARIMA-Model Based Approach to Seasonal Adjustment", Journal of the American Statistical Association, 77, 63-70.

Maravall, A. (1986), "Revisions in ARIMA Signal Extraction", Journal of the American Statistical Association, 81, 736-740.

Maravall, A. and Pierce, D.A. (1986) "The Transmission of Data Noise into Policy Noise in U.S. Monetary Control", Econometrica, 54, 4, 961-979.

Maravall, A. and Pierce, D.A. (1987), "A Prototypical Seasonal Adjustment Model", Journal of Time Series Analysis. (forth.)

Moore, G.H., Box, G.E.P., Kaitz, H.B., Sthephenson, J.A. and Zellner, A. (1981), Seasonal Adjustment of the Monetary Aggregates: Report of the Committee of Experts on Seasonal Adjustment Techniques, Washington, D.C.: Board of Governors of the Federal Reserve System.

Pierce, D.A. (1980), "Data Revisions in Moving Average Seasonal Adjustment Procedures", Journal of Econometrics, 14, 1, 95-114.

Pierce, D.A. (1979), "Signal Extraction Error in Nonstationary Time Series", Annals of Statistics, 7, 1303-20.

Pierce, D.A. (1978), "Seasonal Adjustment When Both Deterministic and Stochastic Seasonality are Present", in Seasonal Analysis of Economic Time Series, ed. A. Zellner, Washington, D.C.: U.S. Dept. of Commerce - Bureau of the Census, 242-269.

Sims, C.A. (1985), "Comment on 'Issues Involved with the Seasonal Adjustment of Economic Time Series' by W.R. Bell and S.C. Hillmer", Journal of Business and Economic Statistics, 3, 1, 92-94.

Whittle, P. (1963), Prediction and Regulation by Linear Least-Square Methods, London: English Universities Press.

Table 1

Standard Deviation of Components

	$\nabla^2 z_t^a$	$\nabla^2 p_t$	$S s_t$	u_t
Theoretical Component	1.05	.67	1.38	.33
Theoretical Estimator	.94	.48	.34	.19

$\mathrm{Corr}\ (\nabla^2 \hat{p}_t,\ S\hat{s}_t) = -.11$

$\mathrm{Corr}\ (\nabla^2 \hat{p}_t,\ \hat{u}_t) = .06$

$\mathrm{Corr}\ (S\hat{s}_t,\ \hat{u}_t) = .05$

Table 2

Component Moments: Simulation

a) Lag-1 autocorrelation (ρ_1)

	$\nabla^2 \hat{z}_t^a$	$\nabla^2 \hat{p}_t$	$S\ \hat{s}_t$	$\hat{u}_t$
Simulation (Standard Error)	-.39 (.07)	.18 (.06)	.84 (.02)	-.59 (.06)
Theoretical Estimator	-.40	.18	.83	-.60
Estimate	-.44	.21	.81	-.64

b) Lag-12 autocorrelation (ρ_{12})

	$\nabla^2 \hat{z}_t^a$	$\nabla^2 \hat{p}_t$	$S\ \hat{s}_t$	$\hat{u}_t$
Simulation (Standard Error)	-.22 (.08)	-.22 (.08)	.52 (.16)	-.22 (.08)
Theoretical Estimator	-.19	-.19	.62	-.19
Estimate	-.19	-.27	.31	-.18

c) Standard Deviation

	$\nabla^2 \hat{z}_t^a$	$\nabla^2 \hat{p}_t$	$S\ \hat{s}_t$	$\hat{u}_t$
Simulation (Standard Error)	.96 (.04)	.49 (.03)	.33 (.06)	.19 (.01)
Theoretical Estimator	.94	.48	.34	.19
Estimate	.90	.44	.22	.18

