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The behavior of real wages over the business cycle: Evidence from structural time series modeling and Kalman Filter

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THE BEHAVIOR OF REAL WAGES OVER THE BUSINESS CYCLE : EVIDENCE FROM STRUCTURAL TIME SERIES MODELING AND KALMAN FILTER

by

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INTRODUCTION

This work employs structural time series techniques with stochastic trend (and additive cycle and/or seasonal) to analyze the real wage and employment relationship. This relationship has been evaluated by many studies since 1938 (Dunlop 1938) following the General Theory. These studies never agree on a unique solution. As one can classify three different groups of conclusions, it is no exaggeration to say that this is the one of the most interesting puzzles of economic theory.

In general we can classify the findings as follows:

a) The contemporaneous correlation between real wages and employment over the business cycle is statistically insignificant. b) There exist a negative correlation between real wages and employment over the business cycle. c) There exist a positive correlation between real wages and employment over the business cycle. The conflicting findings of these studies raise the following questions: Are these real wage-employment regressions useful for evaluation of business cycles? What are the possible reasons of this "no consensus" situation? Is there any way to obtain a unique or more comprehensive explanation?

i) SURVEY OF PAST STUDIES

A survey of past studies presents many different methodologies, sample periods, and conclusions. In summary,the neoclassical and Keynesian theories of employment anticipates negative (inverse) relationship between employment and real wages in the short run (i.e. real wages are countercyclical). Under the assumption that firms in the short run operates with fixed level of capital and technology and sell their output at market clearing prices in the competitive markets, one will have a stable demand for labor in the short run implying observed real wage employment observations will lie along a given demand curve and real wages will move countercyclically. (As a matter of fact there is no a priori reason for labor supply to be less stable than labor demand in the short run.) Neftci (1978) and Sargent (1978) are supporting studies of that hypothesis. On the other hand, Dunlop (1938) and Tarshis (1939) found evidence that real wage moved procyclicaly (i.e. employment and real wages are positively correlated). Recently, Bills (1985) has reached the same conclusion. In the third group, Ruggles (1940), Tobin (1948), Kuh (1966), Lucas (1977), Bodkin (1969), and Geary and Kennan (1982) failed to detect any statistically significant relationship. Beside these conclusions, some contributions were made by Solow and Stiglitz (1968), Barro and Grossman (1971, 1976), and Modigliani (1977). These are basically different approaches for a universal solution to old puzzle. Neftci (1978) and Sargent (1978) estimated distributed lags. Bills (1985) used disaggregated panel data. Barro and Grossman used a macro model where markets did not clear, Modigliani (1977) argued that "observed relationship between employment and real wages could be accounted for in an oligopolistic model of firm behavior. Some authors used CPI to deflate the nominal wages, while some others used WPI (wholesale price index) or PPI (production price index) for the same purpose and preferred to use manufacturing wages. Another discrepancy is the sample periods used in these works:

Geary and Kennan : 1947-77.

Neftci : 1948-71.

Bills : 1966-80.

Sargent : 1949-72.

Sumner and Silver: several different periods.

Naturally, model specifications and variables are quite different in these different models. For example, Neftci (1978) estimates distributed lag relationship between real wages and employment, with monthly data while Sargent (1978) employs vector autoregression for real wage and employment, with quarterly data. Neftci's model is log-linear and Sargent's model is linear. Neftci uses employment in manufacturing while Sargent uses civilian employment. In short, these different approaches tries to determine a unique answer whether the real wages are countercyclical.

ii) BUSINESS CYCLE THEORIES :

Initially, following two crucial points should be explained:

a) What are the "business cycles" and how they occur?

b) How "business cycles" are to be dealt with?

As underlined by Lucas, we should not touch (b) without complete understanding of (a). In Lucas's words:

> "Why is it that, in capitalist economies, aggregate variables undergo repeated fluctuations about the trend, all of essentially the same character? Prior to Keynes' general Theory the resolution of this question was regarded as one of the main outstanding challenges to economic research, and attempts to meet this challenge were called business cycle theory. Moreover, among the interwar business cycle theorists, there was wide agreement as to what it would mean to solve this problem. ..... A primary consequence of the Keynesian Revolution was the redirection of research effort away from this question onto the apparently simpler question of the determination output at a point in time, taking history as

given. ....The effort to 'explain business cycles' had been directed at identifying institutional sources of instability, with the hope that, once understood, these sources could be removed or their influence mitigated by appropriate institutional changes. ...Technically, movements about trend in gross national product in any country can be well described by a stochastically disturbed difference equation of very low order. These movements do not exhibit uniformity of either period or amplitude, which is to say they do not resemble the deterministic wave motions which sometimes arise in the natural sciences. Those regularities which are observed are in co movements among different aggregative time series. The principal among these are the following. (i) Output movements across broadly defined sectors move together. (ii)Production of producer and consumer durables exhibits much greater amplitude than does the production of nondurables. (iii) Production and prices of agricultural goods and natural resources have lower than average conformity. (iv) Business

> profits show high conformity and much greater amplitude than other series. (v) Prices generally are procyclical. (vi) Short-term interest rates are procyclical; longterm rates slightly so. (vii)Monetary aggregates and velocity measures are procyclical. There is, as far as I know, no need to qualify these observations by restricting them to particular countries or time periods: they appear to be regularities common to all decentralized market economies. " (Lucas 1977)

This very informative little passage concludes that business cycles are all alike, worldwide. Therefore a unified explanation of business cycles is impossible.

Within this context, one may use the terminology of business cycle theory to extend the analysis. The real business cycle (RBC) models, which represent one of the two dominant approaches, "attribute fluctuations in real quantities like output primarily to shocks in aggregate supply, stressing the role of technology and agents' preferences."(Mocan and Baytas, Forthcoming, Applied Economics) RBC models consider monetary policy ineffective.(Money is neutral.)

Basically, RBC models, by attributing business cycles to shift in technology, explain the movement of output and productivity jointly and the same direction. Naturally, a positive shock to productivity shifts aggregate supply, causing more output and lower prices, finally produces procyclical real wages. On the contrary,an unanticipated increase in, say, money supply (see: Fischer 1977; Taylor 1980, Friedman 1968, Sargent and Wallace 1976) shifts aggregate demand (to right), causing higher prices and output and reduces the real wages. (Countercyclical real wage) On the other hand, as outlined in Mocan and Baytas (1991, Forthcoming, Applied Economics), "some current Keynesian versions of disequilibrium models stress aggregate demand shocks as the primary source of business cycles. "They explain procyclicality of real wages not by supply shocks but excess capacity or labor hoarding theories (Shapiro 1987). In summary, RBC models explain output fluctuations primarily through shocks to technology (Real shock). In the light of recent studies, one can conclude that procyclical real wages can be supported by RBC models.

CHAPTER 1
STATE SPACE MODELING AND COMPONENTS OF TIME SERIES

i. State space modeling

In discussing linear systems it is generally more convenient to use the so-called **"state space"** (or **"Markovian"**) representation of the relationship between input and output rather than the explicit form, given in the scalar case. State space representation is very compact and forms **minimal dimensional** models.[1] As noted by Harvey (1989), the state space form is an enormously powerful tool which opens the way to handling many different time series models. Once a model is in the state space form, the way is open for the application of many important algorithms.

To see how we can proceed in state space representation, consider the following ARMA(p,q) model

$$y_t = \phi_1 y_{t-1} +..+ \phi_m y_{t-m} + \epsilon_t + \theta_1 \epsilon_{t-1} +..+ \theta_{m-1} \epsilon_{t-m+1}$$

where $m = \max(p,q+1)$.

1 Please note that any finite order differential or difference equation can be expressed as a vector first order equation. (see Priestley 1981, p.797)

The state space representation of the above equation is obtained by an mx1 vector (α_t), which obeys the multivariate AR(1) model.

In general,

$$\alpha = \begin{bmatrix} \phi_1 & \\ \phi_2 & \\ \cdot & I_{m-1} \\ \cdot & \\ \phi_m & 0' \end{bmatrix} \alpha_{t-1} + \begin{bmatrix} 1 \\ \theta_1 \\ \theta_2 \\ \cdot \\ \cdot \\ \theta_{m-1} \end{bmatrix} \epsilon_t$$

This is a transition equation (α). Any ARMA model may easily be recovered from this general form. For example, we can recover the above general ARMA(p.q) model by simply assuming that $\alpha_t = y_t$. To be more specific, consider the following state space representations:

a. MA(1) model:

Usual form :

$y_t = \theta\epsilon_{t-1} + \epsilon_t$

State space form :

$y_t = [1 \ 0] \ \alpha_t$

$$\alpha_t = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \alpha_{t-1} + \begin{bmatrix} 1 \\ \theta \end{bmatrix} \epsilon_t$$

b. AR(2) model:

Usual form :

$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \epsilon_t$

State space form :

$y_t = [1\ 0]\ \alpha_t$

$$\alpha_t = \begin{bmatrix} y_t \\ \phi_2 y_{t-1} \end{bmatrix} = \begin{bmatrix} \phi_1 & 1 \\ \phi_2 & 0 \end{bmatrix} \alpha_{t-1} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \epsilon_t$$

or alternatively, the transition equation can be written as follows:

$$\alpha_t = \begin{bmatrix} y_t \\ y_{t-1} \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 \\ 1 & 0 \end{bmatrix} \alpha_{t-1} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \epsilon_t$$

c. "Random walk plus drift" model:

Usual form :

$y_t = \mu_{t-1} + \beta_{t-1} + \eta_t + \epsilon_t$

State space form :

$y_t = [1\ 0]\ \alpha_t + \epsilon_t$

$$\alpha_t = \begin{bmatrix} \mu_t \\ \beta_t \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0 \end{bmatrix}$$

Any model can be put a proper state space form. Once the model is transformed into the state space form, it would be very easy to deal with it; so, one can easily apply many algorithms including Kalman filter.[1]

General Kalman filter application is as follows:

a. Measurement equation :

$Y_t = Z_t A_t + S_t \epsilon_t$ where Y_t is Nx1, Z_t is NxM, A_t is Mx1, S_t is NxN, and ϵ_t is Nx1. $\epsilon_t \sim (0,H_t)$

b. Transition equation :

$A_t = T_t A_{t-1} + R_t N_t$ where T_t is MxM, R_t is MxG, and N_t is Gx1. $N_t \sim (0,Q_t)$

Note that the example at the end of chapter 3, signal plus noise model is just a special case of the general form given above.

(i.e. $T_t = S_t = Z_t = R_t = I$; A_t and Y_t are scalars, and $Q_t = qH_t$)

1 Matlab programs, as well as the examples at the end of chapter 3 explain this point clearly.

ii. Components of time series

In this study, an observed time series is assumed as consisting of trend, seasonal, cyclical, and irregular components :

Observation = Trend + Seasonal + Cycle + Irregular

This model can be extended by adding observable explanatory variables :

Observation =Trend+Explanatory variable+Seasonal+Cycle+Irregular

Once a model in this form has been specified, it can be estimated and the series may then be broken down into its components. As a final step, forecasts of future values of the components and of the series as a whole can be made.

Of special interest is the trend and cycle components. These components are assumed to be stochastic. This is a very important assumption. On the other hand, seasonal component is the "trigonometric seasonals" .

In our model, the above equation may be rewritten as follows:

$$W_t = M_t + Z_t + C_t + EMP\ EE_t + \epsilon_t$$

where

W_t is the real wage (observed),

M_t is the stochastic trend component,

Z_t is the seasonal component,

EMP is the coefficient of employment which will be estimated,

EE is the employment (observed)'

ϵ_t is the irregular component (random and mutually uncorrelated with other disturbances),

N_t and R_t are mutually uncorrelated white-noises with zero means and variances $\sigma^2{}_N$ and $\sigma^2{}_R$, respectively.

a. Stochastic trend (M_t):

$$M_t = M_{t-1} + B_{t-1} + N_t$$

$$B_t = B_{t-1} + R_t , \quad t = \ldots.,-1,0,1,\ldots..$$

or

$$\begin{bmatrix} M_t \\ B_t \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} M_{t-1} \\ B_{t-1} \end{bmatrix} + \begin{bmatrix} N_t \\ R_t \end{bmatrix}$$

This process is a first order vector autoregression. Taking the conditional expectations at lead times $\iota = 1,2,\ldots.$ and solving the resulting difference equation gives[1]

$$m_{T+l/T} = m_T + b_T \iota$$

where m_T and b_T are the conditional expectations of M_T and B_T at time T. So, it is worth noting that if the observations are equal to a trend plus a white noise disturbance term ($W_t = M_t + \epsilon_t$), the above equation is also the forecast function for the series itself.

i.e.

$$w_{T+l/T} = m_T + b_T \iota , \quad \iota = 1,2,3,...$$

When the disturbances ϵ_t , N_t , and R_t are normally distributed, the computation of m_T and b_T can be carried out by putting the model state space form and then applying the Kalman filter. (see Harvey 1989)

---

1 solution is as follows: say, $Y_t = aY_{t-1} + e_t$, $t=1,2,...,T$ at time "T+ι" take the expectations conditional on the information at time "T" to yield $y_{T+\iota/T} = a\, y_{T+\iota-1/T}$, $\iota=1,2,.....$ Therefore, $y_{T/T} = y_T$ and $Y_{T+1/T} = a\, Y_T$ $y_{T+2/T} = a\, y_{T+1/T} = a^2\, Y_T$ So, the solution of the difference equation is $y_{T+\iota/T} = a^{\iota}\, Y_T$, $\iota=1,2,...$

N_t allows level of the trend to shift up or down and R_t allows the slope to change.[1] If both variances are equal to zero, this process collapses to deterministic trend. In other words, stochastic movement in the trend directly correlated with these variances. Therefore deterministic trend is nothing but a limiting case of a stochastic trend.

b. Additive cycle (C_t):

C_t is a cyclical function of time with frequency λ_c , which is measured in radians. The period of cycle[2] is $2\pi/\lambda_c$. As shown by Harvey (1989), a cycle can be expressed as a sine wave, a cosine wave, or a mixture of sine and cosine waves with additional parameters representing amplitude and phase.[3]

---

1 Since $M_t = M_{t-1} + B_{t-1} + N_t$, or $\Delta M_t = B_{t-1} + N_t$ and similarly $\Delta B_t = R_t$ or $B_t = R_t / \Delta$, therefore, $M_t = N_t / \Delta + R_{t-1} / \Delta^2$ finally, $W_t = N_t / \Delta + R_{t-1} / \Delta_2 + \epsilon_t$ (assuming no cycle or seasonal for simplicity) The first part on the right-hand side of the final form is that part of the trend which derives from movements in the level. The second component is the contribution of the slope. Note that, if σ^2_R is zero, then the final form reduces to $W_t = N_t / \Delta + B t + \epsilon_t$

2 Time which is taken to go through its complete sequence of values.

3 See Bloomfield (1976) for technical details.

As a result, a following cycle is used in the model:

$$C_t = \delta \cos \lambda_c t + \psi \sin \lambda_c t$$

where $(\delta^2 + \psi^2)^{1/2}$ is the amplitude and $\tan^{-1}(\psi/\delta)$ is the phase. On the other hand, in order to introduce some discounting into the system the cycle needs to be made stochastic by allowing the parameter δ and ψ to evolve over time.

For continuity, the following recursion is required:

$$\begin{bmatrix} C_t \\ C^*_t \end{bmatrix} = \begin{bmatrix} \cos \lambda_c & \sin \lambda_c \\ -\sin \lambda_c & \cos \lambda \end{bmatrix} \begin{bmatrix} C_{t-1} \\ C^*_{t-1} \end{bmatrix} + \begin{bmatrix} k_t \\ k^*_t \end{bmatrix}$$

where k_t and k^*_t are white noise disturbances[1] , $C_0 = \delta$, and $C^*_0 = \psi$. Notice that the new parameters are C_t , the current value of the cycle, and C^*_t, which appears by construction in order to form C_t .[2]

1 For the model to be identifiable it must be assumed either these two disturbances have the same variance or that they are uncorrelated. (see Harvey 1989)

2 For trigonometric identities, see Harvey (1981, p.95)

In finalizing the model, a dumping factor (ρ) can be introduced to assure more flexibility :

$$\begin{bmatrix} C_t \\ C^*_t \end{bmatrix} = \rho \begin{bmatrix} \cos \lambda_c & \sin \lambda_c \\ -\sin \lambda_c & \cos \lambda \end{bmatrix} \begin{bmatrix} C_{t-1} \\ C^*_{t-1} \end{bmatrix} + \begin{bmatrix} k_t \\ k^*_t \end{bmatrix}$$

where $0 \leq \rho \leq 1.$[1]

Assuming $E[C_T] : \hat{C}_T$ and $E[C^*_T] : \hat{C}^*_T$, the ι-step-ahead prediction of C_t under the assumption of independent disturbances is :

$$\hat{C}_{T+1\backslash T} = \rho^{\iota} (\hat{C}_T \cos \lambda_c \iota + \hat{C}^*_T \sin \lambda_c \iota) , \quad \iota = 1,2,....$$

If $0 < \rho < 1$, the forecast function is a dumped sine, or cosine wave.

---

1 This model is a vector AR(1) process. Process collapses to AR(1) process when $\lambda_c = 0$ or π. (i.e. second equation will be redundant and the cycle is $C_t = \rho C_{t-1} + k_t$.

c. Seasonality (Z_t):

$$Z_t = \sum_{j=1}^{[s/2]} Z^*_{t,j}$$

where

$Z^*_{t,j}$ is a nonstationary cycle,[1] with $\lambda_c = \lambda_j = 2\pi j/s$, [2]

$j = 1,2,\ldots\ldots\ldots,[s/2]$

When s is even, the sin term disappears for j=s/2 , therefore, the number of trigonometric parameters will always be s-1. This is just one of many alternative seasonality formulations. A deterministic seasonality as well as stochastic dummy variable seasonality may be considered as alternatives although trigonometric seasonals are more satisfactory.[3] If the series are seasonally adjusted, this particular seasonality component will not take place in the basic estimation equation. On the other hand, using seasonally adjusted series is open to serious criticism. (see Harvey 1989, p.300-10)

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1 This is the cycle component with $\rho = 1$. i.e $Z_t = \sum_{j=1}^{[s/2]} (\gamma_j \cos \lambda_j t + \gamma^*_j \sin \lambda_j t)$

2 see Hannan, Terrel and Tuckwell (1970) and Harvey (1989, p.40-9)

3 for details on deterministic and stochashic seasonals, see Harvey (1989).

CHAPTER 2

KALMAN FILTER

Prediction of economic time series by means of Kalman filter has been analyzed by many researchers. Vishwakarma, in 1970 has noticed the importance of Kalman filter: "In this method, the observations of a time series Y are forecast as functions of one or more variables X. These variables are updated recursively with each new observation of Y as it becomes available. The updating procedure consists of taking the weighted averages of the previous value of X and latest information about Y. The method is simple to use once the weighing coefficients also known as the smoothing constants have been determined. This determination is a key problem. One way of selecting the coefficients is to formulate explicitly a stochastic mathematical model for the process generating the series and to determine the coefficients so as to minimize the mean squared forecast error." [1] Many important applications of Kalman filter algorithm

1 Wishwakarma (1970)

can be found in recent economic literature. It has been used by Stock to explain the behavior of GNP (see, Stock 1987). Otter and Van Dal used this algorithm instead of usual ARMA-models and applied to Dutch Economy (see, Otter, P.W. and Van Dal, R. 1987). Similarly Aoki (1983; 1987), Otter (1985; 1986),Watson and Engle (1983; 1985) and Harvey (1989) explain very important features of state-space approach and Kalman filter and present several applications of the algorithm for different situations. State space models which underlie the Kalman filter were originally developed by control engineers.[1] As noted by Otter (1987), "...the state is a memory function which accumulates the information from the past behavior of the system in as much it is relevant for the future behavior of the system." In Harvey's words "in a typical application, attention is focused on a set of "m" state variables which change over time. These variables may be a signal, denoting, for example, the position of a rocket. In most cases the signal will not

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1 Meinhold and Singpurwalla (1983) shows how the successfully used Kalman filter, can be easily understood by statisticians.

be directly observable, being subject to systematic distortion by 'noise'. With the help of state space modelling, we can efficiently use the Kalman filter. The Kalman filter is a set of equations which allows an estimator to be updated once a new observation becomes available. This process is carried out in two parts. The first step consists of forming the optimal predictor of the observation, given all the information currently available. This is affected by means of the prediction equations. The new observation is then incorporated into the estimator of the state vector using the updating equations. The Kalman filter provides an optimal solution to the problems of prediction and updating. If the observations are normally distributed, and the current estimator of the state vector is the best available, the predictor and the updated estimator will also be the best available (see, Harvey 1989). It can easily be shown that because of its Bayesian character, the Kalman Filter is a possible alternative for the maximum likelihood estimation method. So the Kalman Filter's one-period-ahead predictor is equivalent that of Box-Jenkins predictor (see, Otter 1978).

Suppose that the structure of a regression equation changes from one period to the next. Such a model can be obtained by assuming that the vector of parameters is generated by a stochastic process. Within the framework of basic structural model this can be done by adding an explanatory variable to the right side of equation: One can define this explanatory variable as time varying. There is no reason, in principle, why the parameters of the explanatory variables should not also be allowed to change over time. Thus, each EMP can be replaced by a time-varying parameter, which is assumed to be generated by a random walk process. Notice that "given the relative variance of disturbance term driving each of these random walks, updating and prediction can be carried out by the Kalman filter." [1] Methodologically, for many known reasons structural models have considerable intuitive appeal. Let us have a time series in the following form once again:

Observation = Trend + Seasonal + Cycle + Irregular

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1 Harvey (1984)

In such a representation, a trend is not seen as a deterministic function of time. Similarly the seasonal components must be flexible enough to respond to changes in the seasonal pattern. Therefore, a structural time series model needs to be set up in such a way that its components are stochastic, in other words, they are regarded as being driven by random disturbances. A model in above form could be formulated as a regression with explanatory variables consisting of a time trend and set of seasonal dummies. But, the necessary flexibility can be achieved by letting the regression coefficients change over time in other words, a basic structural time series model is a regression model in which the explanatory variables are functions of time and parameters are time-varying.

Macroeconomic time series generally exhibit a clear tendency to grow over time. This violates the covariance stationarity assumption (see, Watson 1986). So that we have to analyze the deviation from the trend value. An economic equation can be formulated in levels or differences. On the hand, prior to the regression, variables may be detrended by regressing each one individually on time. These are different competing techniques. (Notice that including time trend in a levels regression is equivalent to prior detrending of variables.)

As noted by Cochrane "macroeconomics once viewed fluctuations in GNP as temporary deviations from a trend." Cochrane, on the other hand, discusses the GNP following a persistent shock, and constructs a model with partly temporary and partly permanent fluctuations as a combination of a stationary series and a random walk (see, Cochrane 1988).

In this study, we used a "stochastic trend" regression model. Instead of a deterministic trend, a stochastic trend forms definitely more efficient model due to its flexibility. Stochastic trend offers an intuitively more appealing way of modelling variables like productivity and technical progress, and offers a way out of the problems caused by constraining them to be deterministic." (see, Henry,Peters, and Harvey 1986).

State space or Markovian representation gives a very compact description which is valid provided the relationship between input and output can be expressed in terms of a finite order linear difference equation.

Basic idea is that any finite order linear difference equation can be expressed as a vector first order equation. (see chapter 1, for details)

DERIVATION OF KALMAN FILTER [1]

i. $Y_t = Z_t A_t + S_t \epsilon_t$, $t = 1, \ldots\ldots, T$

where Y_t is N x 1, Z_t is N x M, A_t is M x 1, S_t is N x N, and

ϵ_t is N x 1.

$\epsilon_t \sim (0, H_t)$

1 In addition to the references given before, for detailed technical and theoretical backgraund on Kalman filter and related topics, see : Anderson and Moore (1978), Aoki (1989), Arora (1973), Bailey (1974), Belsley (1973a,b,c), Belsley and Kuh (1973), Conrad and Corrado (1979), Cooley and Prescott (1973), Cooper (1973), Garbade (1977), Gardner, Harvey, Phillips (1980), Harvey and Phillips (1979, 1982), Otter (1988),Otter and Tempelear (1980), Sarris (1973), Swamy (1973), McGee andCarlton (1970), Hinkley (1971), Hamilton (1989, 1990),Quandt (1958), Goldfeld and Quandt (1973a,b), Godfrey (1978), Brown, Durbin, and Evans (19**), Cholette (1982), Cosslett and Lee (1985), Day (1969).

ii. $A_t = T_t A_{t-1} + R_t N_t$, $t = 1, \ldots\ldots, T$

where T_t is $M \times M$, R_t is $M \times G$, and N_t is $G \times 1$.

$N_t \sim (0, Q_t)$

Given a_{t-1}, the MMSLE of A_{t-1} at time t-1, with $(a_{t-1} - A_{t-1}) \sim WS(0, P_{t-1})$ then the prediction equations are

a. $a_{t/t-1} = T_t a_{t-1}$

b. $P_{t/t-1} = T_t P_{t-1} T'_t + R_t Q_t R'_t$, $t = 1, \ldots T$

and the updating equations are

a'. $a_t = a_{t/t-1} + P_{t/t-1} Z'_t F^{-1}_t (Y_t - Z_t a_{t/t-1})$

b'. $P_t = P_{t/t-1} - P_{t/t-1} Z'_t F^{-1}_t Z_t P_{t/t-1}$

where $F_t = Z_t P_{t/t-1} Z'_t + S_t H_t S'_t$

note that $Y_t = Z_t A_t + S_t E_t$

And the prediction error is

$$V_t = Y_t - Z_t a_{t/t-1} , \quad t = 1, \ldots, T$$

is now an $N \times 1$ vector. It has zero mean and covariance matrix F_t.

i.e. $E(V_t) = 0$ and $E(V_t V'_t) = F_t$.

At this stage, one may want to see the less than clear points of Kalman filter derivation :

In a general formulation, the **transition equation** is

$A_t = T_t A_{t-1} + R_t N_t$, for simplicity, ignore subscripts and assume $B=A_{t-1}$

$A = T B + R N$, $t = 1,\ldots\ldots\ldots,T$

T and R are fixed matrices of order mxm and mxg; respectively.

N is a gx1 vector of disturbances with zero mean and covariance matrix Q.

At time t-1, all the available information is incorporated in a_{t-1};the MMSLE of A_{t-1} . This has a covariance matrix which can be written as $\sigma^2 P_{t-1}$ where P_{t-1} is known. The form of the transition equation suggest that the MMSLE of A_t at time t-1 is given by $a_{t/t-1} = T a_{t-1}$ subtracting A_t from both sides yields:

$(a_{t/t-1} - A_t) = T (a_{t-1} - A_{t-1}) - R N_t$

Now, let us use our notation with no subscripts again:

$A = T B + R N$

$A_0 = T_0 B + R_0 N_0$, sampling model for T_0 sample.

then

$A\hat{}_0 = T_0\, b$ is the least square prediction function.

And

$E[A\hat{}_0 - A_0] = E[T_0\, b - A_0] = E[T_0\, b - T_0\, B - R_0\, N_0]$

$= T_0\, E[b - B] - R_0\, E[N_0] = 0$

and,

$E[(A\hat{}_0 - A_0)(A\hat{}_0 - A_0)'] =$

$= E[(T_0\, b - T_0\, B - R_0\, N_0)(T_0\, b - T_0\, B - R_0\, N_0)']$

$= E[(T_0\, (b - B) - R_0\, N_0)\ ((b - B)'T_0' - N_0'R_0')]$

$= T_0\, (b - B)(b - B)'\, T_0' + R_0\, N_0\, N_0'R_0'$

$= T_0\, \sigma^2\, P_{t-1}\, T_0' + R_0\, \sigma^2\, Q\, R_0'$

$= \sigma^2\, [(T_0\, P_{t-1}\, T_0') + (R_0\, Q\, R_0')]$

in other words

$(a_{t/t-1} - A_t) \sim WS(0, \sigma^2\, P_{t/t-1})$

where

$P_{t/t-1} = T\, P_{t-1}\, T' + R\, Q\, R'$

On the other hand:

$Y_t = Z_t\, A_t + \epsilon_t$ (assuming $S_t = I$ for simplicity.)

$Y\hat{}_{t/t-1} = Z_t\, a_{t/t-1}$ prediction equation

$v_t = Y_t - Y\hat{}_{t/t-1} = Z_t\, A_t + \epsilon_t - Z_t\, a_{t/t-1}$

$= Z_t\, (A_t - a_{t/t-1}) + \epsilon_t$

$E[v_t] = 0$, since $E[A_t - a_{t/t-1}] = E[\epsilon_t] = 0$

$$E[v_t \; v_t'] = Var[v_t] = E[Z_t \; (A_t - a_{t/t-1} \;)$$
$$(A_t - a_{t/t-1} \;)' \; Z_t \;] \; + E[\epsilon_t \epsilon_t'] \; +$$
$$2 \; E[Z_t \; (A_t - a_{t/t-1} \;) \epsilon_t \;]$$

and since;

$$E[Z_t \; (A_t - a_{t/t-1} \;) \; (A_t - a_{t/t-1} \;)' \; Z_t \;] \; = \sigma^2 \; P_{t/t-1}$$
$$E[\epsilon_t \epsilon_t'] \; = \sigma^2 \; h_t$$
$$E[Z_t \; (A_t - a_{t/t-1} \;) \epsilon_t \;] \; = \; 0$$

$$Var(v_t) = \sigma_2 \; Z_t \; P_{t/t-1} \; Z_t' + \sigma^2 \; h_t$$
$$= \sigma^2 \; F_t$$

where $F_t = (Z_t \; P_{t/t-1} \; Z_t') + h_t$

Note that, if we do not assume that $S_t = I$, then

$F_t = (Z_t \; P_{t/t-1} \; Z_t') + \; S_t \; H_t \; S_t'$

In summary, in the simplified form;

$a_{t/t-1} = T \; a_{t-1}$ is the prediction equation for the state vector, and

$P_{t/t-1} = T \; P_{t-1} \; T' + R \; Q \; R'$ is its covariance matrix, while

$v_t = Y_t - Y\hat{}_{t/t-1} = Z_t \; (\; A_t - a_{t/t-1} \;) + \epsilon_t$ is the error made in predictiong Y_t at time t-1 .

(See Goldberger and Theil (1961) Mixed Estimation)

Combining all these clear steps lets us to reduce the model in the following compact form:

The augmented model is

$$\begin{bmatrix} a_{t/t-1} \\ Y_t \end{bmatrix} = \begin{bmatrix} I \\ Z_t \end{bmatrix} A_t + \begin{bmatrix} a_{t/t-1} - A_t \\ \epsilon_t \end{bmatrix}$$

the disturbance term has zero expectation and **covariance matrix**

$$E \begin{bmatrix} a_{t/t-1} - A_t \\ \epsilon_t \end{bmatrix} [a_{t/t-1}' - A_t', \quad \epsilon_t'] = \sigma^2 \begin{bmatrix} P_{t/t-1} & 0 \\ 0 & h_t \end{bmatrix}$$

Now, the problem once again is that the prior information was to be combined with the sample information. (i.e. this is a mixed regression)

The prior information is now contained in

$(a_{t/t-1} - A_t) \sim WS(0, \sigma^2 P_{t/t-1})$

while the sample consists of a single observation derived from the measurement equation :

$Y_t = Z_t A_t + \epsilon_t , \quad t = 1, \ldots . T$

where

$\epsilon_t \sim WN(0, \sigma^2 h_t)$

On the other hand, the MMSLE of A_t is given by

$$a_t = P_t \, (P^{-1}_{t/t-1} \, a_{t/t-1} + Z_t \, Y_t \; / \; h_t)$$

this is the **updating formula.**

Notice that, by the same way :

$$\begin{bmatrix} a_{t/t-1} \\ Y_t \end{bmatrix} = \begin{bmatrix} I \\ Z_t \end{bmatrix} A_t + \begin{bmatrix} a_{t/t-1} - A_t \\ \epsilon_t \end{bmatrix} \quad x$$

$$\begin{bmatrix} [I \quad Z_t] \begin{bmatrix} P_{t/t-1} & 0 \\ 0 & h_t \end{bmatrix}^{-1} \begin{bmatrix} I \\ Z_t \end{bmatrix} \end{bmatrix} \quad x$$

$$\begin{bmatrix} [I \quad Z_t] \begin{bmatrix} P_{t/t-1} & 0 \\ 0 & h_t \end{bmatrix}^{-1} \begin{bmatrix} a_{t/t-1} \\ Y_t \end{bmatrix} \end{bmatrix}$$

therefore

$$a_t = [P^{-1}_{t/t-1} + Z_t \, Z'_t \, (1/h_t)]^{-1} \, [P^{-1}_{t/t-1} \, a_{t/t-1} + Z_t \, Y_t \, (1/h_t)]$$

since

$$[P^{-1}_{t/t-1} + Z_t \, Z'_t \, (1/h_t)]^{-1} = P_t$$

$$a_t = P_t \, [P^{-1}_{t/t-1} \, a_{t/t-1} + Z_t \, Y_t \, (1/h_t)]$$

Thus

$(a_t - A_t) \sim WS(0, \sigma^2 P_t)$

Now, the above given updating formula may be put in a different form using a matrix inversion lemma (See Harvey 1981, p.118) :

The new form of the updating formula is

$P_t = P_{t/t-1} - P_{t/t-1} \; Z_t \; Z'_t \; P_{t/t-1} \; / \; f_t$

where

$f_t = Z_t \; P_{t/t-1} \; Z'_t \; + h_t$

This new form of the updating formula **does not require any matrix inversion.**

Substituting the new form into the old gives :

$$a_t = (P_{t/t-1} - P_{t/t-1} \; Z_t \; Z'_t \; P_{t/t-1} \; / \; f_t) \; *$$
$$(P^{-1}_{t/t-1} \; a_{t/t-1} + Z_t \; Y_t \; / \; h_t)$$
$$= (a_{t/t-1} + f^{-1}_t \; P_{t/t-1} \; Z_t) \; *$$
$$(Y_t \; f_t \; / h_t - Z'_t \; a_{t/t-1} - Z'_t \; P_{t/t-1} \; Z_t \; Y_t \; / \; h_t)$$

Using the definition of f_t , cancelling, and rearranging the terms leads to the state updating equation :

$$a_t = a_{t/t-1} + P_{t/t-1} \; Z_t \; (Y_t - Z'_t \; a_{t/t-1}) \; / \; f_t$$

this formula contains all the new information in Y_t and used to update $a_{t/t-1}$ via the **Kalman gain.**

Note that

$(Y_t - Z'_t\ a_{t/t-1}) =$ prediction error and

$P_{t/t-1}\ Z_t\ /\ f_t$ is the **Kalman gain.** (mx1 vector)

It is quite easy to see that Kalman gain (like P_t and P_{t-1}) is independent of Y_t's and so may be calculated in advance. Also note that the updating equations are still valid if $h_t = 0$. (See Thail 1971, pp 282-7)

In a single equation case, the prediction error plays a key rolein updating the state vector. The 'correction' made to $a_{t/t-1}$ in

$$a_t = a_{t/t-1} + P_{t/t-1}\ Z'_t\ F^{-1}_t\ (Y_t - Z_t\ a_{t/t-1})$$

is equal to **kalman gain** : $P_{t/t-1}\ Z'_t\ F^{-1}_t$ multiplied by V_t. If prior information is available, i.e. $a_0 \sim ws(a_0,P_0)$ where a_0 and P_0 are known, the Kalman filter will yield the MMSLE of A_T based on all T observations.

Let us consider an example,[1]

i.Prediction equation: $Y_t = A_t + \epsilon_t$, $\epsilon_t \sim WN(0,\sigma^2)$

ii.Updating equation : $A_t = A_{t-1} + N_t$,$N_t \sim WN(0A,\sigma^2\ q)$

where the state A_t and the observation Y_t are scalars.

