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by

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Abstract

In the context of an application, the paper deals with unobserved components in ARIMA models with GARCH errors. The application is seasonal adjustment of the monthly Spanish money supply series, which shows clear evidence of (moderate) nonlinearity, that does not disappear with simple outlier correction. The GARCH structure explains reasonably well the nonlinearity, and this explanation is robust with respect to the GARCH specification. The time variation of the standard error of the adjusted series estimator is of applied interest. We first show how to measure this variation, and the implications it may have on short–term monetary control. The nonlinearity seems to have a small effect in practice. It is further seen that the conditional variance of the GARCH process may, in turn, be decomposed into components. In fact, the conditional variance of the money supply series is the sum of a weak linear trend, a strong nonlinear seasonal component, and a moderate nonlinear irregular component. This information has policy implications: for example there are periods in the year when policy can be more assertive because information is more precise. Finally, a comment is made on the interaction among nonlinearity in the components of the money supply that shows how linear combinations of nonlinear series can produce series that behave linearly.

Key Words: ARIMA Models, Autoregressive Conditional Heteroskedasticity, Nonlinearity, Unobserved Components, Seasonal Adjustment, Monetary Aggregates.

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1 Introduction

Short–term monetary policy centers around the intrayear evolution of the seasonally adjusted monetary aggregate series. For the case of Spain, the monetary aggregate is the series of Liquid Assets in the Hands of the Public (ALP, in short), and seasonal adjustment is performed with a model–based method, as described in Bank of Spain (1993). The method follows the so–called ARIMA model–based approach, originally developed by Cleveland and Tiao (1976); Box, Hillmer, and Tiao (1978); Burman (1980); and Hillmer and Tiao (1982). The particular application to the Spanish ALP series is discussed in Maravall (1988).

In brief, if $x_t = \log \text{ALP}_t$, seasonal adjustment is based on the decomposition

$$x_t = s_t + p_t + u_t = s_t + n_t, \tag{1.1}$$

where s_t, p_t, and u_t denote the seasonal, trend, and irregular components, which are assumed mutually orthogonal, and n_t denotes the seasonally adjusted series. The method consists of several steps. First, an ARIMA model is identified for the observed series x_t. Then, from this "aggregate" model, appropriate models for the components are derived. (These component models have also ARIMA–type expressions.) Finally, estimates (and forecasts) of the components are obtained with linear filters that are a straightforward generalization of the Wiener–Kolmogorov (WK) filter to finite realizations of typically nonstationary series (see Cleveland and Tiao, 1976; Bell, 1984; and Maravall, 1989). The filter provides the minimum Mean Square Error (MSE) estimator of the component and, under suitable starting conditions, is equal to the conditional expectation of the unobserved component given the available series. The WK filter represents, thus, an alternative algorithm to the Kalman filter for computation of the above conditional expectations; details of the algorithm can be found in Burman (1980).

The method relies on ARIMA models that have normally distributed innovations, with zero mean and constant variance; that is, the process for x_t is assumed linear. In this paper, we look at some of the issues that arise when those innovations display some evidence of nonlinearity. In choosing a real application, where nonlinearity is clearly present, but in moderate amount, we shall be also interested in to what extent this nonlinearity may have, in practice, relevant implications for short–term policy. To capture nonlinear effects, we shall use Generalized Autoregressive Conditional Heteroskedastic (GARCH) models, of the type introduced by Engle (1982); Weiss (1984); and Bollerslev (1986).

2 ARIMA Estimation

We consider the monthly ALP series from January 1974 to December 1990 (i.e., $T = 204$ observations); the log of the series is plotted in figure 1. The ARIMA model identified for log ALP is given by

$$\nabla \nabla_{12}\, x_t = (1 - \theta_1 B)\,(1 - \theta_{12} B^{12})\, a_t + \mu, \tag{2.1}$$

where B is the backward operator (such that $B^j\, x_t = x_{t-j}$), $\nabla = 1 - B$, and $\nabla_{12} = 1 - B^{12}$. Maximum Likelihood estimation produced $\hat{\theta}_1 = -.160\,(.073)$, $\hat{\theta}_{12} = -.701\,(.055)$, and $\hat{\mu} = -.000351\,(.000129)$, where the standard errors (SE) of the estimators are given in parenthesis. The variance of the residuals $\hat{a}_t$ (the innovations in the observed series) is $V_a = (.00376)^2$, and figure 2 displays the series $\hat{a}_t$. The residuals seem to fluctuate randomly around zero, and their Autocorrelation Function (ACF) confirms that randomness. Table 1 presents some statistics of interest: Q_{12} is the usual Box-Ljung statistics for the first 12 autocorrelations, Q_s is similarly defined for the first two seasonal autocorrelations, and ρ_1, ρ_6, and ρ_{12} are the lag–1, lag–6, and lag–12 autocorrelations. Under the assumption that the series is white noise, Q_{12} has an asymptotic χ^2 (9) distribution (Ljung and Box, 1978), Q_s can be roughly approximated by a χ^2 (2) distribution (Pierce, 1976), and the asymptotic standard error of ρ_6 and of ρ_{12} is approximately .07 (Box and Jenkins, 1970).

The first row of table 1 presents the four statistics for the series $\hat{a}_t$: all of them are clearly compatible with the white–noise hypothesis. As suggested by Granger and Andersen (1978), the autocorrelations of the squared residuals provide an interesting tool to check the linearity hypothesis (in this case, the normality of a_t). If a series z_t is linear, then the lag–k autocorrelation satisfies $\rho_k\,(z_t^2) = [\rho_k\,(z_t)]^2$ (Maravall, 1983). Moreover, $Q_{12}\,(\hat{a}_t^2)$ has the same asymptotic distribution as $Q_{12}\,(\hat{a}_t)$ (McLeod and Li, 1983), and hence increases in the autocorrelations of $\hat{a}_t^2$ or in the associated Q values would be an indication of nonlinearity. The second row of table 1 presents Q_{12}, Q_s, ρ_1, ρ_6, and ρ_{12} for the series $\hat{a}_t^2$. All the statistics, except ρ_1, show clear indications of nonlinearity and, in particular, of nonlinearity associated with seasonal lags.

The nonlinearity of $\hat{a}_t$ is further reinforced by the skewness and kurtosis estimators, equal to $s = -.67$ (SE $= .17$) and $k = 4.55$ (SE $= .34$), respectively. The n.i.d. assumption of the residuals a_t is, as a consequence, rejected.

Table 1

	Q_{12}	Q_s	ρ_1	ρ_6	ρ_{12}
$\hat{a}_t$	9.1	1.4	.02	.05	.02
$\hat{a}_t^2$	27.2	18.5	.06	.14	.30

3 Outliers

Since it is well known that nonlinear behavior can be explained by the presence of outliers, the next step is to check for the presence of outliers in the series $\hat{a}_t$. In fact, three relatively large outliers are detected for the periods 139, 151, and 192. The associated t–values are -3.7, -3.3, and -3.5, respectively, and hence a simple and parsimonious way to attempt to reduce the outliers effect is through a single parameter, ω_0, as in

$$x_t = \omega_0\, d_t + u_t,$$

where $d_t = 1$ for $t = 139, 151, 192$, and $d_t = 0$ otherwise, and u_t follows an ARIMA model similar to (2.1). The parameter estimators are slightly modified ($\hat{\theta}_1 = -.183$, $\hat{\theta}_{12} = .684$), and the new series of residuals $\hat{a}_t$ contains no value larger than $3\,\sigma_a$ in absolute value. Moreover, the skewness and kurtosis become $s = -.29\,(.17)$, and $k = 3.39\,(.35)$, and hence both values are now compatible with the linearity assumption. As shown in table 2, the autocorrelations of $\hat{a}_t$ are, as before, compatible with a white–noise behavior; however, looking at the squared residuals, the Q–statistics still show a significant increase, and the autocorrelations ρ_1, ρ_6, and ρ_{12} also display clear signs of nonlinearity, which this time also affects the low–order autocorrelation.