Table 3

ACF of Estimation Errors

a) Seasonally Adjusted Series

Lag	Final Estimation Error	Revision Error
1	.67	.67
2	.28	.32
3	-.03	.03
4	-.25	-.20
5	-.39	-.35
6	-.45	-.43
7	-.43	-.44
8	-.34	-.37
9	-.17	-.22
10	.06	.01
11	.36	.33
12	.63	.63

b) Trend

Lag	Final Estimation Error	Revision Error
1	.68	.61
2	.24	.35
3	-.01	.07
4	-.20	-.13
5	-.32	-.28
6	-.37	-.36
7	-.35	-.38
8	-.27	-.34
9	-.13	-.22
10	.07	.04
11	.30	.24
12	.43	.47

Table 4

Variance of the Estimation Errors

	Revision Error	Error in Final Estimator	Total Estimation Error
Trend	.231	.217	.448
Seasonally Adjusted Series	.197	.184	.381

Table 5

Variance of Revision Error

	r_t^o	r_t^{12}	r_t^{24}	r_t^{36}	r_t^{48}	r_t^{60}
Revision in Trend	.231	.061	.024	.009	.004	.001
Revision in Seasonally Adjusted Series	.197	.077	.033	.012	.005	.002

Table 6

Variance of Revision Error:

Seasonally Adjusted Series

Revision in Forecasted Component	Variance
Concurrent	.197
1 month ahead	.215
2 " "	.246
3 " "	.265
4 " "	.274
5 " "	.278
6 " "	.279
7 " "	.279
8 " "	.282
9 " "	.289
10 " "	.305
11 " "	.331

Table 7

Confidence Intervals around
a seasonal factor of 100

Level of Confidence	Concurrent Estimator	Final Estimator
95%	99.54 , 100.46	99.68 , 100.32
67%	99.78 , 100.23	99.84 , 100.16

Table 8

Confidence Interval for
the monthly rate of growth
of the monthly series
(95% confidence level)

	Concurrent Estimator	Final Estimator
Seasonally Adjusted Series	±4.45	±3.09
Trend	±5.02	±3.31

Table 9

Confidence Interval for
the monthly rate of growth of
a three-month moving average
(95% confidence level)

	Concurrent Estimator	Final Estimator
Seasonally Adjusted Series	± 2.58	± 1.82
Trend	± 2.76	± 1.96