1 The structure of the example is taken from Harvey (1989) and revised for different initial values.

The state, which is known to follow a random walk process, cannot be observed directly and subject to the unobservable disturbance, E_t. In here, "we therefore have a very simple example of what an engineer would call a 'signal plus noise' model. It is assumed that 'q' , the signal-to-noise ratio is known." Harvey (1989)

Given $q = 4$, $a_{t-1} = 4$, and $P_{t-1} = 12$

and the observed Y_t s : $Y_1 = 4.4$, $Y_2 = 4.0$, $Y_3 = 3.5$,

and $Y_4 = 4.6$

it is clear that $a^*_t = a_{t-1}$ and $P^*_t = P_{t-1} + q$.

and $a_t = a^*_t + P^*_t\ (Y_t - a^*_t\ ) \ /\ (P^*_t + 1)$

$P_t = P^*_t - [P^{*2}_t \ /\ (P^*_t + 1)]$

for $t = 1$

$a_1 = a^*_1 + P^*_1\ (Y_1 - a^*_1\ )\ /\ (P^*_1 + 1)$

$a_1 = 4 + (12+4)(4.4-4)\ /\ (12+4) + 1$

$a_1 = 4.376 \quad (a_1 = a^*_2)$

$P_1 = P^*_1 - [P^{*2}_1\ /\ (P^*_1 + 1)]$

$P_1 = (12+4) - [(12+4)^2\ /\ ((12+4) + 1)]$

$P_1 = 0.941 \quad (P_1 + 4 = P^*_2) \quad$ [since $q = 4$]

for $t = 2$

$$a_2 = a^*_2 + [P^*_2 (Y_2 - a^*_2) / (P^*_2 + 1)]$$

$$a_2 = 4.376 + (0.941+4)(4-4.37)/4.941+1$$

$$a_2 = 4.0682 \quad (a_2 = a^*_3)$$

$$P_2 = P^*_2 - [P^{*2}_2 / (P^*_2 + 1)]$$

$$P_2 = 4.941-(4.941)^2 / 5.941$$

$$P_2 = 0.83 \quad (P_2 + 4 = P^*_3)$$

for $t = 3$

$$a_3 = a^*_3 + [P^*_3 (Y_3 - a^*_3) / (P^*_3 + 1)]$$

$$a_3 = 4.063+4.0832(3.5-4.063) / 4.832+1$$

$$a_3 = 3.597 \quad (a_3 = a^*_4)$$

$$P_3 = P^*_3 - [P^{*2}_3 / (P^*_3 + 1)]$$

$$P_3 = 4.832-(4.832^2/5.832)$$

$$P_3 = 0.8286$$

for $t = 4$

$$a_4 = a^*_4 + [P^*_4 (Y_4 - a^*_4) / (P^*_4 + 1)]$$

$$a_4 = 3.597+4.8286(4.6-3.597/5.8286)$$

$$a_4 = 4.4279 \quad (a_4 = a^*_5)$$

$P_4 = P^*_4 - [P^*_4 / (P^*_4 + 1)]$

$P_4 = 4.8286 - (4.8286^2/5.8286)$

$P_4 = 0.8284$

This example uses the simplest form of the model to illustrate the logic of the Kalman filter. What is the importance of our initial mean and variance values? (i.e. a_0, and P_0) To illustrate this point the following program may be used :[1]

```
function k=kal1(y,r,z,q)
b1=[ ];b2=[ ];b3=[ ];b4=[ ];b5=[ ];
h=max(size(y));
for t=1:h
p(t)=r+q; r=p(t)-((p(t)^2)/(p(t)+1));
a(t)=z+p(t)*(y(t)-z)/(p(t)+1); v=y(t)-z; z=a(t);
b1=[b1 t];b2=[b2 y(t)];b3=[b3 r];b4=[b4 z];b5=[b5 v];
end
k=[b1;b2;b3;b4;b5]';
```

1 This is a MATLAB program. Refer MATLAB manual for details of MATLAB. This program is written for scalar a_0, P_0, and q. To start the program type kal2(y,r,z,q) where y is the column vector of observations, r is the P_0, z is the a_0, and q is q. (i.e. signal-to-noise ratio)

With the help of this simple program we can analyze the effects of different starting values to a signal plus noise model.(This can easily be generalized to more sophisticated models.) As a second step, we can anlyze the "smoothing". Since each step in Kalman filter yields the MMSLE of A_t, given all current and past observations. The only estimator which utilizes all the sample observations is a_T. This is the estimator of the state in final period. Therefore the smoothed equations begin from a_T and P_T, and works backwards.

$a_{t/T}$ denotes **smoothed estimator,** and

$P_{t/T}$ denotes **its covariance matrix**, at time "t".

And the smoothing equations may be written as :

$$a_{t/T} = a_t + P^*_t \, (a_{t-1/T} - a_t \,)$$

$$P_{t/T} = P_t + P^*_t \, (P_{t+1/T} - P_{t+1/t} \,) \, P^{*\prime}_t$$

where $P^*_t = P_t \, P^{-1}_{t+1/t}$, $t = T-1, \ldots\ldots, 1$

with $a_{T/T} = a_T$ and $P_{T/T} = P_T$.

On the other hand, we may obtain a set of **direct residuals** from the smoothed estimators.

$$e_t = Y_t - a_{t/T} \, , \qquad t = 1, \ldots\ldots, T$$

e_t has zero mean and the variance $P_{t/T}$.

Similarly, we may figure out the **prediction error residuals.**

$$v_t = Y_t - a_{t-1} , \qquad t = 1,.....,T$$

Now, we can figure out all these values for our previous example:

In our example, we have figured out a_1, a_2, a_3, and a_4 together with P_1, P_2, P_3, and P_4. Therefore given $P_{4/4}$ and $a_{4/4}$, we can go backward and figure out $a_{3/4}$, $a_{2/4}$, and $a_{1/4}$ as well as $P_{3/4}$, $P_{2/4}$, and $P_{1/4}$.

$$a_{3/4} = a_3 + P_3 P^{-1}{}_{4/4} (a_{4/4} - a_3), \qquad t = T-1,....,1$$

$$P_{3/4} = P_3 + [P_3 P^{-1}{}_{4/3}]^2 (P_{4/4} - P_{4/3}),$$
$$t = T-1,.....,1$$

or

$$a_{3/4} = 3.5971+0.8286(4.4279-3.5971)/4.8286 \quad = 3.7396$$

$$P_{3/4} = 0.8286+(0.8284-4.8286)(0.8286/4.8286)^2 = 0.7108$$

similarly;

$$v_4 = Y_4 - a_3$$

$$e_4 = Y_4 - a_{4/4}$$

or

$$v_4 = 4.6 - 3.5971 = 1.0029$$

$$e_4 = 4.6 - 4.4279 = 0.1721$$

We can figure out all these values (Y_t, a_t, P_t, v_t, $a_{t/T}$, $P_{t/T}$, and e_t)

by using the following MATLAB programs:

1.

```
function k=kal33(y,r,z,q)
[a]=kal2(y,r,z,q); [b]=kal22(y,r,z,q);
a(:,6:8)=b(:,1:3); k=[a];
```

2.

```
function k=kel1(y,r,z,q)
b2=[ ];b3=[ ];b4=[ ];
h=max(size(y)); [a]=kal2(y,r,z,q);
p=a(:,3);  aa=a(:,4); ww=p(h); zz=aa(h);
l=y(h)-aa(h); g=[ww zz l]; for t=1:h-1
j(h-t)=p(h-t)+((p(h-t)/(p(h-t)+q))^2)*(ww-(p(h-t)+q));
k(h-t)=aa(h-t)+((p(h-t)/(p(h-t)+q))*(aa(h+1-t)-aa(h-
t)));
ww=j(h-t); zz=k(h-t); l=y(h-t)-zz;
b2=[b2 ww];b3=[b3 zz];b4=[b4 l];
end
d=[b2;b3;b4]'; d=[g;d]; for i=1:m
kk(i,1:n)=d(m+1-i,1:n);
end
k=[kk];
```

INITIAL VALUES AND KALMAN FILTER

Kalman filter needs some starting values. Many different method may be used to handle this point. [see Harvey (1989) and Otter (1985)] In order to have some insights regarding this point we have applied the following procedure :

i.Use a data set of 10 observations. (Y_t = 1,....,10)

ii. Use our initial values for a reference base. (P_0=12, a_0=4, q=4)

iii. Replace 0,1,10, and 100 for P_0, ceteris paribus. Save them separately.

iv. Replace 0,1,10, and 100 for a_0, ceteris paribus. Save them separately.

v. Replace 0,1,10, and 100 for q, ceteris paribus. Save them separately.

vi. Compare and contrast all results.

Computer outputs and corresponding graphs are in appendix to chapter 2.

CHAPTER 3

I.CYCLES

This chapter analysis the effect of a cycle in structural time series models. Inclusion of cycles into the structural time series models is not very common basically because of the testing difficulties. Testing the presence of a cyclical component in a structural model raises a number of issues. As underlined by Harvey (1989), "identifiability" is the first concern: Y_t may be analyzed as follows when a cycle is added to a white noise disturbance term;

$Y_t = C_t + \epsilon_t$ [1]

where C_t is the cyclical component.

A test for presence of a cycle in the above equation amounts to a test of $H_0 : \rho=0$ against $H_1 : \rho > 0$. However, when $\rho = 0$, C_t reduces to white noise and cannot be distinguished from ϵ_t. This problem is specially important for Wald and LR tests, but can be solved by dropping the ϵ_t from the unrestricted model in case of LM tests since the unknown frequency of the

1 This equation may include a stochastic trend and a seasonal, presence of such terms would not affect the analysis.

cycle (λ_c) poses no problem in the LM tests but does present a problem since when ρ is zero, λ_c is not identifiable even if the irregular term, ϵ_t , is dropped from the equation.

The best solution, as suggested by Harvey (1989) is to test for a cycle before estimating an unrestricted model.[1] These tests are specially valuable to minimize unnecessary computational difficulties, and to use a parsimonious models. On the other hand, there is an alternative for a researcher using a special software that easily figures out a model with cycle as well as the one without a cycle.[2] In this chapter, we have analyzed two different structural time series models by simply comparing the post estimation characteristics. With special software STAMP, we have first formed a structural time series model with a stochastic trend,

---

1 For a detailed explanation of tests see Harvey (1989) pp.234 -54.

2 STAMP (Structural Time Series Analyzer, Modeller and Predictor) is a good software that can be used for this purpose.

a seasonal, and an irregular component. Then we have included a cycle to the model and reestimated it. As a third step, we have compared all specification tests and irregular terms.

Basic feature of this analysis is to assume "stochastic trend". The superiority of this assumption may be understood better if compared with a "traditional trend" model. Neither detrending nor differencing achieves the flexibility of "stochastic trend". "Deterministic trend" is just a limiting case of "stochastic trend". (Harvey,A.C. 1989) This point is more important for models with explanatory variables. The part of the information that can not be captured by the deterministic trend (since it is not flexible enough) may be attributed to explanatory variable and creates an information bias. Same problem arises in specification problems; a less than perfect specification creates similar information bias by affecting distribution of information among trend, explanatory variable, cycle, and irregular. Even two "good" models would give us quite different information depending on specification differences. For instance, let us assume that we have two competing models, they both satisfy all necessary model specification tests, (such as normality, heteroscedasticity, autocorrelation, and Box-Ljung tests, as applied in this work) and have very close R2 and RD2[1] . Under the circumstances outlined, how one can choose the better model or which model is better? The variables in question are real wage and employment. The sample period in question is 1968 Q1-1990 Q1. Table 1. shows the first model's results and diagnostics. According to those statistics first model is acceptable overall, no single statistics is against the model specification except one autocorrelation (at lag 8) which is just outside of 5% confidence interval, but all Box-Ljung values are very satisfactory. They reject the null hypothesis of incorrect model specification, at 1% level , for all lags.

The examination of second model,(model with cycle) on the other hand, presents slightly better autocorrelations and Box-Ljung statistics. Normality

---

1 RD2 compares the prediction error variance with the sums of squares of the first differences about the mean. This is superior to R2, since R2 will be very close to unity in case of a strong upward or downward movement in the time series with a proper trend. Therefore, R2 is of a little value except when series are stationary. (Harvey 1989, pp 263-70)

test, although it is closer to the borderline, rejects the non-normality hypothesis.(see Table 3 and Table 4) Heteroscedasticity is at least as satisfactory as the one in the first model. R2 and RD2 are also slightly better.

One can easily conclude that, although they both are "good" models, second model is slightly "better" according to the model specification statistics and other statistics as well. (Compare Table 1. and 2. with Table 3. and 4.) A careful review of Table 1. and Table 3. or Figure 5. and Figure 11. shows that in the first model the coefficient of employment, EMP, is -.1955 while it is only -.1733 in the model with cycle. This difference is significant since the variables are in logs. First model which has no cycle component simply overestimates the real wage countercyclicality. Since the model can not capture the whole information, the lost information will be attributed partly to the explanatory variable and will stay partly in irregular component. If stochastic trend term can capture the whole information then nothing will be lost, and there will be no estimation bias. In this example, since the cycle is significant, stochastic trend cannot capture it with its limited step size. If the magnitude of a cycle is smaller than the stochastic trend's step size then there will be no information loss as well as estimation bias.

Before attempting to build two competing models, it is useful to compare a graph of the explanatory variable with the graph of the dependant variable. Employment is given in Figure 1. while real wage can be observed in Figure 2. This is particularly useful to see what properties the real wage has in common with the employment.

II. Structure of alternative models:[1]

A. A stochastic model with no cycle:

$$W_t = M_t + Z_t + EMP\ EE_t + \epsilon_t, \qquad t = 1,\dots\dots,T$$

where

$$M_t = M_{t-1} + B_{t-1} + N_t$$

$$B_t = B_{t-1} + R_t,^{2} \qquad t = \dots\dots,-1,0,1,\dots\dots$$

---

1 For an excellent discussion on model construction see: Harvey (1984) and Harvey,Henry,Peters,and Wren-Lewis (1986)

2 This process is a first order vector autoregression:

$$\begin{bmatrix} M_t \\ B_t \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} M_{t-1} \\ B_{t-1} \end{bmatrix} + \begin{bmatrix} N_t \\ R_t \end{bmatrix}$$

where

W_t is the real wage(observed), M_t is stochastic trend component, Z_t is seasonal component, EMP is the coefficient of employment which will be estimated, EE_t is employment(observed), ϵ_t is irregular component, (random and mutually uncorrelated with other disturbances.) N_t and R_t are mutually uncorrelated white-noises with zero means and variances $\sigma^2{}_N$ and $\sigma^2{}_R$, respectively. N_t allows level of the trend to shift up or down and R_t allows the slope to change.[1] Estimation of the unknown parameters handled by exact maximum likelihood estimation in time domain with numerical optimization carried out by quasi-Newton algorithm. Given the values of unobservable parameters obtained from the ML estimation, Kalman Filter provides the latest estimates of the state. Therefore the last value simply shows the estimates of the state vector at the end of the sample period.

---

1 Please note that the larger the variances, the greater the stochastic movement in the trend. If both variances are equal to zero, this process collapses to deterministic trend. (This also proves that deterministic trend is a limiting case.) (Harvey,A.C. 1989 Chp. 2)

Table 1.

Regression results and diagnostics for the model with no cycle		
Coefficient of EE (EMP)	:	- .1955
(t- ratio)	:	(- 2.6416)
Residual skewness	:	.3137
Residual kurtosis	:	3.7979
Normality chi-square (2)	:	3.6059[1]
Heteroscedasticity test F(28,28)	:	.4188
Mean of standardized residuals	:	- .0188
Prediction error variance	:	.0001
R2	:	.9931
RD2	:	.4213
Seasonality test Chi-Square(3)	:	21.8714

Heteroscedasticity is tested against F(T/3,T/3) although this distribution is only an approximation. (See Harvey,1989) Seasonality test is an overall significance test.This test is valid if the seasonal pattern is fixed.(i.e. unobserved seasonal state parameter is zero.) Seasonality test has a chi-square distribution with s-1 degrees of freedom where s is the number of seasons.

---

1 The standardized third and fourth moments (b1,b2) of the residuals about the mean are asymptotically normal, with

sqrt(b1) AN(0,6/T) and
b2 AN(3,24/T)

when the model is correctly specified. Therefore the statistics for normality is NOR = $(T/6)b1 + (T/24)(b2-3)^2$ Bowman and Shenton (1975)

First model yields a statistically significant negative coefficient, (EMP = -.1955, t = -2.6416) This coefficient represents the elasticity (employment on real wage) since the variables are in logs. Table 1. shows a satisfactory model specification and significantly countercyclical real wages. Simply, a 1% increase in employment creates .2% decline in real wages. Although there is no reason to revise the model, an alternative stands: What if there exist a cyclical behavior of real wages but we cannot capture it. This proposition never degrades our present model but implies an information bias which may be significant in long run forecasts. A simple observation of real wage data (Figure 2.) also supports the inclusion of a cycle to the model.(This is actually a benefit of structural models, we can analyze the salient feature of the series.)

Table 2.

Autocorrelations and Box-Ljung statistics

Lag----------0----------Autocorrelation----Box-Ljung (Q)			
1	|*	.034474	.1034
2	***|	-.100060	.9855
3	**|	-.064320	1.3540
4	|**	.083446	1.9830
5	**|	-.054887	2.2590
6	|**	.097960	3.1470
7	**|	-.060987	3.4960
8	******|	-.259444	9.8950
9	***|	-.144223	11.9000
10	**|	-.086162	12.6200
11	|*	.037786	12.7600
12	***|	-.108502	13.9500
13	|**	.082791	14.6400
14	***|	-.103747	15.7500
15	|**	.053237	16.0500
16	*|	-.034467	16.1800
17	|*	.018390	16.2100
18	**|	-.069616	16.7400

+++++0+++++
95% Confidence interval.

[2/sqrt (84) = .218218]

For the Box-Ljung Q-statistic, the appropriate distribution is chi-square with degrees with degrees of freedom given by (L-(NUS-1)) where L is the lag number and NUS is the number of nonzero unobserved state parameters.

Box-Ljung Q-statistic is the modified Box-Pierce statistic. Ljung and Box (1978). It is a "reliable" model specification statistics, although it is not "optimal". In model one, Box-Ljung Q-statistic is extremely supportive at any lag.

Figure 3. and Figure 4. show the actual and the fitted values and the normalized residuals of the model with no stochastic cycle, respectively. The obtained fit is very satisfactory.The stochastic trend component, Figure 5. smoothes the real wage series considerably. Figure 6. explains the exogenous component while Figure 7. shows the statistically insignificant seasonal component. Finally Figure 8. is the irregular component. It is stationary by definition.It is worth noting that the optimal estimator of the irregular component is zero. In other words, as long as we have an irregular component, the model is not optimal. This component simply contains the information which could not explained by the existing components of the model. (i.e. stochastic trend, seasonal, and explanatory variable.) This is the alternative of LM, LR, or Wald test for cyclical component. Inclusion of a component such as a cycle may reduce this irregular component to zero, as well as changing the present distribution of information among the components. An existing post estimation irregular component will imply the possibility of a "better"

model. What are the other possibilities : inclusion of a different type of seasonal component, or a cycle component (many different forms may be checked) may improve the model significantly.

Many alternative seasonal components as well as cycles should be tried before the conclusion, if optimality desired. (For these alternative forms and the possible effects, Harvey (1989) is an excellent reference.) Post estimation decomposition of these components are especially important. Unlike an ARIMA model, the interpretation of these components are quite easy.[1] One may simply want to observe the seasonal path or stochastic trend given the structure of a model. In here, for instance, trend component in the first model (Figure 5.) and the trend component in the second model(Figure 11) follow quite different paths. The stochastic trend in "no cycle" model simply tries to capture the movement caused by cycle, but can not capture it entirely. This effort makes the trend seems like smoothed observations. In the other model, trend only captures the general tendency of the

1 For differences and similarities between some unobserved component models and ARIMA models see Watson, M.W.(1986)

data, and cyclical fluctuations are explained by stochastic cycle. (Figure 14.) As a result, trend in the second model yields more reliable information on tendency.

B. A stochastic trend model with cycle :

$$W_t = M_t + Z_t + EMP\ EE_t + C_t + \epsilon_t \quad , \qquad t = 1,.....,T$$

where

W_t, M_t, Z_t, h, EE_t, and ϵ_t are as in previous model.

C_t is a cycle component.

(C_t is in its usual form, see chapter 1)

Table 3.

Regression results and diagnostics for the model with cycle

Coefficient of EE (EMP)	:	- .1733
t- ratio	:	-2.1404
Residual skewness	:	- .3780
Residual kurtosis	:	4.3952
Normality chi-square(2)	:	8.8136
Heteroscedasticity test F(28,28)	:	.4010
Mean of standardized residuals	:	- .0240
Prediction error variance	:	.0001
R2	:	.9652
RD2	:	.4548
Seasonality test Chi-Square(3)	:	19.1640

The regression with cycle (form of the cycle is explained in appendix) yields a negative and statistically significant coefficient. (EMP = -.1733, "t" = -2.1404)

Now, a 1% increase in employment causes 0.1733% decline in real wages.[in case of an employment increases of 10%, our first model expects a real wage decrease of 1.95% while the second model expects only 1.73%] There is only, approximately, quarter of a 1% difference in the estimated coefficient in case of a remarkable 10% change in employment.

At this point one may ask the benefit of searching a better model over an already qualified one. Of course the difference in the estimated coefficient is not crucially important. On the other hand, second model is an "optimal" one while the first is not.

Table 4.

Autocorrelations and Box-Ljung statistics

```
Lag---------0----------Autocorrelation----Box-Ljung (Q)
1          *|                -.035881            .1121
2           |**               .070508            .5500
3           |**               .052144            .7925
4           |****             .182156           3.7890
5          *|                -.025897           3.8500
6           |****             .157842           6.1580
7           |*                .013912           6.1760
8        ***|                -.148303           8.2660
9          *|                -.017483           8.2960
10         *|                -.018162           8.3280
11          |***              .120195           9.7580
12        **|                -.077961          10.3700
13          |****             .165174          13.1400
14        **|                -.079298          13.7900
15          |***              .107459          15.0000
16         *|                -.019513          15.0400
17          |**               .073373          15.6200
18        **|                -.070802          16.1700
       +++++0+++++
       95% Confidence interval
```

[2/sqrt(84) = .218218]

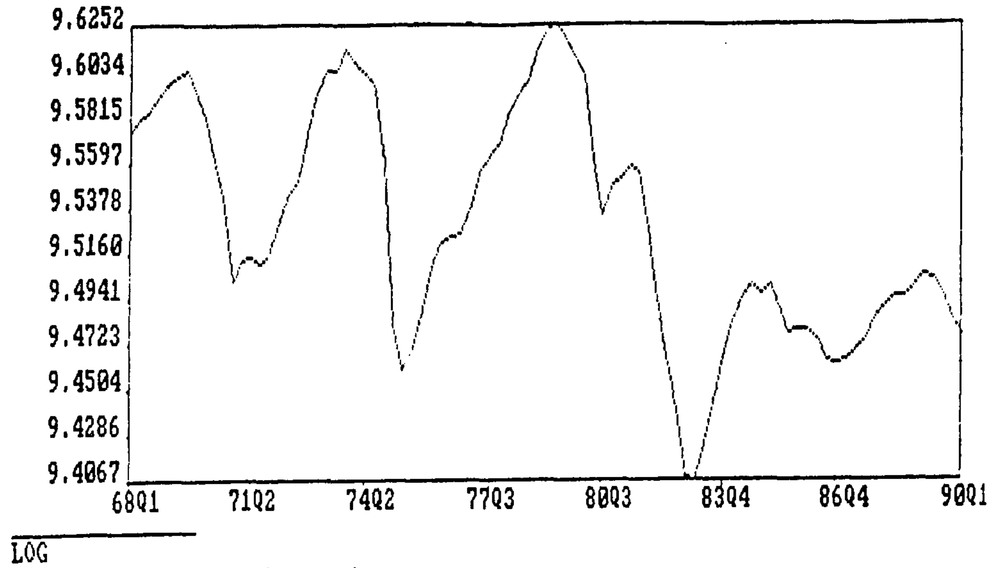


Figure 1. The employment

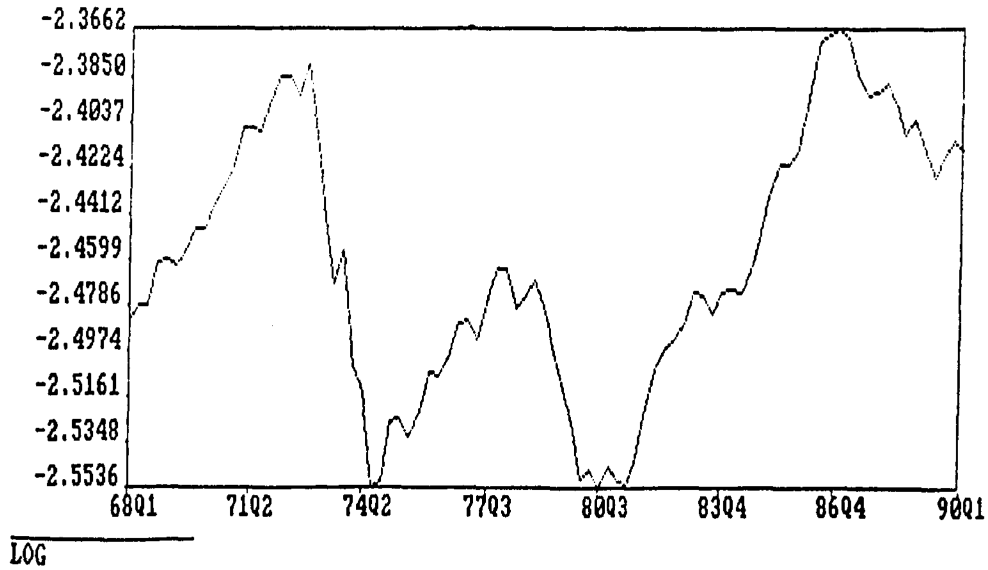


Figure 2. The real wage

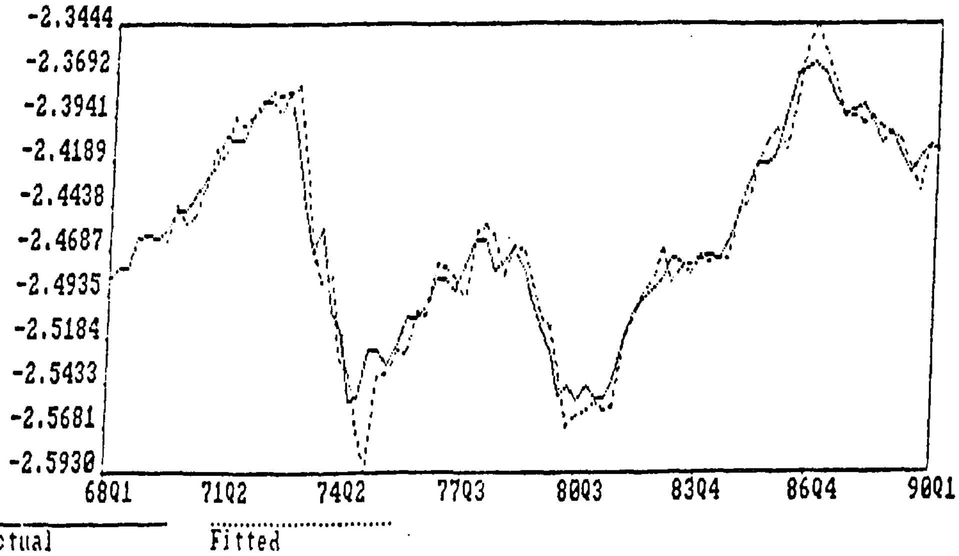


Figure 3. Actual and fitted values of real wage

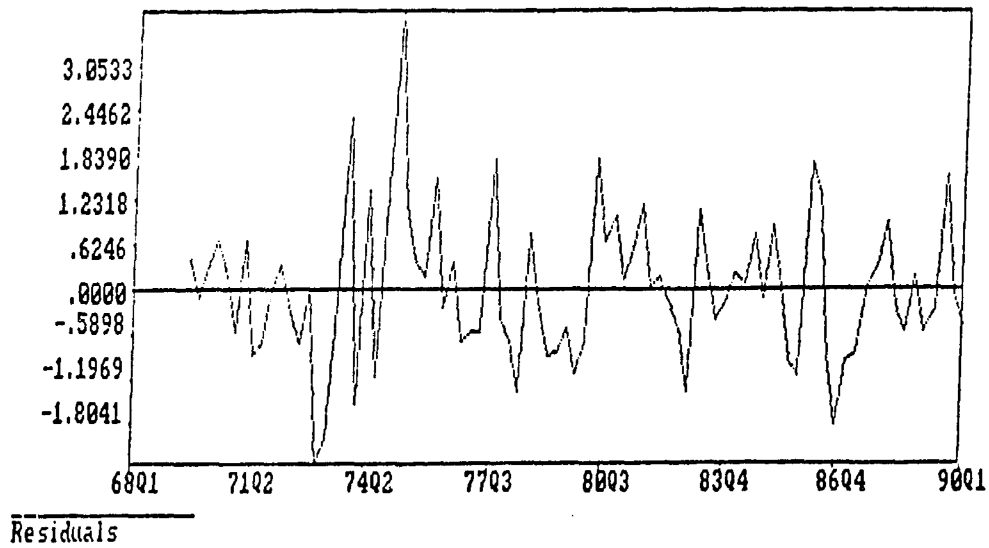
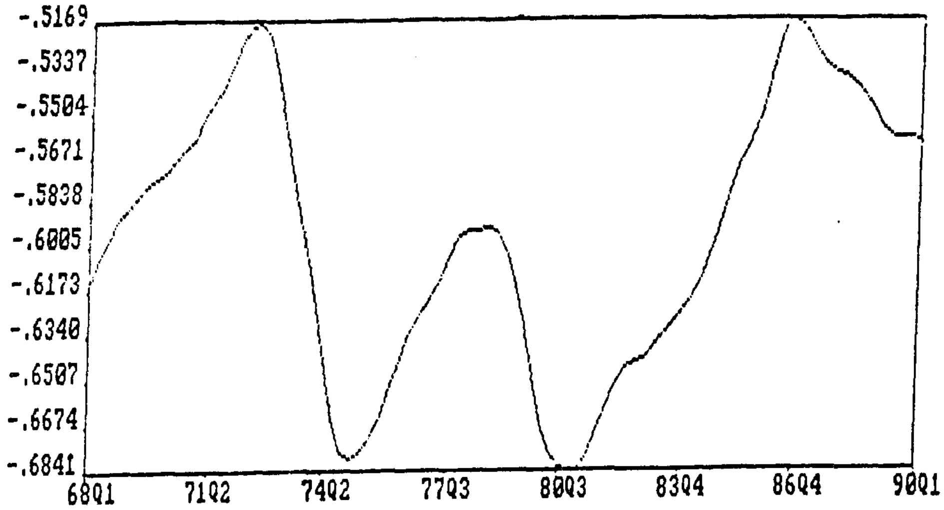
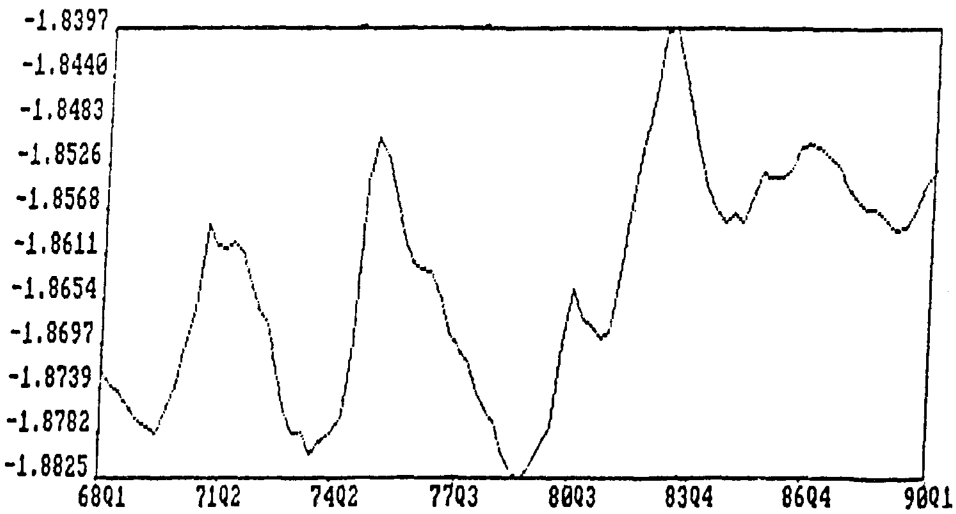


Figure 4. Normalized residuals



Trend

Figure 5. Trend Component



Exogenous

Figure 6. Exogenous component

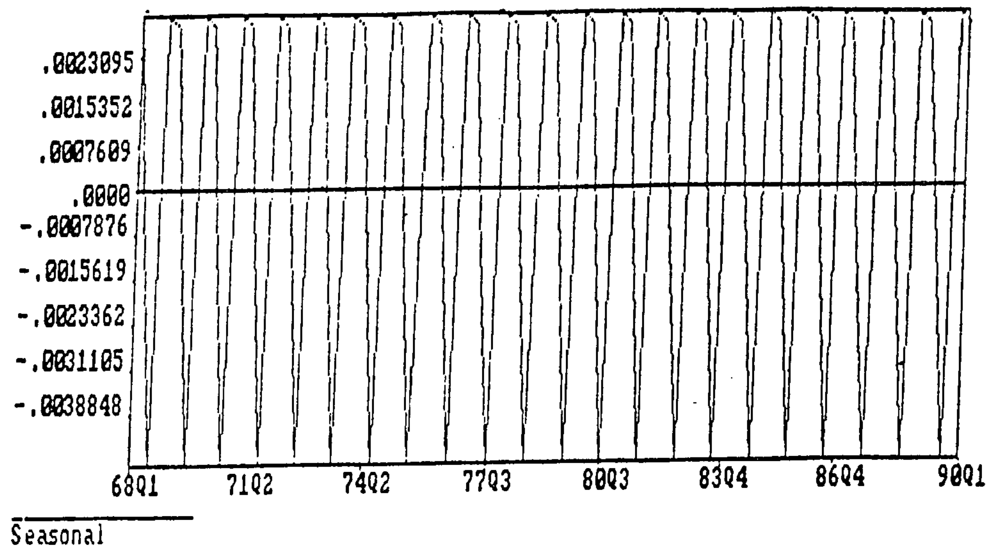


Figure 7. Seasonal component

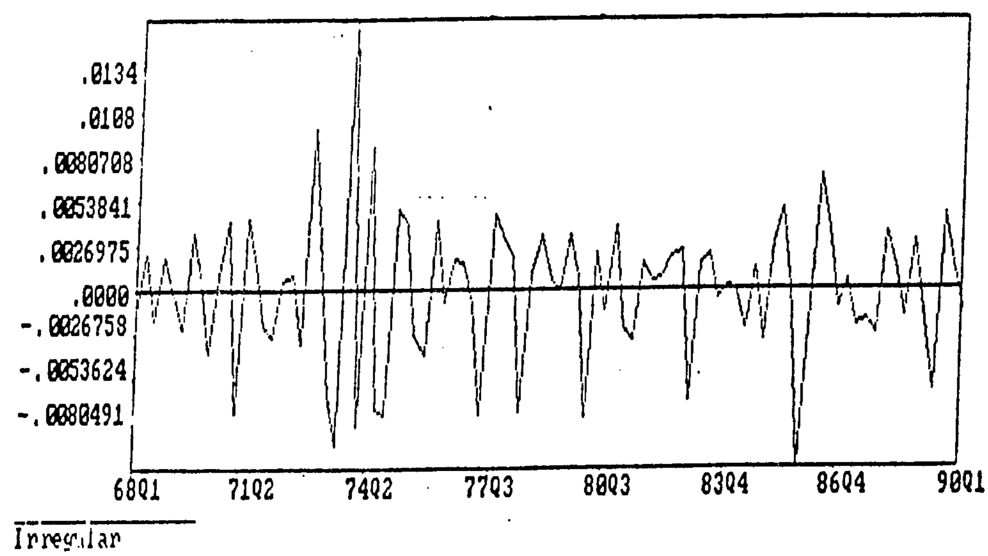


Figure 8. Irregular component

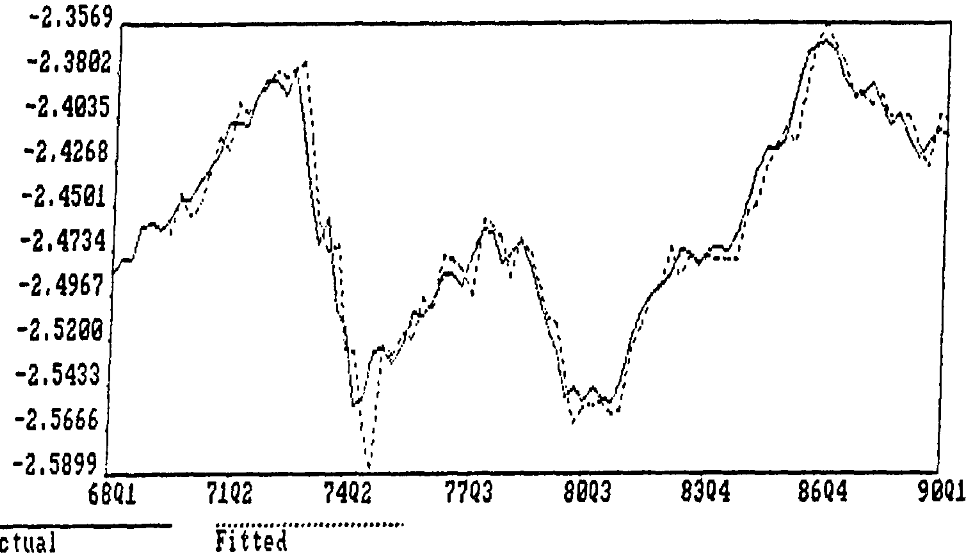


Figure 9. Actual and fitted values of real wage
(Model with cycle)

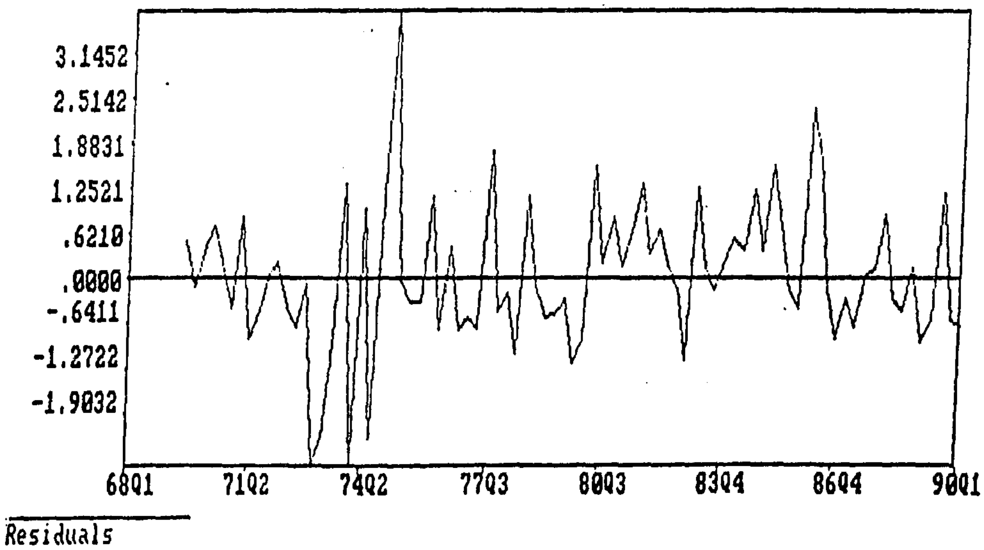


Figure 10. Normalized residuals
(Model with cycle)