Table 2

	Q_{12}	Q_s	ρ_1	ρ_6	ρ_{12}
$\hat{a}_t$	7.8	1.8	.00	.01	.02
$\hat{a}_t^2$	28.1	11.2	.19	.14	.23

In view of the results in table 2, we conclude that the nonlinearity in the ALP series does not appear to be caused by the presence of the three outliers detected. We shall attempt, as an alternative, to model the series nonlinearity with the ARIMA–GARCH approach mentioned earlier. But before doing this, there is a point concerning outlier removal that seems to us worth stating.

The way in which we have removed outlier effects is simple and parsimonious, yet it is clearly possible to carry a more sophisticated outlier treatment. Using the approach in Chen and Liu (1993), and setting a critical value of 3, seven highly significant outliers are detected: two are additive outliers, two are innovation outliers, and three represent level shifts. Reestimating by exact maximum likelihood model (2.1) jointly with the seven outliers, the residuals obtained display the characteristics shown in table 3,

Table 3

	Q_{12}	Q_s	ρ_1	ρ_6	ρ_{12}
$\hat{a}_t$	8.2	.9	-.01	-.01	.01
$\hat{a}_t^2$	9.4	.3	.05	.04	.05

and the skewness and kurtosis statistics became $s = -.17\,(.18)$, and $k = 2.77\,(.36)$. The series of residuals does not display in this case any evidence of nonlinearity. Furthermore, we generated many GARCH series and applied the Chen and Liu procedure to all of them. We found that it was always the case that the procedure yielded apparently linear residuals after correcting for a moderate number of outliers (of different types). Thus we convinced ourselves that the linear–outlier method and the nonlinear–GARCH approach offered two alternative ways of linearizing a series and that, in practice, it would be extremely difficult to detect situations in which one of the two methods is undoubtedly appropriate. The selection of one of the two approaches is likely to require, at present, some prior preference, and cannot be simply resolved by sample evidence. This methodological underidentification seems to us an important subject for further research. For the remaining of the paper, we shall stick to the GARCH approach, and shall use the original series unmodified for outliers, with the expectation that the GARCH structure will make it unnecessary.

4 ARIMA–GARCH Modelling of the (Unmodified) Series

To test for the presence of AutoRegressive Conditionally Heteroskedastik (ARCH) effects, we use a slight modification of the Lagrange Multiplier test suggested by Engle (1982). With the residuals $\hat{a}_t$ from model (2.1) on the series x_t (with no outlier treatment), we run the regression

$$\hat{a}_t^2 = c_0 + c_1\, \hat{a}_{t-6}^2 + c_2\, \hat{a}_{t-12}^2,$$

and obtained $TR^2 = 13.8$. Since this value is considerably larger than $\chi^2_{.05}\,(2) = 5.99$, we reject the hypothesis that there is no ARCH structure.

In order to accomodate the nonlinear structure, we modify model (2.1) in the following way. The residuals a_t, instead of being white noise, are assumed to have a time–dependent variance. If I_{t-1} denotes the information available at period $t-1$ (i.e., the series x up to and including x_{t-1}), then the distribution of a_t conditional on this information set is

$$a_t/I_{t-1} \sim N(0, h_t), \tag{4.1}$$

where the conditional variance h_t follows the GARCH (p, q) process

$$(1 - \beta_1 B - \ldots - \beta_p B^p)\, h_t = \alpha_0 + (\alpha_1 B + \ldots + \alpha_q B^q)\, a_t^2, \tag{4.2}$$

or, in short, $\beta(B)\, h_t = \alpha_0 + \alpha(B)\, a_t^2$. To identify the order p and q of (4.2) we use the following result (Baillie and Bollerslev, 1990):

Result 1: A GARCH (p, q) process for h_t implies that a_t^2 displays the ACF of an ARMA (m, p) process, with $m = \max(p, q)$. ∎

From figure 3, the most noticeable feature of the ACF of $\hat{a}_t^2$ is the positive autocorrelation present at the seasonal lags 6 and 12. (Notice that ρ_{18} and ρ_{24} are also positive.) It will prove convenient to modify Result 1 in the following way. Let τ denote a positive integer, and write GARCH$_\tau$ (r, s) and ARMA$_\tau$ (r, s) to represent processes with polynomials of order r and s in B^τ. Then Corollary 1 is a straightforward extension of Result 1.

Corollary 1: A GARCH$_\tau$ (p, q) process for h_t implies that a_t^2 displays the ACF of an ARMA$_\tau$ (m, p), with $m = \max(p, q)$. ∎

The ACF of $\hat{a}_t^2$ leads us to consider models in B^6, for which, in accordance with the two previous results, the order of the AR polynomial is equal or larger than that of the MA polynomial (in the terminology of Burman, balanced or top–heavy models). In fact, the AR_6 (2) model

$$(1 - \varphi_6 B^6 - \varphi_{12} B^{12})\, \hat{a}_t^2 = \varepsilon_t \tag{4.3}$$

cleans very well the ACF of $\hat{a}_t^2$. Using Corollary 1, this implies a GARCH_6 (0, 2) model for h_t.

Since the ACF of $\hat{a}_t^2$ can be compatible with models moderately different from (4.3), we are interested in the robustness of the results with respect to the GARCH specification for h_t. Thus we consider two additional specifications: the GARCH_6 (1, 1) model, which implies an ARMA_6 (1, 1) model for $\hat{a}_t^2$, and the GARCH_6 (2, 1) model, which implies an ARMA_6 (2, 2) model for $\hat{a}_t^2$. The first ARMA model cleaned reasonably well the ACF of $\hat{a}_t^2$; the second ARMA model seems overparametrized, but it is also certainly compatible with the ACF of $\hat{a}_t^2$.

We consider, thus, 3 models. All of them share equation (2.1) and assumption (4.1). For Model 1:

$$h_t = \alpha_0 + \alpha_6\, a_{t-6}^2 + \alpha_{12}\, a_{t-12}^2; \tag{4.4}$$

for Model 2:

$$h_t = \alpha_0 + \alpha_6\, a_{t-6}^2 + \beta_6\, h_{t-6}; \tag{4.5}$$

finally, for Model 3:

$$h_t = \alpha_0 + \alpha_6\, a_{t-6}^2 + \beta_{12}\, h_{t-12}; \tag{4.6}$$

(Several additional specifications were used, but the 3 models chosen provided the most satisfactory results. The three contain the same number of parameters and their specifications are different in a nontrivial way.) The three complete ARIMA–GARCH models were estimated by maximum likelihood, and a summary of the results is contained in table 4, where the numbers in parenthesis are t–values and α_0 has been multiplied by 10^5.

Since the standardized residual $\hat{e}_t = \hat{a}_t / \sqrt{\hat{h}_t}$ is n.i.d. (0, 1), an important diagnostic tool is the ACF of the estimated standardized residuals, and of their squared value. Table 5 summarizes this information. For the three models, the ACF of the standardized residuals are clean and, when squared, no evidence of nonlinearity is found. This is confirmed by the skewness and kurtosis values of table 6. Since the asymptotic standard error of the skewness estimator is .18, and that of the kurtosis estimator is .34, all values in table 6 are compatible with the normality assumption. Finally, the only outlier found in the standardized residual series (with absolute value larger than 3) is found for observation 179

Table 4

	θ_1	θ_{12}	α_0	α_6	α_{12}	β_6	β_{12}	$\log L$
Model 1	-.213	.711	.84	.367	.096	—	—	536.1
	(-3.0)	(12.8)	(4.6)	(1.9)	(1.4)	—	—	
Model 2	-.218	.691	.30	.320	—	.511	—	537.2
	(-3.4)	(10.4)	(1.0)	(2.2)	—	(1.9)	—	
Model 3	-.247	.716	.52	.423	—	—	.283	536.0
	(-3.6)	(14.6)	(2.2)	(2.5)	—	—	(1.4)	

Table 5

		Q_{12}	Q_s	ρ_1	ρ_6	ρ_{12}
Model 1	$\hat{e}_t$	6.9	1.6	-.02	.06	-.03
	$\hat{e}_t^2$	9.3	2.0	-.06	.00	.11
Model 2	$\hat{e}_t$	6.9	1.3	-.01	.04	-.02
	$\hat{e}_t^2$	8.7	1.0	-.03	-.04	.11
Model 3	$\hat{e}_t$	9.0	3.0	-.01	.09	-.05
	$\hat{e}_t^2$	12.5	4.1	-.01	.10	.06

Table 6

	skewness	kurtosis
Model 1	-.30	3.25
Model 2	-.28	3.21
Model 3	-.26	3.03

for the cases of Model 1 and Model 2; the associated t–values are -3.2 and -3.3, respectively. For Model 3 no outlier is detected. Since the probability of occurrence of at least one value larger than 3 in a sample of 200 observations from an $N(0,1)$ distribution is relatively large, we conclude that the GARCH structure has dealt reasonably well with the outlier problem and the estimation results for the 3 models seem acceptable. Figure 4 displays the conditional variance series (h_t) estimated by the 3 models. Although they are not identical, the three series basically tell the same story. The nonlinear evolution of the conditional variance appears to be captured in a fairly robust way.