Figure 1

SPECTRA OF SERIES AND OF COMPONENTS

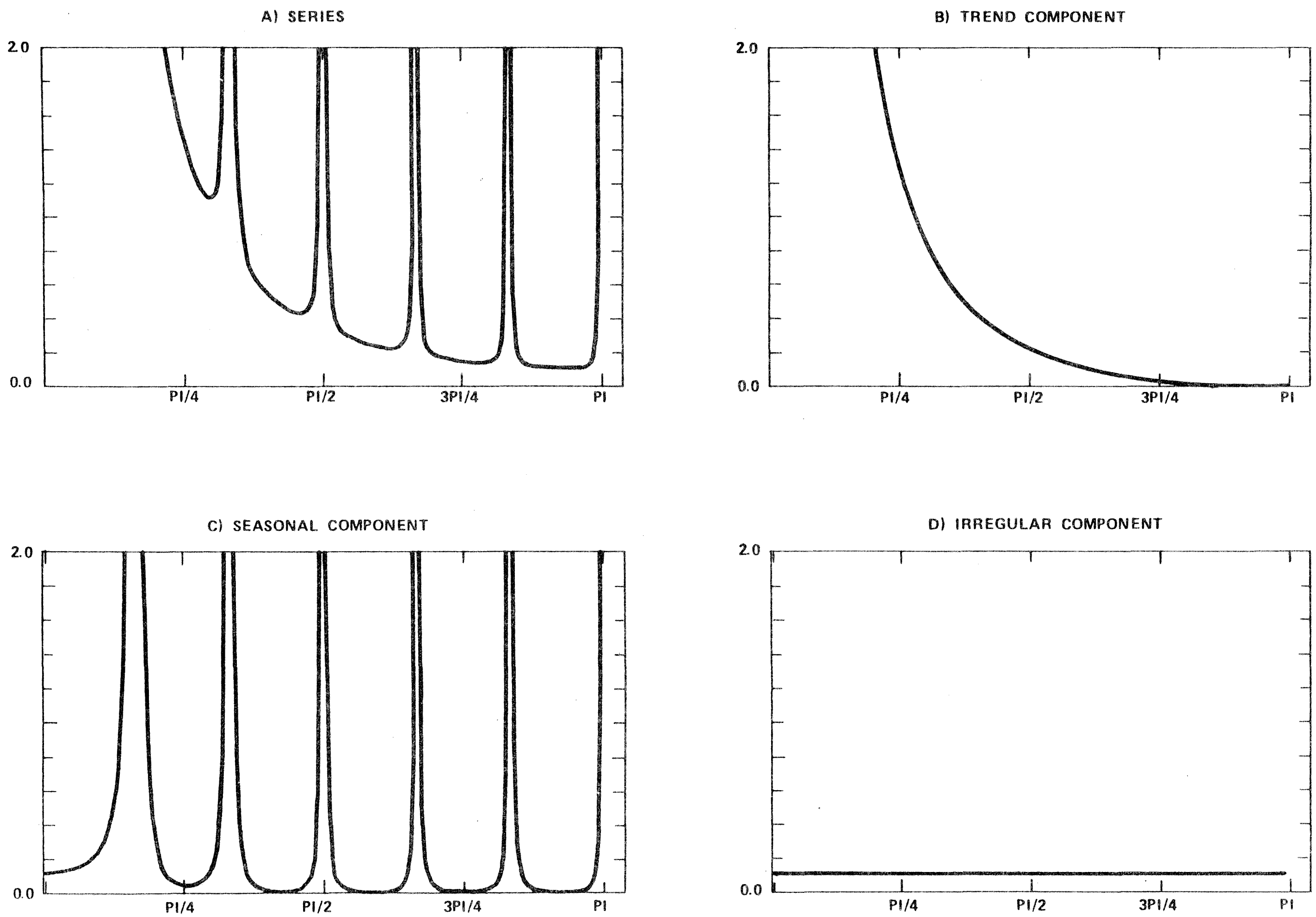


Figure 2