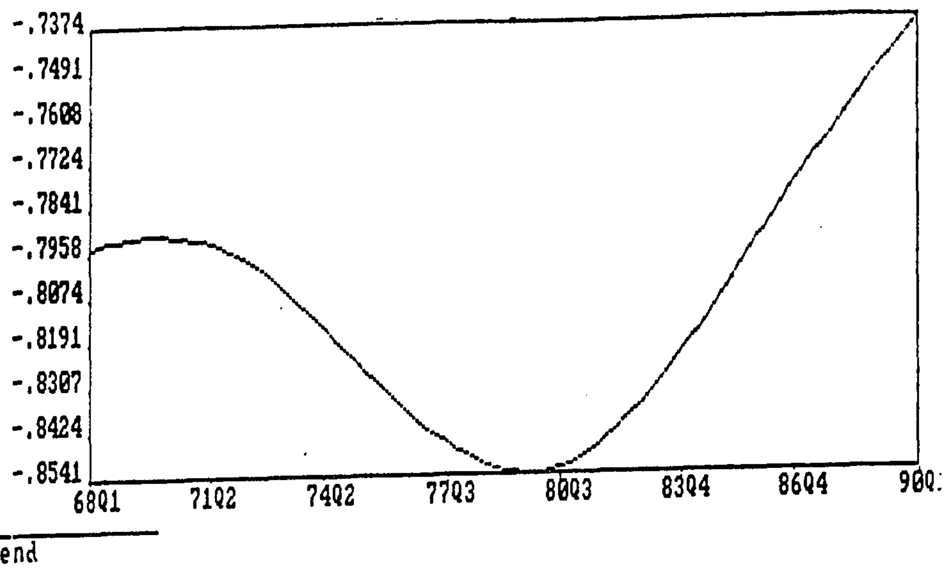


Figure 11 Trend component
(Model with cycle)

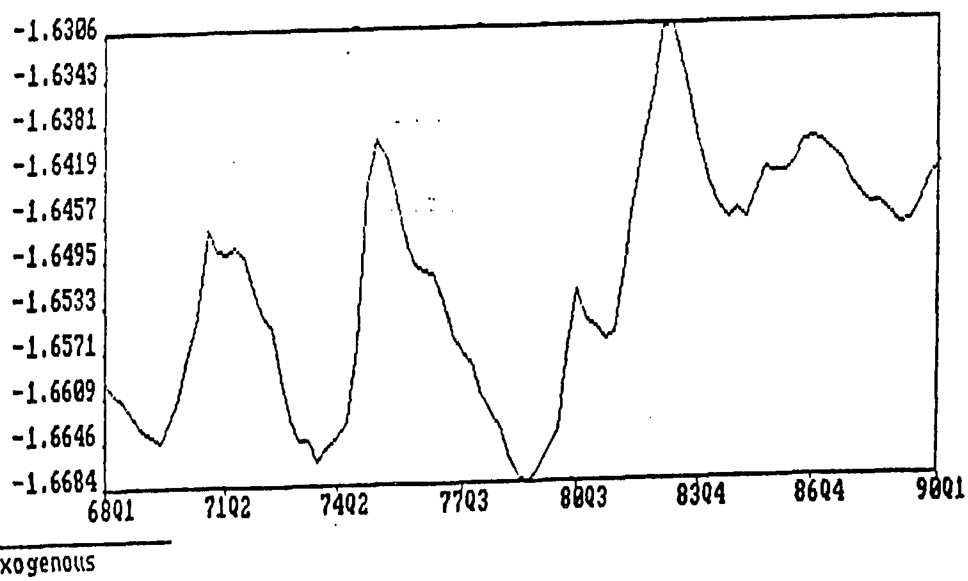


Figure 12 Exogenous component
(Model with cycle)

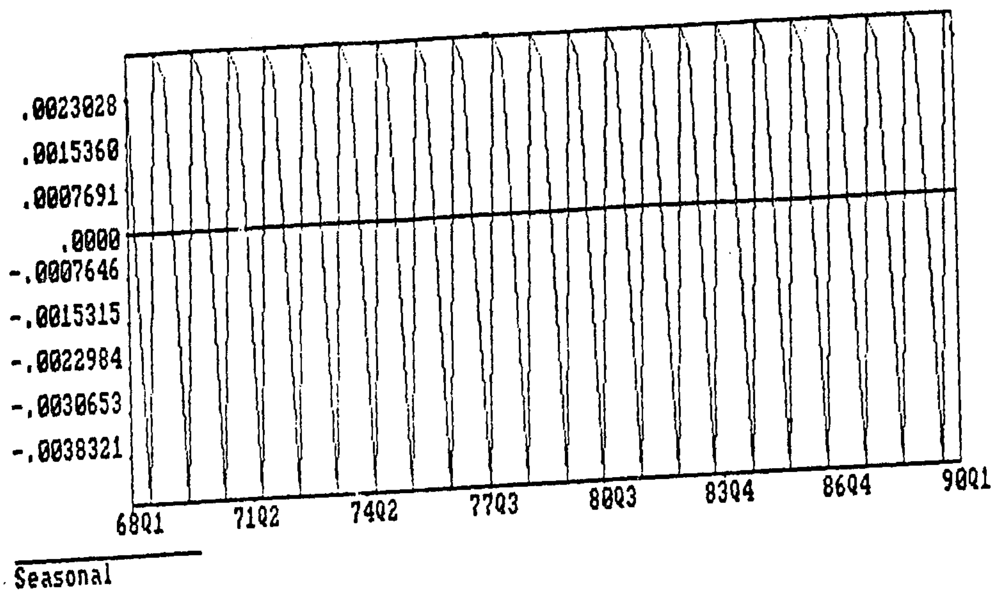


Figure 13. Seasonal component (Model with cycle)

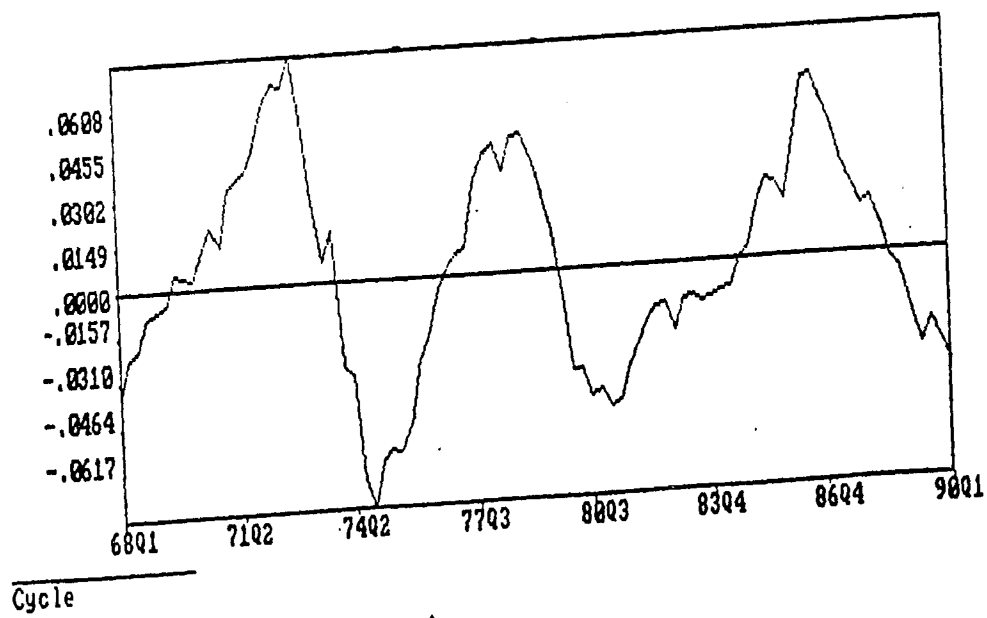


Figure 14. Cyclical component (Model with cycle)

CHAPTER 4

THE MODEL

In this section, first, a model for the period of 1947Q1-1990Q1 has been constructed and then estimated. This is the longest period examined in this study. As a next step, this period was divided to some subsections according to the information given by trial regressions. So, first duty was to decide about these subsections. Consequently, separate regressions have been run for these subsections and all results have been saved to analyze and compare later.

Table 5

Regression of REAL WAGE on EMPLOYMENT.

General information on model

EMP	:coefficient of employment. (time invariant)
WAGE	:"Average Hourly Earnings Excluding Overtime per Production Worker on Payroll of Manufacturing Establishments"
R.WAGE	:Real Wage = WAGE / PPI
PPI	:Producer Price Index, all commodities.
EMPLOYMENT	:Production Workers in Manufacturing Establishments.
Sample period	: 1947Q1-1990Q1 (quarterly data)

Variables are in logs. All regressions are in time-domain.

All models are with stochastic trend, stochastic slope, trigonometric seasonal, and irregular. Same model specification has been used to compare different periods. (This implies that rather than looking for best model in each different sample period, the most parsimonious satisfactory model settings has been used to create consistent comparisons.)

Table 6

Regression results

parameter	estimate	t-ratio
σ^2_N (level)	.0000899	6.6334
σ^2_R (slope)	.0000197	2.9257
σ^2_ϵ (irregular)	.0000000	.0000

state	estimate	t-ratio
Level	-1.2145000	-2.4913
Slope	-.0025580	-.3491
EMP	-.1271000	-2.4720

To summarize the results of first regression, we have shown that EMP is negative and statistically significant. Since the variables are in logs, -.1271 is the elasticity of real wage with respect to employment.

Computer output (STAMP) for this regression is in the appendix to chapter 4.

As a second step, we have to decide if this result is totally independent of the sample period chosen? To answer this question we have to apply the following procedure:

a) start with a base period of 47Q1-56Q4 (which is a 10-year period with 40 quarterly observations) and save EMP,

b) expand this period three years at each time, save EMPs.

Table 7

Expansion table

sample size		EMP	t
47Q1-56Q4	:	-.2644	-2.427
47Q1-59Q4	:	-.1674	-1.943
47Q1-62Q4	:	-.1291	-1.720
47Q1-65Q4	:	-.1413	-2.084
47Q1-68Q4	:	-.1459	-2.324
47Q1-71Q4	:	-.1283	-2.223
47Q1-74Q4	:	-.0512	- .812
47Q1-77Q4	:	-.1226	-2.043
47Q1-80Q4	:	-.1179	-2.048
47Q1-83Q4	:	-.1189	-2.210
47Q1-86Q4	:	-.1235	-2.345
47Q1-90Q1	:	-.1271	-2.472

These results imply that EMP is negative and mostly statistically significant. Expanding the initial 10 years sample period does not have significant effects on this coefficient. On the other hand, this procedure raises the following question: Is the base period properly chosen? By adding 3 years at a time,it would be difficult to affect a negative coefficient produced by 10 years.Therefore one may ask, if there is any other base period of 10 years that yields a positive EMP. To understand this, the following procedure has been applied:

Divide the entire sample period to 10-year-long sub-samples and run separate regressions for each of these periods:

Table 8

Four sub-samples

sample period		EMP	t	
47Q1-56Q4	:	-.2644	-2.42	negative base
57Q1-66Q4	:	.1081	1.82	positive base
67Q1-76Q4	:	-.1918	-1.80	negative base
77Q1-90Q1	:	-.1727	-1.60	negative base

Table 8. shows that 57Q1-66Q4 is a 10-year-base which has a positive EMP. Although "t" values are not satisfactory this information is valuable as an initial step.

Second step is to expand this period.

Following procedure has been employed for this purpose:

Expand the sample backward with one-year frequency

Save EMP at each time.

Stop when EMP turns out to be negative.

Expand the sample forward with one-year frequency.

Save EMP at each time.

Stop when EMP turns out to be negative.

Table 9

Expansions of 57Q1-66Q4

sample period		emp	t
57Q1-66Q4	:	.1081	1.829
56Q1-66Q4	:	.0877	1.510
55Q1-66Q4	:	.0843	1.627
54Q1-66Q4	:	.0758	1.666
53Q1-66Q4	:	.0764	1.860
52Q1-66Q4	:	.1353	3.167
51Q1-66Q4	:	.1244	2.793
50Q1-66Q4	:	.0394	.556
49Q1-66Q4	:	-.0837	-1.308
48Q1-66Q4	:	-.1230	-1.935
47Q1-66Q4	:	-.1461	-2.210

stop at 50Q1-66Q4 and proceed opposite direction

Table 10

Expansions of 56Q1-67Q4

sample period		emp	t
56Q1-67Q4	:	.0492	.957
56Q1-68Q4	:	.0519	1.047
56Q1-69Q4	:	.0537	1.070
56Q1-70Q4	:	.0508	1.098
56Q1-71Q4	:	.0543	1.189
56Q1-72Q4	:	.0440	1.008
56Q1-73Q4	:	.0957	1.461
56Q1-74Q4	:	.1220	2.016
56Q1-75Q4	:	-.0396	- .611
56Q1-76Q4	:	-.0428	- .720
56Q1-77Q4	:	-.0388	- .624

stop at 57Q1-74Q4.

Final step is to combine these two way progress and find out the _widest_ sample period that yields a positive EMP. Table 11. shows the _widest_ sample period with positive EMP and the positive EMP period with the highest "t" value.

Table 11

"Widest" and "most significant 't'" periods.

sample period		emp	t
50Q1-74Q4	:	.0605	.975
52Q1-66Q4	:	.1353	3.167

If a researcher , by chance, runs a regression for 50Q1-74Q4 he would obtain a positive EMP. (statistically insignificant) If researcher uses some shorter sub-samples within 50Q1-74Q4 he would possibly obtains statistically significant (+) EMP.

It is not difficult to see that by proceeding toward edges "t" values get smaller since we get closer to the negative EMP. regions. Therefore a shorter sub-sample within 50Q1-74Q4 may normally give a significant "t".

Please note that inclusion of 1951, 1952, and 1974 significantly affects the value of EMP. So these years must be dominated by supply shocks. On the other hand, turning points, (the years that value of EMP declines significantly) 1950 (EMP declines from .1244 to .0394 and then becomes continuously negative) and 1975 (EMP declines from .1220 to -.0396) must be the years dominated by significant demand shocks. Another important point is that if we start with a base which initially has a negative EMP value, expanding the sample size to both directions never makes this value positive. In other words, demand shocks definitely have relatively stronger effect on EMP.

[i.e. If a negative base is expanded to a supply shock dominated range, EMP only gets smaller in absolute value, but if a positive base is expanded to a demand shock dominated range, EMP gets smaller pretty fast and eventually its sign becomes negative.]

On the other hand, while most of the negative EMPs are statistically significant, only a few positive EMPs are statistically significant. (see corresponding "t" values)

Table 12

Expansion table of the negative base
67Q1-76Q4

sample period		emp	t
67Q1-76Q4	:	-.1919	-1.802
67Q1-77Q4	:	-.1980	-1.911
67Q1-78Q4	:	-.2000	-1.980
67Q1-79Q4	:	-.1831	-1.837
67Q1-80Q4	:	-.1975	-2.110
67Q1-81Q4	:	-.1968	-2.243
67Q1-82Q4	:	-.1985	-2.347
67Q1-83Q4	:	-.1838	-2.384
67Q1-84Q4	:	-.1888	-2.535
67Q1-85Q4	:	-.1872	-2.550
67Q1-86Q4	:	-.1836	-2.445
67Q1-87Q4	:	-.1906	-2.533
67Q1-88Q4	:	-.1898	-2.570
67Q1-90Q1	:	-.1964	-2.713

stop, no data after 90Q1, proceed opposite direction

see figure 18

Table 12 cont'd

Expansion table of the negative base 67Q1-76Q4

sample period		emp	t
66Q1-90Q1	:	-.2004	-2.838
65Q1-90Q1	:	-.1912	-2.510
64Q1-90Q1	:	-.1878	-2.551
63Q1-90Q1	:	-.1857	-2.602
62Q1-90Q1	:	-.1845	-2.731
61Q1-90Q1	:	-.1835	-2.728
60Q1-90Q1	:	-.1564	-2.446
59Q1-90Q1	:	-.0934	-1.456
58Q1-90Q1	:	-.0789	-1.339
57Q1-90Q1	:	-.0615	-1.076
56Q1-90Q1	:	-.0633	-1.144
55Q1-90Q1	:	-.0564	-1.035
54Q1-90Q1	:	-.0530	-1.009
53Q1-90Q1	:	-.0429	- .850
52Q1-90Q1	:	-.0153	- .313
51Q1-90Q1	:	-.0174	- .359
50Q1-90Q1	:	-.0682	-1.306
49Q1-90Q1	:	-.0919	-1.815
48Q1-90Q1	:	-.1022	-2.029
47Q1-90Q1	:	-.1271	-2.473

stop, no data before 1947Q1.

As a next step we focused on those important turning points such as 47-52 and 73-76. In order to follow the change in EMP in detail, it is appropriate to pay particular attention to these turning points. A careful observation of Figure 22, or Figure 23-26 significantly relates the GNP-PPI relationship with the real wage-employment relationship.

At this point, we should recall the Sumner and Silver (1989). In this article, there are many questions unanswered and directions to go in. Sumner and Silver have been checked the signs of change in inflation rate and change in unemployment to distinguish between a supply shock and a demand shock. If these two variables have similar signs [(+)(+) or (-)(-)] that means AD (aggregate demand) shifts to left or right, so this is a demand shock. If the signs, on the other hand, appears to be opposite for the same year it shows the shift of AS (aggregate supply) along the AD, so this must be a supply shock. Further they save the supply shock years and demand shock years separately and run a separate regression for each. Finally they found (+) EMP for collected supply shock years and (-)

EMP for collected demand shock years. While this result appears to be meaningful, beside using annual data, their methodology suffers from another two basic points:

1) They certainly disturb the time dimension therefore their study must be considered as a cross section work rather than time series. As a result a (-) or (+) coefficient cannot be interpreted meaningfully: they are valid if we have only supply shocks or demand shocks.
2) They just check the signs. In their analysis (-.001)(-.01) and (-1)(-2) they both are demand shocks, but in reality second demand shock is more than 100 times stronger than the first one.
   In addition to this, sizes and relative sizes of these fluctuations are extremely important and it is quite possible to make dramatic mistakes, if disregarded. As an example, assume we are analyzing an AD-AS graph which has PPI at vertical axis and Real GNP at horizontal axis. If we check change in PPI (ΔPPI) and change in Real GNP (ΔGNP), and if we have a negative demand shock, then following outcomes are possible :

Table 13

Possible outcomes

	Δ ppi	Δ gnp
1)	-.001	-.85
2)	-.001	-.00001
3)	-.89	-.86

It is quite easy to see that in 1) PPI falls very insignificantly while GNP falls significantly. This could be the result of two totally different phenomena:

a)Combination shock : While AD shifts to left, AS shifts to left as well. ....Figure 20
b)A demand shock accompanied by a very elastic AS..............................Figure 21

on the other hand, in 2) demand shock is very insignificant so it may not have any significant effect to any economic variable. And, finally in 3) we have a significant (-) demand shock. [In other words, Sumner and Silver should care about this shock and should eliminate the others; but they cannot do this by just

Figure 15.

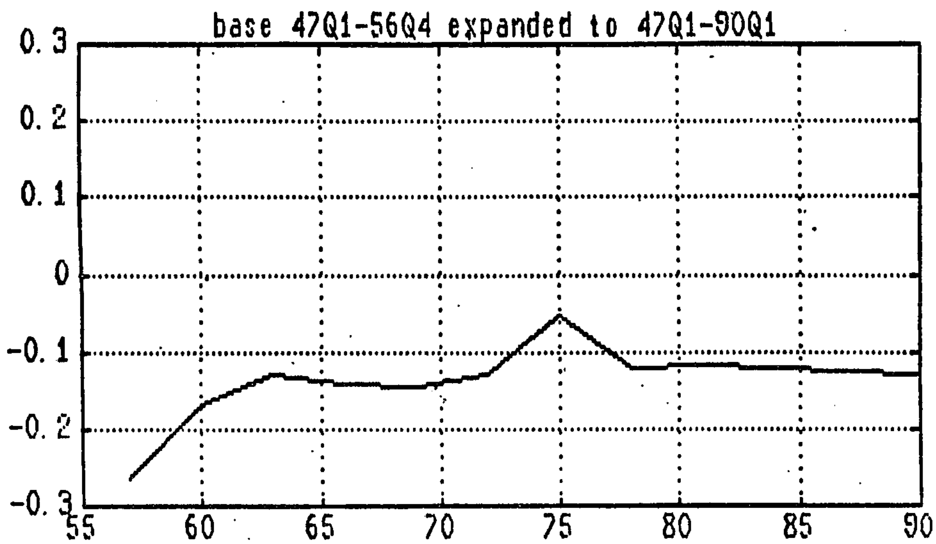


Figure 16.

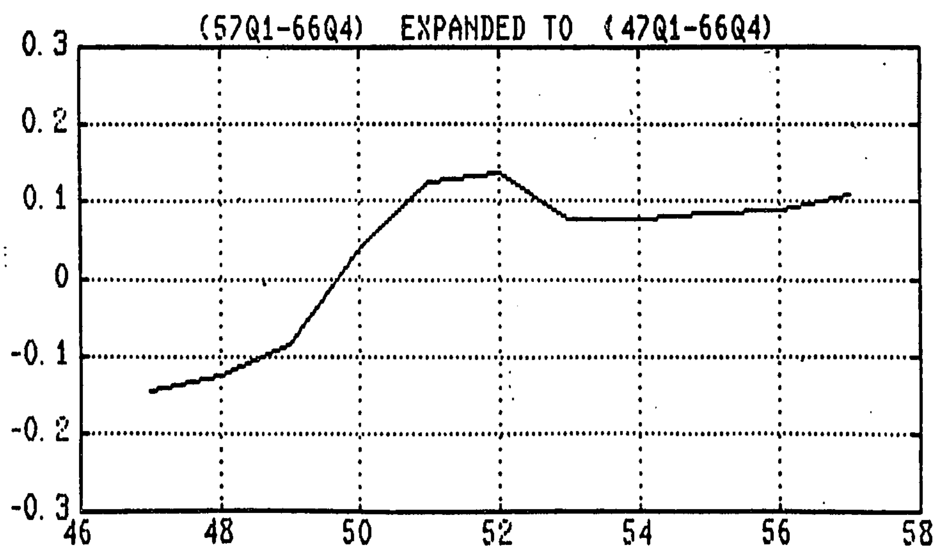


Figure 17.

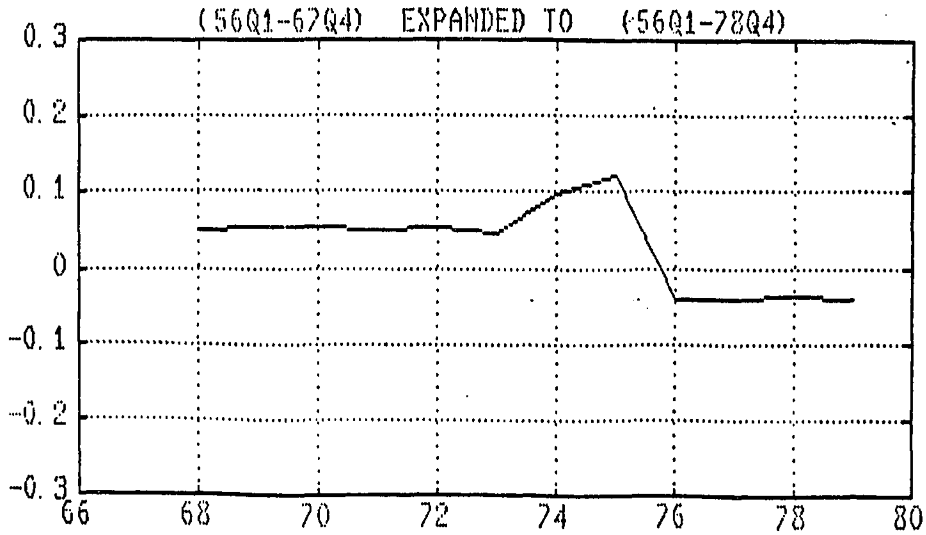


Figure 18.

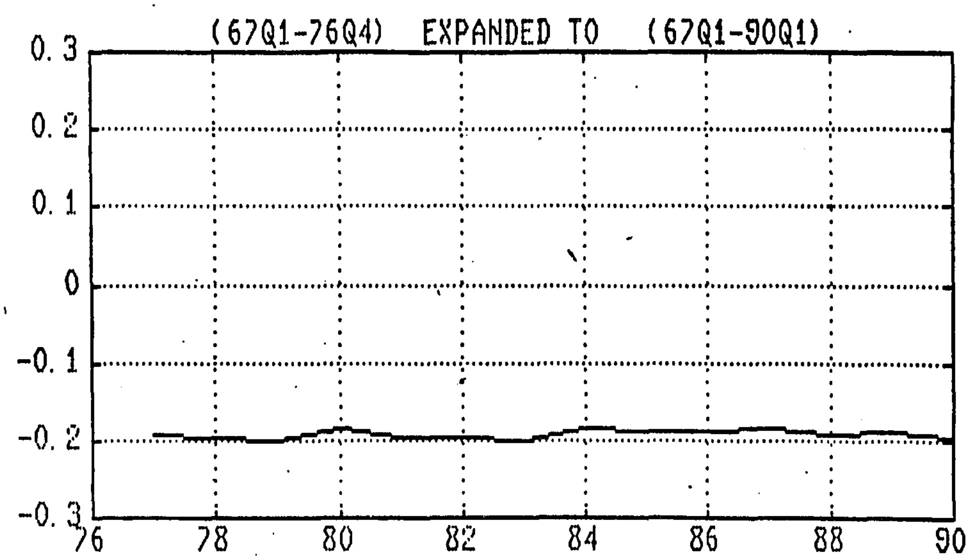


Figure 19.

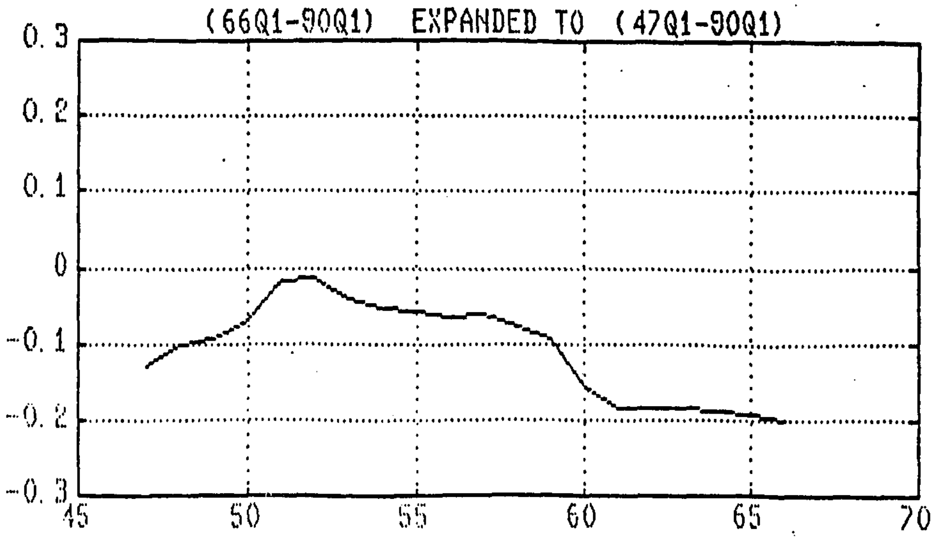

(66Q1-90Q1) EXPANDED TO (47Q1-90Q1)
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
45
50
55
60
65
70

Figure 20. Simultaneous shifts in AD and AS

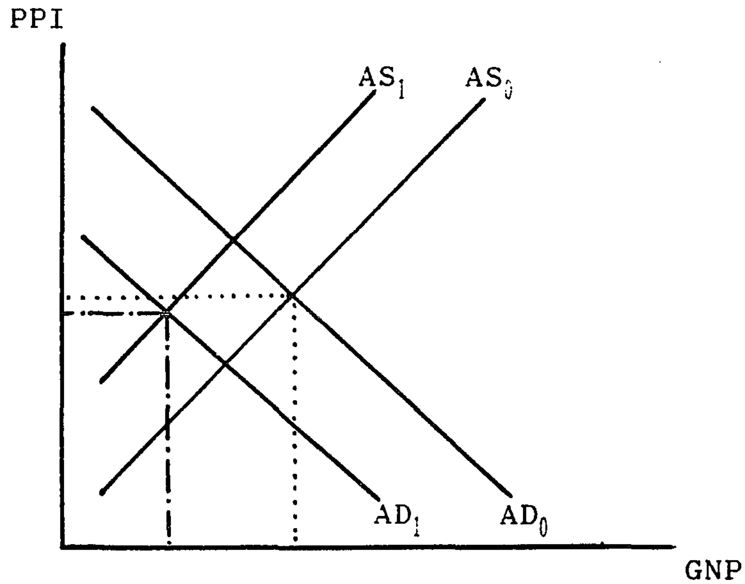
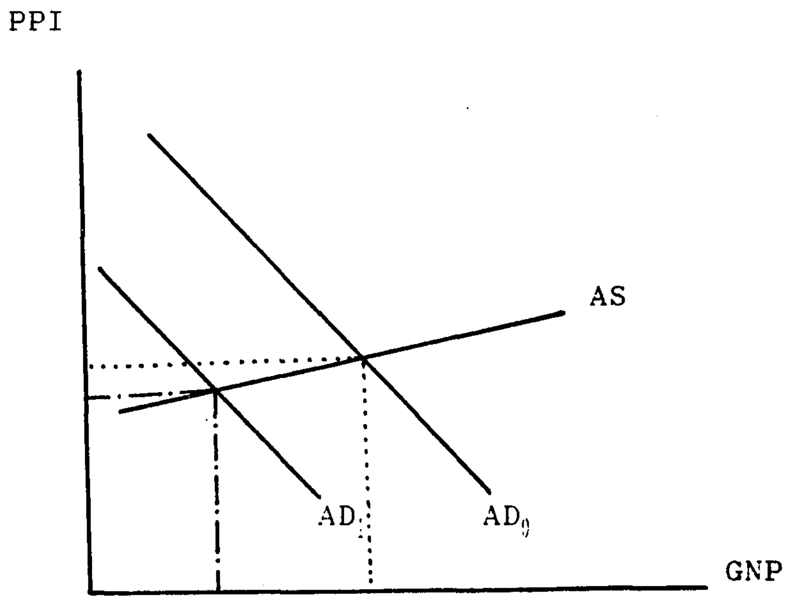


Figure 21. Flatter AS curve



looking at the signs.] In order to eliminate these problems we obtained the overimposition of ΔPPI and ΔGNP. (Figure 22) Since it is hard to follow the Figure 22, four partial magnified figures (Figure 23,24,25,and 26) are used.

This information is very useful for the following reasons :

1) We can observe the relative sizes and tendencies of the shocks over time.

2) We can easily eliminate the combination shocks. (But we do not have any information on the slopes of AD and AS.)

3) We can observe several different shocks in one year so we do not have to make misleading aggregation because of using annual data instead of quarterly.

Please note that Figure 16,19,25 and Figure 15,17,18,22 should be analyzed together. First group explains 47-51 period while the second one explains 73-76.