5 Decomposition of the Series and Seasonal Adjustment

Model–based nonlinear estimation of unobserved components in ARIMA–GARCH models would require, first, to properly define the components. This raises a relatively complicated problem due to the poor aggregation properties of ARCH models (in particular, the sum of ARCH components is not an ARCH process). Thus we base the decomposition of the series in the ARIMA model–based approach applied to model (2.1). The approach uses a linear WK–type of filter, which still provides, for the ARIMA–GARCH case, the linear function of the observed series x_t with minimum MSE; see Bell (1984). (For a related application, see Harvey, Ruiz, and Sentana, 1992.)

In brief, the WK filter is found as follows. The pseudo–spectrum (hereafter, simply denoted spectrum) of model (2.1) is split into two spectra, as shown in figure 5. One of these spectra corresponds to the seasonal component; the other one to the seasonally adjusted series. These two spectra correspond to the models

$$S(B)\, s_t = \theta_s(B)\, a_{st}, \tag{5.1}$$

$$\nabla^2\, n_t = \theta_n(B)\, a_{nt}, \tag{5.2.a}$$

where s_t and n_t are as in (1.1), $S(B) = 1 + B + \ldots + B^{11}$, and $\theta_s(B)$ and $\theta_n(B)$ are polynomials in B of order 11 and 2, respectively; in particular

$$\theta_n(B) = 1 - .764B - .202B^2. \tag{5.2.b}$$

The pseudo–innovations a_{st} and a_{nt} are orthogonal white noises, with zero mean and variances V_s and V_n.

The WK filter that yields the seasonally adjusted series is given by

$$\nu_n(B,F) = k_n \, \frac{\theta_n(B)\,\theta_n(F)\,S(B)\,S(F)}{\theta(B)\,\theta(F)} \tag{5.3}$$

where $\theta(B)$ is the right–hand–side polynomial in B in (2.1), $k_n = V_n/V_a$, and $F = B^{-1}$ is the forward operator (see Maravall, 1988). The filter is, thus, equal to the Autocovariance Generating Function of the stationary ARMA model

$$\theta(B)\,z_t = \theta_n(B)\,S(B)\,b_t,$$

and hence it is symmetric and convergent; its time and frequency domain representations are given in figures 6 and 7. The filter filters out frequencies near the seasonal ones, and the narrow width of the holes reflects the relatively stable character of the seasonality being removed.

Since, for model (2.1), $\theta(B) \neq 1$, the filter will extend towards infinity. For a finite time series, the optimal estimator of n_t can be expressed as

$$\hat{n}_t = \nu_n(B,F)\,x_t^e, \tag{5.4}$$

where x_t^e is the available series extended at both ends with forecasts and backcasts computed with model (2.1); see Cleveland and Tiao (1976). An efficient way of applying the exact filter to a finite series is described in Burman (1980); in what follows, the derivations of the models (5.1) and (5.2), as well as estimation of unobserved components (and, in particular, of the seasonally adjusted series) has been performed with program SEATS ("Signal Extraction in ARIMA Time Series"), which emerged from a program originally developed by Burman, and is documented in Maravall and Gómez (1992).

Given that estimation of the seasonally adjusted series of x_t involves the application of a linear filter to a nonlinear series, the estimator will yield a nonlinear time series. It is of interest to see how the linear seasonal adjustment filter affects the nonlinearity of the series.

Fitting an ARIMA model to the seasonally adjusted series $\hat{n}_t$, the following model is obtained

$$\nabla^2\,\hat{n}_t = (1 - .774B - .167B^2)\,\hat{a}_{st}, \tag{5.5}$$

which is very close indeed to the theoretical model for n_t, given by (5.2). (Notice that the two roots — for B^{-1} — of the MA polynomial in (5.5) are .95 and $-.17$. Since the first one is close to 1 and the second one is small, the model for the seasonally adjusted series is relatively close to the well–known "random walk plus drift" specification.)

The ACF of $\hat{a}_{st}$ can be easily accepted as that of white noise. As in the case of the series residuals $\hat{a}_t$, the ACF of $(\hat{a}_{st})^2$ displays some evidence of nonlinearity. The results are summarized in table 7. The nonlinearity is associated with seasonal lags; comparing table 7 with table 1, the lag–6 autocorrelation has disappeared and the lag–12 autocorrelation is now included. Altogether, the linear seasonal adjustment filter, by filtering out seasonal frequencies, has reduced the amount of nonlinearity in the series (compare the two values of Q_{12}). But some nonlinearity still remains in the adjusted series. This nonlinearity has an important implication: although the point estimator of the component obtained with the WK filter is still the best linear estimator, the estimator standard error will vary in time. We try next to measure that variation and, for the particular case of the ALP series, the practical importance that this variation may have for ALP watchers.

Table 7

	Q_{12}	Q_s	ρ_6	ρ_{12}	ρ_{24}
$\hat{a}_{st}$	12.0	1.3	.04	-.08	-.15
$\hat{a}_{st}^2$	16.2	5.7	.01	.16	.16

6 The Standard Error of the Seasonally Adjusted Series

6.1 Levels

Let d_t denote the error in the estimator of the seasonally adjusted series, so that $d_t = n_t - \hat{n}_t$, where $\hat{n}_t$ is given by (5.4). The estimator $\hat{n}_t$, and hence the error d_t, depend on the series x_t^e or, equivalently, on the finite realization available. Let this finite realization be $[x_1, \ldots, x_T]$, and denote the estimator obtained with (5.4) by $\hat{n}_{t/T}$. Further, let $\hat{n}_{t/\infty}$ denote the estimator obtained with (5.4) when $x_t^e = x_t$, that is, when an infinite realization is available; it will be called the "final estimator". In order to derive the time varying standard error of $\hat{n}_{t/T}$, write

$$d_{t/T} = f_t + r_{t/T}, \tag{6.1}$$

where $f_t = n_t - \hat{n}_{t/\infty}$ is the error in the final estimator, and $r_{t/T} = \hat{n}_{t/\infty} - \hat{n}_{t/T}$ is the revision the "preliminary estimator" $\hat{n}_{t/T}$ will undergo as T goes to ∞.

Since the final estimator is obtained when $T \to \infty$, it is easily seen that the ARCH assumption does not alter the result that the two errors f_t and $r_{t/T}$ are uncorrelated. Moreover, f_t will still display constant variance and, following Pierce (1979), it is easily found that its ACGF will be that of the ARMA model

$$\theta(B)\, f_t = \theta_n(B)\, \theta_s(B)\, g_t, \tag{6.2}$$

where g_t is white noise with variance $V_n\, V_s / V_a$.

