DYNAMIC MODELLING AND THE DEMAND FOR NARROW MONEY IN NORWAY*

by

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ABSTRACT

Useful results on statistical inference and reparameterizations when estimating error correction models are summarized. The suggested approach is tested in a pilot Monte Carlo study and illustrated by estimating a money demand function for Norway. The estimated model forecasts well 21 period ahead in spite of deregulation of credit markets during the forecast period.

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The error correction model is a popular representation in dynamic econometric modelling. It is usually estimated by a "general–to–specific" search in a dynamic linear regression model.[1] I summarize results on statistical inference and reparameterizations relevant in this framework.

After the approach is tested in a pilot Monte Carlo study it is used to estimate a demand function for narrow money in Norway. The preferred model forecasts well 21 periods ahead in spite of a massive deregulation of credit markets during the forecast period. One of the features of the model is the inclusion of the own yield on money and an alternative yield in the cointegrating vector.

1. STATISTICAL INFERENCE AND REPARAMETERIZATIONS IN THE DYNAMIC LINEAR REGRESSION MODEL

The model is:

$$y_t = a + \boldsymbol{y}_{-1}'\boldsymbol{\alpha} + \Sigma_{j=1}^{k}\boldsymbol{x}_j'\boldsymbol{\beta}_j + u_t, \tag{1}$$

but can equivalently be written as

$$\Delta y_t = a + \boldsymbol{y}_{-1}'\boldsymbol{\alpha}_{-1} + \Sigma_{j=1}^{k}\boldsymbol{x}_j'\boldsymbol{\beta}_j + u_t, \tag{2}$$

where $\Delta y_t = y_t - y_{t-1}$, $\boldsymbol{y}_{-1} = [y_{t-1}\ y_{t-2}\cdots y_{t-m}]'$, $\boldsymbol{\alpha} = [\alpha_1\ \alpha_2\cdots\alpha_m]'$, $\boldsymbol{\alpha}_{-1} = [(\alpha_1 - 1)\ \alpha_2\cdots\alpha_m]'$, $\boldsymbol{x}_j = [x_{jt}\ x_{jt-1}\cdots x_{jt-n}]'$, and $\boldsymbol{\beta}_j = [\beta_{j0}\ \beta_{j1}\cdots\beta_{jn}]'$. Maximum lag orders of the exogenous variables are made equal to make the exposition easier.

Standard statistical inference assumes weakly stationary data series but can be valid even if the series in equations (1) and (2) are *I(1)*.[2] The conditions for this to

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[1] Harvey (1990, ch.8), Hendry (1989, ch. 1), and Spanos (1986, ch. 23) give introductions to these concepts. Spanos introduces "dynamic linear regression model instead of "autoregressive distributed lag".

[2] The notation *I(1)* means "integrated of order 1". Introductions to integration, and cointegration

hold are derived by P. C. B Phillips and his co–authors, and Sims, Stock and Watson (1990).

The first result of interest, from Sims, Stock and Watson (1990), is formulated by Stock and West (1988, p. 86) as: "...the usual testing procedures are asymptotically valid if a regression can be rewritten so that the coefficients of interest are on stationary, zero mean regressors".

The second result needed is due to Park and Phillips (1989, p. 117). Their theorem 5.3 ensures asymptotically normally distributed parameter estimates if the regressors are cointegrated. A stylized example might give some intuition.

The data generation process is the error correction model:

$$(3) \qquad \begin{Bmatrix} \Delta y_t = a + \alpha_1 \Delta y_{t-1} + \beta_0 \Delta x_t + \beta_1 \Delta x_{t-1} - \gamma_2[y_{t-2} - \theta x_{t-2}] + u_t, \\ \Delta x_t = \mu_x + e_t \end{Bmatrix}.$$

The OLS estimates of the parameters are asymptotically normally distributed conditional on θ if y_t and x_t are cointegrated – so all variables in (3) are $I(0)$ – and if $u_t \sim NI(0, \sigma^2)$.

Equation (3) can also be written

$$(4) \qquad \Delta y_t = a + \alpha_1 \Delta y_{t-1} - \gamma_2 y_{t-2} + \beta_0 \Delta x_t + \beta_1 \Delta x_{t-1} + \gamma_2 \theta x_{t-2} + u_t,$$

or like a dynamic linear regression model:

$$(5) \qquad y_t = a + (\alpha_1+1) y_{t-1} - (\alpha_1+\gamma_2) y_{t-2} + \beta_0 x_t + (\beta_1-\beta_0) x_{t-1} + (\gamma_2\theta-\beta_1) x_{t-2} + u_t.$$

If y_t and x_t are cointegrated in (5), the Granger representation theorem states the

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which is encountered later on, can be found in Hendry (1986) and Granger (1986).

existence of the error correction model (3).[3] Since the OLS estimators of the parameters of (4) and (5), apart from $\gamma_2\theta$, then are linear combinations of normally distributed variables they are themselves normally distributed. And if the error correction mechanism $[y_t - \theta x_t]$ is $I(0)$, so is $[x_t - (1/\theta)y_t]$. (Normalization of a cointegrating vector is arbitrary since properties of a time series are invariant to scaling.) So $\widehat{\gamma_2\theta}$ will be asymptotically normally distributed as well – given θ.