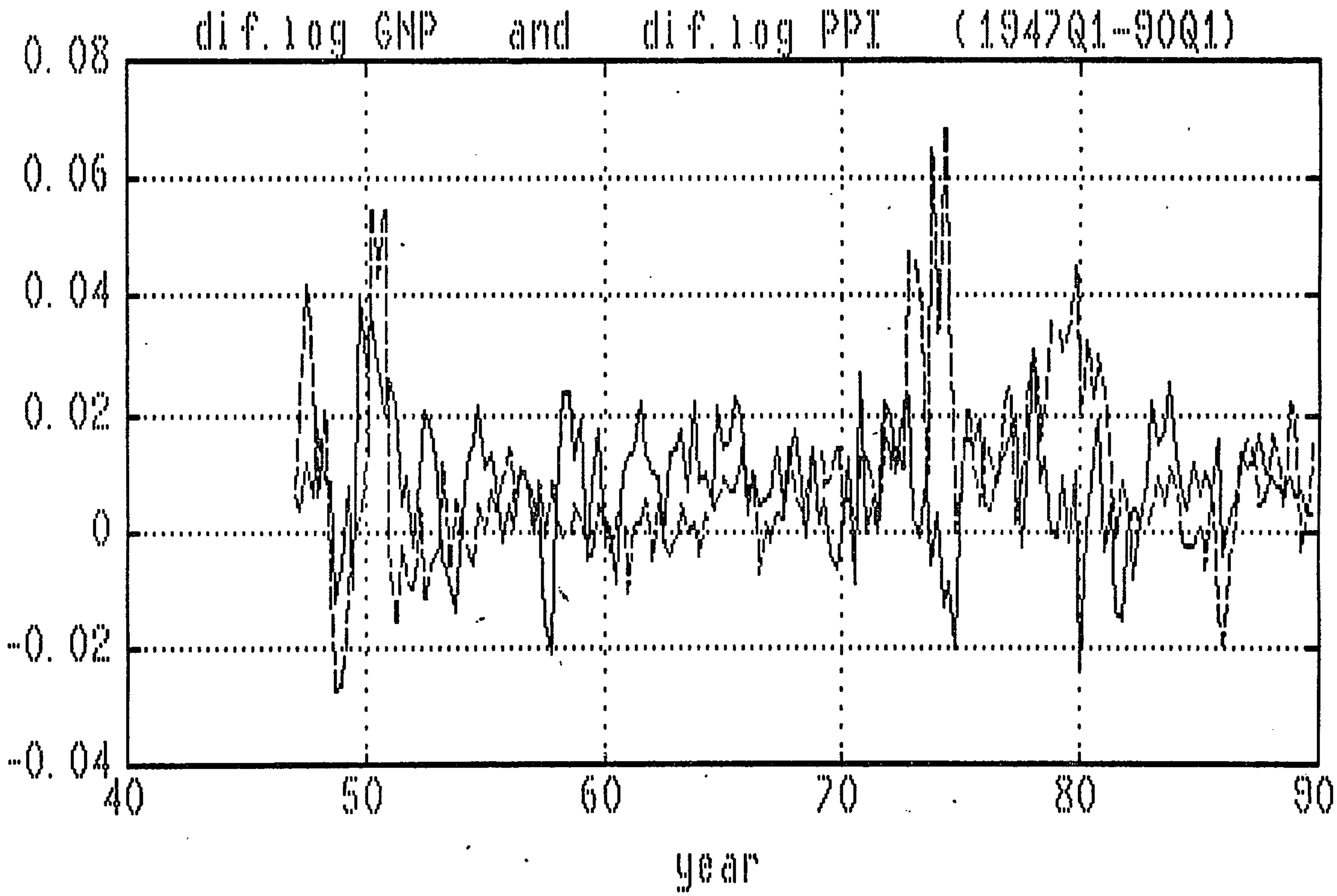


Figure 22. Difference in log GNP and difference in log PPI - 1947Q1-90Q1

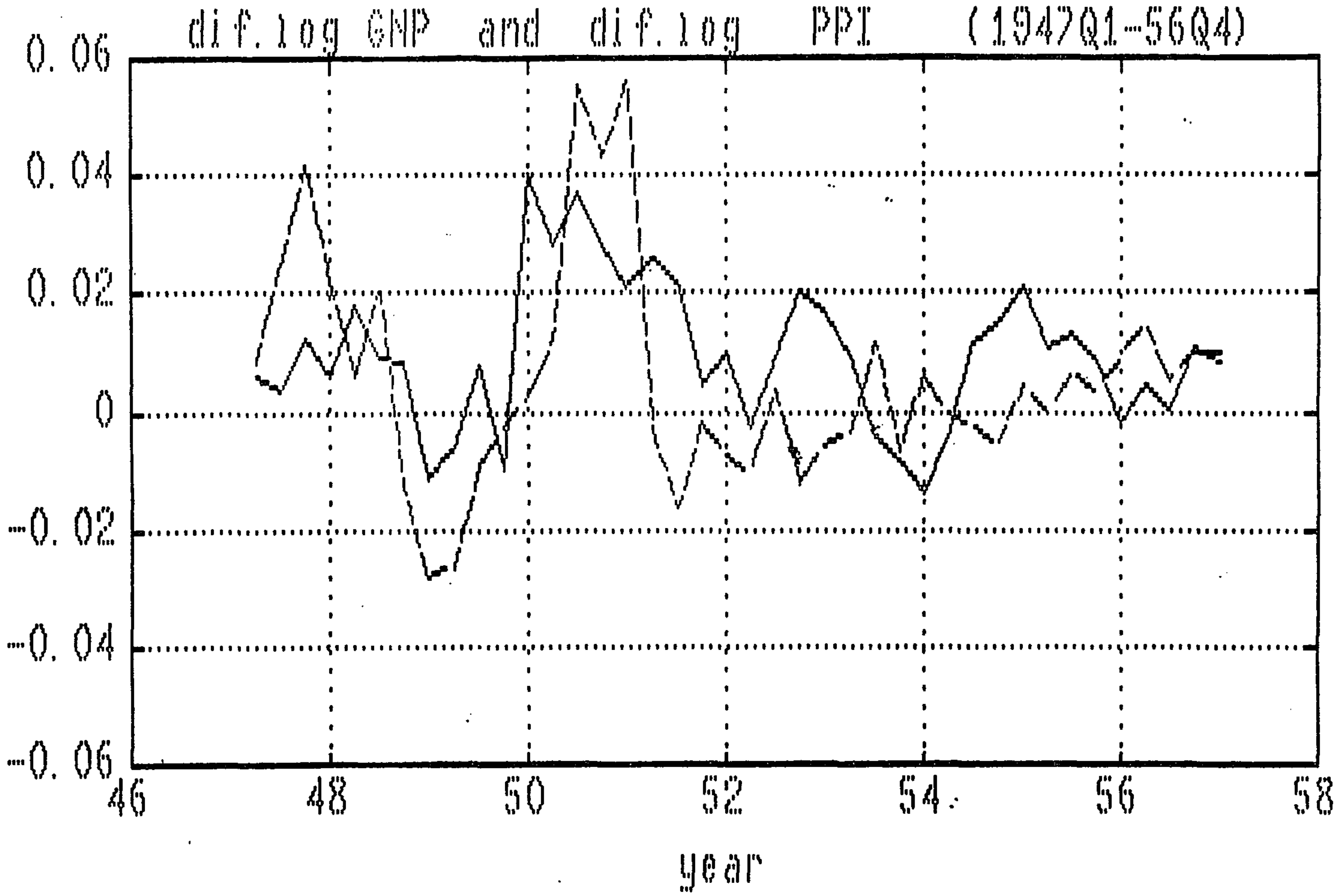


Figure 23. Difference in log GNP and difference in log PPI - 1947Q1-56Q1

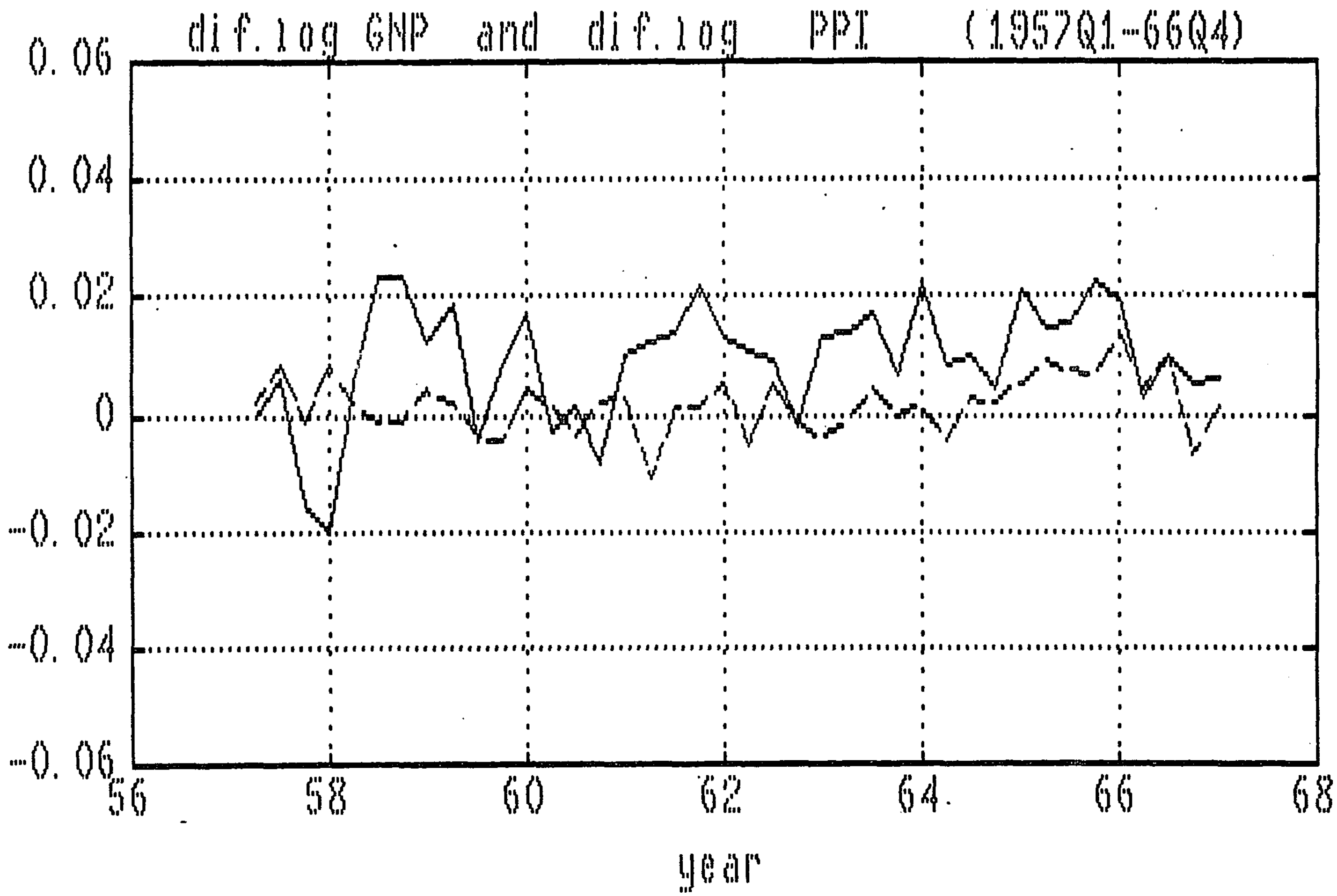


Figure 24. Difference in log GNP and difference in log PPI - 1957Q1-66Q1

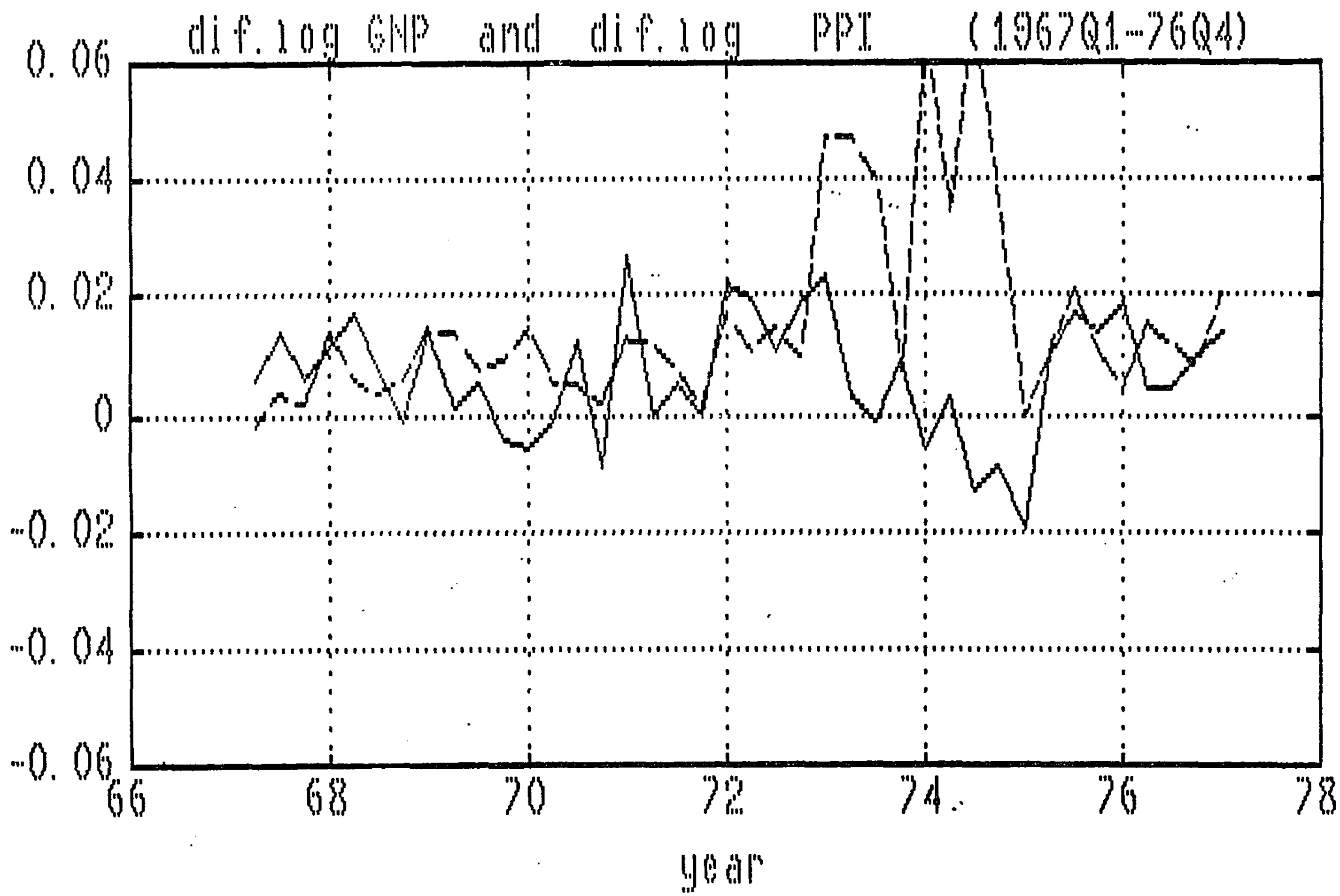


Figure 25. Difference in log GNP and difference in log PPI - 1967Q1-76Q1

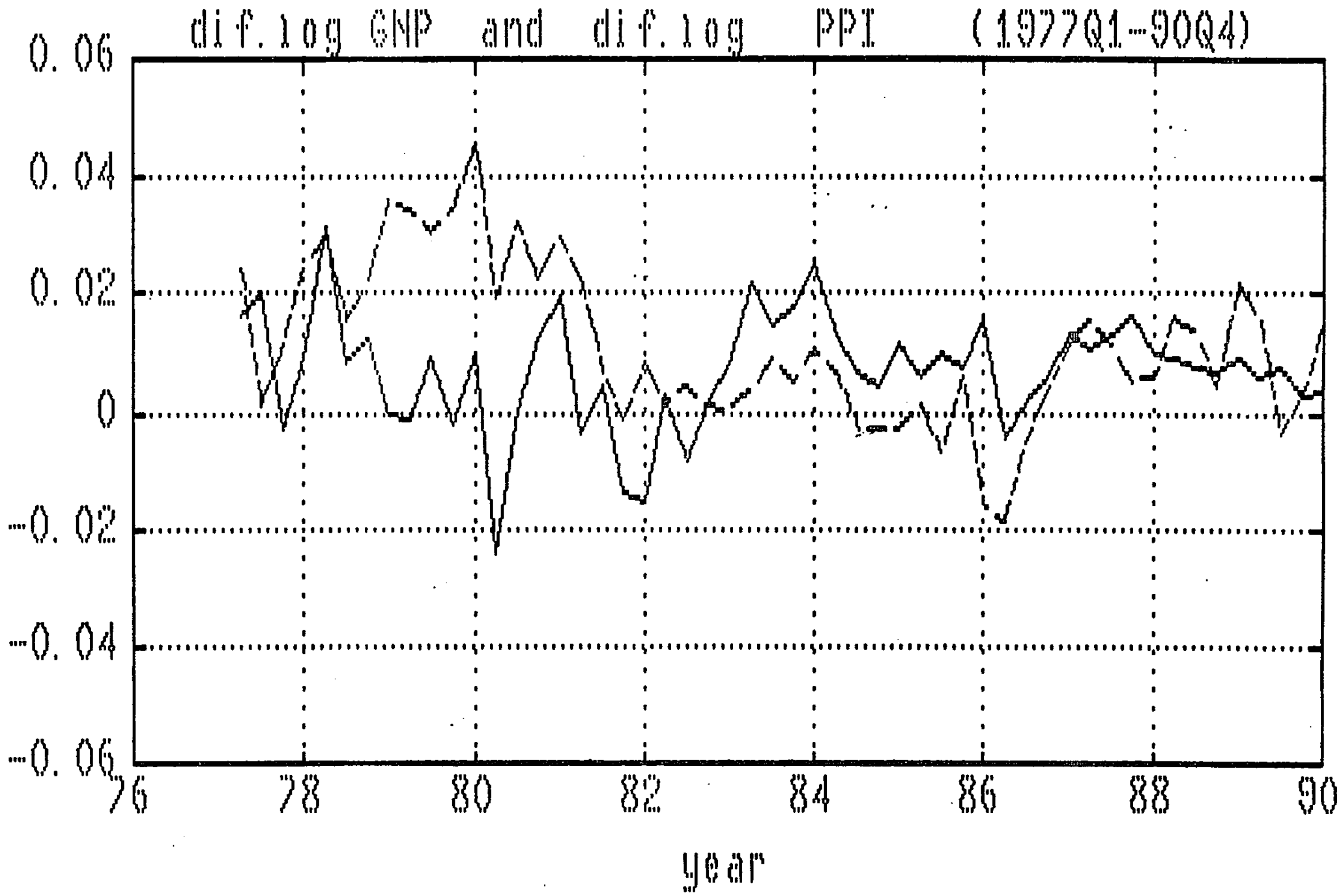


Figure 26. Difference in log GNP and difference in log PPI - 1977Q1-90Q1

This study concludes that :

1) Between 1947-90 demand shocks are relatively more important, therefore there exist a countercyclicality between real wage and employment, and this is statistically significant.

2) "Long sample periods" have some shortcomings since some periods such as 47-51 or 74-75 may have very strong supply or demand shocks and creates significant biases if used as an extension of a normal sample period.

3) An EMP coefficient for a long sample such as 47-90 should be interpreted only an average value, and may not reflect a correct relationship for all sub-samples covered by 47-90. So a (-) EMP means that we have more demand shocks therefore we have countercyclicality.

4) This study shows that addition of a supply shock dominated period creates clear procyclical tendency while addition of a demand shock dominated period creates a clear and stronger countercyclical tendency. (Please note that if (-) EMP gets smaller in absolute value we call this procyclical tendency as well as (+) EMP gets bigger and vice versa.)

5) On the other hand, most important conclusion is the following: Insignificant demand and supply shocks have very little effect on coefficient EMP. Therefore a long sample of insignificant demand shocks may still have a (+) EMP since they cannot change the previous high (+) EMP coefficient to (-) EMP.

Sample periods should not be considered as isolated, they are simply extension of past samples. So, there exist a transition between a supply shock dominated sample and a demand shock dominated sample. If shock is stronger, transition would be faster. This is very important and explains ,say, why 55q1-57q3 (13 demand shock period) has a (+) EMP. [i.e. only very strong supply or demand shocks can change the sign of EMP.] Disregarding this conclusion will make us to expect (-) EMP for demand shock dominated samples and (+) EMP for supply shock dominated samples. [Actually, a (+) EMP in a demand shock dominated sample implies a strong supply shock right before our sample period starts, and vice versa.]

6) Between 1947 and 1990, our data show a very erratic pattern, so some values affect the regression as if they are outlier. To eliminate this problem Bowman-

Shenton normality test has been applied and showed that 47-90 as well as some other sub-samples strongly violate the normality. So a separation should take place for more reliable regression coefficients.

As a result, we strongly suggest to look at the periods that takes place <u>before</u> our sample starts, and <u>after</u> our sample ends. (One should be aware of second derivative, actually it implies counter-or-procyclical tendencies.)

As an example,we take 47Q1-51Q4 sample period which is dominated by very strong supply shocks. For this sample EMP = -.5303, t = -3.723 and model satisfies all model specification conditions. Then, we use 51Q1-54Q4 period which has quite significant and persistent supply shocks : Now EMP = .2024, t = 2.184

Model specifications are satisfactory as well.

Finally we combine these two periods, 47Q1-54Q4, and the result :

EMP = -.2834, t = -2.214.

Our comment should include followings :

a) 47Q1-50Q4 has a high (-) EMP. ('t' significant)

b) 51Q1-54Q4 has (+) EMP ('t' significant)

c) 47Q1-54Q4 has (-) EMP ('t' significant)

d) (+) EMP for 51Q1-54Q4 is an underestimation since it follows a high (-) EMP period. (i.e. If this sample would follow an ordinary period then (+) EMP could be grater.)

e) (-) EMP for 47Q1-54Q4 underestimates the countercyclicality in 47Q1-50Q4 and procyclicality in 51Q1-54Q4. But it is the best estimator for this period. For preciser estimates of demand shock dominated subsample or supply shock dominated subsample, either these periods should be separated or sample period should be enlarged to reduce this underestimation.

CHAPTER 5

TESTS AND RELATED TEST STATISTICS

This chapter explains all tests and other related test statistics
used throughout this work in the following sequence:

1. Normality test.
2. Heteroscedasticity test.
3. Seasonality test.
4. Cyclicality test.
5. Box-Ljung test.

1. Normality test :

As noted before, Bowman-Shenton test is used to test normality. (see, Bowman and Shenton 1975, and Jarque and Bera 1980)
This statistic is

$$N = (T^{*} /6)\ b_1 + (T^{*} /24)(b_2 - 3)^2 .$$

where $T^{*} = T - d$, (d : number of differencing, if any),

$$b_1 = (\sigma^{-3} \sum (U_t - \tilde{U})^3 / T^{*})^2$$

$$b_2 = \sigma^{-4} \sum (U_t - \tilde{U})^4 / T^{*}$$

$$\text{where} \quad \sigma^2 = (T-d-1)^{-1} \sum_{t=d+1}^{T} (U_t - \bar{U})^2$$

with $\bar{U}$ being the mean of the residuals.

The standardized third and fourth moments of the residuals about the mean are $\sqrt{b_1}$ and b_2. These are basic measures of skewness and

kurtosis. For a normal distribution, they should be centered around zero and three, respectively. When a model is correctly specified,

they are asymptotically normal:

$$\sqrt{b_1} \sim AN(0, 6/T^*)$$
$$b_2 \sim AN(3, 24/T^*)$$

Under null hypothesis, N has a chi-square distribution in large samples. (with two degrees of freedom)

Without the assumption of normality, uncorrelatedness of disturbances (ϵ_t , N_t , and R_t) is sufficient for the Kalman filter to yield optimal linear forecasts. (See Harvey 1989, chapter 4)

2. Heteroscedasticity test :

This test is used by Harvey as a simple diagnostics test for heteroscedasticity. It can be constructed from the residuals.

Let h is the nearest integer to T^* / 3. The proper test statistic is :

$$H(h) = \frac{\sum_{t=T-h+1}^{T} U^2{}_t}{\sum_{t=d+1}^{d+1+h} U^2{}_t}$$

As noted by Harvey (1989), if the only unknown parameter in the model were σ^2 , this statistic would have an F(h,h) distributed under the null hypothesis. Or alternatively, one may base the test on the asymptotic distribution of hH(h), which is chi-square (h), under the null hypothesis. "If it is thought that the variances may be bigger (smaller) towards the end of the sample, then the upper (lower) tail of the F-distribution should be used as the critical region in a one-sided test. A two-sided allows both possibilities but at the expense of loss in power." (Harvey 1989, p.260-1)

3. Seasonality test :

The seasonality test is a test of overall significance of the seasonal effects. The test is valid only if the seasonal hyperparameter is zero. (i.e. seasonal pattern is fixed) This statistic has a chi-square distribution with s-1 degrees of freedom, where s is the number of seasons. On the other hand, conditional on any hyperparameters in the trend or cycle, the seasonality statistic divided by s-1 has an F-distribution. (see STAMP Manual)

4. Cyclicality test :

As explained in chapter 4, testing the presence of a cycle is not straightforward. One way of testing the cycle is to check the diagnostics of the model with a cycle. On the other hand, theoretically, inclusion of a cycle creates identifiability problems. This is the case when $H_0 : \rho = 0$, since if H_0 is true, cycle reduces to a white noise and cannot be distinguished from ϵ_t. Similarly, if the frequency of the cycle (λ_c) is unknown, then frequency is not identifiable in Wald and LR tests when ρ is zero. In short, proper tests for the presence of a cycle are LM, LR, and Wald tests. The best test is the LM test since it handles the above identification problems better than the other two.[1]

5. Box-Ljung Test :

This is a model selection test. Once a tentative specification has been obtained, the model may be estimated. As a second step, residuals must be examined to see if they indicate a departure from randomness. This stage is known as diagnostic checking. Generally, the main test is the 'portmanteau' test (also known as "Box-Pierce" test). A more satisfactory version of this statistic is the Box-Ljung statistic. (see Ljung and Box, 1978) It is only a modified version of the Box-Pierce statistic. It is usually argued that box-Ljung statistic has better small sample properties.

---

1 For details of these tests, see Harvey 1989.

Box-Ljung Q statistic:

$$Q = T^{*} \ (T^{*} + 2) \sum_{t=1}^{P} (T^{*} - \tau)^{-1} \ r^{2} \ (\tau)$$

where T_{*} = T-d (d: number of differencing), and

$$r(\tau) = \frac{\sum_{t=d+1+\tau}^{T} (u_t - \bar{u})(u_{t-\tau} - \bar{u})}{\sum_{t=d+1}^{T} (u_t - \bar{u})^2} \quad , \ \tau = 1,2,3,.$$

This is a joint test of significance of the first P residual autocorrelations. For other serial correlation tests constructed by means of the LM principle in the frequency domain, see Harvey 1989, sub-section 5.4.4.

A P P E N D I X

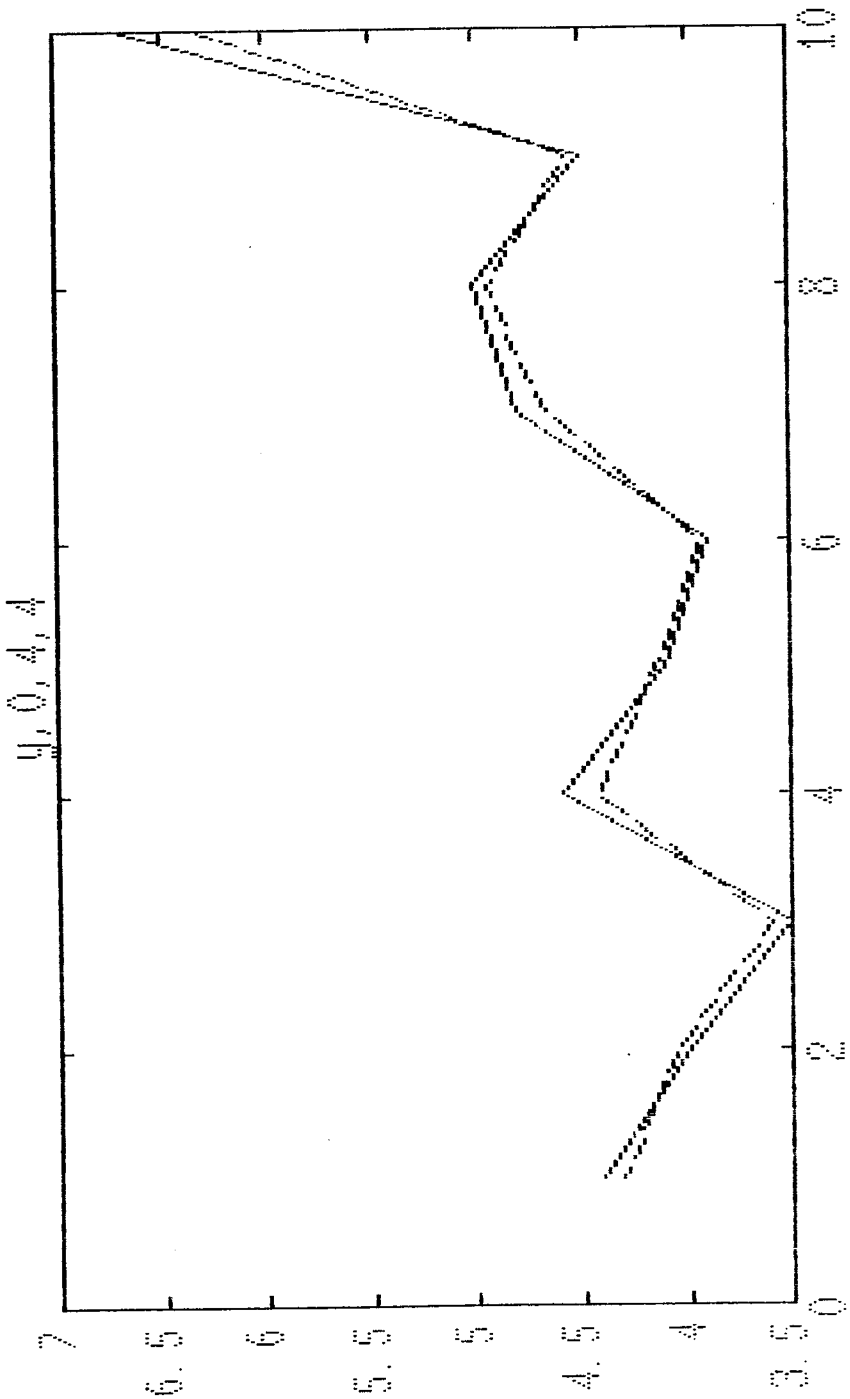
T O

C H A P T E R 2

M A T L A B O U T P U T S

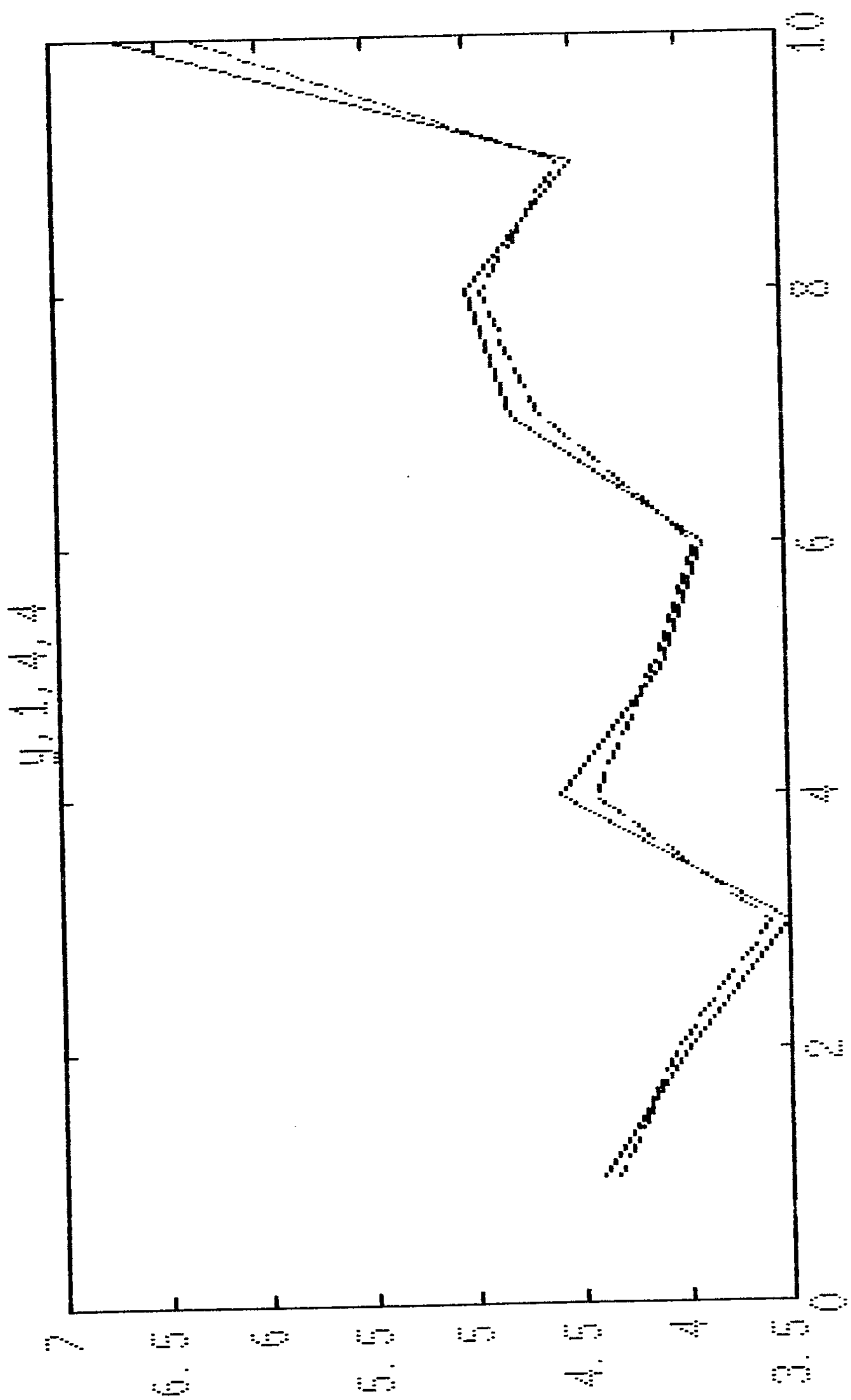
kal33(y,0,4,4)

t	Y_t	P_t	a_t	v_t	$P_{t/T}$	$a_{t/T}$	e_t
1.0000	4.4000	0.8000	4.3200	0.4000	0.6863	4.2759	0.1241
2.0000	4.0000	0.8276	4.0552	-0.3200	0.7065	3.9763	0.0237
3.0000	3.5000	0.8284	3.5953	-0.5552	0.7071	3.7381	-0.2381
4.0000	4.6000	0.8284	4.4276	1.0047	0.7071	4.3810	0.2190
5.0000	4.1000	0.8284	4.1562	-0.3276	0.7071	4.1198	-0.0198
6.0000	3.9000	0.8284	3.9440	-0.2562	0.7071	4.0656	-0.1656
7.0000	4.8000	0.8284	4.6531	0.8560	0.7071	4.7024	0.0976
8.0000	5.0000	0.8284	4.9405	0.3469	0.7072	4.8779	0.1221
9.0000	4.5000	0.8284	4.5756	-0.4405	0.7107	4.8775	-0.3775
10.000	6.7000	0.8284	6.3355	2.1244	0.8284	6.3355	0.3645


0
2
4
6
8
10
3.5
4
4.5
5
5.5
6
6.5
7

kal33(y,1,4,4)

t	Y_t	P_t	a_t	v_t	$P_{t/T}$	$a_{t/T}$	e_t
1.0000	4.4000	0.8333	4.3333	0.4000	0.7107	4.2857	0.1143
2.0000	4.0000	0.8286	4.0571	-0.3333	0.7072	3.9779	0.0221
3.0000	3.5000	0.8284	3.5956	-0.5571	0.7071	3.7384	-0.2384
4.0000	4.6000	0.8284	4.4277	1.0044	0.7071	4.3811	0.2189
5.0000	4.1000	0.8284	4.1562	-0.3277	0.7071	4.1198	-0.0198
6.0000	3.9000	0.8284	3.9440	-0.2562	0.7071	4.0656	-0.1656
7.0000	4.8000	0.8284	4.6531	0.8560	0.7071	4.7024	0.0976
8.0000	5.0000	0.8284	4.9405	0.3469	0.7072	4.8779	0.1221
9.0000	4.5000	0.8284	4.5756	-0.4405	0.7107	4.8775	-0.3775
10.000	6.7000	0.8284	6.3355	2.1244	0.8284	6.3355	0.3645


0
2
4
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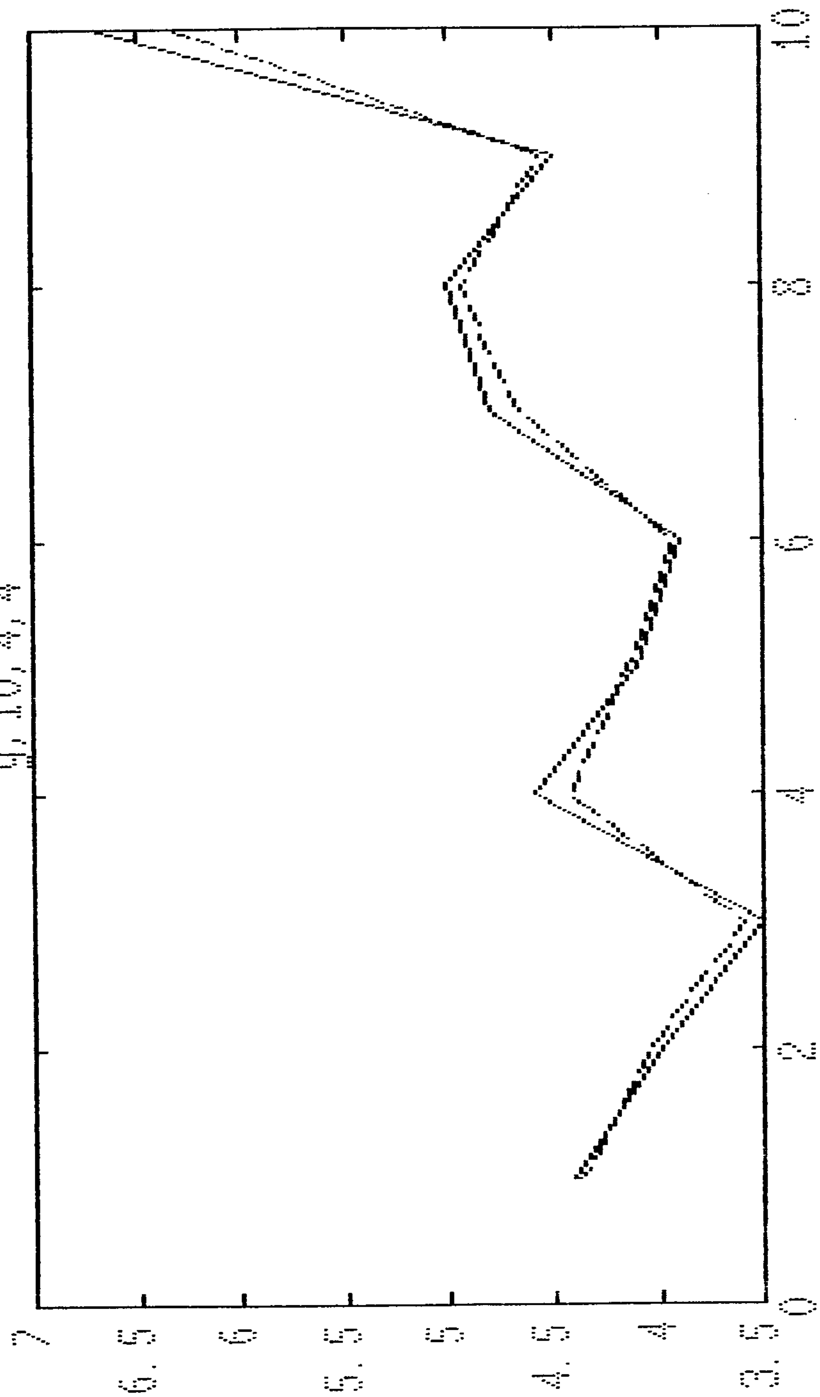
8
10
3.5
4
4.5
5
5.5
6
6.5
7

kal33(y,10,4,4)

t	Y_t	P_t	a_t	v_t	$P_{t/T}$	$a_{t/T}$	e_t
1.0000	4.4000	0.9333	4.3733	0.4000	0.7821	4.3146	0.0854
2.0000	4.0000	0.8315	4.0629	-0.3733	0.7093	3.9827	0.0173
3.0000	3.5000	0.8285	3.5965	-0.5629	0.7072	3.7392	-0.2392
4.0000	4.6000	0.8284	4.4278	1.0035	0.7071	4.3812	0.2188
5.0000	4.1000	0.8284	4.1562	-0.3278	0.7071	4.1198	-0.0198
6.0000	3.9000	0.8284	3.9440	-0.2562	0.7071	4.0656	-0.1656
7.0000	4.8000	0.8284	4.6531	0.8560	0.7071	4.7024	0.0976
8.0000	5.0000	0.8284	4.9405	0.3469	0.7072	4.8779	0.1221
9.0000	4.5000	0.8284	4.5756	-0.4405	0.7107	4.8775	-0.3775
10.000	6.7000	0.8284	6.3355	2.1244	0.8284	6.3355	0.3645


y,10,4,4
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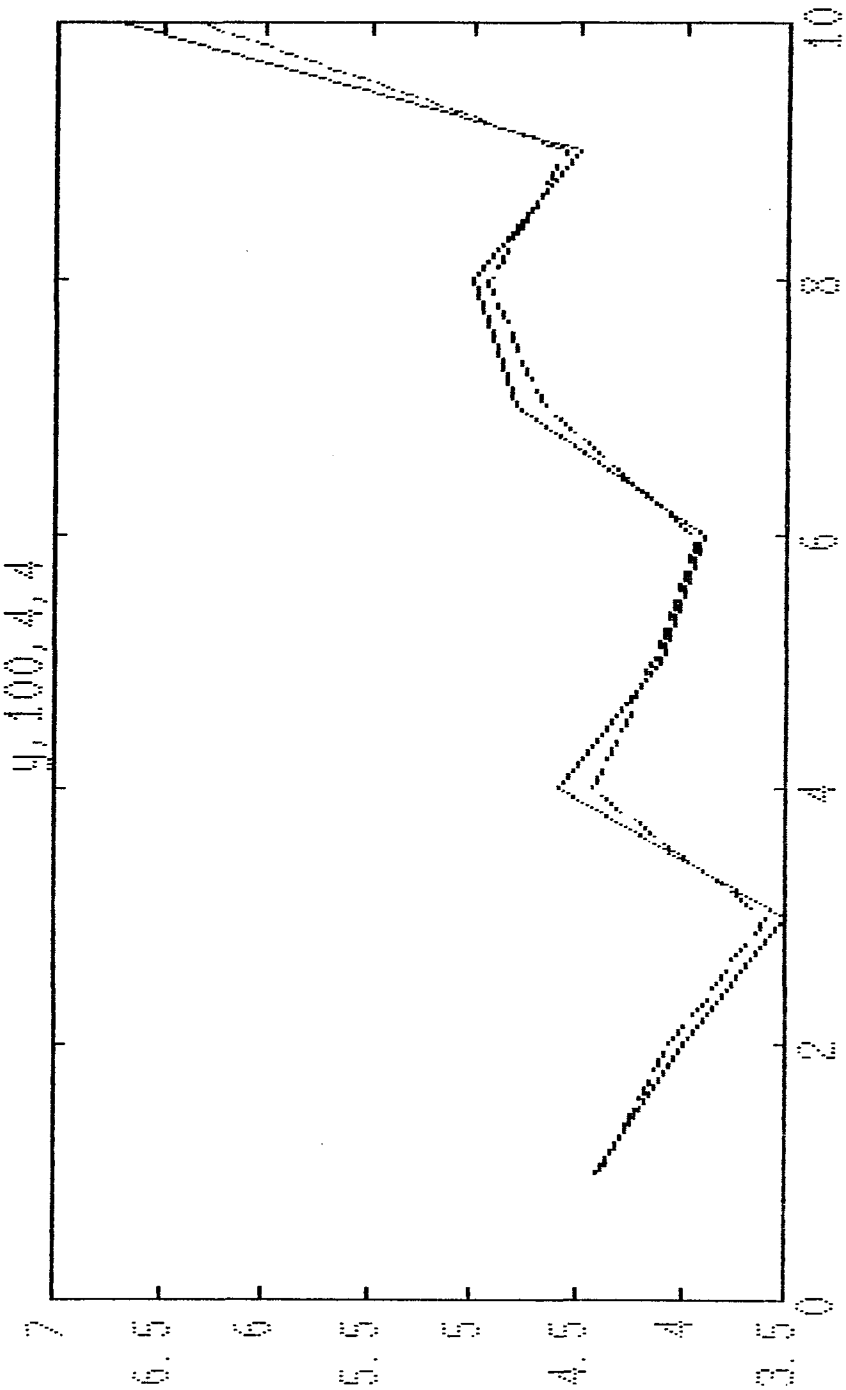
2
4
6
8
10
3.5
4
4.5
5
5.5
6
6.5
7

ka133(y,100,4,4)

t	Y_t	P_t	a_t	v_t	$P_{t/T}$	$a_{t/T}$	e_t
1.0000	4.4000	0.9905	4.3962	0.4000	0.8219	4.3307	0.0693
2.0000	4.0000	0.8331	4.0661	-0.3962	0.7105	3.9853	0.0147
3.0000	3.5000	0.8286	3.5971	-0.5661	0.7072	3.7396	-0.2396
4.0000	4.6000	0.8284	4.4279	1.0029	0.7071	4.3813	0.2187
5.0000	4.1000	0.8284	4.1563	-0.3279	0.7071	4.1198	-0.0198
6.0000	3.9000	0.8284	3.9440	-0.2563	0.7071	4.0656	-0.1656
7.0000	4.8000	0.8284	4.6531	0.8560	0.7071	4.7024	0.0976
8.0000	5.0000	0.8284	4.9405	0.3469	0.7072	4.8779	0.1221
9.0000	4.5000	0.8284	4.5756	-0.4405	0.7107	4.8775	-0.3775
10.000	6.7000	0.8284	6.3355	2.1244	0.8284	6.3355	0.3645