As for $r_{t/T}$, following Maravall (1993), we first express the final estimator $\hat{n}_t$ as a function not of x_t but of its innovations a_t. This yields

$$\hat{n}_t = \eta(B, F)\, a_t,$$

where $\eta(B, F)$ is the convolution of the WK filter (5.3) with the filter $\psi(B) = \theta(B)/\nabla\, \nabla_{12}$ (i.e., the MA representation of model (2.1)), and hence

$$\eta(B, F) = k_n\, \frac{\theta_n(B)}{\nabla^2}\, \frac{\theta_n(F)\, S(F)}{\theta(F)}.$$

The filter is not convergent in B, but invertibility of (2.1) guarantees its convergence in F. Assuming suitable initial conditions (Bell, 1984), the estimator $\hat{n}_t$ can be expressed as

$$\hat{n}_t = \eta_B(B)\, a_t + \eta_F(F)\, a_{T+1}, \tag{6.3}$$

where

$$\begin{aligned} \eta_B(B) &= \eta_{T-t} + \eta_{T-t-1}\, B + \ldots + \eta_{-t}\, B^T, \\ \eta_F(F) &= \eta_{T-t+1} + \eta_{T-t+2}\, F + \ldots . \end{aligned}$$

The term $\eta_B(B)\, a_T$ represents the effect of the starting conditions and of the innovations up to and including a_T on the estimator of n_t; the filter $\eta_F(F)$ reflects the way "future" innovations will be incorporated. Since $E_T\, a_{T+k} = 0$ for $k > 0$, from (6.3),

$$\hat{n}_{t/T} = \eta_B(B)\, a_T, \tag{6.4}$$

so that, substracting (6.4) from (6.3), the revision error is found to be

$$r_{t/T} = \eta_F(F)\, a_{T+1}, \tag{6.5}$$

a convergent moving average. Properly truncated, (6.5) can be used to derive the ACGF of $r_{t/T}$. Invertibility of (2.1) implies that the variance will be finite and that the ACF will converge. From (6.5), the variance of $r_{t/T}$ for the ARIMA–GARCH case is found equal to

$$V(r_{t/T}) = \sum_{j=1}^{k} r_{T-t+j}^2 \, h_{T+j/T}, \tag{6.6}$$

where k denotes the truncation point. Computation of the variance (6.6) at period T requires the estimators $h_{T+j/T}$, that is, the forecasts of the conditional variance for future periods. These forecasts can be obtained as in Baillie and Bollerslev (1992), a relatively complicated procedure, or, in a simpler way, in the following manner.

Consider the GARCH (p, q) process (4.2) and define the variable $\nu_t = a_t^2 - h_t$, a zero–mean uncorrelated variable (see Bollerslev, 1986). Then, adding and substracting $\alpha_i \, h_{t-i}$ $(i = 1, \ldots, q)$, h_t can be expressed as

$$h_t = \alpha_0 + \sum_{i=1}^{m} (\beta_i + \alpha_i) \, h_{t-i} + \sum_{i=1}^{q} \alpha_i \, \nu_{t-i}, \tag{6.7}$$

which proves the following result.

Result 2: A GARCH (p, q) process for h_t implies that h_t displays the ACF of an ARMA $(m, q-1)$ process, with $m = \max(p, q)$, with the ith AR coefficient given by $(\beta_i + \alpha_i)$, and the ith MA coefficient given by α_i / α_1. ∎

By noticing that in (6.7) the most recent value of the "innovation" is ν_{t-1}, which will enter the forecast function at t, the following result also holds.

Result 3: The forecast function of the GARCH (p, q) conditional variance is the same as that obtained with an ARMA (m, q) model, with the ith AR coefficient given by $(\beta_i + \alpha_i)$, and the ith MA coefficient equal to α_i, using the series ν_t as innovations. ∎

Since an estimator of ν_t is available (namely $\hat{\nu}_t = \hat{a}_t^2 - \hat{h}_t$), Result 3 provides a very easy way of computing forecasts for h_t by standard Box–Jenkins forecasting formulas. Using these forecasts in (6.6), an estimator of $V(r_{t/T})$ can be obtained. Then, the variance of the seasonally adjusted series estimation error can be obtained through

$$V(d_{t/T}) = V(f_t) + V(r_{t/T}).$$

Of particular importance among the preliminary estimators is the "concurrent" estimator $\hat{n}_{t/t}$, i.e., the estimator for the most recent period. Figure 8 displays the time–varying variance of the concurrent estimator of the seasonally adjusted series for Models 1, 2 and 3. For the three models, setting $k = 150$ was enough for expression (6.6) to converge. As was the case with figure 4, the three models provide similar descriptions of the variation in time of $V(d_{T/t})$, although the amplitudes of the movements are different, with Model 3 exhibiting the largest oscillations, and Model 1 the smallest ones. Altogether, estimation of the nonlinear evolution of the conditional variance of the seasonally adjusted series concurrent estimator appears to be robust with respect to the GARCH specification.

6.2 Rates of Growth

For policy makers and analysts, the rate of growth of the seasonally adjusted ALP series is more informative than the bare level of the series. Since, as figure 1 evidences, the monthly increases in the ALP series are relatively small, the monthly rate of growth (N_t) can be approximated by the difference in the logs, so that, for the concurrent estimator of the rate of growth of the seasonally adjusted series,

$$\hat{N}_{t/t} = \hat{n}_{t/t} - \hat{n}_{t-1/t}.$$

Given that $N_t = n_t - n_{t-1}$, the error (D_t) in the rate of growth estimator $\hat{N}_{t/t}$ is equal to $D_t = d_{t/t} - d_{t-1/t}$, or $D_t = F_t + R_t$, where $F_t = f_t - f_{t-1}$, and $R_t = r_{t/t} - r_{r-1/t}$. Thus the variance of D_t can be obtained through

$$V(D_t) = V(F_t) + V(R_t), \tag{6.8}$$

where $V(F_t) = 2(1 - \rho_1)\, V(f_t)$, with ρ_1 and $V(f_t)$ being the variance and lag–1 autocorrelation of model (6.2), and

$$V(R_t) = V(r_{t/t} - r_{t-1/t}) = V(r_{t/t}) + V(r_{t-1/t}) - 2\mathrm{Cov}\,(r_{t/t},\ r_{t-1/t}),$$

where, proceeding as in (6.6), the three terms in the r.h.s. are straightforward to obtain from (6.5).

In order to get an insight into the practical importance of using the time varying variances $V(R_t)$ instead of the constant variance implied by the linear model, we use a simple example that mimics the most basic element of short–run monetary policy operating procedures:

Assume that, for the last two years of the period there was a constant annual growth target of 10% for the monetary aggregate. In order to judge whether growth is on target, we proceed as follows: Every month during the two–year period, we look at the monthly rate of growth of the (concurrent estimator of the) seasonally adjusted series, annualized and expressed in percent points. Since that concurrent estimator is subject to error, we adopt the following criterion: Let σ denote the standard deviation of the error; if the measured rate falls in the interval $(10 \pm 2\sigma)$, growth is acceptable (and interest rates should be left unchanged). If the measurement is larger (lower) than the upper (lower) limit of the range, then growth is excessive (insufficient), and interest rates should go up (down). We are interested in answering the following question: If the monetary authority ignores the nonlinear structure of the series, and proceeds with the constant variance from the linear model, how many times would he have been fooled? In other words, how many times would have linear analysis indicated that growth was not acceptable when in fact it was, and viceversa?

Proceeding in the way described earlier, the σ of the interval is trivially obtained from $V(D_t)$, in (6.8). Figure 9 plots the actual series of concurrent estimators of the rate of growth of the seasonally adjusted series over the 24–month period, together with the interval $(10 \pm 2\sigma)$, with σ computed with and without the nonlinear structure. The nonlinearity is seen to have a relatively small effect and, out of 24 months, only for 3 of them the two intervals provided different answers to the question of whether growth was acceptable; all three cases, however, are borderline ones.

7 Decomposition of the Conditional Variance

We saw in section 5 that the ARIMA model that captures the autocovariance structure of the series x_t can be used to derive WK filters for estimation of its unobserved components. Result 2 states that the autocovariance structure of the conditional variance h_t is that of an ARMA model. It is then possible to derive WK filters to estimate unobserved components also in h_t. The purpose of the decomposition would be to find out to what extent the time variation of the variance reflects a long–term evolution (i.e., a trend), as opposed to reflecting seasonal variation or a purely random (irregular) volatility.