ACF OF THEORETICAL COMPONENT AND ESTIMATOR

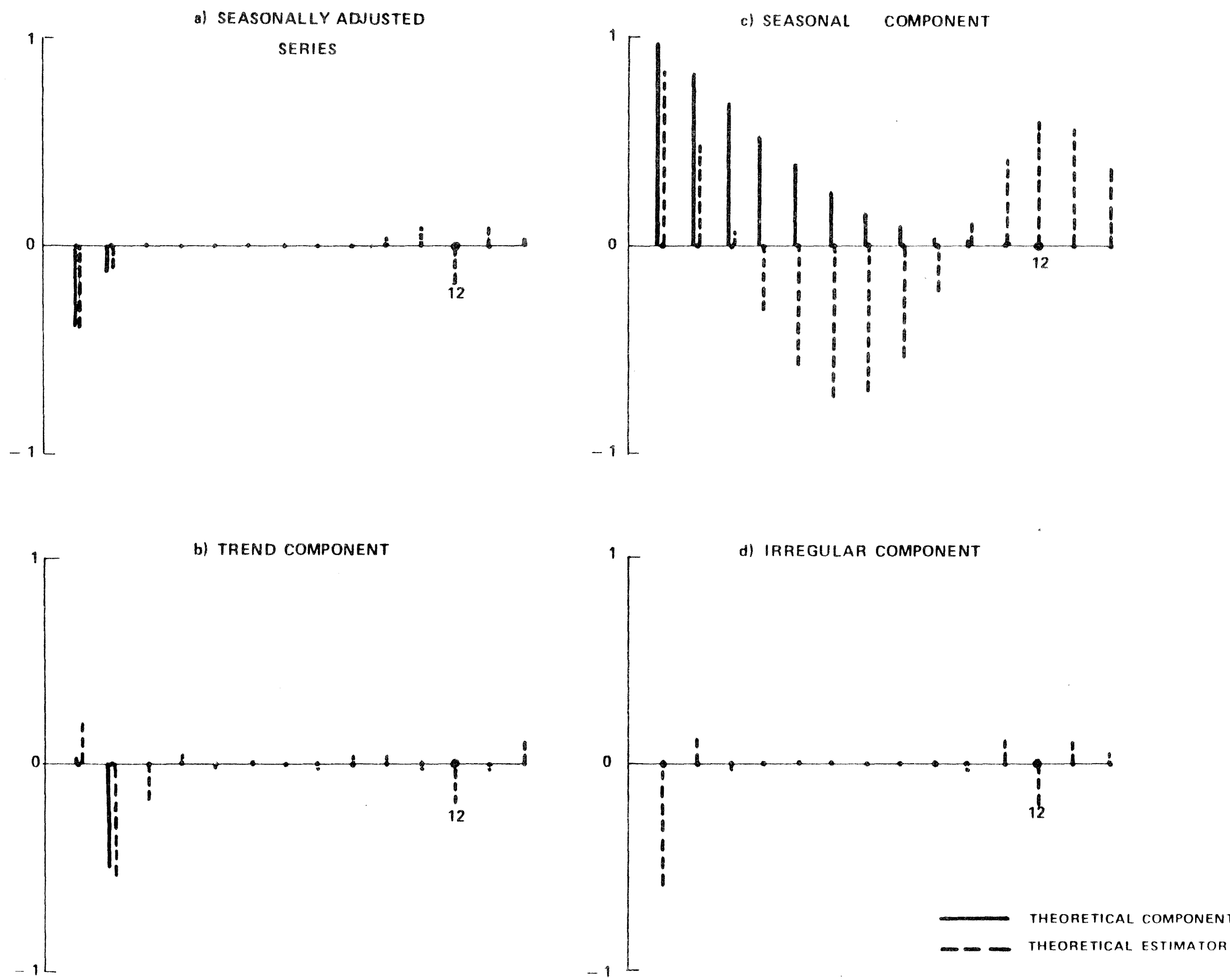


Figure 3

FILTERS FOR ESTIMATORS