9,100,4,4
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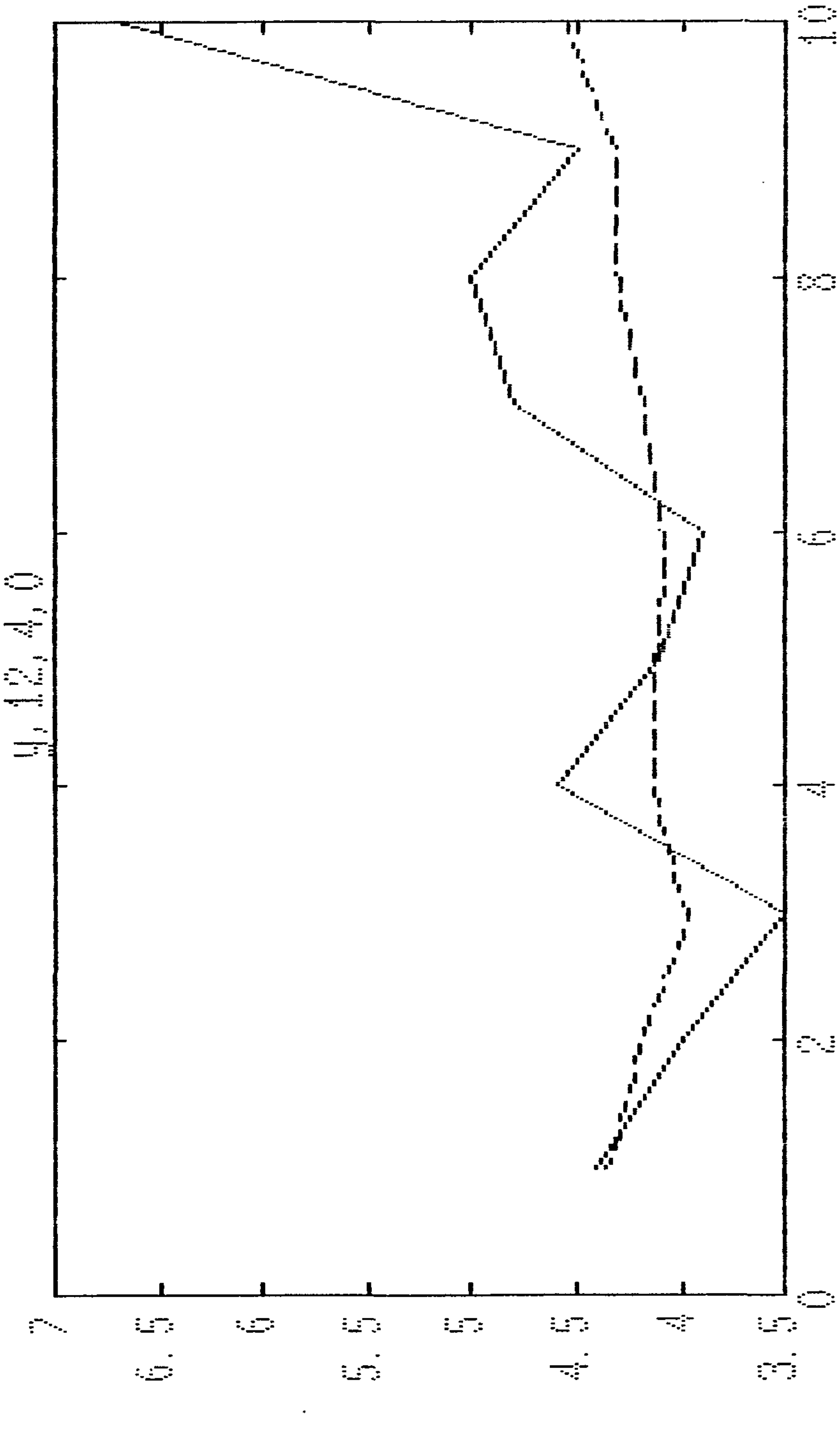
6
8
10
3.5
4
4.5
5
5.5
6
6.5
7

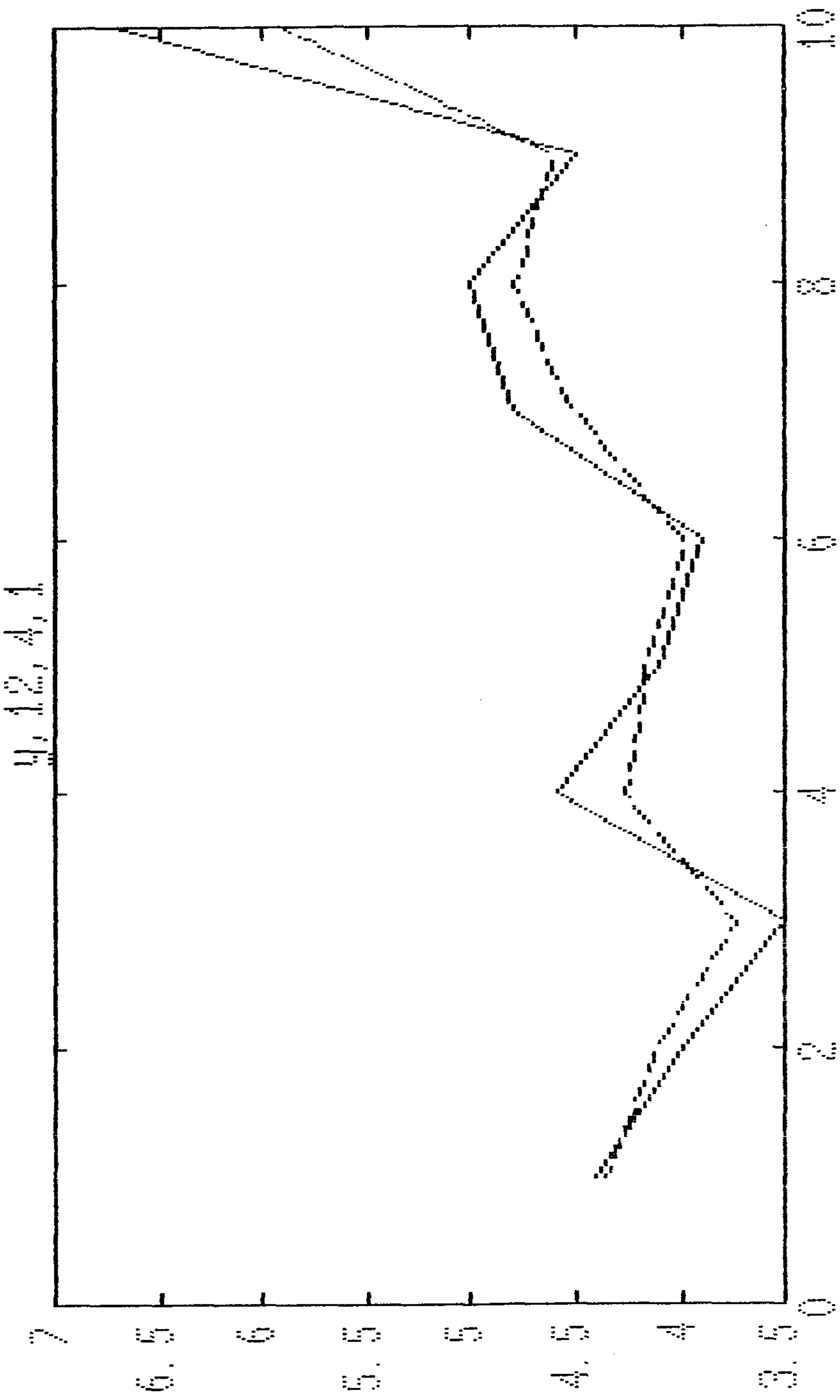
```
kal33(y,12,4,0)
```

t	Y_t	P_t	a_t	v_t	$P_{t|T}$	$a_{t|T}$	e_t
1.0000	4.4000	0.9231	4.3692	0.4000	0.0992	4.1920	0.2080
2.0000	4.0000	0.4800	4.1920	-0.3692	0.0992	3.9676	0.0324
3.0000	3.5000	0.3243	3.9676	-0.6920	0.0992	4.1224	-0.6224
4.0000	4.6000	0.2449	4.1224	0.6324	0.0992	4.1180	0.4820
5.0000	4.1000	0.1967	4.1180	-0.0224	0.0992	4.0822	0.0178
6.0000	3.9000	0.1644	4.0822	-0.2180	0.0992	4.1835	-0.2835
7.0000	4.8000	0.1412	4.1835	0.7178	0.0992	4.2845	0.5155
8.0000	5.0000	0.1237	4.2845	0.8165	0.0992	4.3083	0.6917
9.0000	4.5000	0.1101	4.3083	0.2155	0.0992	4.5455	-0.0455
10.000	6.7000	0.0992	4.5455	2.3917	0.0992	4.5455	2.1545


4, 12, 4, 0
0
2
4
6
8
10
3.5
4
4.5
5
5.5
6
6.5
7

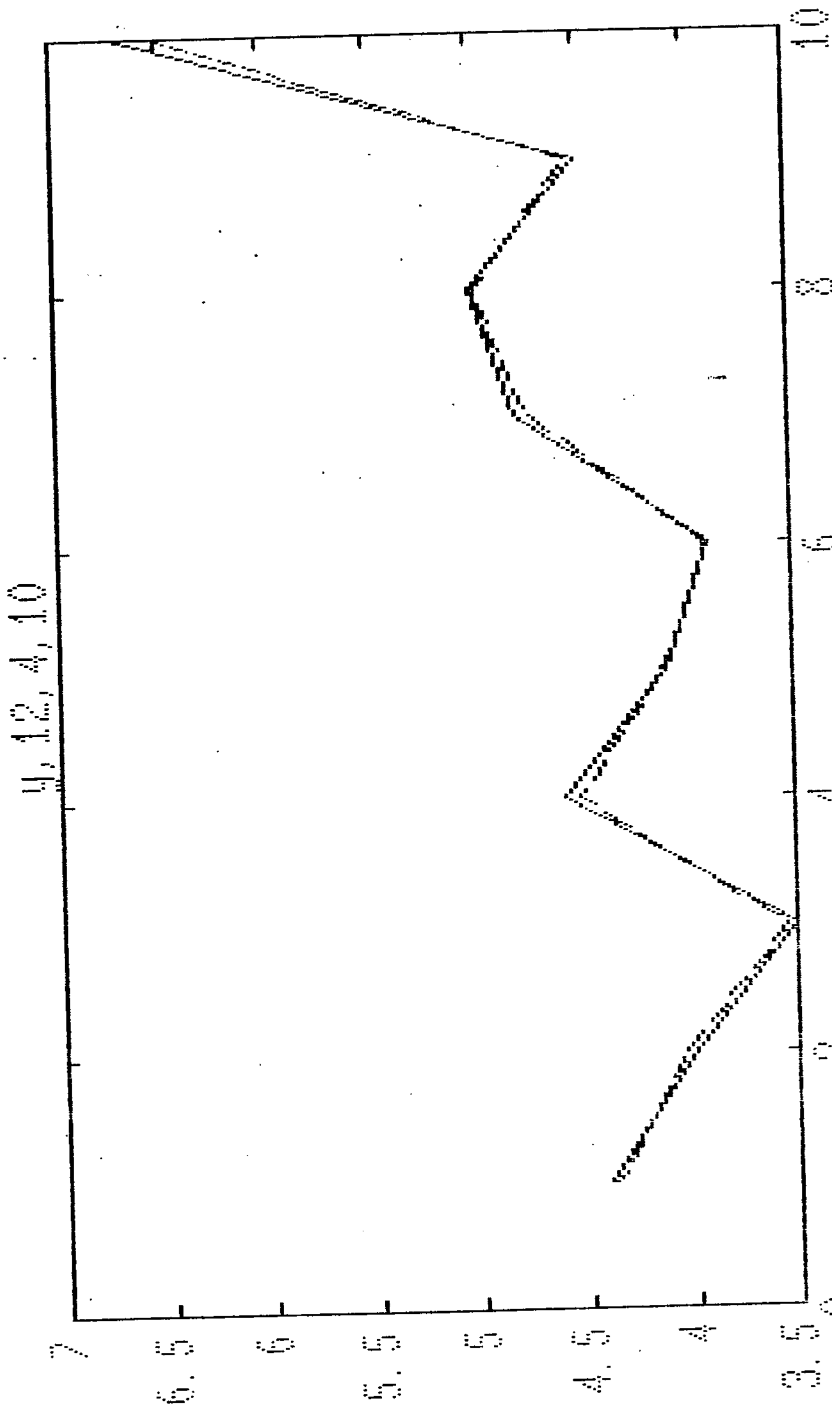
kal33(y,12,4,1)

t	Y_t	P_t	a_t	v_t	$P_{t\|\cdot}$	$a_{t\|\cdot}$	e_t
1.0000	4.4000	0.9286	4.3714	0.4000	0.5900	4.2537	0.1463
2.0000	4.0000	0.6585	4.1268	-0.3714	0.4680	3.9716	0.0284
3.0000	3.5000	0.6239	3.7358	-0.6268	0.4503	3.9413	-0.4413
4.0000	4.6000	0.6189	4.2706	0.8642	0.4477	4.2303	0.3697
5.0000	4.1000	0.6182	4.1652	-0.1706	0.4473	4.1025	-0.0025
6.0000	3.9000	0.6181	4.0013	-0.2652	0.4473	4.1898	-0.2898
7.0000	4.8000	0.6180	4.4949	0.7987	0.4477	4.6142	0.1858
8.0000	5.0000	0.6180	4.8071	0.5051	0.4508	4.7346	0.2654
9.0000	4.5000	0.6180	4.6173	-0.3071	0.4721	5.1090	-0.6090
10.000	6.7000	0.6180	5.9045	2.0827	0.6180	5.9045	0.7955


y, 12, 4, 1
0
2
4
6
8
10
3.5
4
4.5
5
5.5
6
6.5
7

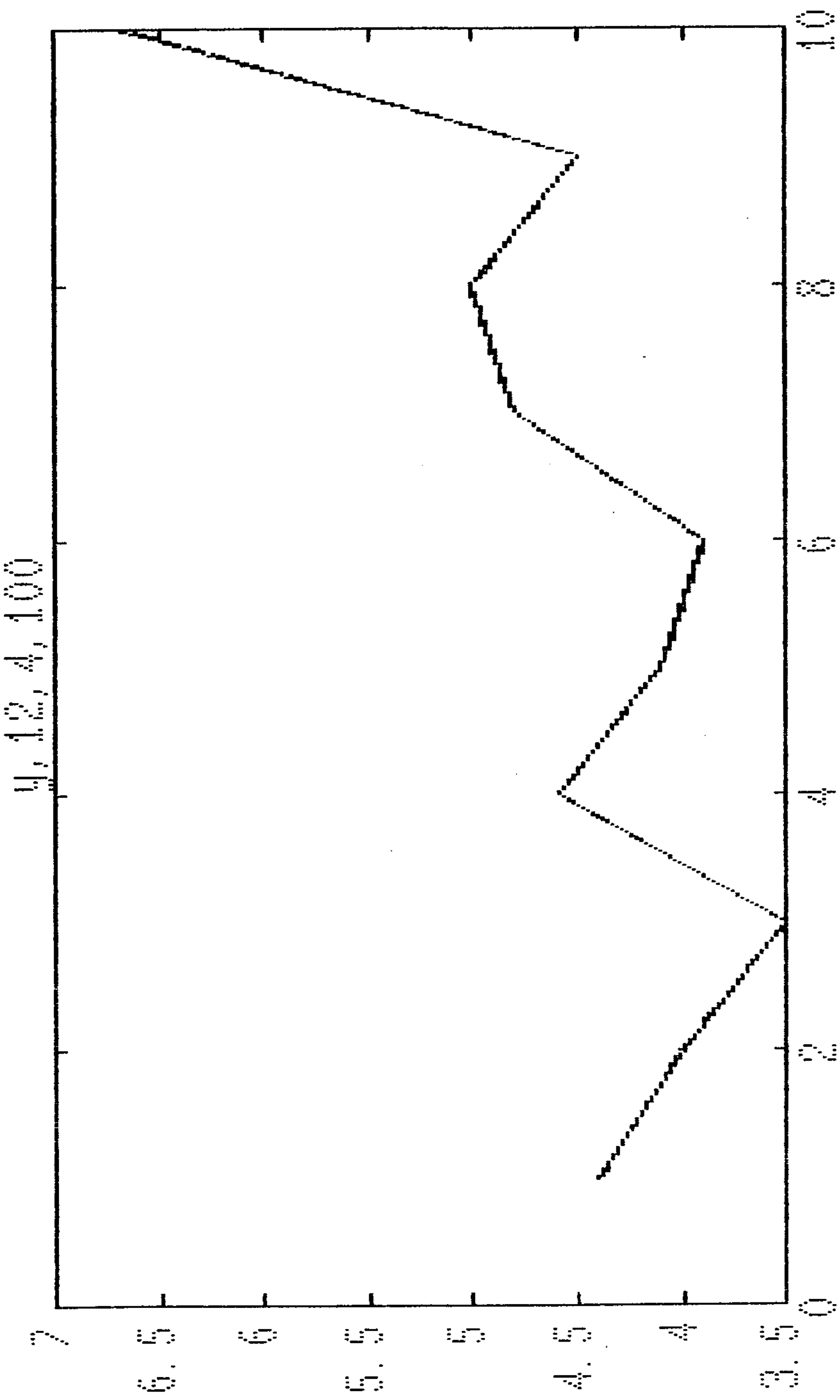
kal33(y,12,4,10)

t	Y_t	P_t	a_t	v_t	$P_{t/T}$	$a_{t/T}$	e_t
1.0000	4.4000	0.9565	4.3826	0.4000	0.8795	4.3520	0.0480
2.0000	4.0000	0.9164	4.0320	-0.3826	0.8454	3.9911	0.0089
3.0000	3.5000	0.9161	3.5446	-0.5320	0.8452	3.6258	-0.1258
4.0000	4.6000	0.9161	4.5114	1.0554	0.8452	4.4798	0.1202
5.0000	4.1000	0.9161	4.1345	-0.4114	0.8452	4.1165	-0.0165
6.0000	3.9000	0.9161	3.9197	-0.2345	0.8452	3.9874	-0.0874
7.0000	4.8000	0.9161	4.7261	0.8803	0.8452	4.7472	0.0528
8.0000	5.0000	0.9161	4.9770	0.2739	0.8452	4.9403	0.0597
9.0000	4.5000	0.9161	4.5400	-0.4770	0.8457	4.7061	-0.2061
10.000	6.7000	0.9161	6.5187	2.1600	0.9161	6.5187	0.1813


4,12,4,10
7
6.5
6
5.5
5
4.5
4
3.5
0
2
4
6
8
10

kal33(y,12,4,100)

t	Y_t	P_t	a_t	v_t	$P_{t/T}$	$a_{t/T}$	e_t
1.0000	4.4000	0.9912	4.3965	0.4000	0.9815	4.3926	0.0074
2.0000	4.0000	0.9902	4.0039	-0.3965	0.9806	3.9990	0.0010
3.0000	3.5000	0.9902	3.5049	-0.5039	0.9806	3.5156	-0.0156
4.0000	4.6000	0.9902	4.5893	1.0951	0.9806	4.5845	0.0155
5.0000	4.1000	0.9902	4.1048	-0.4893	0.9806	4.1028	-0.0028
6.0000	3.9000	0.9902	3.9020	-0.2048	0.9806	3.9107	-0.0107
7.0000	4.8000	0.9902	4.7912	0.8980	0.9806	4.7932	0.0068
8.0000	5.0000	0.9902	4.9980	0.2088	0.9806	4.9931	0.0069
9.0000	4.5000	0.9902	4.5049	-0.4980	0.9806	4.5262	-0.0262
10.000	6.7000	0.9902	6.6785	2.1951	0.9902	6.6785	0.0215


y, 12, 4, 100
0
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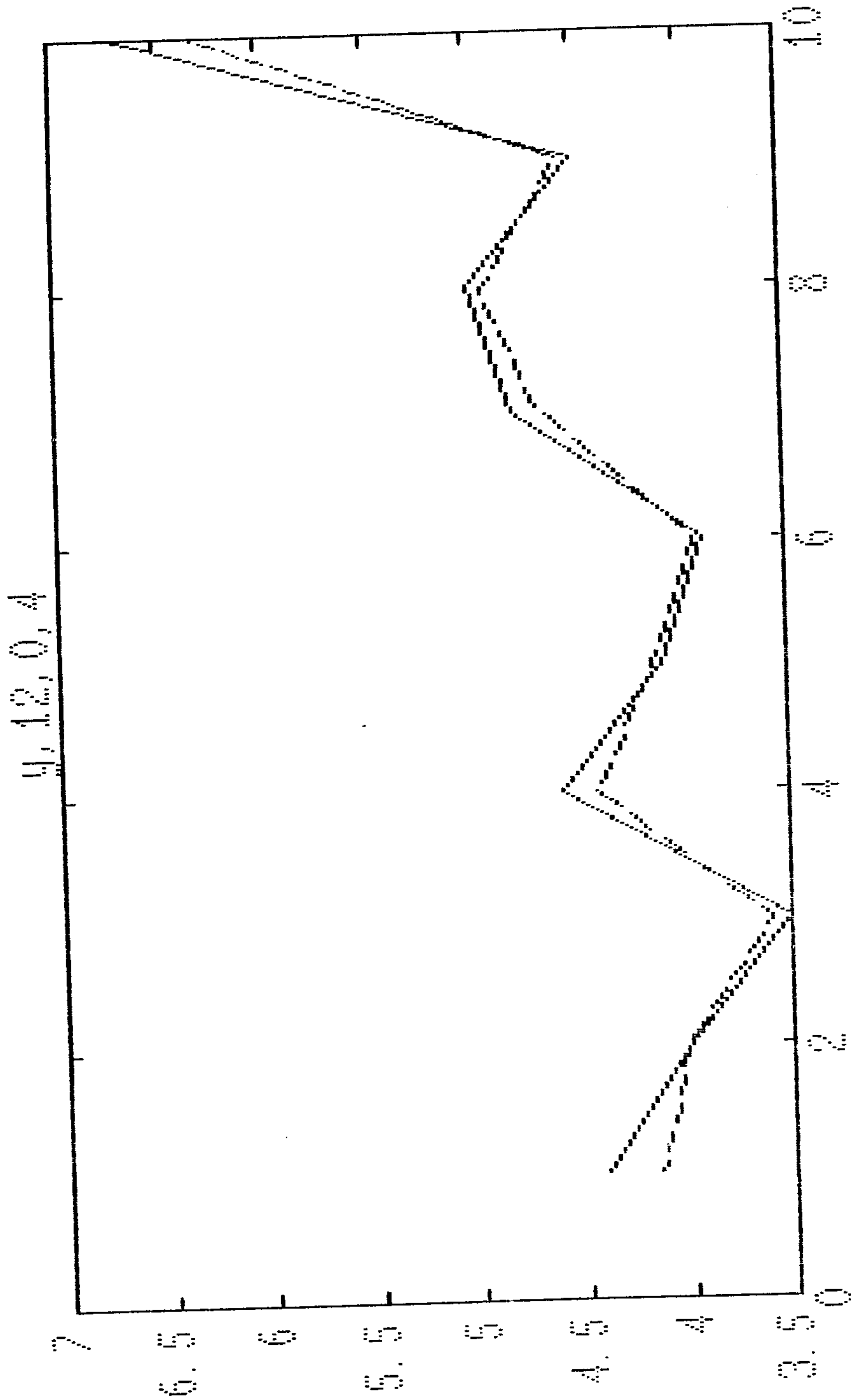
4
6
8
10
3.5
4
4.5
5
5.5
6
6.5
7

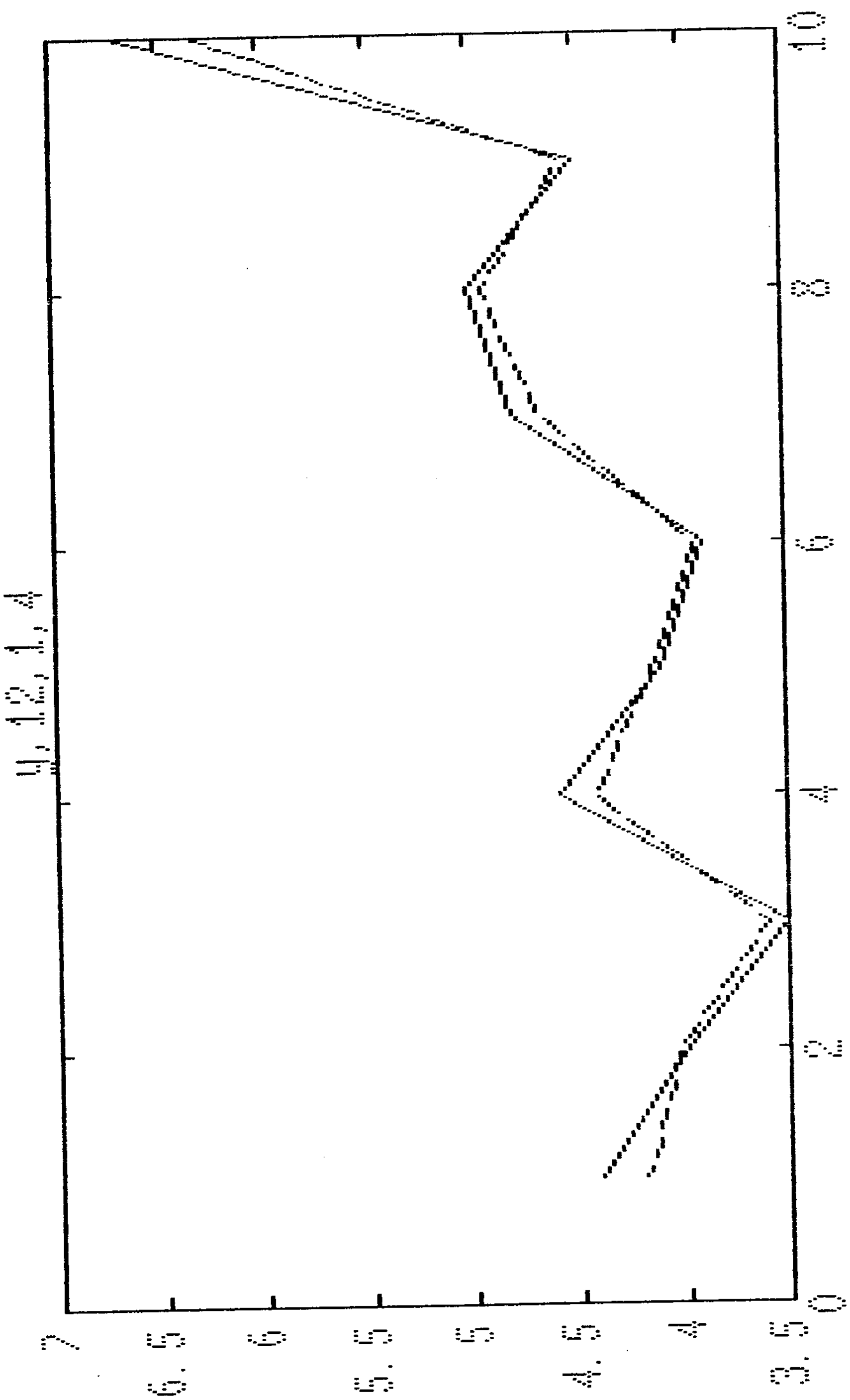
ka133(y,12,0,4)

t	Y_t	P_t	a_t	v_t	$P_{t/T}$	$a_{t/T}$	e_t
1.0000	4.4000	0.9412	4.1412	4.4000	0.7876	4.1188	0.2812
2.0000	4.0000	0.8317	4.0238	-0.1412	0.7095	3.9491	0.0509
3.0000	3.5000	0.8285	3.5898	-0.5238	0.7072	3.7334	-0.2334
4.0000	4.6000	0.8284	4.4267	1.0102	0.7071	4.3802	0.2198
5.0000	4.1000	0.8284	4.1560	-0.3267	0.7071	4.1197	-0.0197
6.0000	3.9000	0.8284	3.9439	-0.2560	0.7071	4.0656	-0.1656
7.0000	4.8000	0.8284	4.6531	0.8561	0.7071	4.7024	0.0976
8.0000	5.0000	0.8284	4.9405	0.3469	0.7072	4.8779	0.1221
9.0000	4.5000	0.8284	4.5756	-0.4405	0.7107	4.8775	-0.3775
10.000	6.7000	0.8284	6.3355	2.1244	0.8284	6.3355	0.3645


4,12,0,4
0
2
4
6
8
10
3.5
4
4.5
5
5.5
6
6.5
7

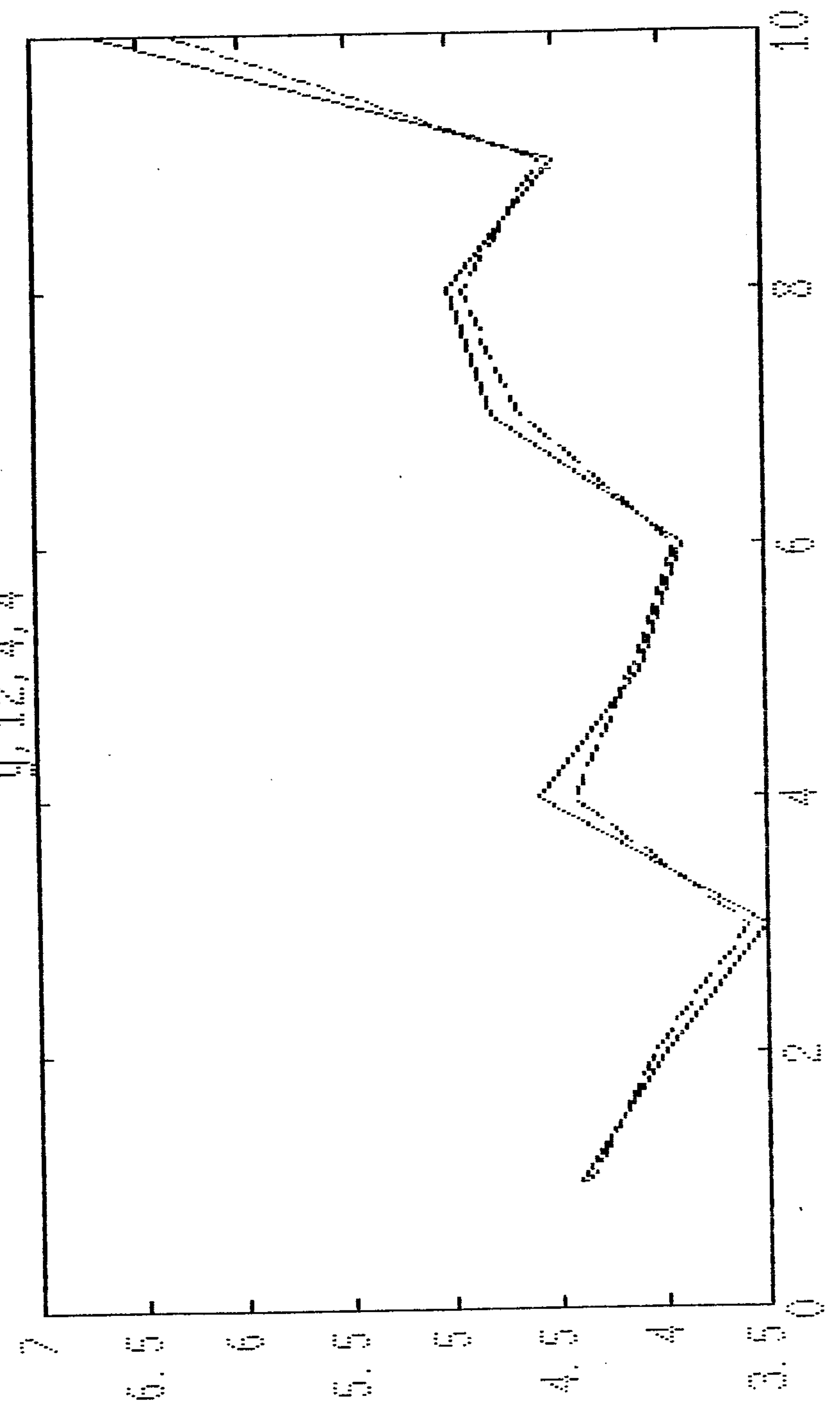
```
kal33(y,12,1,4)
```

t	Y_t	P_t	a_t	v_t	$P_{t/T}$	$a_{t/T}$	e_t
1.0000	4.4000	0.9412	4.2000	3.4000	0.7876	4.1683	0.2317
2.0000	4.0000	0.8317	4.0337	-0.2000	0.7095	3.9576	0.0424
3.0000	3.5000	0.8285	3.5915	-0.5337	0.7072	3.7349	-0.2349
4.0000	4.6000	0.8284	4.4270	1.0085	0.7071	4.3805	0.2195
5.0000	4.1000	0.8284	4.1561	-0.3270	0.7071	4.1197	-0.0197
6.0000	3.9000	0.8284	3.9439	-0.2561	0.7071	4.0656	-0.1656
7.0000	4.8000	0.8284	4.6531	0.8561	0.7071	4.7024	0.0976
8.0000	5.0000	0.8284	4.9405	0.3469	0.7072	4.8779	0.1221
9.0000	4.5000	0.8284	4.5756	-0.4405	0.7107	4.8775	-0.3775
10.000	6.7000	0.8284	6.3355	2.1244	0.8284	6.3355	0.3645