From Result 2, the ARMA model associated with the ACF of h_t can be directly obtained from the GARCH specification for h_t. For the three specifications considered, model (4.4) yields the ARMA$_6$ (2.1) expression

$$(1 - .367B^6 - .096B^{12})\, h_t = (1 + .262B^6)\, v_t, \qquad (7.1)$$

model (4.5) yields the AR_6 (1) expression

$$(1 - .831B^6)\, h_t = v_t, \tag{7.2}$$

and model (4.5) yields the AR_6 (2) specification

$$(1 - .423B^6 - .283B^{12})\, h_t = v_t, \tag{7.3}$$

where, in each case, v_t is a zero–mean uncorrelated variable, equal to $\alpha_6\, \nu_t$, with ν_t that of expression (6.7). In fact applying the filter (7.1), (7.2), or (7.3) to h_t cleans reasonable well the ACF, as evidenced by the Q_{24} statistics, equal to 32.0, 23.2, and 40.5, respectively. Moreover, direct fits of an ARMA_6 (2, 1), an AR_6 (1), and an AR_6 (2) model to $\hat{h}_t$ yields results broadly in agreement with the specifications (7.1)–(7.3); the most noticeable difference happens for the AR_6 (2) model, where estimation yields a smaller ϕ_6 and a larger ϕ_{12} value. The spectra of the three models are shown in figure 10; they display similar shapes, which consist of three important peaks for the 2, 4, and 6–times–a–year seasonal frequencies, and a relatively narrow peak for the trend frequency.

The variable h_t given by (7.1), (7.2), or (7.3), accepts a decomposition into mutually uncorrelated trend (p_t), seasonal (s_t), and irregular (u_t) components, as in

$$h_t = p_t + s_t + u_t.$$

For the three cases, the trend follows an ARMA (1, 1) process of the type

$$(1 - \phi B)\, p_t = (1 + B)\, a_{pt},$$

the seasonal component follows a process of the type:

$$\left[\sum_{j=0}^{\tau} (\phi B)^{\tau}\right] \; s_t = \theta_s(B)\, a_{st},$$

where $\theta_s(B)$ is of order τ ($\tau = 12$ for models 1 and 3, $\tau = 6$ for model 2), and the irregular component is white noise. Table 8 presents the most relevant parameter values. It is seen that ϕ is always close to 1, and that the stochastic variation of the series h_t is mostly driven by the seasonal innovation, with the trend being of little importance.

Estimating the components by means of the WK filters, the results for Models 1, 2, and 3 are displayed in figures 11, 12, and 13. The trend component of the conditional variance is seen to behave rather linearly, accounting for little variation. In fact, most of the variation in the conditional variance is

Table 8

	ϕ	Var (a_{pt})	Var (a_{st})	Var (u_t)
Model 1	.904	.013	.298	.098
Model 2	.970	.008	.358	.105
Model 3	.960	.005	.474	.192

seasonal, with the irregular variation playing a nonnegligible role. These last two components, seasonal and irregular, display a discernible nonlinear behavior, which can also be detected in the pseudo–innovations in the components (see Harvey and Koopman, 1992). Table 9 displays the skewness and kurtosis of the pseudo–innovations of the components (averaged over the 3 models). It can be safely concluded that the evolution in time of the conditional variance is the sum of a weak linear trend effect, plus a strong nonlinear seasonal effect, and a moderate, highly nonlinear, irregular effect.

Table 9

p–innov. in	skewness	kurtosis
Trend	.71	3.33
Seasonal	.90	10.78
Irregular	2.16	14.94

The above conclusion may be of applied interest. We have seen that V_a, the variance of the one–period–ahead forecast error of the monetary aggregate series is not a constant fraction of the level of the series (i.e., a constant for the logs), but that the fraction varies in time. This variation happens in two ways: one, a purely random way, and the other, following a seasonal pattern. The random component would be hard to predict and would have limited policy relevance (besides a general attitude of caution). But the seasonal component can be forecast, and these forecasts may be useful: they tell us that there are periods in the year when the monetary authority can be more assertive because information is then more precise. As an example, figure 14 presents the one–year–ahead forecast function of the seasonal component of the one–period–ahead forecast error variance. From the figure, it would seem reasonable to pay more attention to the forecast error made in March or in September, than to the forecast errors for June or December; the variances of the former are much smaller.

8 A Final Comment

Seasonal adjustment of the monetary aggregate involves adjustment of the ALP series as well as adjustment of its components. The nonlinearity detected in the aggregate may well reflect different types of nonlinearities present in the components. The way these nonlinearities interact may present interesting features. Consider, for example, the two component decomposition:

$$\text{ALP} = \text{M1} + \text{Rest}, \tag{8.1}$$

where M1 is the sum of currency plus demand deposits, and the series "Rest" includes saving and time deposits plus other liquid assets. Figure 15 plots the three series. For the period we consider, M1 represents between 23 and 35% of ALP, and it is clear that the two series are not cointegrated. The three series in (8.1) are, in fact, nonstationary. As was the case for the ALP series, a model of the type (2.1) cleans well the ACF of the series log M1 and, as seen in table 10, is borderline acceptable for the "Rest" series, the only noticeable anomaly being a value $\rho_3 = .16$ in the ACF of the residuals.

Table 10 shows that the series ALP and M1 display clear evidence of nonlinearity. For the ALP case , this nonlinearity is associated with the large value $\rho_{12}\ (\hat{a}_t^2) = .30$, while for the M1 case, the ACF of the squared residuals has large values for $\rho_2\ (\hat{a}_t^2) = .18$, and $\rho_3\ (\hat{a}_t^2) = .25$. The series "Rest", on the other hand, can be safely accepted as linear. (A closer look indicates that the lag–2 and lag–3 autocorrelations of $\hat{a}_t^2$ for M_1 represent seasonal harmonics that contribute in an important manner to the lag–12 autocorrelation of $\hat{a}_t^2$ for ALP. In fact, for the series "Rest", $\rho_{12}\ (\hat{a}_t^2)$ still displays a slightly large value of .14.) But, letting y_t, x_t, and z_t denote the ALP, M1, and "Rest" series, table 10 indicates that

$$z_t = y_t - x_t$$

represents a linear combination of two nonlinear series that can be accepted as linear. In this sense, one could refer to the pair of series $(y_t,\ x_t)$ as being "co–nonlinear", with the linear combination that renders the series linear given by the vector $[1, -1]$.

Table 10

	θ_1	θ_{12}	σ_a	$Q_{12}(a_t)$	$Q_{12}(a_t^2)$	skewness	kurtosis
ALP	-.160	.727*	.0038	9.1	27.2*	-.67*	4.55*
$M1$	.125	.614*	.0127	12.9	26.5*	-.07	4.74*
Rest	.079	.539*	.0070	18.6	12.3	.04	3.43
Critical values	.146	.110	—	18.3	18.3	.34	3.68

* Values significant at the 99% level.

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Figure 1:**Series ALP (logs)**