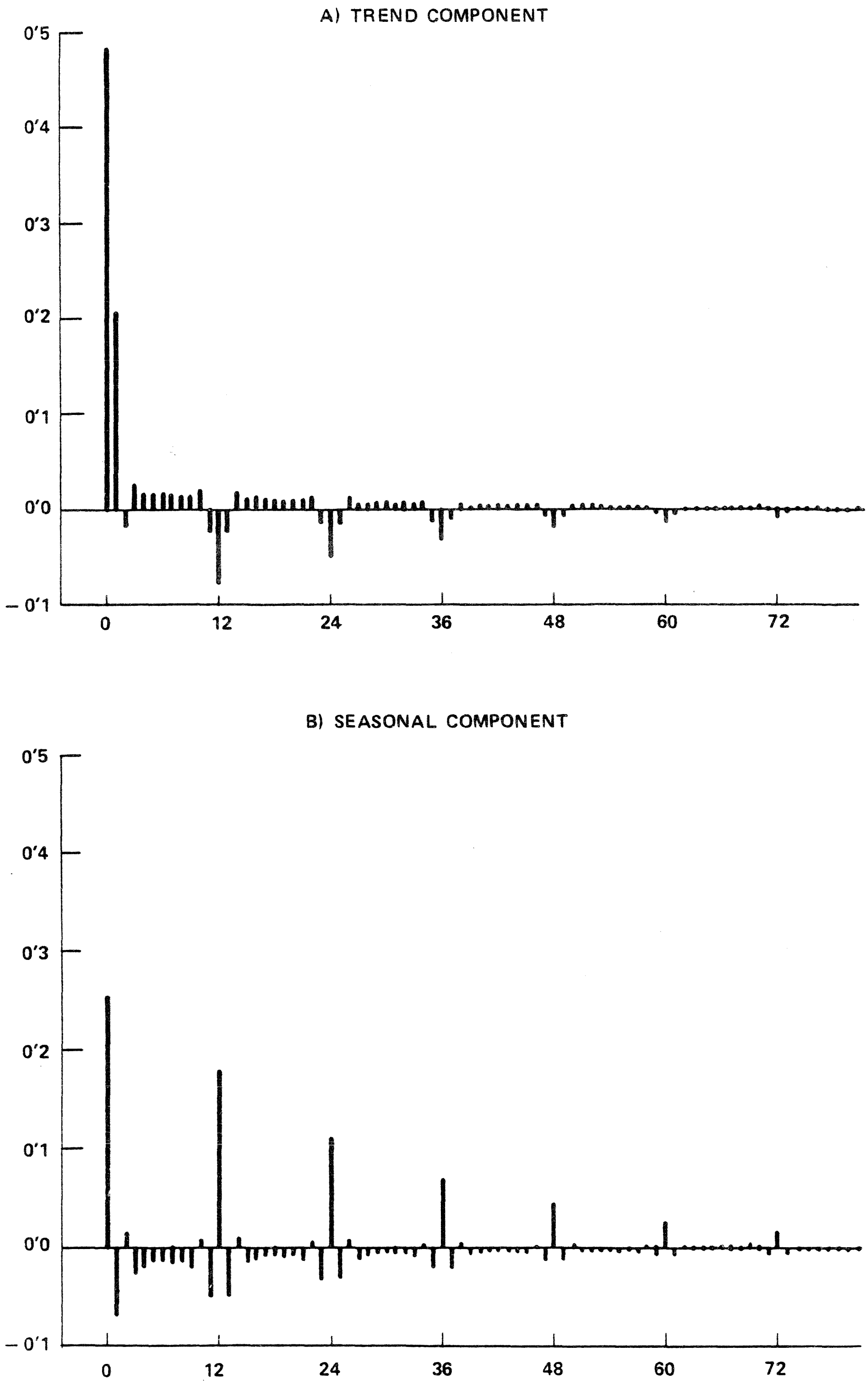


Figure 4

ESTIMATED COMPONENTS

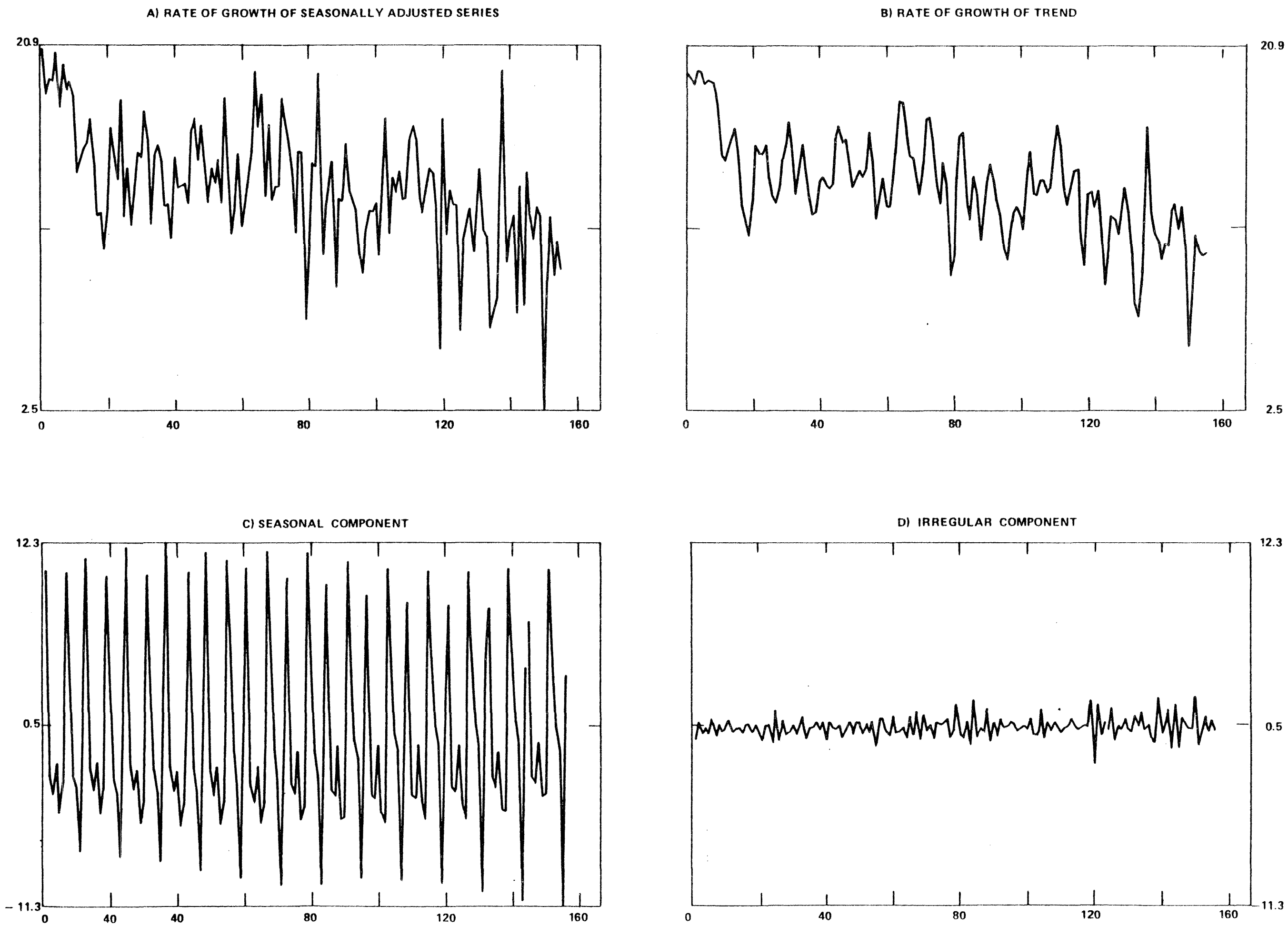


Figure 5