4,12,1,4
0
2
4
6
8
10
3.5
4
4.5
5
5.5
6
6.5
7

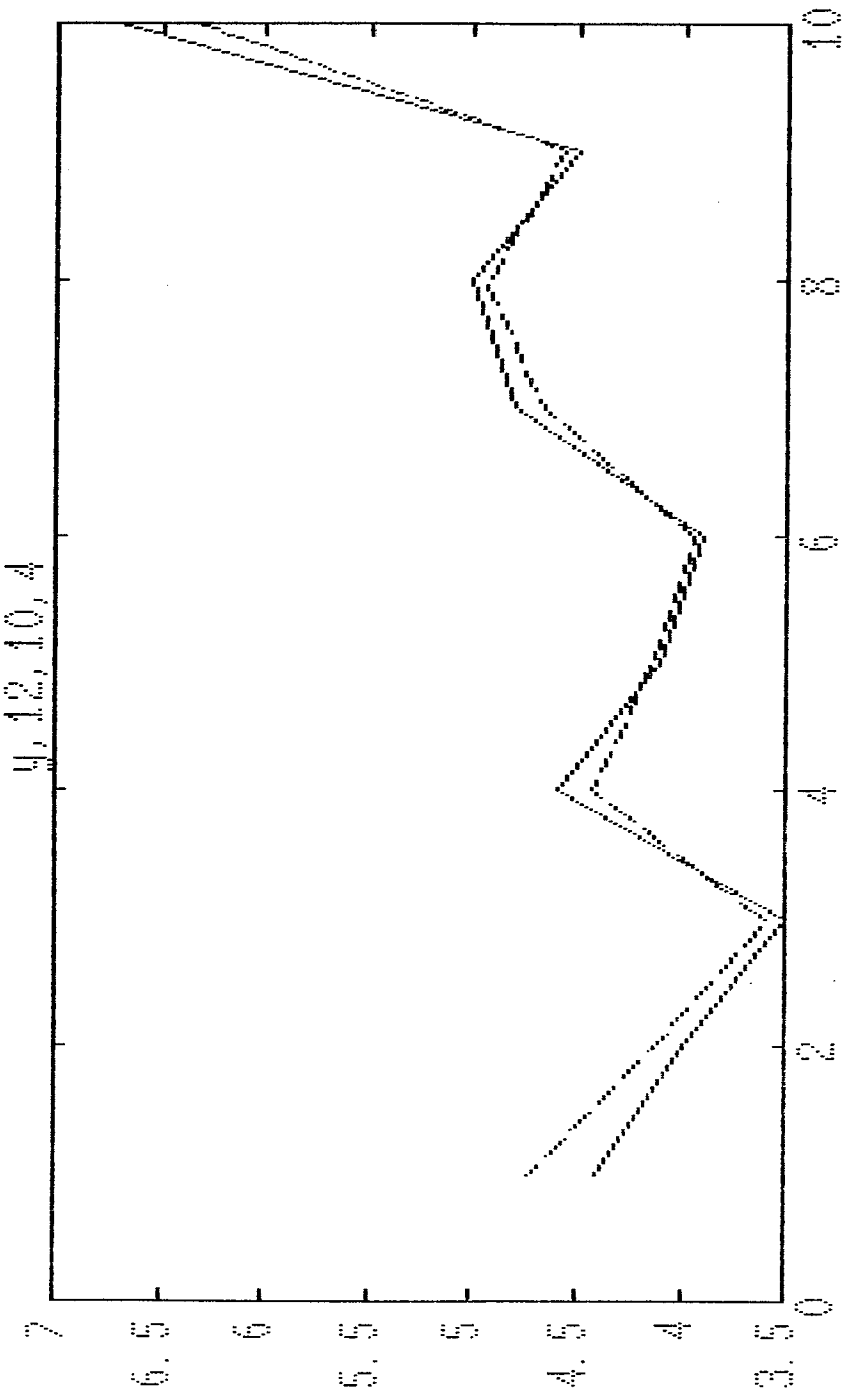
ka133(y,12,4,4)

t	Y_t	P_t	a_t	v_t	$P_{t|n}$	$a_{t|n}$	e_t
1.0000	4.4000	0.9412	4.3765	0.4000	0.7876	4.3168	0.0832
2.0000	4.0000	0.8317	4.0634	-0.3765	0.7095	3.9830	0.0170
3.0000	3.5000	0.8285	3.5966	-0.5634	0.7072	3.7392	-0.2392
4.0000	4.6000	0.8284	4.4278	1.0034	0.7071	4.3812	0.2188
5.0000	4.1000	0.8284	4.1562	-0.3278	0.7071	4.1198	-0.0198
6.0000	3.9000	0.8284	3.9440	-0.2562	0.7071	4.0656	-0.1656
7.0000	4.8000	0.8284	4.6531	0.8560	0.7071	4.7024	0.0976
8.0000	5.0000	0.8284	4.9405	0.3469	0.7072	4.8779	0.1221
9.0000	4.5000	0.8284	4.5756	-0.4405	0.7107	4.8775	-0.3775
10.000	6.7000	0.8284	6.3355	2.1244	0.8284	6.3355	0.3645


y, 12, 4, 4
0
2
4
6
8
10
3.5
4
4.5
5
5.5
6
6.5
7

kal33(y,12,10,4)

t	Y_t	P_t	a_t	v_t	$P_{t/T}$	$a_{t/T}$	e_t
1.0000	4.4000	0.9412	4.7294	-5.6000	0.7876	4.6139	-0.2139
2.0000	4.0000	0.8317	4.1228	-0.7294	0.7095	4.0340	-0.0340
3.0000	3.5000	0.8285	3.6068	-0.6228	0.7072	3.7480	-0.2480
4.0000	4.6000	0.8284	4.4296	0.9932	0.7071	4.3827	0.2173
5.0000	4.1000	0.8284	4.1565	-0.3296	0.7071	4.1201	-0.0201
6.0000	3.9000	0.8284	3.9440	-0.2565	0.7071	4.0657	-0.1675
7.0000	4.8000	0.8284	4.6531	0.8560	0.7071	4.7024	0.0976
8.0000	5.0000	0.8284	4.9405	0.3469	0.7072	4.8779	0.1221
9.0000	4.5000	0.8284	4.5756	-0.4405	0.7107	4.8775	-0.3775
10.000	6.7000	0.8284	6.3355	2.1244	0.8284	6.3355	0.3645


y,12,10,4
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5.5
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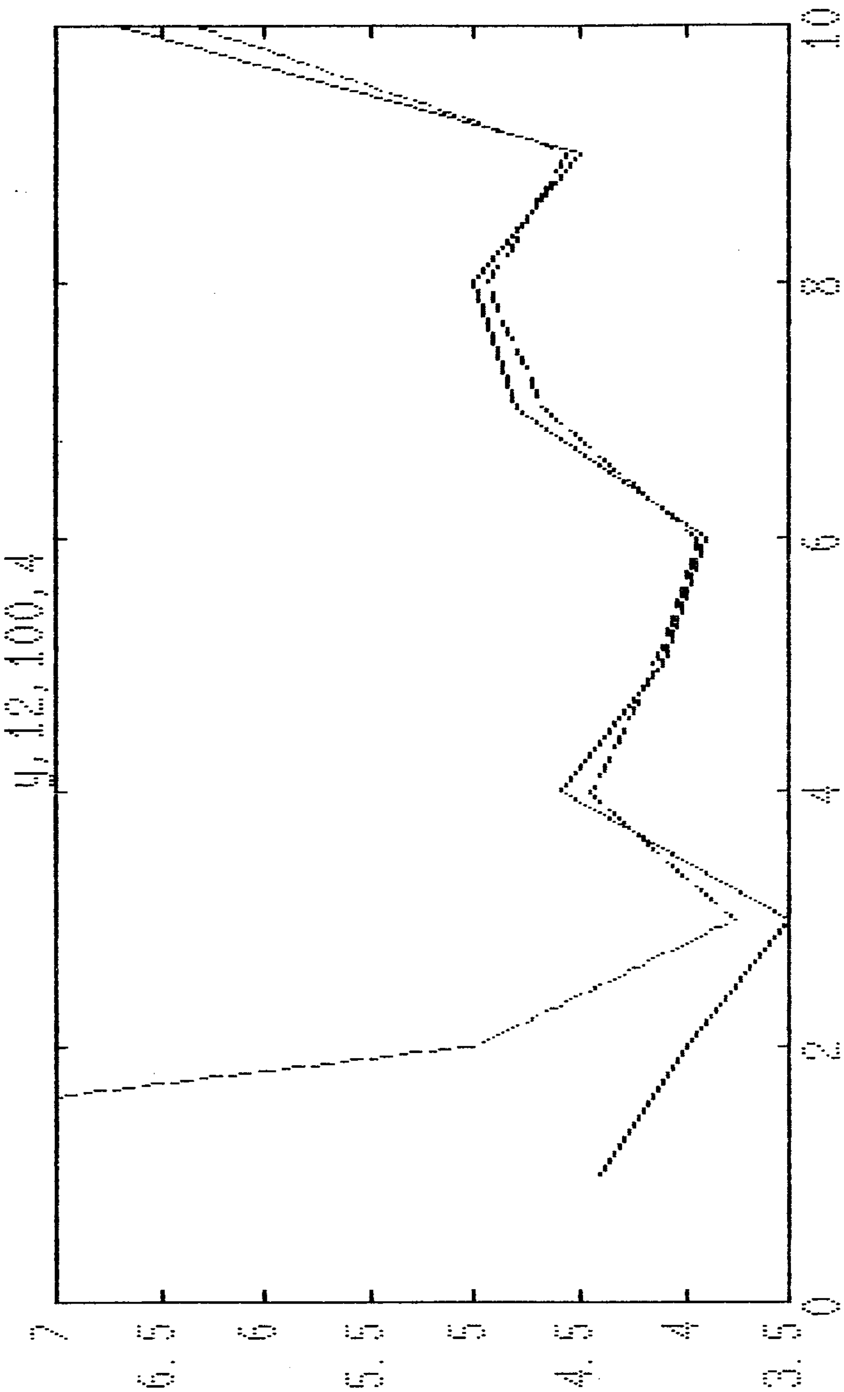
6.5
7

kal33(y,12,100,4)

t	Y_t	P_t	a_t	v_t	$P_{t/T}$	$a_{t/T}$	e_t
1.0000	4.4000	0.9412	10.0235	-95.6000	0.7876	9.0693	-4.6693
2.0000	4.0000	0.8317	5.0139	-6.0235	0.7095	4.7980	-0.7980
3.0000	3.5000	0.8285	3.7596	-1.5139	0.7072	3.8791	-0.3791
4.0000	4.6000	0.8284	4.4558	0.8404	0.7071	4.4052	0.1948
5.0000	4.1000	0.8284	4.1610	-0.3558	0.7071	4.1239	-0.0239
6.0000	3.9000	0.8284	3.9448	-0.2610	0.7071	4.0663	-0.1663
7.0000	4.8000	0.8284	4.6533	0.8552	0.7071	4.7026	0.0974
8.0000	5.0000	0.8284	4.9405	0.3467	0.7072	4.8779	0.1221
9.0000	4.5000	0.8284	4.5756	-0.4405	0.7107	4.8775	-0.3775
10.000	6.7000	0.8284	6.3355	2.1244	0.8284	6.3355	0.3645


4,12,100,4
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5.5
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6.5
7

A P P E N D I X

T O

C H A P T E R 3

S T A M P O U T P U T S

STAMP

OUTPUT # 1

OUTPUT FOR MODEL I

Model with stochastic trend, trigonometric seasonal, and irregular.

```
***********************************************************
Gradient norm =       .152577E-04
Parameter tolerance =      .191058
Function value change =     .287884E-05

STRONG CONVERGENCE.

Iterations:Function evaluations:Function value:Gradient norm
    19              139            -1.00537           .152577E-04
  Parameter        Value              Gradient
e}(Irregular)     1096.97           .966522E-06
e}(Trend)         1190.71          -.930895E-06
e}(Seasonal)      .143167E-03      -.151986E-04

***********************************************************
```

Time Domain Estimation

Dependent variable is LOG(AAAA)

Sample period 68Q1 to 90Q1 89 Observations

Estimate	Parameter	Standard Error	t-ratio
.0000000	e}(Level)	.0000428	.0006977
.0000356	e}(Trend)	.0000149	2.3913
.0000000	e}(Seasonal)	.0000	Missing
.0000328	e}(Irregular)	.0000166	1.9763

Time Domain Estimation

Dependent variable is LOG(AAAA)

Sample period 68Q1 to 90Q1 89 Observations

Estimate	State	RMSE	t-ratio
-.5631	Level	.7015	-.8026
-.0021413	Trend	.0075540	-.2835
.0037893	Harmonic	.0009779	3.8747
-.0020592	Harmonic	.0009780	-2.1054
-.0009728	Harmonic	.0006300	-1.5442
-.1955	LOG(AAAEMP1)	.0740	-2.6416

Time Domain Estimation

Residual skewness	.3137
Residual kurtosis	3.7979

Normality tests

Skewness chi^2(1)=	1.3779
Kurtosis chi^2(1)=	2.2281
Normality chi^2(2)=	3.6059

Sum of squares of standardized residuals	82.6513
Sum of squares about the mean	82.6216
Mean of standardized residuals	-.0188

Heteroscedasticity test F(28, 28) = .4188

Time Domain Estimation

Log-likelihood kernel	317.6333
Prediction error variance	.0001116

Prior and missing observations 6

Steady State 89

R2 =	.9631
RD2=	.4213
RS2=	.3418

Time Domain Estimation

Seasonality test 21.8714 Chi^2(3)

Seasonal effects from 90Q1

Q1	.0028165
Q2	-.0010864
Q3	-.0047620
Q4	.0030319

Time Domain Estimation

Observation	Actual	Fitted	Error	Residual	RMSE
68Q1	-2.4851	.0000	-2.4851	Missing	Missing
68Q2	-2.4781	-2.4351	-.0430	Missing	Missing
68Q3	-2.4785	-2.5124	.0339	Missing	Missing
68Q4	-2.4614	-2.5090	.0476	Missing	Missing
69Q1	-2.4601	-2.5505	.0904	Missing	Missing
69Q2	-2.4621	-2.4520	-.0101	Missing	Missing
69Q3	-2.4564	-2.4637	.0072652	.4421	.0164
69Q4	-2.4474	-2.4442	-.0032288	-.1090	.0296
70Q1	-2.4472	-2.4533	.0060855	.2828	.0215
70Q2	-2.4381	-2.4508	.0127	.6785	.0187
70Q3	-2.4311	-2.4353	.0041942	.2918	.0144
70Q4	-2.4227	-2.4131	-.0096777	-.5331	.0182
71Q1	-2.4062	-2.4181	.0120	.6608	.0181
71Q2	-2.4068	-2.3938	-.0130	-.8610	.0151
71Q3	-2.4078	-2.3984	-.0094931	-.6963	.0136
71Q4	-2.3943	-2.3948	.0004704	.0330	.0143
72Q1	-2.3853	-2.3897	.0044706	.3311	.0135
72Q2	-2.3852	-2.3813	-.0039374	-.2946	.0134
72Q3	-2.3921	-2.3826	-.0094800	-.7156	.0132
72Q4	-2.3804	-2.3806	.0001259	.0089543	.0141
73Q1	-2.4085	-2.3778	-.0307	-2.3304	.0132
73Q2	-2.4438	-2.4171	-.0267	-2.0198	.0132
73Q3	-2.4705	-2.4680	-.0025343	-.1907	.0133
73Q4	-2.4565	-2.4865	.0300	2.3058	.0130
74Q1	-2.5041	-2.4831	-.0209	-1.5110	.0139
74Q2	-2.5132	-2.5308	.0176	1.3552	.0130
74Q3	-2.5536	-2.5385	-.0150	-1.1716	.0128
74Q4	-2.5514	-2.5701	.0187	1.3356	.0140
75Q1	-2.5257	-2.5930	.0672	3.7820	.0178
75Q2	-2.5244	-2.5393	.0148	1.1546	.0129
75Q3	-2.5327	-2.5387	.0060785	.4136	.0147
75Q4	-2.5222	-2.5249	.0026248	.1855	.0142
76Q1	-2.5067	-2.5262	.0195	1.4999	.0130
76Q2	-2.5073	-2.5042	-.0030412	-.2399	.0127
76Q3	-2.5000	-2.5048	.0048095	.3761	.0128
76Q4	-2.4858	-2.4774	-.0083823	-.6596	.0127
77Q1	-2.4853	-2.4782	-.0070909	-.5598	.0127
77Q2	-2.4922	-2.4853	-.0068703	-.5431	.0126
77Q3	-2.4753	-2.4973	.0220	1.7469	.0126
77Q4	-2.4631	-2.4584	-.0046637	-.3701	.0126
78Q1	-2.4642	-2.4555	-.0086990	-.6905	.0126
78Q2	-2.4795	-2.4623	-.0172	-1.3698	.0126
78Q3	-2.4748	-2.4841	.0093313	.7428	.0126
78Q4	-2.4690	-2.4669	-.0020443	-.1627	.0126
79Q1	-2.4811	-2.4702	-.0108	-.8642	.0125
79Q2	-2.4982	-2.4879	-.0103	-.8235	.0126
79Q3	-2.5136	-2.5074	-.0062468	-.4956	.0126
79Q4	-2.5256	-2.5116	-.0140	-1.1184	.0125
80Q1	-2.5495	-2.5404	-.0090981	-.7267	.0125
80Q2	-2.5455	-2.5679	.0225	1.7409	.0129
80Q3	-2.5531	-2.5613	.0082611	.6608	.0125
80Q4	-2.5449	-2.5575	.0127	.9692	.0131
81Q1	-2.5509	-2.5528	.0018850	.1497	.0126
81Q2	-2.5521	-2.5587	.0065951	.5282	.0125
81Q3	-2.5416	-2.5560	.0144	1.1561	.0125
81Q4	-2.5203	-2.5210	.0007487	.0586	.0128

STAMP Time Domain Estimation

Observation	Actual	Fitted	Error	Residual	RMSE
82Q1	-2.5054	-2.5077	.0022775	.1793	.0127
82Q2	-2.4970	-2.4952	-.0017999	-.1447	.0124
82Q3	-2.4925	-2.4863	-.0061546	-.4952	.0124
82Q4	-2.4858	-2.4689	-.0170	-1.3651	.0124
83Q1	-2.4731	-2.4864	.0133	1.0544	.0126
83Q2	-2.4752	-2.4790	.0038890	.3034	.0128
83Q3	-2.4820	-2.4773	-.0047021	-.3734	.0126
83Q4	-2.4736	-2.4719	-.0016805	-.1350	.0124
84Q1	-2.4720	-2.4749	.0029039	.2341	.0124
84Q2	-2.4734	-2.4743	.0009707	.0782	.0124
84Q3	-2.4643	-2.4733	.0090245	.7260	.0124
84Q4	-2.4486	-2.4471	-.0015394	-.1237	.0124
85Q1	-2.4316	-2.4421	.0105	.8505	.0124
85Q2	-2.4213	-2.4220	.0007871	.0633	.0124
85Q3	-2.4207	-2.4088	-.0119	-.9586	.0124
85Q4	-2.4152	-2.4010	-.0141	-1.1402	.0124
86Q1	-2.3902	-2.4116	.0214	1.7268	.0124
86Q2	-2.3703	-2.3863	.0160	1.2967	.0124
86Q3	-2.3677	-2.3564	-.0113	-.9136	.0124
86Q4	-2.3650	-2.3427	-.0223	-1.8034	.0124
87Q1	-2.3692	-2.3572	-.0120	-.9691	.0124
87Q2	-2.3831	-2.3729	-.0103	-.8327	.0124
87Q3	-2.3931	-2.3937	.0006791	.0550	.0124
87Q4	-2.3908	-2.3944	.0035985	.2913	.0124
88Q1	-2.3869	-2.3982	.0114	.9201	.0123
88Q2	-2.3967	-2.3938	-.0028848	-.2339	.0123
88Q3	-2.4083	-2.4014	-.0068922	-.5586	.0123
88Q4	-2.4023	-2.4044	.0020437	.1657	.0123
89Q1	-2.4140	-2.4072	-.0068637	-.5566	.0123
89Q2	-2.4260	-2.4230	-.0030527	-.2477	.0123
89Q3	-2.4171	-2.4363	.0191	1.5489	.0123
89Q4	-2.4111	-2.4105	-.0005729	-.0464	.0123
90Q1	-2.4146	-2.4090	-.0055675	-.4519	.0123

Time Domain Estimation

Observation	Actual	Trend	Cycle	Seasonal	Exogenous	Irregular
68Q1	-2.4851	-.6144	.0000	.0028164	-1.8722	-.0013279
68Q2	-2.4781	-.6054	.0000	-.0010863	-1.8737	.0020712
68Q3	-2.4785	-.5978	.0000	-.0047623	-1.8742	-.0017465
68Q4	-2.4614	-.5908	.0000	.0030322	-1.8755	.0018959
69Q1	-2.4601	-.5856	.0000	.0028164	-1.8769	-.0003616
69Q2	-2.4621	-.5811	.0000	-.0010863	-1.8776	-.0022305
69Q3	-2.4564	-.5768	.0000	-.0047623	-1.8782	.0033786
69Q4	-2.4474	-.5745	.0000	.0030322	-1.8763	.0003713
70Q1	-2.4472	-.5724	.0000	.0028164	-1.8739	-.0036866
70Q2	-2.4381	-.5683	.0000	-.0010863	-1.8696	.0009326
70Q3	-2.4311	-.5640	.0000	-.0047623	-1.8666	.0042106
70Q4	-2.4227	-.5601	.0000	.0030322	-1.8583	-.0073827
71Q1	-2.4062	-.5530	.0000	.0028164	-1.8603	.0042705
71Q2	-2.4068	-.5467	.0000	-.0010863	-1.8604	.0014981
71Q3	-2.4078	-.5410	.0000	-.0047623	-1.8599	-.0021603
71Q4	-2.3943	-.5337	.0000	.0030322	-1.8609	-.0027737
72Q1	-2.3853	-.5251	.0000	.0028164	-1.8636	.0005780
72Q2	-2.3852	-.5185	.0000	-.0010863	-1.8666	.0009887
72Q3	-2.3921	-.5166	.0000	-.0047623	-1.8675	-.0031780
72Q4	-2.3804	-.5210	.0000	.0030322	-1.8722	.0097498
73Q1	-2.4085	-.5368	.0000	.0028164	-1.8764	.0018551
73Q2	-2.4438	-.5584	.0000	-.0010863	-1.8781	-.0063294
73Q3	-2.4705	-.5782	.0000	-.0047623	-1.8783	-.0092572
73Q4	-2.4565	-.5956	.0000	.0030322	-1.8802	.0163
74Q1	-2.5041	-.6200	.0000	.0028164	-1.8787	-.0081683
74Q2	-2.5132	-.6430	.0000	-.0010863	-1.8778	.0086820
74Q3	-2.5536	-.6652	.0000	-.0047623	-1.8764	-.0072052
74Q4	-2.5514	-.6776	.0000	.0030322	-1.8692	-.0075991
75Q1	-2.5257	-.6792	.0000	.0028164	-1.8542	.0049316
75Q2	-2.5244	-.6773	.0000	-.0010863	-1.8500	.0038840
75Q3	-2.5327	-.6735	.0000	-.0047622	-1.8517	-.0027144
75Q4	-2.5222	-.6656	.0000	.0030321	-1.8558	-.0038803
76Q1	-2.5067	-.6540	.0000	.0028164	-1.8598	.0042179
76Q2	-2.5073	-.6436	.0000	-.0010863	-1.8619	-.0006874
76Q3	-2.5000	-.6345	.0000	-.0047622	-1.8625	.0017904
76Q4	-2.4858	-.6277	.0000	.0030321	-1.8627	.0016055
77Q1	-2.4853	-.6222	.0000	.0028164	-1.8651	-.0008799
77Q2	-2.4922	-.6152	.0000	-.0010863	-1.8685	-.0074589
77Q3	-2.4753	-.6049	.0000	-.0047622	-1.8701	.0044338
77Q4	-2.4631	-.5977	.0000	.0030321	-1.8715	.0030181
78Q1	-2.4642	-.5949	.0000	.0028164	-1.8741	.0020374
78Q2	-2.4795	-.5949	.0000	-.0010864	-1.8760	-.0073782
78Q3	-2.4748	-.5937	.0000	-.0047622	-1.8773	.0009508
78Q4	-2.4690	-.5952	.0000	.0030321	-1.8802	.0033013
79Q1	-2.4811	-.6024	.0000	.0028164	-1.8821	.0005317
79Q2	-2.4982	-.6147	.0000	-.0010864	-1.8825	-.0000078
79Q3	-2.5136	-.6309	.0000	-.0047621	-1.8811	.0031775
79Q4	-2.5256	-.6500	.0000	.0030321	-1.8794	.0007232
80Q1	-2.5495	-.6671	.0000	.0028164	-1.8776	-.0076436
80Q2	-2.5455	-.6770	.0000	-.0010864	-1.8696	.0022345
80Q3	-2.5531	-.6825	.0000	-.0047621	-1.8645	-.0012616
80Q4	-2.5449	-.6841	.0000	.0030320	-1.8675	.0037395
81Q1	-2.5509	-.6837	.0000	.0028164	-1.8678	-.0022481
81Q2	-2.5521	-.6789	.0000	-.0010864	-1.8690	-.0031077
81Q3	-2.5416	-.6700	.0000	-.0047621	-1.8686	.0017106
81Q4	-2.5203	-.6606	.0000	.0030320	-1.8632	.0004609

STAMP Time Domain Estimation

Observation	Actual	Trend	Cycle	Seasonal	Exogenous	Irregular
82Q1	-2.5054	-.6524	.0000	.0028165	-1.8564	.0006730
82Q2	-2.4970	-.6467	.0000	-.0010864	-1.8512	.0020121
82Q3	-2.4925	-.6440	.0000	-.0047621	-1.8461	.0023787
82Q4	-2.4858	-.6425	.0000	.0030320	-1.8398	-.0065344
83Q1	-2.4731	-.6381	.0000	.0028165	-1.8395	.0016293
83Q2	-2.4752	-.6334	.0000	-.0010864	-1.8428	.0022019
83Q3	-2.4820	-.6297	.0000	-.0047621	-1.8469	-.0006063
83Q4	-2.4736	-.6255	.0000	.0030320	-1.8513	.0001393
84Q1	-2.4720	-.6202	.0000	.0028165	-1.8546	.0000865
84Q2	-2.4734	-.6130	.0000	-.0010864	-1.8570	-.0023141
84Q3	-2.4643	-.6029	.0000	-.0047621	-1.8578	.0012228
84Q4	-2.4486	-.5916	.0000	.0030319	-1.8570	-.0030187
85Q1	-2.4316	-.5792	.0000	.0028165	-1.8581	.0028769
85Q2	-2.4213	-.5694	.0000	-.0010864	-1.8556	.0048345
85Q3	-2.4207	-.5626	.0000	-.0047621	-1.8533	-.0000027
85Q4	-2.4152	-.5539	.0000	.0030319	-1.8536	-.0107
86Q1	-2.3902	-.5385	.0000	.0028165	-1.8537	-.0007999
86Q2	-2.3703	-.5232	.0000	-.0010864	-1.8528	.0068492
86Q3	-2.3677	-.5158	.0000	-.0047621	-1.8508	.0036653
86Q4	-2.3650	-.5165	.0000	.0030319	-1.8505	-.0009767
87Q1	-2.3692	-.5216	.0000	.0028165	-1.8510	.0005823
87Q2	-2.3831	-.5284	.0000	-.0010864	-1.8516	-.0020917
87Q3	-2.3931	-.5336	.0000	-.0047621	-1.8530	-.0017078
87Q4	-2.3908	-.5363	.0000	.0030319	-1.8549	-.0027128
88Q1	-2.3869	-.5372	.0000	.0028165	-1.8560	.0034726
88Q2	-2.3967	-.5401	.0000	-.0010864	-1.8569	.0014355
88Q3	-2.4083	-.5451	.0000	-.0047621	-1.8569	-.0015299
88Q4	-2.4023	-.5506	.0000	.0030319	-1.8577	.0029110
89Q1	-2.4140	-.5567	.0000	.0028165	-1.8587	-.0014254
89Q2	-2.4260	-.5604	.0000	-.0010864	-1.8586	-.0060186
89Q3	-2.4171	-.5601	.0000	-.0047620	-1.8567	.0044506
89Q4	-2.4111	-.5609	.0000	.0030319	-1.8546	.0013886
90Q1	-2.4146	-.5631	.0000	.0028165	-1.8531	-.0012017

STAMP

OUTPUT # 2

OUTPUT FOR MODEL II

Model with stochastic trend, cycle, trigonometric seasonal, and irregular.

****

Gradient norm = .100261E-04
Parameter tolerance = .249753E-04
Function value change = .299073E-09
Little change in function values over the last 2 iterations.

STRONG CONVERGENCE.

Iterations:Function evaluations:Function value:Gradient norm

Iterations	Function evaluations	Function value	Gradient norm
40	374	-1.03038	.100261E-04

Parameter	Value	Gradient
e}(Irregular)	.763046E-08	.000000
e}(Trend)	172.378	-.257572E-07
e}(Cycle)	32395.9	.301877E-08
e}(Seasonal)	.510077E-02	-.439614E-05
Damping Factor	.965583	-.106767E-07
Frequency	.214913	-.901092E-05

****

Time Domain Estimation

Dependent variable is LOG(AAAA)

Sample period 68Q1 to 90Q1 89 Observations

Estimate	Parameter	Standard Error	t-ratio
.0000000	e}(Level)	.0000892	.0000317
.0000005	e}(Trend)	.0000005	.9872
.0000917	e}(Cycle)	.0000778	1.1783
.0000000	e}(Seasonal)	.0000	Missing
.9656	Damping Factor	.0241	40.0901
.2149	Frequency	.0343	6.2649
29.2360	Period		
.0000	e}(Irregular)	1.0000	.0000

Time Domain Estimation

Dependent variable is LOG(AAAA)

Sample period 68Q1 to 90Q1 89 Observations

Estimate	State	RMSE	t-ratio
-.7366	Level	.7664	-.9612
.0031158	Trend	.0024821	1.2553
-.0382	Cycle	.0216	-1.7684
-.0105	Cycle	.0222	-.4743
.0036526	Harmonic	.0010682	3.4195
-.0020721	Harmonic	.0010659	-1.9441
-.0009966	Harmonic	.0005234	-1.9040
-.1733	LOG(AAAEMP1)	.0810	-2.1406

Time Domain Estimation

```
Residual skewness     -.3780
Residual kurtosis     4.3952

Normality tests

 Skewness chi^2(1)=     2.0005
 Kurtosis chi^2(1)=     6.8133
Normality chi^2(2)=     8.8138

Sum of squares of standardized residuals   86.0635
           Sum of squares about the mean   86.0153
          Mean of standardized residuals    -.0240

Heteroscedasticity test  F( 28, 28) =       .4010
```

Time Domain Estimation

Log-likelihood kernel	321.3244
Prediction error variance	.0001010

Prior and missing observations 6

Steady State 89

R2 =	.9652
RD2=	.4548
RS2=	.3800

Time Domain Estimation

Seasonality test 19.1640 Chi^2(3)

Seasonal effects from 90Q1

Q1	.0026560
Q2	-.0010756
Q3	-.0046491
Q4	.0030687

Time Domain Estimation

Observation	Actual	Fitted	Error	Residual	RMSE
68Q1	-2.4851	.0000	-2.4851	Missing	Missing
68Q2	-2.4781	-2.4351	-.0430	Missing	Missing
68Q3	-2.4785	-2.5124	.0339	Missing	Missing
68Q4	-2.4614	-2.5090	.0476	Missing	Missing
69Q1	-2.4601	-2.5505	.0904	Missing	Missing
69Q2	-2.4621	-2.4520	-.0101	Missing	Missing
69Q3	-2.4564	-2.4640	.0075535	.4846	.0156
69Q4	-2.4474	-2.4435	-.0039249	-.1305	.0301
70Q1	-2.4472	-2.4543	.0070827	.3487	.0203
70Q2	-2.4381	-2.4517	.0137	.7062	.0194
70Q3	-2.4311	-2.4340	.0029344	.2065	.0142
70Q4	-2.4227	-2.4142	-.0085134	-.4452	.0191
71Q1	-2.4062	-2.4199	.0137	.8442	.0162
71Q2	-2.4068	-2.3953	-.0115	-.8576	.0134
71Q3	-2.4078	-2.4012	-.0066532	-.5073	.0131
71Q4	-2.3943	-2.3940	-.0003033	-.0217	.0140
72Q1	-2.3853	-2.3877	.0024483	.1864	.0131
72Q2	-2.3852	-2.3796	-.0056090	-.4367	.0128
72Q3	-2.3921	-2.3833	-.0087709	-.6914	.0127
72Q4	-2.3804	-2.3794	-.0010509	-.0763	.0138
73Q1	-2.4085	-2.3754	-.0331	-2.6184	.0126
73Q2	-2.4438	-2.4160	-.0279	-2.2542	.0124
73Q3	-2.4705	-2.4595	-.0110	-.8824	.0124
73Q4	-2.4565	-2.4727	.0162	1.3043	.0124
74Q1	-2.5041	-2.4703	-.0338	-2.5628	.0132
74Q2	-2.5132	-2.5246	.0114	.9396	.0121
74Q3	-2.5536	-2.5263	-.0273	-2.2608	.0121
74Q4	-2.5514	-2.5658	.0144	1.0692	.0135
75Q1	-2.5257	-2.5899	.0642	3.7336	.0172
75Q2	-2.5244	-2.5237	-.0007564	-.0635	.0119
75Q3	-2.5327	-2.5282	-.0045060	-.3576	.0126
75Q4	-2.5222	-2.5177	-.0045760	-.3597	.0127
76Q1	-2.5067	-2.5204	.0137	1.1236	.0122
76Q2	-2.5073	-2.4989	-.0083908	-.7112	.0118
76Q3	-2.5000	-2.5050	.0050310	.4260	.0118
76Q4	-2.4858	-2.4770	-.0087965	-.7453	.0118
77Q1	-2.4853	-2.4785	-.0067872	-.5744	.0118
77Q2	-2.4922	-2.4835	-.0087574	-.7450	.0118
77Q3	-2.4753	-2.4961	.0207	1.7690	.0117
77Q4	-2.4631	-2.4577	-.0053615	-.4575	.0117
78Q1	-2.4642	-2.4613	-.0028332	-.2412	.0117
78Q2	-2.4795	-2.4672	-.0123	-1.0496	.0117
78Q3	-2.4748	-2.4879	.0131	1.1227	.0117
78Q4	-2.4690	-2.4673	-.0016506	-.1405	.0117
79Q1	-2.4811	-2.4748	-.0062979	-.5390	.0117
79Q2	-2.4982	-2.4923	-.0059200	-.5084	.0116
79Q3	-2.5136	-2.5098	-.0037562	-.3220	.0117
79Q4	-2.5256	-2.5119	-.0137	-1.1777	.0116
80Q1	-2.5495	-2.5393	-.0103	-.8810	.0116
80Q2	-2.5455	-2.5643	.0188	1.5497	.0122
80Q3	-2.5531	-2.5552	.0021087	.1811	.0116
80Q4	-2.5449	-2.5550	.0101	.8389	.0121
81Q1	-2.5509	-2.5527	.0017838	.1534	.0116
81Q2	-2.5521	-2.5596	.0074432	.6398	.0116
81Q3	-2.5416	-2.5567	.0151	1.3062	.0116
81Q4	-2.5203	-2.5241	.0038245	.3215	.0119

STAMP Time Domain Estimation

Observation	Actual	Fitted	Error	Residual	RMSE
82Q1	-2.5054	-2.5133	.0078790	.6620	.0119
82Q2	-2.4970	-2.4989	.0019423	.1666	.0117
82Q3	-2.4925	-2.4903	-.0021206	-.1824	.0116
82Q4	-2.4858	-2.4726	-.0132	-1.1282	.0117
83Q1	-2.4731	-2.4875	.0145	1.2478	.0116
83Q2	-2.4752	-2.4765	.0013616	.1162	.0117
83Q3	-2.4820	-2.4797	-.0022275	-.1914	.0116
83Q4	-2.4736	-2.4759	.0022556	.1947	.0116
84Q1	-2.4720	-2.4782	.0062563	.5425	.0115
84Q2	-2.4734	-2.4776	.0042424	.3680	.0115
84Q3	-2.4643	-2.4781	.0138	1.1949	.0115
84Q4	-2.4486	-2.4527	.0041364	.3571	.0116
85Q1	-2.4316	-2.4496	.0180	1.5637	.0115
85Q2	-2.4213	-2.4293	.0080152	.6906	.0116
85Q3	-2.4207	-2.4185	-.0021467	-.1861	.0115
85Q4	-2.4152	-2.4102	-.0050122	-.4353	.0115
86Q1	-2.3902	-2.4173	.0271	2.3540	.0115
86Q2	-2.3703	-2.3892	.0189	1.6437	.0115
86Q3	-2.3677	-2.3659	-.0018357	-.1597	.0115
86Q4	-2.3650	-2.3554	-.0096232	-.8369	.0115
87Q1	-2.3692	-2.3657	-.0034820	-.3027	.0115
87Q2	-2.3831	-2.3751	-.0080458	-.6998	.0115
87Q3	-2.3931	-2.3935	.0004648	.0404	.0115
87Q4	-2.3908	-2.3924	.0015305	.1329	.0115
88Q1	-2.3869	-2.3969	.0100	.8724	.0115
88Q2	-2.3967	-2.3931	-.0036409	-.3173	.0115
88Q3	-2.4083	-2.4029	-.0053414	-.4659	.0115
88Q4	-2.4023	-2.4039	.0015241	.1328	.0115
89Q1	-2.4140	-2.4040	-.0100	-.8729	.0115
89Q2	-2.4260	-2.4193	-.0067348	-.5878	.0115
89Q3	-2.4171	-2.4303	.0132	1.1509	.0115
89Q4	-2.4111	-2.4040	-.0071015	-.6194	.0115
90Q1	-2.4146	-2.4067	-.0079396	-.6931	.0115