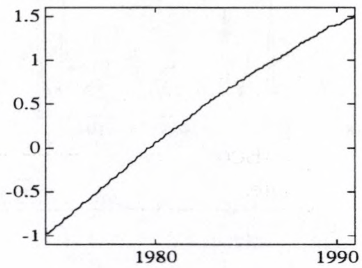


Figure 2:**Residuals**

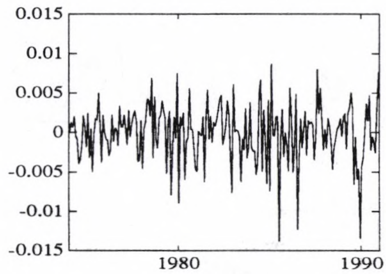


Figure 3:**ACF of residuals**

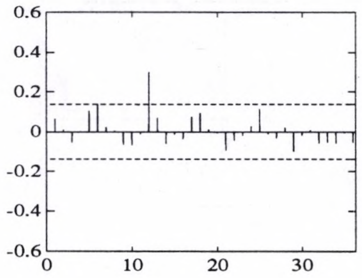


Figure 4: **ALP Estimated Conditional Variance**

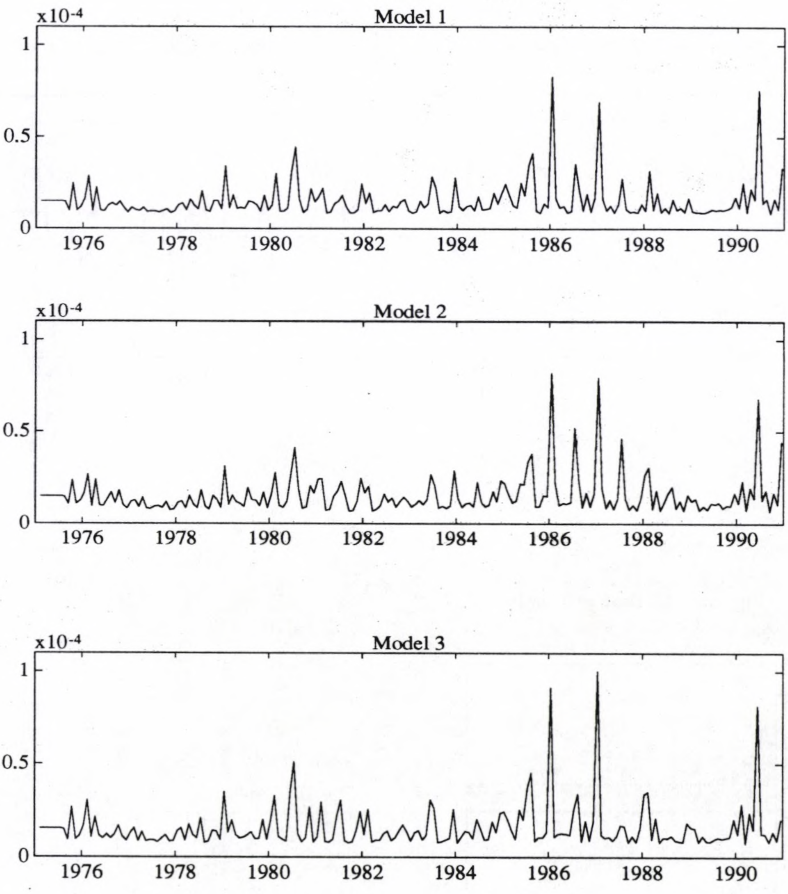


Figure 5: **ALP Pseudo-Spectra of Components**

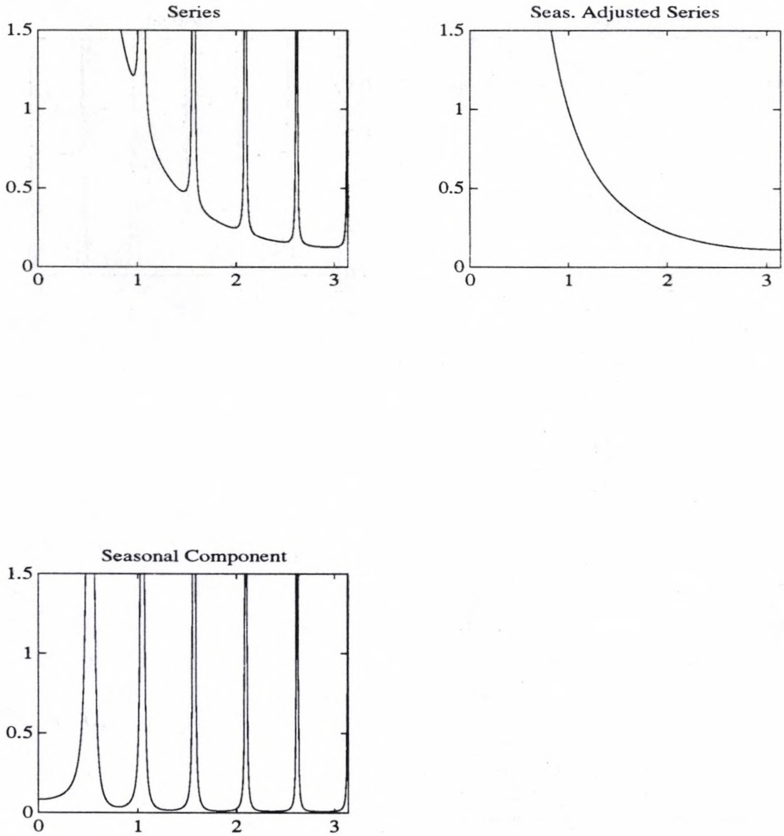


Figure 6: **ALP Squared Gain Component Filters**