SPECTRA OF THEORETICAL COMPONENTS AND ESTIMATORS

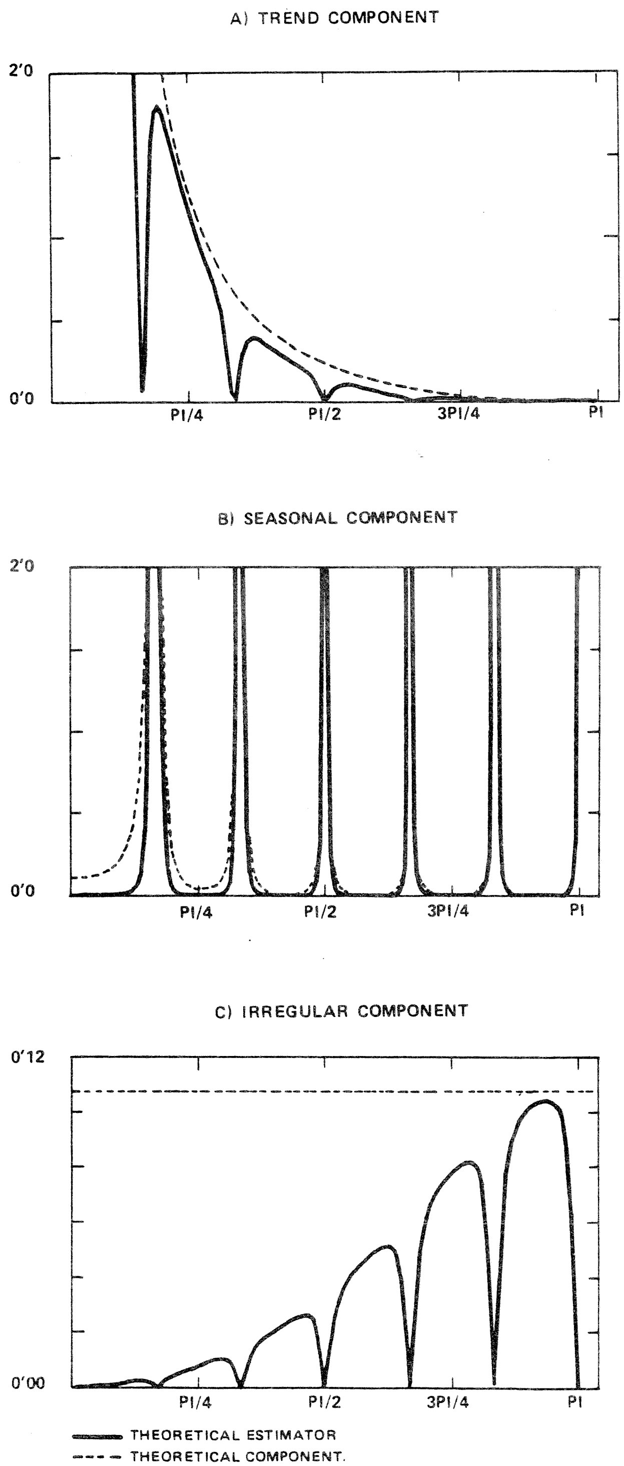


Figure 6