Time Domain Estimation

Observation	Actual	Trend	Cycle	Seasonal	Exogenous	Irregular
68Q1	-2.4851	-.7943	-.0341	.0026553	-1.6594	.0000000
68Q2	-2.4781	-.7936	-.0227	-.0010749	-1.6607	.0000000
68Q3	-2.4785	-.7930	-.0197	-.0046501	-1.6612	.0000000
68Q4	-2.4614	-.7924	-.0097878	.0030697	-1.6623	.0000000
69Q1	-2.4601	-.7919	-.0072447	.0026553	-1.6636	.0000000
69Q2	-2.4621	-.7915	-.0052390	-.0010749	-1.6642	.0000000
69Q3	-2.4564	-.7913	.0042712	-.0046501	-1.6647	.0000000
69Q4	-2.4474	-.7912	.0037605	.0030697	-1.6630	.0000000
70Q1	-2.4472	-.7913	.0023068	.0026553	-1.6609	.0000000
70Q2	-2.4381	-.7915	.0115	-.0010749	-1.6571	.0000000
70Q3	-2.4311	-.7918	.0197	-.0046501	-1.6544	.0000000
70Q4	-2.4227	-.7922	.0135	.0030697	-1.6470	.0000000
71Q1	-2.4062	-.7928	.0328	.0026554	-1.6488	.0000000
71Q2	-2.4068	-.7936	.0368	-.0010749	-1.6490	.0000000
71Q3	-2.4078	-.7944	.0397	-.0046501	-1.6485	.0000000
71Q4	-2.3943	-.7955	.0474	.0030697	-1.6494	.0000000
72Q1	-2.3853	-.7966	.0604	.0026554	-1.6517	.0000000
72Q2	-2.3852	-.7980	.0683	-.0010749	-1.6544	.0000000
72Q3	-2.3921	-.7995	.0673	-.0046501	-1.6552	.0000000
72Q4	-2.3804	-.8013	.0771	.0030697	-1.6594	.0000000
73Q1	-2.4085	-.8033	.0552	.0026554	-1.6631	.0000000
73Q2	-2.4438	-.8055	.0273	-.0010749	-1.6646	.0000000
73Q3	-2.4705	-.8078	.0067523	-.0046501	-1.6648	.0000000
73Q4	-2.4565	-.8102	.0172	.0030697	-1.6665	.0000000
74Q1	-2.5041	-.8128	-.0287	.0026554	-1.6652	.0000000
74Q2	-2.5132	-.8154	-.0323	-.0010750	-1.6644	.0000000
74Q3	-2.5536	-.8181	-.0677	-.0046501	-1.6631	.0000000
74Q4	-2.5514	-.8207	-.0770	.0030696	-1.6568	.0000000
75Q1	-2.5257	-.8233	-.0616	.0026555	-1.6435	.0000000
75Q2	-2.5244	-.8258	-.0579	-.0010750	-1.6397	.0000000
75Q3	-2.5327	-.8283	-.0585	-.0046500	-1.6412	.0000000
75Q4	-2.5222	-.8308	-.0497	.0030695	-1.6449	.0000000
76Q1	-2.5067	-.8331	-.0279	.0026555	-1.6484	.0000000
76Q2	-2.5073	-.8355	-.0204	-.0010751	-1.6503	.0000000
76Q3	-2.5000	-.8378	-.0067793	-.0046498	-1.6508	.0000000
76Q4	-2.4858	-.8400	.0020827	.0030694	-1.6510	.0000000
77Q1	-2.4853	-.8421	.0071498	.0026556	-1.6531	.0000000
77Q2	-2.4922	-.8440	.0089755	-.0010752	-1.6561	.0000000
77Q3	-2.4753	-.8458	.0326	-.0046497	-1.6575	.0000000
77Q4	-2.4631	-.8474	.0400	.0030693	-1.6587	.0000000
78Q1	-2.4642	-.8489	.0431	.0026556	-1.6611	.0000000
78Q2	-2.4795	-.8502	.0346	-.0010753	-1.6628	.0000000
78Q3	-2.4748	-.8513	.0451	-.0046496	-1.6639	.0000000
78Q4	-2.4690	-.8522	.0466	.0030693	-1.6664	.0000000
79Q1	-2.4811	-.8530	.0374	.0026557	-1.6681	.0000000
79Q2	-2.4982	-.8535	.0248	-.0010753	-1.6685	.0000000
79Q3	-2.5136	-.8539	.0122	-.0046496	-1.6673	.0000000
79Q4	-2.5256	-.8540	-.0089078	.0030692	-1.6658	.0000000
80Q1	-2.5495	-.8539	-.0342	.0026557	-1.6641	.0000000
80Q2	-2.5455	-.8534	-.0339	-.0010753	-1.6571	.0000000
80Q3	-2.5531	-.8527	-.0432	-.0046495	-1.6526	.0000000
80Q4	-2.5449	-.8517	-.0411	.0030691	-1.6552	.0000000
81Q1	-2.5509	-.8504	-.0477	.0026557	-1.6555	.0000000
81Q2	-2.5521	-.8488	-.0456	-.0010753	-1.6566	.0000000
81Q3	-2.5416	-.8470	-.0338	-.0046494	-1.6562	.0000000
81Q4	-2.5203	-.8450	-.0270	.0030690	-1.6514	.0000000

STAMP

Time Domain Estimation

Observation	Actual	Trend	Cycle	Seasonal	Exogenous	Irregular
82Q1	-2.5054	-.8427	-.0199	.0026558	-1.6454	.0000000
82Q2	-2.4970	-.8404	-.0148	-.0010754	-1.6408	.0000000
82Q3	-2.4925	-.8378	-.0137	-.0046494	-1.6362	.0000000
82Q4	-2.4858	-.8352	-.0230	.0030689	-1.6307	.0000000
83Q1	-2.4731	-.8324	-.0130	.0026559	-1.6304	.0000000
83Q2	-2.4752	-.8294	-.0113	-.0010754	-1.6334	.0000000
83Q3	-2.4820	-.8263	-.0140	-.0046493	-1.6369	.0000000
83Q4	-2.4736	-.8232	-.0127	.0030688	-1.6408	.0000000
84Q1	-2.4720	-.8198	-.0110	.0026559	-1.6438	.0000000
84Q2	-2.4734	-.8164	-.0099966	-.0010754	-1.6459	.0000000
84Q3	-2.4643	-.8129	-.0001059	-.0046493	-1.6467	.0000000
84Q4	-2.4486	-.8093	.0035640	.0030688	-1.6460	.0000000
85Q1	-2.4316	-.8056	.0182	.0026560	-1.6469	.0000000
85Q2	-2.4213	-.8019	.0264	-.0010755	-1.6447	.0000000
85Q3	-2.4207	-.7982	.0248	-.0046492	-1.6426	.0000000
85Q4	-2.4152	-.7945	.0191	.0030687	-1.6429	.0000000
86Q1	-2.3902	-.7907	.0408	.0026560	-1.6430	.0000000
86Q2	-2.3703	-.7869	.0599	-.0010755	-1.6422	.0000000
86Q3	-2.3677	-.7832	.0606	-.0046492	-1.6404	.0000000
86Q4	-2.3650	-.7796	.0517	.0030687	-1.6402	.0000000
87Q1	-2.3692	-.7761	.0449	.0026560	-1.6406	.0000000
87Q2	-2.3831	-.7726	.0317	-.0010755	-1.6411	.0000000
87Q3	-2.3931	-.7692	.0231	-.0046492	-1.6423	.0000000
87Q4	-2.3908	-.7658	.0159	.0030687	-1.6440	.0000000
88Q1	-2.3869	-.7623	.0178	.0026560	-1.6450	.0000000
88Q2	-2.3967	-.7590	.0092228	-.0010755	-1.6459	.0000000
88Q3	-2.4083	-.7557	-.0021237	-.0046492	-1.6458	.0000000
88Q4	-2.4023	-.7524	-.0064416	.0030687	-1.6465	.0000000
89Q1	-2.4140	-.7492	-.0200	.0026560	-1.6475	.0000000
89Q2	-2.4260	-.7461	-.0316	-.0010756	-1.6473	.0000000
89Q3	-2.4171	-.7429	-.0240	-.0046491	-1.6457	.0000000
89Q4	-2.4111	-.7397	-.0307	.0030687	-1.6437	.0000000
90Q1	-2.4146	-.7366	-.0382	.0026560	-1.6425	.0000000

A P P E N D I X

T O

C H A P T E R 4

S T A M P O U T P U T S

```
  Parameter         Value              Gradient
e}(Irregular)     .267592E-09       .219824E-04
e}(Trend)         .223850           .387661E-03
e}(Seasonal)      .292939E-03      -.257703E-02
Hessian reset at iteration    13 restarting.

************************************************************
Gradient norm =        .129671E-04
Parameter tolerance =       .109875E-04
Function value change =       .100091E-10
There were      1 Hessian resets
Little change in function values over the last     2 iterations.

STRONG CONVERGENCE.

Iterations:Function evaluations:Function value:Gradient norm
    14               92            -1.01945           .129671E-04
  Parameter         Value              Gradient
e}(Irregular)     .272912E-09      -.435207E-05
e}(Trend)         .219161          -.140333E-05
e}(Seasonal)      .297839E-03       .121341E-04

************************************************************
 e}(Irregular)  set to zero. Its value on exit was    .272912E-09
                       Type any key to continue...
```

Time Domain Estimation

Dependent variable is LOG(AAAA)

Sample period 47Q1 to 90Q1 173 Observations

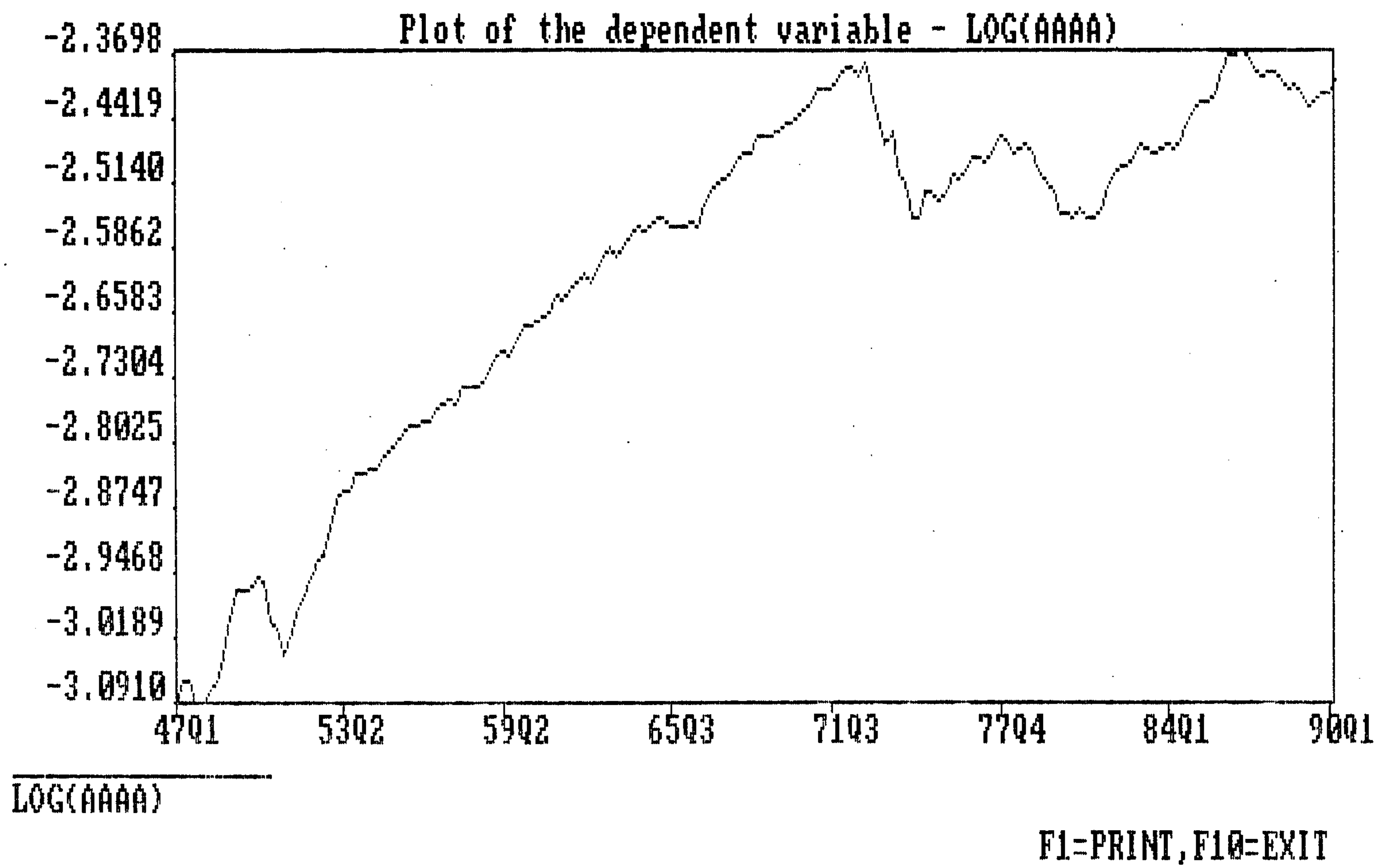
Estimate	Parameter	Standard Error	t-ratio
.0000899	e}(Level)	.0000136	6.6334
.0000197	e}(Trend)	.0000067	2.9257
.0000000	e}(Seasonal)	.0000	Missing
.0000	e}(Irregular)	1.0000	.0000

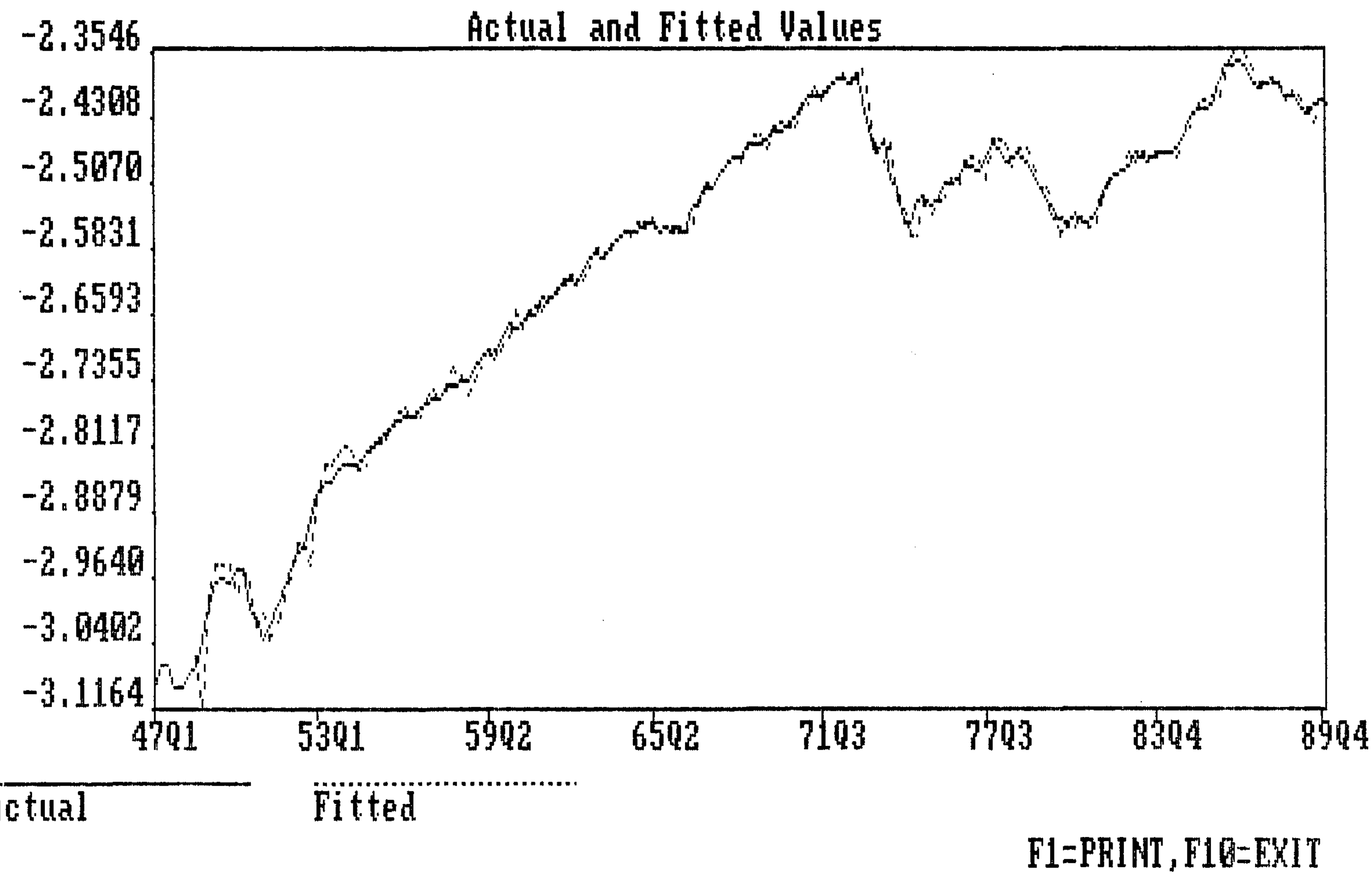
Time Domain Estimation

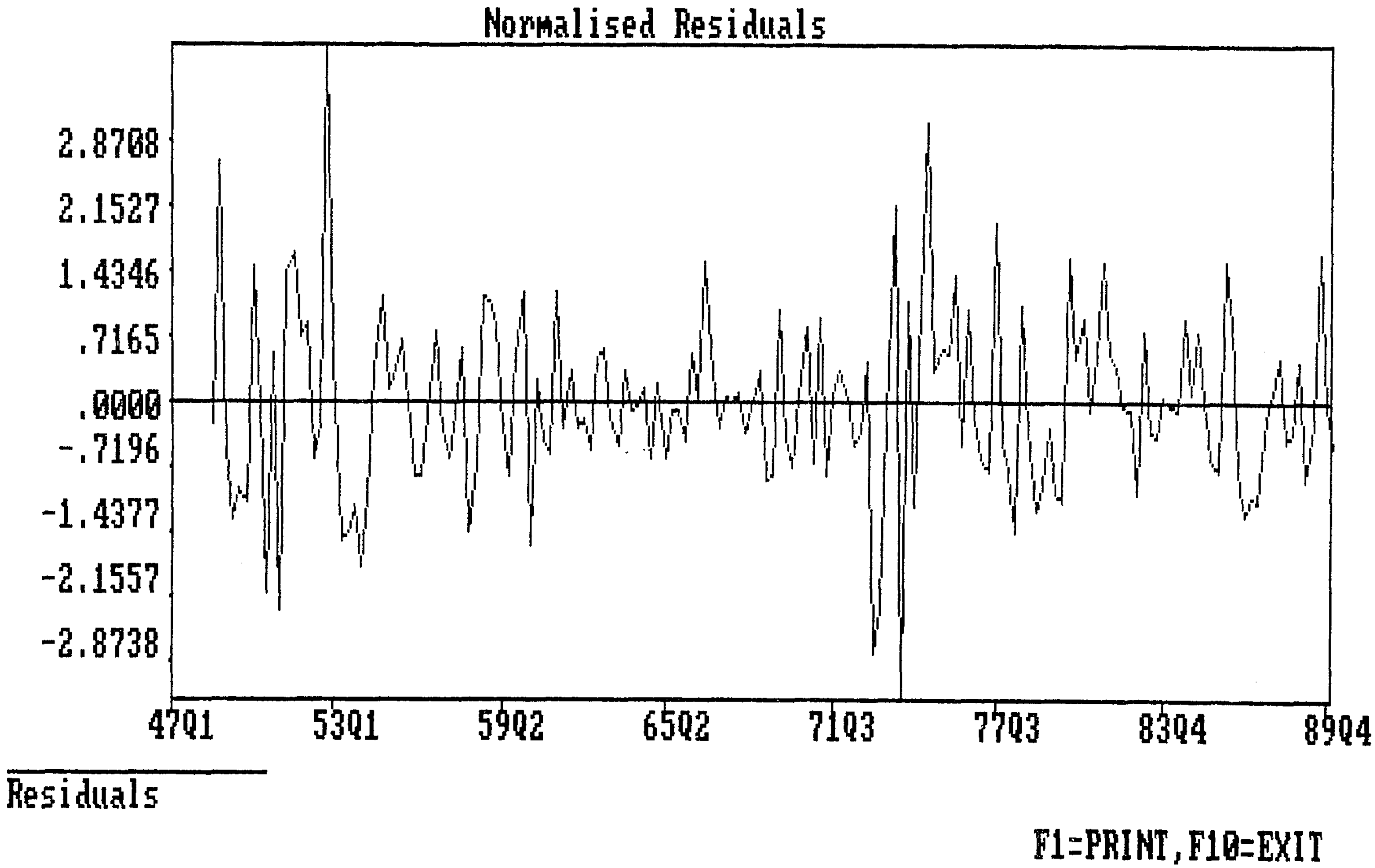
Dependent variable is LOG(AAAA)

Sample period 47Q1 to 90Q1 173 Observations

Estimate	State	RMSE	t-ratio
-1.2135	Level	.4871	-2.4913
-.0025580	Trend	.0073281	-.3491
.0036276	Harmonic	.0012889	2.8146
-.0009874	Harmonic	.0012842	-.7688
-.0005696	Harmonic	.0008949	-.6366
-.1271	LOG(AAAEMP1)	.0514	-2.4720


Plot of the dependent variable - LOG(AAAA)
-2.3698
-2.4419
-2.5140
-2.5862
-2.6583
-2.7304
-2.8025
-2.8747
-2.9468
-3.0189
-3.0910
47Q1
53Q2
59Q2
65Q3
71Q3
77Q4
84Q1
90Q1
LOG(AAAA)
F1=PRINT,F10=EXIT


Actual and Fitted Values
-2.3546
-2.4308
-2.5070
-2.5831
-2.6593
-2.7355
-2.8117
-2.8879
-2.9640
-3.0402
-3.1164
47Q1
53Q1
59Q2
65Q2
71Q3
77Q3
83Q4
89Q4
Actual
Fitted
F1=PRINT,F10=EXIT


Normalised Residuals
2.8708
2.1527
1.4346
.7165
.0000
-.7196
-1.4377
-2.1557
-2.8738
47Q1
53Q1
59Q2
65Q2
71Q3
77Q3
83Q4
89Q4
Residuals
F1=PRINT,F10=EXIT

Time Domain Estimation

```
Residual skewness      .1706
Residual kurtosis     4.6170

Normality tests

 Skewness chi^2(1)=     .8147
 Kurtosis chi^2(1)=   18.3026
Normality chi^2(2)=   19.1173

Sum of squares of standardized residuals  167.3454
           Sum of squares about the mean  167.3421
          Mean of standardized residuals -.0044805

Heteroscedasticity test  F( 56, 56) =       .5116
```

```
Lag===================0====================Autocorrelation:Q-statistic
 1                    ¦**                    .078002       1.041
 2                  **¦                     -.071974       1.932
 3                   *¦                     -.016179       1.977
 4                    ¦*                     .025747       2.093
 5                   *¦                     -.042252       2.405
 6                  **¦                     -.079735       3.526
 7                ****¦                     -.169942       8.649
 8                ****¦                     -.173757       14.04
 9                 ***¦                     -.121605       16.69
10                 ***¦                     -.138088       20.14
11                    ¦**                    .099010       21.92
12                    ¦*                     .029451       22.08
13                    ¦**                    .065317       22.87
14                 ***¦                     -.118048       25.45
15                    ¦**                    .095120       27.14
16                    ¦***                   .131880       30.41
17                    ¦*                     .035805       30.65
18                 ***¦                     -.130679       33.90
19                   *¦                     -.000098       33.90
20                    ¦*                     .022181       34.00
21                  **¦                     -.075374       35.10
22                   *¦                     -.005521       35.11
23                    ¦**                    .061019       35.84
24                    ¦**                    .058942       36.53
25                  **¦                     -.080357       37.82
26                    ¦*                     .041717       38.17
27                   *¦                     -.028150       38.33
28                    ¦**                    .084963       39.80
29                   *¦                     -.047286       40.26
30                   *¦                     -.007457       40.28
31                   *¦                     -.015821       40.33
32                    ¦*                     .028149       40.49
   95% C.I.       ++++0++++             2/sqrt( 168)=  .154303
```

Time Domain Estimation

```
    Log-likelihood kernel   643.6715
Prediction error variance    .0001526

Prior and missing observations    6

                    Steady State 173

                        R2 =     .9964
                        RD2=     .1785
                        RS2=     .0867
```

Time Domain Estimation

```
Seasonality test     8.9295     Chi^2(    3)

Seasonal effects from 90Q1

           Q1      .0030580
           Q2     -.0004177
           Q3     -.0041973
           Q4      .0015570
```

Time Domain Estimation

Observation	Actual	Fitted	Error	Residual	RMSE
47Q1	-3.0900	.0000	-3.0900	Missing	Missing
47Q2	-3.0661	-3.0208	-.0452	Missing	Missing
47Q3	-3.0657	-3.1105	.0448	Missing	Missing
47Q4	-3.0910	-3.1038	.0128	Missing	Missing
48Q1	-3.0889	-3.1938	.1050	Missing	Missing
48Q2	-3.0764	-3.0625	-.0139	Missing	Missing
48Q3	-3.0657	-3.0565	-.0092605	-.2512	.0369
48Q4	-3.0375	-3.1164	.0790	2.6359	.0300
49Q1	-2.9970	-2.9852	-.0117	-.5198	.0226
49Q2	-2.9682	-2.9485	-.0197	-1.3031	.0151
49Q3	-2.9642	-2.9509	-.0133	-.9523	.0140
49Q4	-2.9666	-2.9510	-.0157	-1.1110	.0141
50Q1	-2.9519	-2.9847	.0328	1.4936	.0220
50Q2	-2.9549	-2.9528	-.0020397	-.1146	.0178
50Q3	-2.9981	-2.9686	-.0295	-2.1064	.0140
50Q4	-3.0107	-3.0179	.0071475	.5346	.0134
51Q1	-3.0366	-3.0062	-.0305	-2.2803	.0134
51Q2	-3.0177	-3.0369	.0192	1.4377	.0133
51Q3	-2.9924	-3.0156	.0232	1.6098	.0144
51Q4	-2.9749	-2.9844	.0095203	.7217	.0132
52Q1	-2.9521	-2.9635	.0115	.8766	.0131
52Q2	-2.9313	-2.9234	-.0079830	-.6167	.0129
52Q3	-2.9284	-2.9251	-.0032872	-.2550	.0129
52Q4	-2.8952	-2.9506	.0555	3.9239	.0141
53Q1	-2.8671	-2.8732	.0061406	.4761	.0129
53Q2	-2.8536	-2.8342	-.0194	-1.5143	.0128
53Q3	-2.8532	-2.8343	-.0189	-1.4357	.0131
53Q4	-2.8385	-2.8222	-.0163	-1.1691	.0139
54Q1	-2.8345	-2.8105	-.0240	-1.8382	.0130
54Q2	-2.8306	-2.8173	-.0133	-1.0513	.0127
54Q3	-2.8303	-2.8353	.0050190	.3958	.0127
54Q4	-2.8169	-2.8315	.0146	1.1367	.0129
55Q1	-2.8100	-2.8119	.0019069	.1472	.0130
55Q2	-2.8006	-2.8050	.0044258	.3409	.0130
55Q3	-2.7943	-2.8026	.0082638	.6550	.0126
55Q4	-2.7849	-2.7850	.0001069	.0084758	.0126
56Q1	-2.7811	-2.7706	-.0105	-.8336	.0126
56Q2	-2.7777	-2.7671	-.0105	-.8368	.0126
56Q3	-2.7761	-2.7771	.0009962	.0785	.0127
56Q4	-2.7650	-2.7744	.0093651	.7405	.0126
57Q1	-2.7593	-2.7548	-.0045058	-.3586	.0126
57Q2	-2.7547	-2.7467	-.0080200	-.6386	.0126
57Q3	-2.7582	-2.7567	-.0015572	-.1242	.0125
57Q4	-2.7405	-2.7477	.0071746	.5642	.0127
58Q1	-2.7408	-2.7220	-.0188	-1.4585	.0129
58Q2	-2.7380	-2.7293	-.0087158	-.6946	.0125
58Q3	-2.7369	-2.7517	.0147	1.1323	.0130

58Q4	-2.7213	-2.7351	.0138	1.0837	.0127
59Q1	-2.7081	-2.7186	.0105	.8192	.0128
59Q2	-2.7023	-2.6987	-.0036122	-.2865	.0126
59Q3	-2.7086	-2.6983	-.0103	-.8131	.0127
59Q4	-2.6918	-2.6986	.0068452	.5461	.0125
60Q1	-2.6714	-2.6865	.0152	1.1987	.0127
60Q2	-2.6735	-2.6539	-.0196	-1.5616	.0126
60Q3	-2.6703	-2.6731	.0028033	.2236	.0125
60Q4	-2.6618	-2.6564	-.0054016	-.4287	.0126

STAMP — Time Domain Estimation

Observation	Actual	Fitted	Error	Residual	RMSE
61Q1	-2.6575	-2.6505	-.0069606	-.5568	.0125
61Q2	-2.6395	-2.6543	.0149	1.1735	.0127
61Q3	-2.6435	-2.6401	-.0034401	-.2744	.0125
61Q4	-2.6298	-2.6341	.0042864	.3441	.0125
62Q1	-2.6234	-2.6199	-.0034827	-.2798	.0124
62Q2	-2.6167	-2.6145	-.0021910	-.1761	.0124
62Q3	-2.6249	-2.6180	-.0068146	-.5477	.0124
62Q4	-2.6108	-2.6165	.0056656	.4550	.0125
63Q1	-2.5952	-2.6025	.0072998	.5871	.0124
63Q2	-2.5871	-2.5848	-.0023118	-.1858	.0124
63Q3	-2.5941	-2.5880	-.0060975	-.4909	.0124
63Q4	-2.5801	-2.5843	.0041764	.3362	.0124
64Q1	-2.5715	-2.5706	-.0009328	-.0751	.0124
64Q2	-2.5632	-2.5628	-.0003822	-.0308	.0124
64Q3	-2.5649	-2.5668	.0018042	.1451	.0124
64Q4	-2.5616	-2.5540	-.0075518	-.6085	.0124
65Q1	-2.5533	-2.5554	.0021022	.1694	.0124
65Q2	-2.5546	-2.5466	-.0079980	-.6445	.0124
65Q3	-2.5632	-2.5623	-.0009494	-.0765	.0124
65Q4	-2.5598	-2.5583	-.0014064	-.1134	.0124
66Q1	-2.5621	-2.5567	-.0054256	-.4373	.0124
66Q2	-2.5558	-2.5622	.0064228	.5176	.0124
66Q3	-2.5632	-2.5635	.0003757	.0303	.0124
66Q4	-2.5383	-2.5575	.0192	1.5469	.0124
67Q1	-2.5230	-2.5264	.0034316	.2754	.0125
67Q2	-2.5123	-2.5089	-.0033682	-.2705	.0125
67Q3	-2.5114	-2.5121	.0006836	.0552	.0124
67Q4	-2.4975	-2.4976	.0001029	.0082977	.0124
68Q1	-2.4851	-2.4860	.0008927	.0720	.0124
68Q2	-2.4781	-2.4740	-.0040600	-.3274	.0124
68Q3	-2.4785	-2.4793	.0007773	.0627	.0124
68Q4	-2.4614	-2.4655	.0040949	.3305	.0124
69Q1	-2.4601	-2.4494	-.0106	-.8587	.0124
69Q2	-2.4621	-2.4521	-.0099307	-.8017	.0124
69Q3	-2.4564	-2.4688	.0124	.9981	.0124
69Q4	-2.4474	-2.4428	-.0045776	-.3681	.0124
70Q1	-2.4472	-2.4382	-.0090140	-.7261	.0124
70Q2	-2.4381	-2.4415	.0033942	.2731	.0124
70Q3	-2.4311	-2.4414	.0102	.8274	.0124
70Q4	-2.4227	-2.4144	-.0083167	-.6622	.0126
71Q1	-2.4062	-2.4174	.0112	.8928	.0126
71Q2	-2.4068	-2.3968	-.0099771	-.8034	.0124
71Q3	-2.4078	-2.4090	.0011186	.0903	.0124
71Q4	-2.3943	-2.3986	.0042516	.3428	.0124

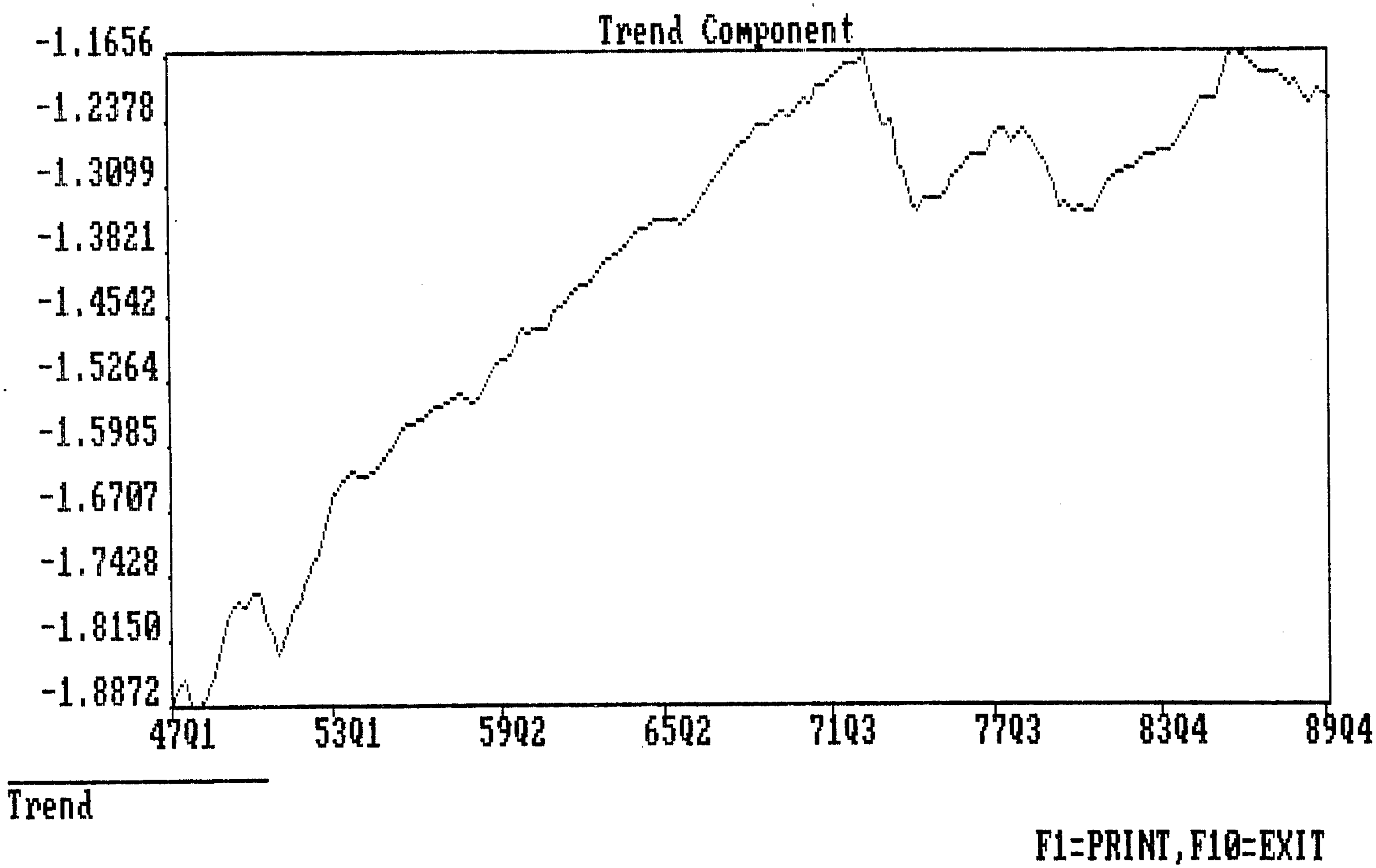
72Q1	-2.3853	-2.3859	.0006616	.0534	.0124
72Q2	-2.3852	-2.3792	-.0060125	-.4845	.0124
72Q3	-2.3921	-2.3880	-.0041008	-.3313	.0124
72Q4	-2.3804	-2.3860	.0056095	.4513	.0124
73Q1	-2.4085	-2.3739	-.0345	-2.7883	.0124
73Q2	-2.4438	-2.4153	-.0285	-2.3054	.0124
73Q3	-2.4705	-2.4682	-.0023322	-.1882	.0124
73Q4	-2.4565	-2.4832	.0267	2.1555	.0124
74Q1	-2.5041	-2.4629	-.0411	-3.3047	.0124
74Q2	-2.5132	-2.5268	.0136	1.0996	.0124
74Q3	-2.5536	-2.5393	-.0142	-1.1482	.0124
74Q4	-2.5514	-2.5655	.0141	1.1202	.0126