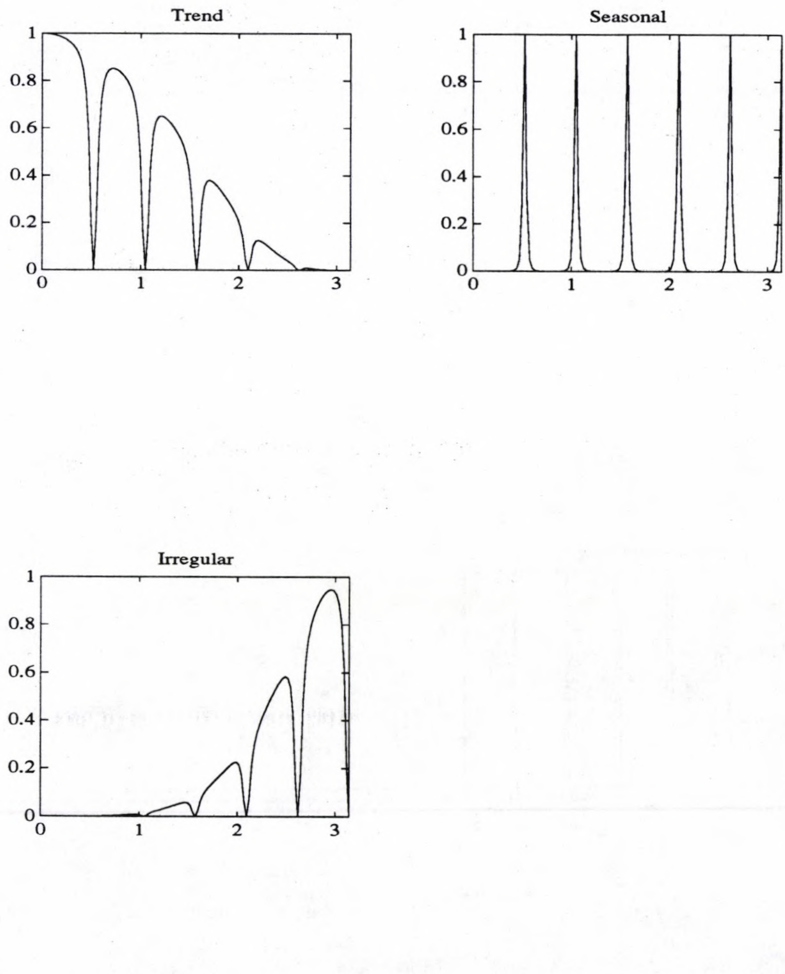


Figure 7: **ALP Estimated Components**

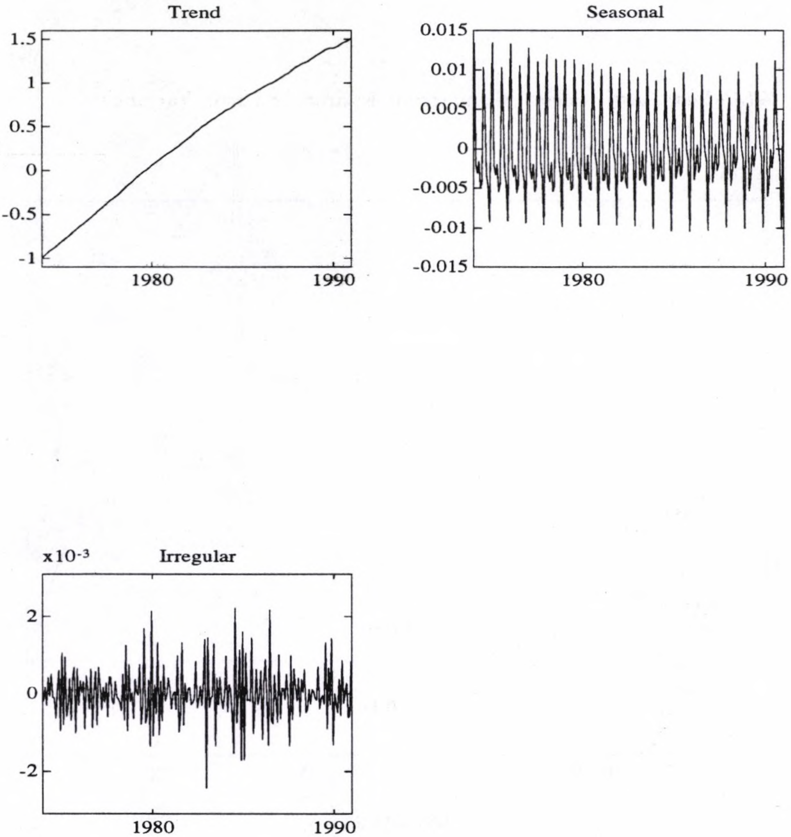


Figure 8
ALP–Seas. Adj. Series, Concurrent Estimator Error Variance

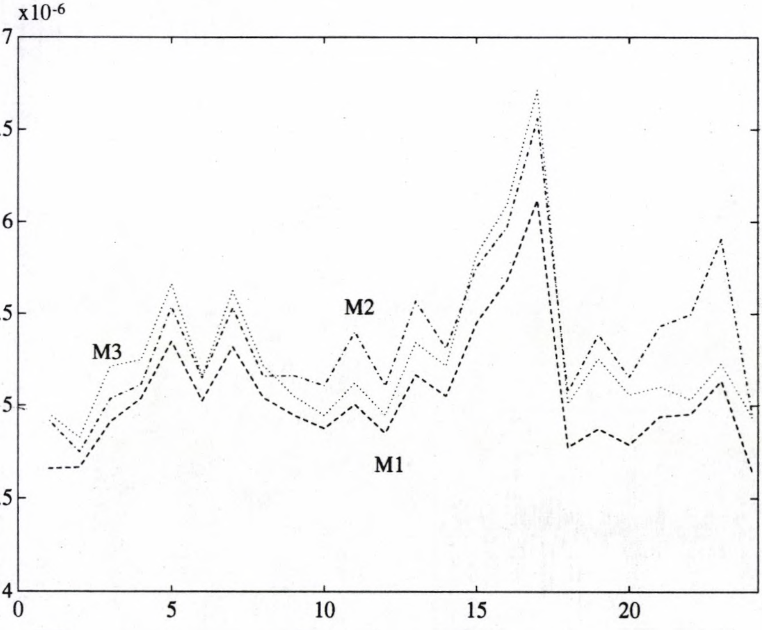
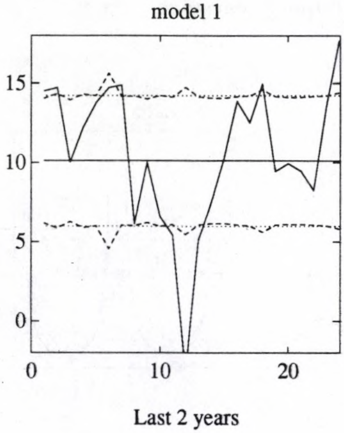
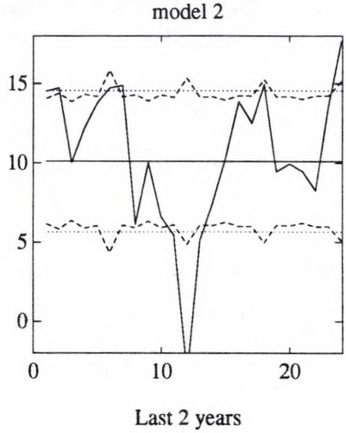


Figure 9

ALP–Annualized Rate of growth of SA series (Concurrent Estimates)