ACF OF THEORETICAL ESTIMATOR AND ESTIMATED COMPONENTS

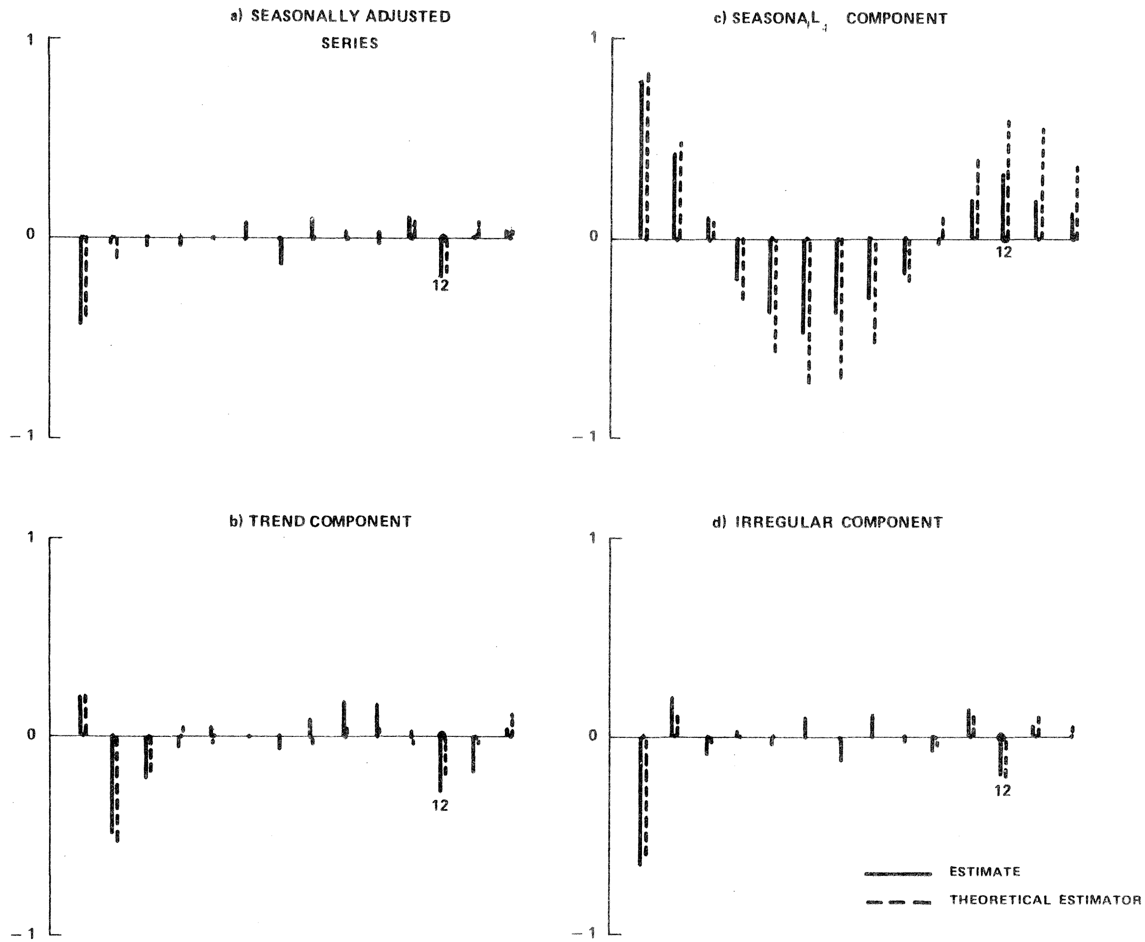
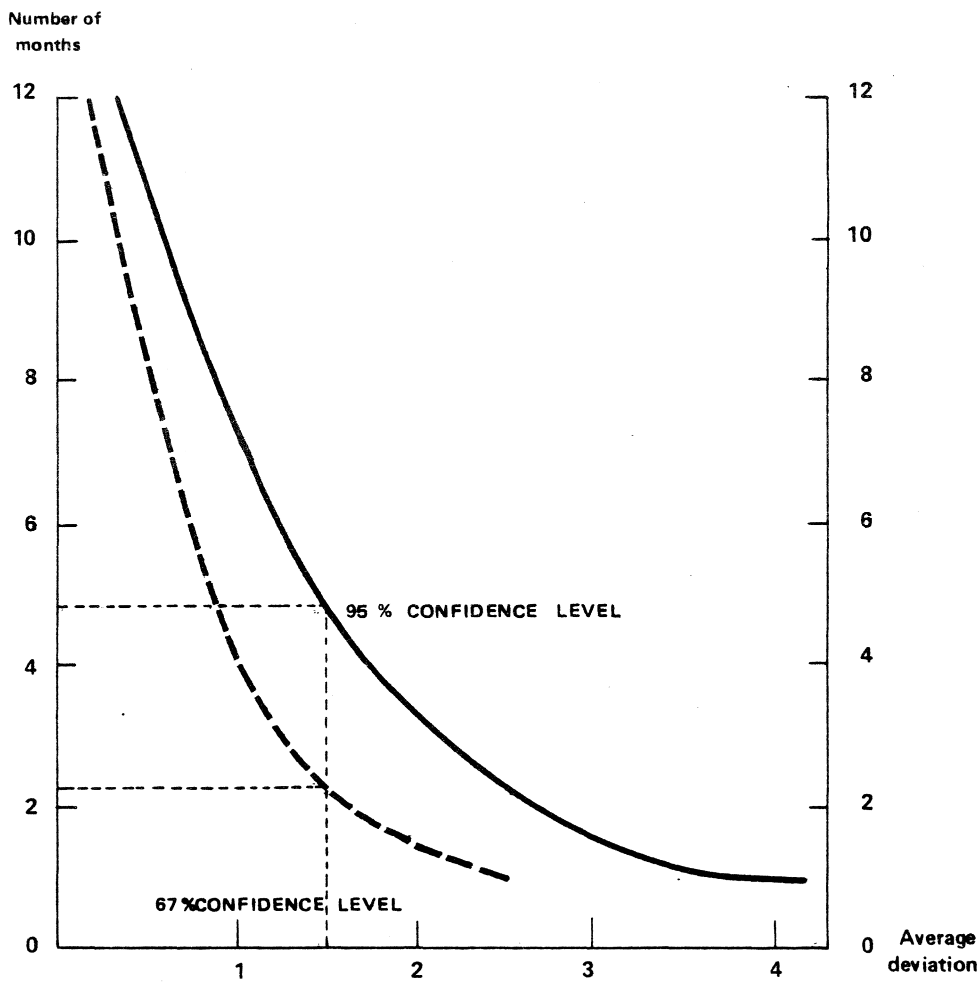


Figure 7

AVERAGE DEVIATION IN MONTHLY RATE OF GROWTH



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