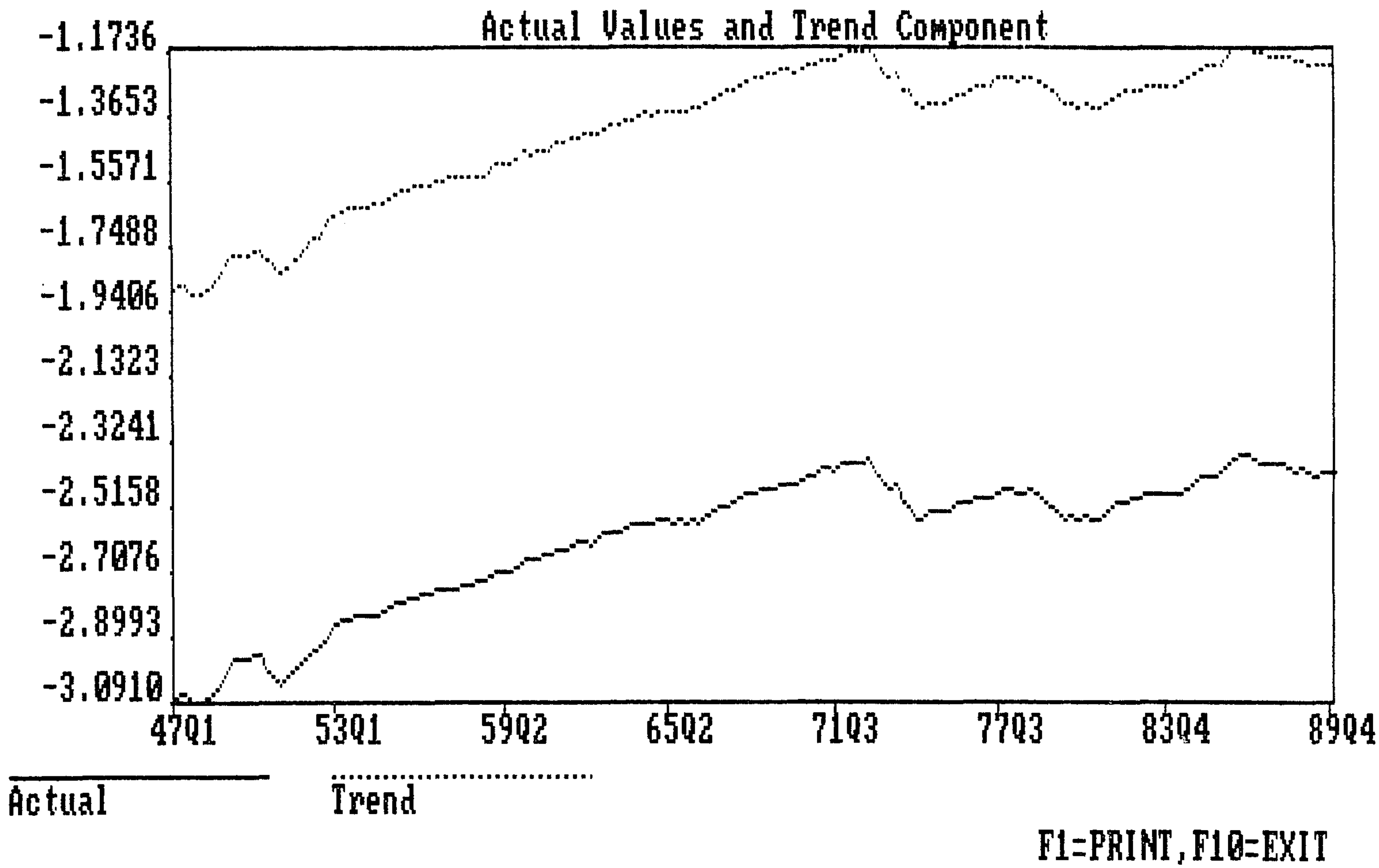
STAMP

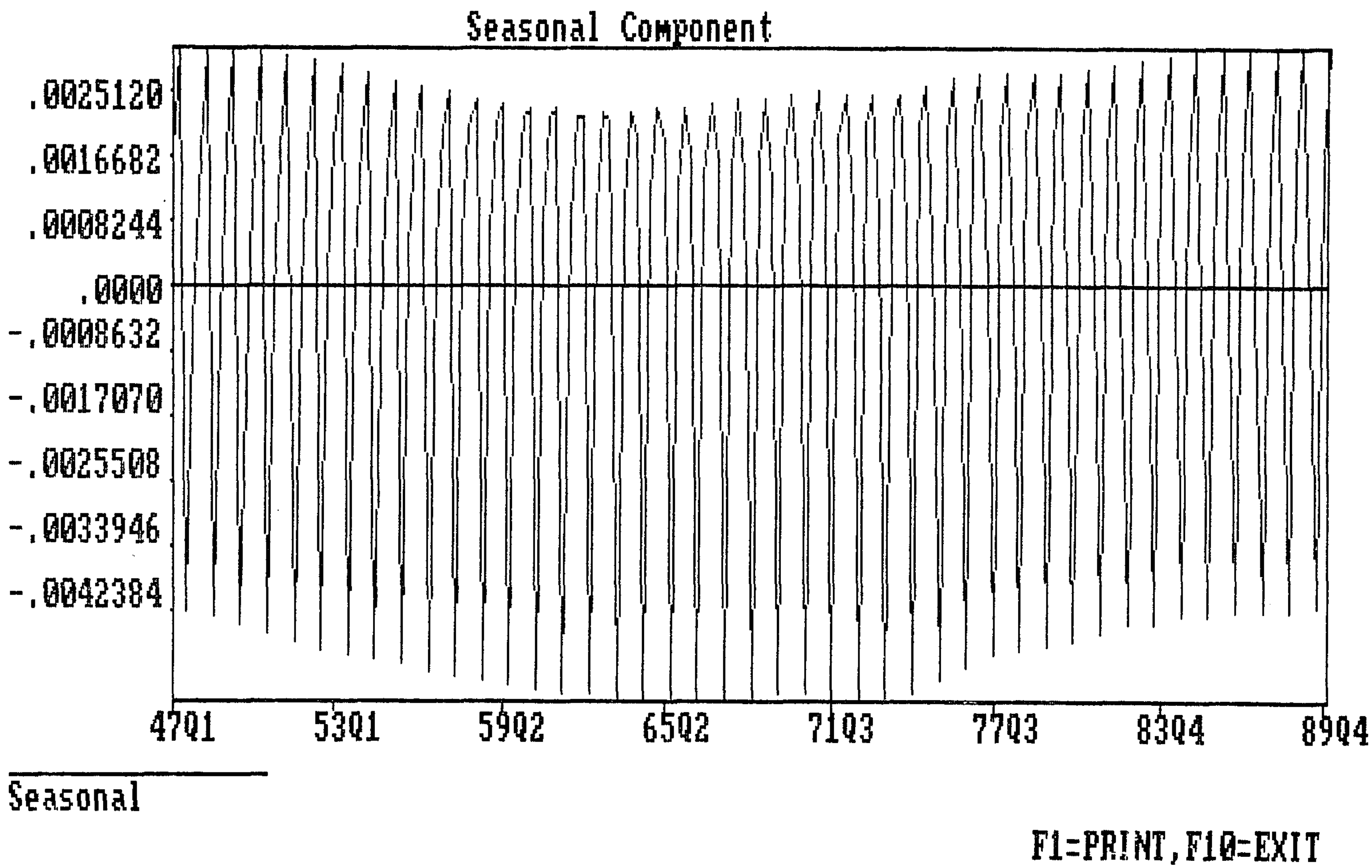
Time Domain Estimation

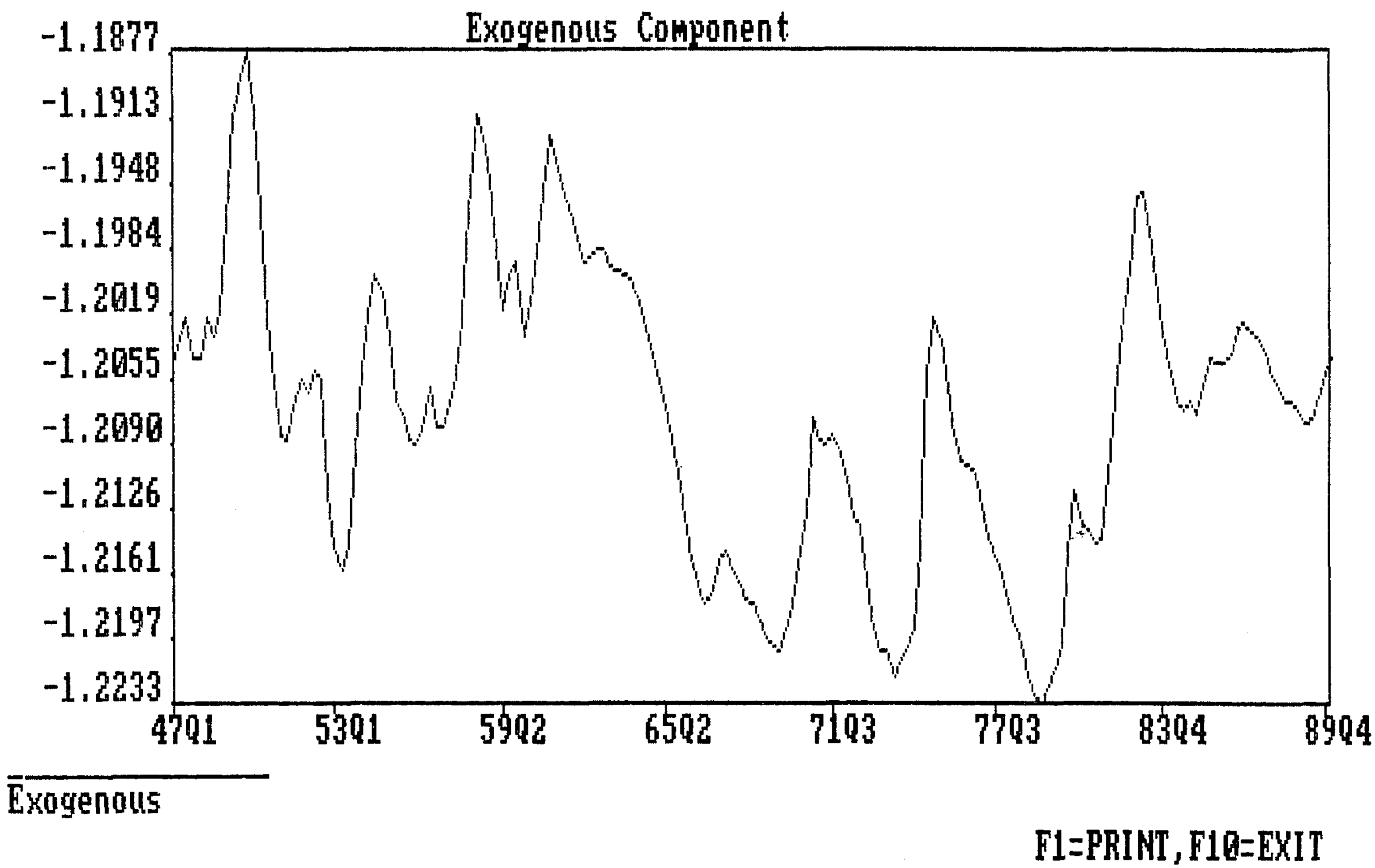
Observation	Actual	Fitted	Error	Residual	RMSE
75Q1	-2.5257	-2.5658	.0401	3.0788	.0130
75Q2	-2.5244	-2.5287	.0042409	.3419	.0124
75Q3	-2.5327	-2.5402	.0074833	.5927	.0126
75Q4	-2.5222	-2.5289	.0066355	.5280	.0126
76Q1	-2.5067	-2.5241	.0174	1.3949	.0125
76Q2	-2.5073	-2.5013	-.0060028	-.4851	.0124
76Q3	-2.5000	-2.5126	.0126	1.0220	.0124
76Q4	-2.4858	-2.4831	-.0026537	-.2144	.0124
77Q1	-2.4853	-2.4778	-.0075579	-.6105	.0124
77Q2	-2.4922	-2.4825	-.0097422	-.7867	.0124
77Q3	-2.4753	-2.4998	.0245	1.9782	.0124
77Q4	-2.4631	-2.4579	-.0051386	-.4154	.0124
78Q1	-2.4642	-2.4545	-.0096656	-.7812	.0124
78Q2	-2.4795	-2.4616	-.0179	-1.4448	.0124
78Q3	-2.4748	-2.4879	.0131	1.0622	.0124
78Q4	-2.4690	-2.4655	-.0034410	-.2781	.0124
79Q1	-2.4811	-2.4663	-.0148	-1.1988	.0124
79Q2	-2.4982	-2.4869	-.0114	-.9200	.0124
79Q3	-2.5136	-2.5100	-.0036001	-.2905	.0124
79Q4	-2.5256	-2.5132	-.0124	-1.0011	.0124
80Q1	-2.5495	-2.5360	-.0135	-1.0913	.0124
80Q2	-2.5455	-2.5654	.0200	1.5931	.0125
80Q3	-2.5531	-2.5587	.0056186	.4541	.0124
80Q4	-2.5449	-2.5563	.0115	.9154	.0125
81Q1	-2.5509	-2.5498	-.0010810	-.0873	.0124
81Q2	-2.5521	-2.5585	.0063830	.5154	.0124
81Q3	-2.5416	-2.5604	.0188	1.5194	.0124
81Q4	-2.5203	-2.5267	.0063938	.5127	.0125
82Q1	-2.5054	-2.5104	.0050194	.4036	.0124
82Q2	-2.4970	-2.4962	-.0007588	-.0613	.0124
82Q3	-2.4925	-2.4911	-.0013706	-.1108	.0124
82Q4	-2.4858	-2.4733	-.0125	-1.0093	.0124
83Q1	-2.4731	-2.4828	.0096882	.7790	.0124
83Q2	-2.4752	-2.4711	-.0041091	-.3284	.0125
83Q3	-2.4820	-2.4773	-.0046397	-.3727	.0124
83Q4	-2.4736	-2.4744	.0007331	.0591	.0124
84Q1	-2.4720	-2.4715	-.0004255	-.0344	.0124
84Q2	-2.4734	-2.4725	-.0009119	-.0737	.0124
84Q3	-2.4643	-2.4758	.0114	.9250	.0124
84Q4	-2.4486	-2.4498	.0011833	.0955	.0124
85Q1	-2.4316	-2.4410	.0094374	.7633	.0124
85Q2	-2.4213	-2.4221	.0008573	.0691	.0124
85Q3	-2.4207	-2.4129	-.0077853	-.6291	.0124
85Q4	-2.4152	-2.4055	-.0096307	-.7786	.0124
86Q1	-2.3902	-2.4089	.0187	1.5155	.0124

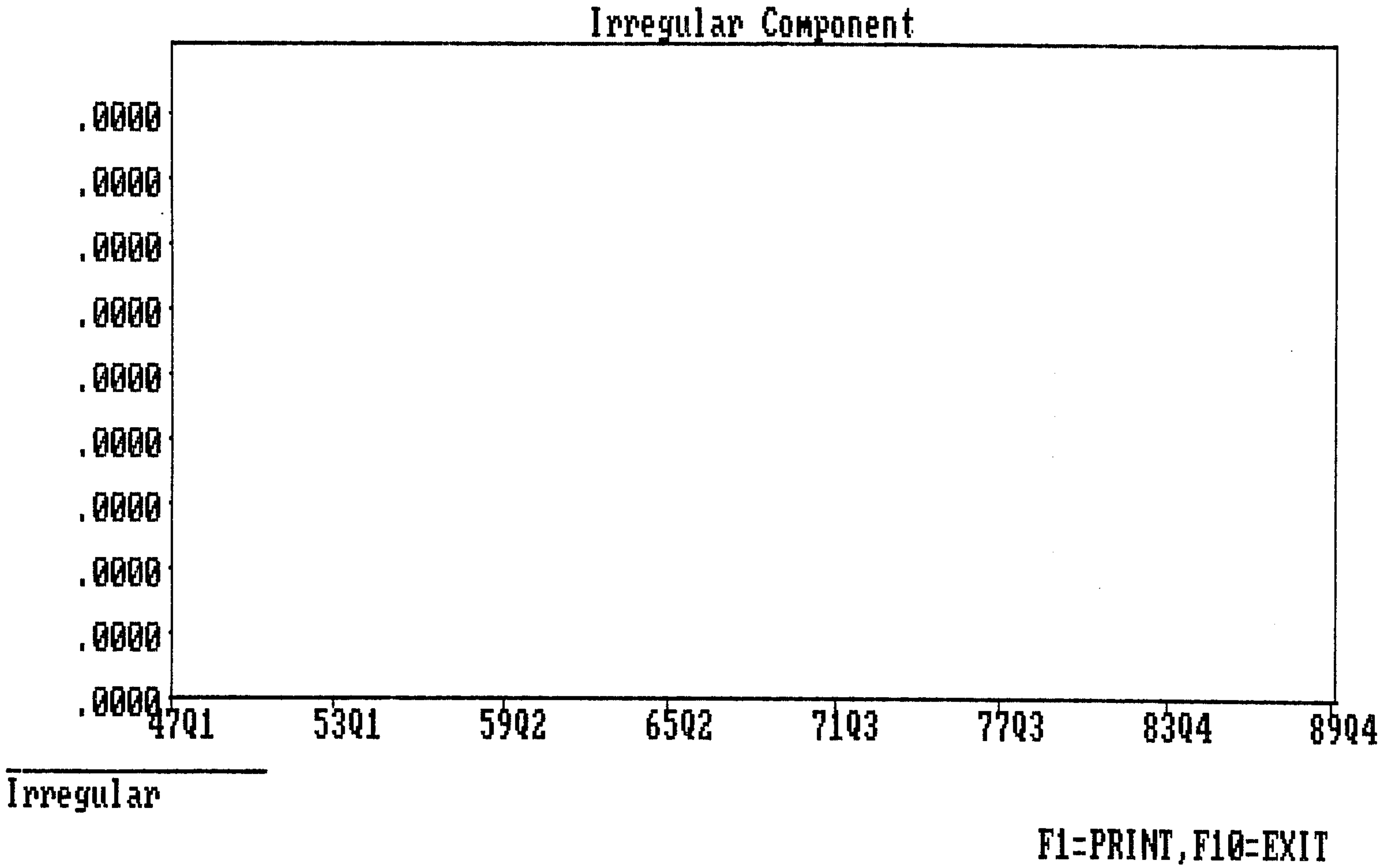
86Q2	-2.3703	-2.3810	.0107	.8681	.0124
86Q3	-2.3677	-2.3581	-.0096633	-.7813	.0124
86Q4	-2.3650	-2.3495	-.0155	-1.2514	.0124
87Q1	-2.3692	-2.3564	-.0128	-1.0319	.0124
87Q2	-2.3831	-2.3695	-.0136	-1.0994	.0124
87Q3	-2.3931	-2.3913	-.0017658	-.1427	.0124
87Q4	-2.3908	-2.3923	.0014280	.1155	.0124
88Q1	-2.3869	-2.3925	.0056727	.4588	.0124
88Q2	-2.3967	-2.3912	-.0054898	-.4440	.0124
88Q3	-2.4083	-2.4040	-.0042736	-.3456	.0124
88Q4	-2.4023	-2.4078	.0054257	.4389	.0124
89Q1	-2.4140	-2.4032	-.0109	-.8801	.0124
89Q2	-2.4260	-2.4231	-.0029711	-.2403	.0124
89Q3	-2.4171	-2.4371	.0200	1.6136	.0124
89Q4	-2.4111	-2.4103	-.0007285	-.0589	.0124
90Q1	-2.4146	-2.4088	-.0057719	-.4668	.0124


Trend Component
-1.1656
-1.2378
-1.3099
-1.3821
-1.4542
-1.5264
-1.5985
-1.6707
-1.7428
-1.8150
-1.8872
47Q1
53Q1
59Q2
65Q2
71Q3
77Q3
83Q4
89Q4
Trend
F1=PRINT,F10=EXIT


Actual Values and Trend Component
-1.1736
-1.3653
-1.5571
-1.7488
-1.9406
-2.1323
-2.3241
-2.5158
-2.7076
-2.8993
-3.0910
47Q1
53Q1
59Q2
65Q2
71Q3
77Q3
83Q4
89Q4
Actual
Trend
F1=PRINT,F10=EXIT


Seasonal Component
.0025120
.0016682
.0008244
.0000
-.0008632
-.0017070
-.0025508
-.0033946
-.0042384
47Q1
53Q1
59Q2
65Q2
71Q3
77Q3
83Q4
89Q4
Seasonal
F1=PRINT,F10=EXIT


Exogenous Component
-1.1877
-1.1913
-1.1948
-1.1984
-1.2019
-1.2055
-1.2090
-1.2126
-1.2161
-1.2197
-1.2233
47Q1
53Q1
59Q2
65Q2
71Q3
77Q3
83Q4
89Q4
Exogenous
F1=PRINT,F10=EXIT


Irregular Component
.0000
.0000
.0000
.0000
.0000
.0000
.0000
.0000
.0000
.0000
47Q1
53Q1
59Q2
65Q2
71Q3
77Q3
83Q4
89Q4
Irregular
F1=PRINT,F10=EXIT

Time Domain Estimation

Observation	Actual	Trend	Cycle	Seasonal	Exogenous	Irregular
47Q1	-3.0900	-1.8872	.0000	.0017007	-1.2045	.0000000
47Q2	-3.0661	-1.8659	.0000	.0030582	-1.2032	.0000000
47Q3	-3.0657	-1.8592	.0000	-.0042189	-1.2023	.0000000
47Q4	-3.0910	-1.8862	.0000	-.0005432	-1.2043	.0000000
48Q1	-3.0889	-1.8862	.0000	.0017355	-1.2044	.0000000
48Q2	-3.0764	-1.8773	.0000	.0030407	-1.2021	.0000000
48Q3	-3.0657	-1.8584	.0000	-.0043011	-1.2031	.0000000
48Q4	-3.0375	-1.8353	.0000	-.0004703	-1.2017	.0000000
49Q1	-2.9970	-1.8021	.0000	.0017557	-1.1966	.0000000
49Q2	-2.9682	-1.7799	.0000	.0030436	-1.1913	.0000000
49Q3	-2.9642	-1.7703	.0000	-.0043981	-1.1895	.0000000
49Q4	-2.9666	-1.7788	.0000	-.0003668	-1.1875	.0000000
50Q1	-2.9519	-1.7627	.0000	.0017453	-1.1909	.0000000
50Q2	-2.9549	-1.7617	.0000	.0030499	-1.1962	.0000000
50Q3	-2.9981	-1.7913	.0000	-.0045388	-1.2023	.0000000
50Q4	-3.0107	-1.8048	.0000	-.0001813	-1.2058	.0000000
51Q1	-3.0366	-1.8299	.0000	.0017159	-1.2085	.0000000
51Q2	-3.0177	-1.8119	.0000	.0029835	-1.2088	.0000000
51Q3	-2.9924	-1.7814	.0000	-.0046164	-1.2064	.0000000
51Q4	-2.9749	-1.7694	.0000	-.0000661	-1.2054	.0000000
52Q1	-2.9521	-1.7476	.0000	.0017820	-1.2062	.0000000
52Q2	-2.9313	-1.7292	.0000	.0029173	-1.2051	.0000000
52Q3	-2.9284	-1.7182	.0000	-.0047488	-1.2054	.0000000
52Q4	-2.8952	-1.6835	.0000	.0000726	-1.2117	.0000000
53Q1	-2.8671	-1.6541	.0000	.0018373	-1.2148	.0000000
53Q2	-2.8536	-1.6406	.0000	.0028261	-1.2158	.0000000
53Q3	-2.8532	-1.6340	.0000	-.0048200	-1.2144	.0000000
53Q4	-2.8385	-1.6292	.0000	.0001942	-1.2095	.0000000
54Q1	-2.8345	-1.6312	.0000	.0018739	-1.2051	.0000000
54Q2	-2.8306	-1.6314	.0000	.0027301	-1.2019	.0000000
54Q3	-2.8303	-1.6257	.0000	-.0048824	-1.1997	.0000000
54Q4	-2.8169	-1.6164	.0000	.0003046	-1.2007	.0000000
55Q1	-2.8100	-1.6087	.0000	.0019172	-1.2032	.0000000
55Q2	-2.8006	-1.5966	.0000	.0026406	-1.2066	.0000000
55Q3	-2.7943	-1.5821	.0000	-.0049406	-1.2073	.0000000
55Q4	-2.7849	-1.5764	.0000	.0004058	-1.2088	.0000000
56Q1	-2.7811	-1.5740	.0000	.0019681	-1.2091	.0000000
56Q2	-2.7777	-1.5718	.0000	.0025597	-1.2084	.0000000
56Q3	-2.7761	-1.5651	.0000	-.0050178	-1.2060	.0000000
56Q4	-2.7650	-1.5574	.0000	.0005072	-1.2081	.0000000
57Q1	-2.7593	-1.5532	.0000	.0020177	-1.2081	.0000000
57Q2	-2.7547	-1.5504	.0000	.0024904	-1.2068	.0000000
57Q3	-2.7582	-1.5480	.0000	-.0050932	-1.2052	.0000000
57Q4	-2.7405	-1.5390	.0000	.0005995	-1.2021	.0000000
58Q1	-2.7408	-1.5467	.0000	.0020711	-1.1962	.0000000
58Q2	-2.7380	-1.5494	.0000	.0024147	-1.1910	.0000000
58Q3	-2.7369	-1.5396	.0000	-.0051414	-1.1922	.0000000
58Q4	-2.7213	-1.5275	.0000	.0006459	-1.1945	.0000000

59Q1	-2.7081	-1.5117	.0000	.0021377	-1.1985	.0000000
59Q2	-2.7023	-1.5029	.0000	.0023590	-1.2017	.0000000
59Q3	-2.7086	-1.5036	.0000	-.0051929	-1.1998	.0000000
59Q4	-2.6918	-1.4934	.0000	.0007002	-1.1991	.0000000
60Q1	-2.6714	-1.4705	.0000	.0021878	-1.2031	.0000000
60Q2	-2.6735	-1.4745	.0000	.0022866	-1.2012	.0000000
60Q3	-2.6703	-1.4664	.0000	-.0052285	-1.1987	.0000000
60Q4	-2.6618	-1.4673	.0000	.0008006	-1.1953	.0000000

STAMP Time Domain Estimation

Observation	Actual	Trend	Cycle	Seasonal	Exogenous	Irregular
61Q1	-2.6575	-1.4673	.0000	.0021603	-1.1923	.0000000
61Q2	-2.6395	-1.4481	.0000	.0022652	-1.1937	.0000000
61Q3	-2.6435	-1.4432	.0000	-.0052949	-1.1951	.0000000
61Q4	-2.6298	-1.4342	.0000	.0008998	-1.1965	.0000000
62Q1	-2.6234	-1.4277	.0000	.0021829	-1.1979	.0000000
62Q2	-2.6167	-1.4197	.0000	.0021940	-1.1991	.0000000
62Q3	-2.6249	-1.4207	.0000	-.0053353	-1.1988	.0000000
62Q4	-2.6108	-1.4133	.0000	.0009817	-1.1985	.0000000
63Q1	-2.5952	-1.3990	.0000	.0022212	-1.1984	.0000000
63Q2	-2.5871	-1.3898	.0000	.0020951	-1.1994	.0000000
63Q3	-2.5941	-1.3893	.0000	-.0053533	-1.1995	.0000000
63Q4	-2.5801	-1.3815	.0000	.0010729	-1.1997	.0000000
64Q1	-2.5715	-1.3737	.0000	.0022524	-1.2001	.0000000
64Q2	-2.5632	-1.3642	.0000	.0019732	-1.2009	.0000000
64Q3	-2.5649	-1.3572	.0000	-.0053494	-1.2024	.0000000
64Q4	-2.5616	-1.3591	.0000	.0011600	-1.2037	.0000000
65Q1	-2.5533	-1.3503	.0000	.0022887	-1.2053	.0000000
65Q2	-2.5546	-1.3497	.0000	.0018527	-1.2068	.0000000
65Q3	-2.5632	-1.3491	.0000	-.0053718	-1.2087	.0000000
65Q4	-2.5598	-1.3504	.0000	.0012855	-1.2106	.0000000
66Q1	-2.5621	-1.3515	.0000	.0022987	-1.2130	.0000000
66Q2	-2.5558	-1.3420	.0000	.0017410	-1.2155	.0000000
66Q3	-2.5632	-1.3409	.0000	-.0053990	-1.2168	.0000000
66Q4	-2.5383	-1.3220	.0000	.0014014	-1.2177	.0000000
67Q1	-2.5230	-1.3082	.0000	.0023395	-1.2171	.0000000
67Q2	-2.5123	-1.2984	.0000	.0015871	-1.2155	.0000000
67Q3	-2.5114	-1.2910	.0000	-.0053755	-1.2150	.0000000
67Q4	-2.4975	-1.2831	.0000	.0014907	-1.2159	.0000000
68Q1	-2.4851	-1.2709	.0000	.0023801	-1.2166	.0000000
68Q2	-2.4781	-1.2620	.0000	.0014272	-1.2176	.0000000
68Q3	-2.4785	-1.2553	.0000	-.0053501	-1.2179	.0000000
68Q4	-2.4614	-1.2443	.0000	.0015912	-1.2187	.0000000
69Q1	-2.4601	-1.2428	.0000	.0024152	-1.2197	.0000000
69Q2	-2.4621	-1.2432	.0000	.0012619	-1.2201	.0000000
69Q3	-2.4564	-1.2306	.0000	-.0053093	-1.2205	.0000000
69Q4	-2.4474	-1.2298	.0000	.0016730	-1.2192	.0000000
70Q1	-2.4472	-1.2320	.0000	.0024447	-1.2177	.0000000
70Q2	-2.4381	-1.2243	.0000	.0011329	-1.2149	.0000000
70Q3	-2.4311	-1.2129	.0000	-.0053017	-1.2129	.0000000
70Q4	-2.4227	-1.2170	.0000	.0017552	-1.2075	.0000000
71Q1	-2.4062	-1.1998	.0000	.0024848	-1.2088	.0000000
71Q2	-2.4068	-1.1989	.0000	.0010248	-1.2089	.0000000
71Q3	-2.4078	-1.1939	.0000	-.0053505	-1.2086	.0000000
71Q4	-2.3943	-1.1870	.0000	.0019083	-1.2092	.0000000
72Q1	-2.3853	-1.1768	.0000	.0024652	-1.2110	.0000000

72Q2	-2.3852	-1.1732	.0000	.0009439	-1.2130	.0000000
72Q3	-2.3921	-1.1731	.0000	-.0054074	-1.2135	.0000000
72Q4	-2.3804	-1.1659	.0000	.0020748	-1.2166	.0000000
73Q1	-2.4085	-1.1916	.0000	.0024385	-1.2193	.0000000
73Q2	-2.4438	-1.2243	.0000	.0008567	-1.2204	.0000000
73Q3	-2.4705	-1.2445	.0000	-.0054197	-1.2205	.0000000
73Q4	-2.4565	-1.2369	.0000	.0021651	-1.2218	.0000000
74Q1	-2.5041	-1.2857	.0000	.0024321	-1.2208	.0000000
74Q2	-2.5132	-1.2937	.0000	.0007635	-1.2202	.0000000
74Q3	-2.5536	-1.3289	.0000	-.0053158	-1.2193	.0000000
74Q4	-2.5514	-1.3388	.0000	.0020671	-1.2147	.0000000

STAMP | Time Domain Estimation

Observation	Actual	Trend	Cycle	Seasonal	Exogenous	Irregular
75Q1	-2.5257	-1.3234	.0000	.0025789	-1.2049	.0000000
75Q2	-2.5244	-1.3228	.0000	.0005487	-1.2021	.0000000
75Q3	-2.5327	-1.3243	.0000	-.0051405	-1.2033	.0000000
75Q4	-2.5222	-1.3183	.0000	.0020002	-1.2059	.0000000
76Q1	-2.5067	-1.3009	.0000	.0026772	-1.2085	.0000000
76Q2	-2.5073	-1.2977	.0000	.0003337	-1.2099	.0000000
76Q3	-2.5000	-1.2847	.0000	-.0049669	-1.2103	.0000000
76Q4	-2.4858	-1.2773	.0000	.0019698	-1.2104	.0000000
77Q1	-2.4853	-1.2761	.0000	.0027283	-1.2119	.0000000
77Q2	-2.4922	-1.2782	.0000	.0001572	-1.2142	.0000000
77Q3	-2.4753	-1.2553	.0000	-.0048183	-1.2152	.0000000
77Q4	-2.4631	-1.2489	.0000	.0019429	-1.2161	.0000000
78Q1	-2.4642	-1.2491	.0000	.0027537	-1.2178	.0000000
78Q2	-2.4795	-1.2604	.0000	.0000566	-1.2191	.0000000
78Q3	-2.4748	-1.2502	.0000	-.0047263	-1.2199	.0000000
78Q4	-2.4690	-1.2492	.0000	.0019303	-1.2217	.0000000
79Q1	-2.4811	-1.2608	.0000	.0027380	-1.2230	.0000000
79Q2	-2.4982	-1.2750	.0000	.0000257	-1.2233	.0000000
79Q3	-2.5136	-1.2866	.0000	-.0046616	-1.2223	.0000000
79Q4	-2.5256	-1.3063	.0000	.0019066	-1.2213	.0000000
80Q1	-2.5495	-1.3322	.0000	.0027225	-1.2201	.0000000
80Q2	-2.5455	-1.3306	.0000	.0000057	-1.2149	.0000000
80Q3	-2.5531	-1.3369	.0000	-.0046051	-1.2116	.0000000
80Q4	-2.5449	-1.3332	.0000	.0018495	-1.2135	.0000000
81Q1	-2.5509	-1.3400	.0000	.0027804	-1.2137	.0000000
81Q2	-2.5521	-1.3375	.0000	-.0000658	-1.2145	.0000000
81Q3	-2.5416	-1.3229	.0000	-.0045121	-1.2142	.0000000
81Q4	-2.5203	-1.3113	.0000	.0017459	-1.2107	.0000000
82Q1	-2.5054	-1.3019	.0000	.0028595	-1.2063	.0000000
82Q2	-2.4970	-1.2940	.0000	-.0001193	-1.2029	.0000000
82Q3	-2.4925	-1.2884	.0000	-.0044312	-1.1996	.0000000
82Q4	-2.4858	-1.2920	.0000	.0016422	-1.1955	.0000000
83Q1	-2.4731	-1.2807	.0000	.0029328	-1.1953	.0000000
83Q2	-2.4752	-1.2775	.0000	-.0001648	-1.1975	.0000000
83Q3	-2.4820	-1.2775	.0000	-.0043793	-1.2001	.0000000
83Q4	-2.4736	-1.2722	.0000	.0015847	-1.2030	.0000000
84Q1	-2.4720	-1.2698	.0000	.0029799	-1.2052	.0000000
84Q2	-2.4734	-1.2665	.0000	-.0002121	-1.2067	.0000000
84Q3	-2.4643	-1.2527	.0000	-.0043177	-1.2072	.0000000
84Q4	-2.4486	-1.2434	.0000	.0015193	-1.2067	.0000000
85Q1	-2.4316	-1.2272	.0000	.0030205	-1.2074	.0000000
85Q2	-2.4213	-1.2152	.0000	-.0002344	-1.2058	.0000000
85Q3	-2.4207	-1.2121	.0000	-.0042782	-1.2043	.0000000
85Q4	-2.4152	-1.2122	.0000	.0014772	-1.2045	.0000000

86Q1	-2.3902	-1.1887	.0000	.0030450	-1.2046	.0000000
86Q2	-2.3703	-1.1660	.0000	-.0002673	-1.2040	.0000000
86Q3	-2.3677	-1.1608	.0000	-.0042569	-1.2027	.0000000
86Q4	-2.3650	-1.1640	.0000	.0014922	-1.2025	.0000000
87Q1	-2.3692	-1.1695	.0000	.0030646	-1.2028	.0000000
87Q2	-2.3831	-1.1796	.0000	-.0003266	-1.2032	.0000000
87Q3	-2.3931	-1.1847	.0000	-.0042429	-1.2041	.0000000
87Q4	-2.3908	-1.1870	.0000	.0015142	-1.2053	.0000000
88Q1	-2.3869	-1.1839	.0000	.0030745	-1.2060	.0000000
88Q2	-2.3967	-1.1897	.0000	-.0003693	-1.2067	.0000000
88Q3	-2.4083	-1.1974	.0000	-.0042320	-1.2066	.0000000
88Q4	-2.4023	-1.1967	.0000	.0015520	-1.2071	.0000000
89Q1	-2.4140	-1.2093	.0000	.0030644	-1.2078	.0000000
89Q2	-2.4260	-1.2179	.0000	-.0004172	-1.2077	.0000000
89Q3	-2.4171	-1.2064	.0000	-.0041961	-1.2065	.0000000
89Q4	-2.4111	-1.2075	.0000	.0015560	-1.2051	.0000000
90Q1	-2.4146	-1.2135	.0000	.0030580	-1.2042	.0000000

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