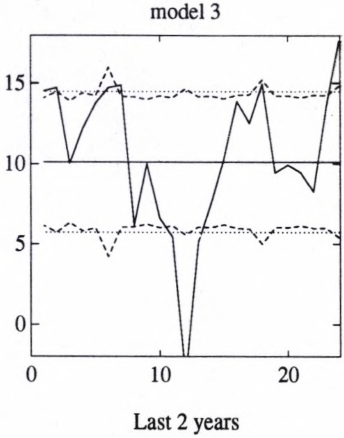


Figure 10: **ALP Spectra of Conditional Variance**

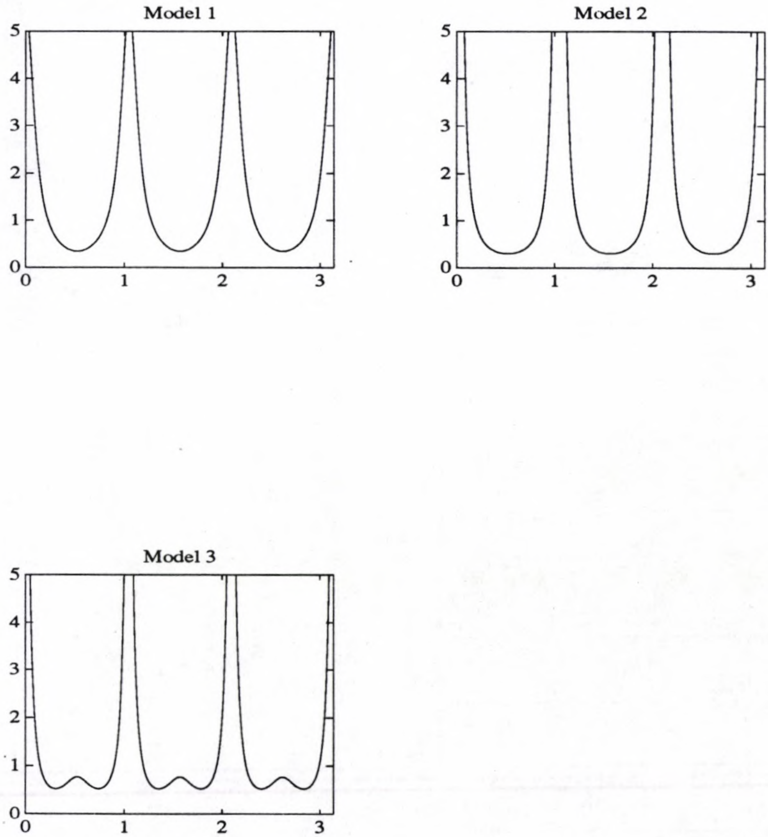


Figure 11: **Model 1 Components of Conditional Variance**

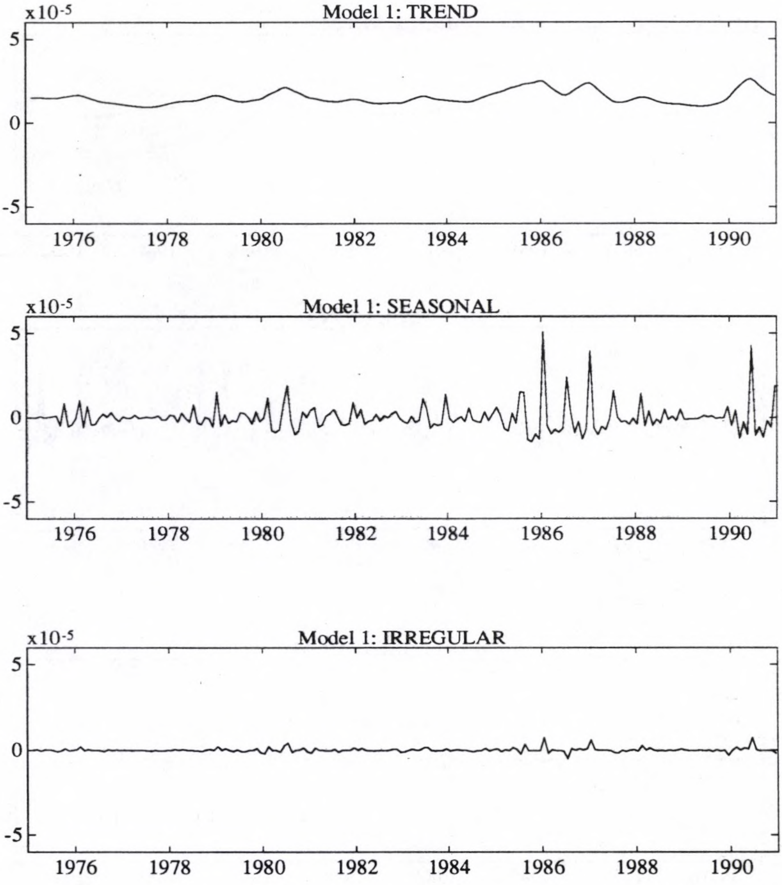


Figure 12: **Model 2 Components of Conditional Variance**

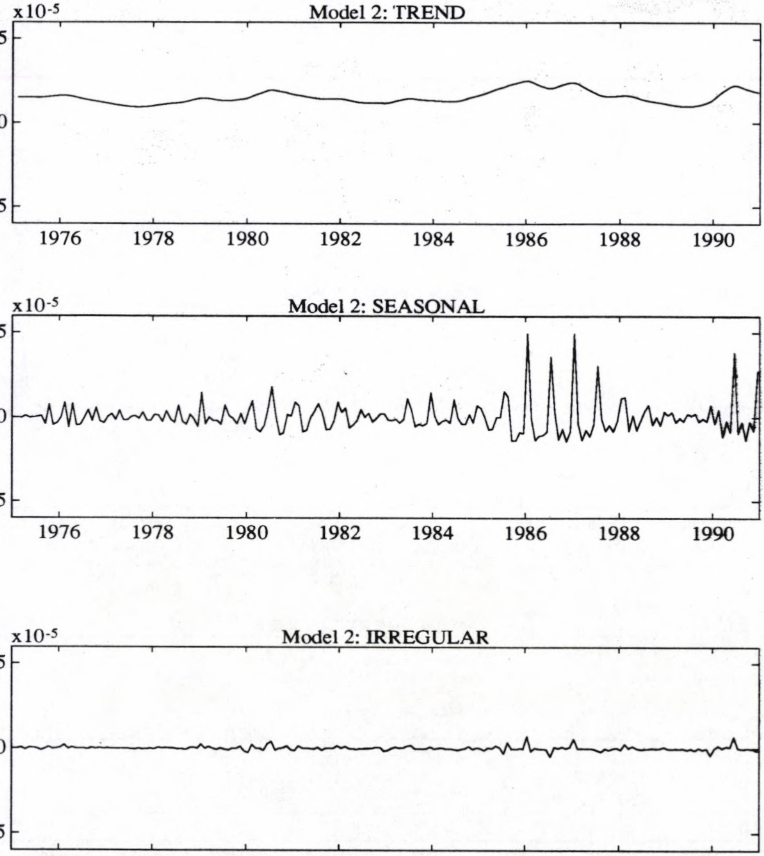


Figure 13: **Model 3 Components of Conditional Variance**

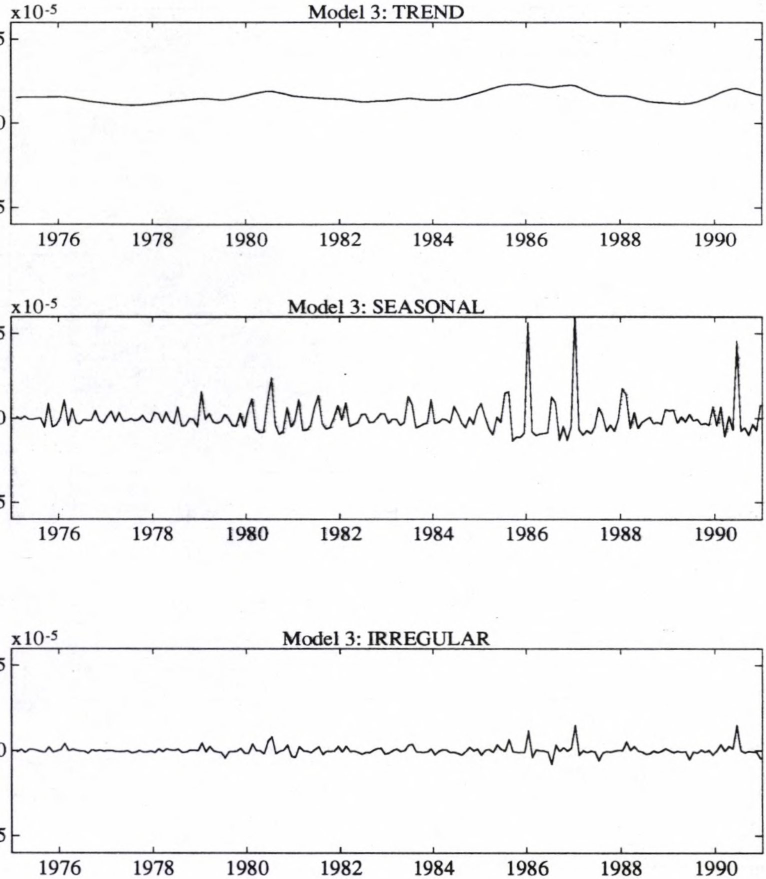


Figure 14
ALP Conditional Variance Seasonal Component Forecasts

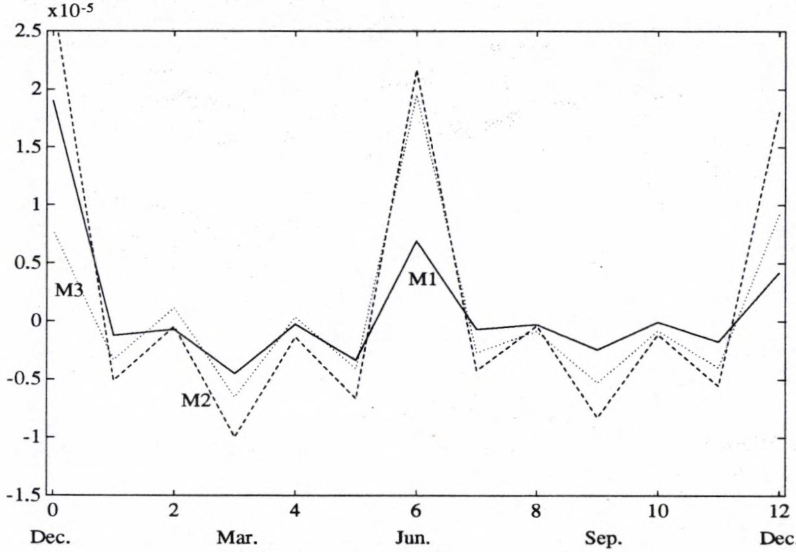
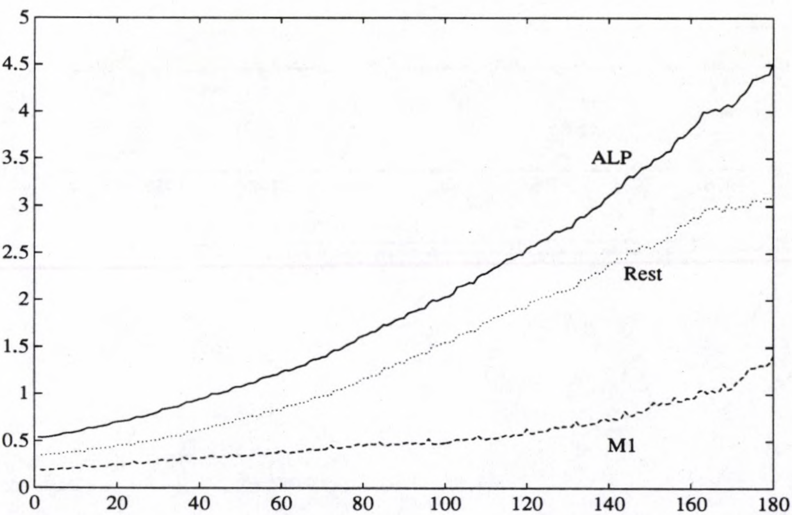


Figure 15: **Monetary Aggregate Series**



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