The example highlights the potential advantages of using equation (4) instead of (5) as a starting point for a "general–to–specific" search. If the null hypothesis is an error correction specification there is no need to take the longer route by (5). The two representations are equivalent: the parameters of (4) are partial sums of (5). Multiply the ratio of the estimated levels coefficients by –1 to get $\hat{\theta}$.[4]

The distribution of $\hat{\theta}$ is the final uncertainty. Phillips (1988, 1989) and Phillips and Loretan (1989) investigate inference in models like (4), and the distribution of $\hat{\theta}$ in particular: The limit distribution is a mixture of normals if x_t is strongly exogenous, otherwise $\hat{\theta}$ will be biased. The strong exogeneity assumption must also hold for the other estimates to be normally distributed.[5]

Return now to the general case. The model (2) is reparameterized as

$$\Delta y_t = \boldsymbol{a} + \overset{*}{\boldsymbol{y}}_{-1}{}' \overset{*}{\boldsymbol{\alpha}} + \Sigma_{j=1}^{k} \overset{*}{\boldsymbol{x}}_j{}' \overset{*}{\boldsymbol{\beta}}_j + u_t, \tag{6}$$

with $\overset{*}{\boldsymbol{y}}_{-1}{}' = \boldsymbol{y}_{-1}{}'\boldsymbol{M}_m = [\Delta y_{t-1}\ \Delta y_{t-2} \cdots \Delta y_{t-m+1}\ y_{t-m}]$, $\overset{*}{\boldsymbol{\alpha}} = \boldsymbol{M}_m^{-1}\boldsymbol{\alpha}_{-1} = [\overset{*}{\alpha}_1\ \overset{*}{\alpha}_2 \cdots \overset{*}{\alpha}_m]'$, $\overset{*}{\boldsymbol{x}}_j{}' = \boldsymbol{x}_j{}'\boldsymbol{N}_n = [\Delta x_{jt}\ \Delta x_{jt-1} \cdots \Delta x_{jt-n+1}\ x_{jt-n}]$, $\overset{*}{\boldsymbol{\beta}}_j = \boldsymbol{N}_n^{-1}\boldsymbol{\beta}_j = [\overset{*}{\beta}_{j0}\ \overset{*}{\beta}_{j1} \cdots \overset{*}{\beta}_{jn}]'$,

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3 Hylleberg and Mizon (1989) extend the Granger representation theorem originally given in Engle and Granger (1987).

4 This is the nonlinear least squares estimator investegated by Stock (1987). An independent derivation can be found in Bårdsen (1989) together with the variance formula given below. The reparameterization (4) is called the interim multiplier representation by Hylleberg and Mizon (1989) and is the starting point of the Johansen (1988) procedure.

5 I would like to thank P. C. B. Phillips for kindly pointing out the relevant distributional results to me. Any errors in the interpretation and use of them are my own responsibility.

$$\underset{(m \times m)}{\boldsymbol{M}_m} = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ -1 & 1 & \ddots & & \vdots \\ 0 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & -1 & 1 \end{bmatrix}, \quad \boldsymbol{M}_m^{-1} = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ \vdots & \ddots & \ddots & & \vdots \\ \vdots & & \ddots & \ddots & \vdots \\ \vdots & & & \ddots & 0 \\ 1 & \cdots & \cdots & \cdots & 1 \end{bmatrix},$$

and

$$(7) \qquad \begin{Bmatrix} \overset{*}{\alpha}_r = \Sigma_{i=1}^{r} \alpha_i - 1, \; r = 1, \ldots, m, \\ \overset{*}{\beta}_{js} = \Sigma_{i=0}^{s} \beta_{ji}, \; s = 0, \ldots, n \end{Bmatrix}.$$

The transformation matrices $\boldsymbol{M}_m$ and $\boldsymbol{N}_n$ differ only in being of order m and $n+1$.

Equation (6) written out gives the general equivalent of (4):

$$(8) \qquad \Delta y_t = \boldsymbol{a} + \Sigma_{i=1}^{m-1} \overset{*}{\alpha}_i \Delta y_{t-i} + \Sigma_{j=1}^{k} \Sigma_{i=0}^{n-1} \overset{*}{\beta}_{ji} \Delta x_{jt-i} + \overset{*}{\alpha}_m y_{t-m} + \Sigma_{j=1}^{k} \overset{*}{\beta}_{jn} x_{jt-n} + u_t,$$

but it is also an error correction model:

$$(9) \qquad \Delta y_t = \boldsymbol{a} + \Sigma_{i=1}^{m-1} \overset{*}{\alpha}_i \Delta y_{t-i} + \Sigma_{j=1}^{k} \Sigma_{i=0}^{n-1} \overset{*}{\beta}_{ji} \Delta x_{jt-i} + \overset{*}{\alpha}_m [y_{t-m} - \Sigma_{j=1}^{k} \theta_j x_{jt-n}] + u_t,$$

where the cointegrating vector, or vector of long–run coefficients, is defined as

$$(10) \qquad \boldsymbol{\theta} = [\theta_1 \cdots \theta_k]' = [\overset{*}{\beta}_{1n} \cdots \overset{*}{\beta}_{kn}]'(-1/\overset{*}{\alpha}_m).$$

And if the OLS estimates of the long–run coefficients are:

$$(11) \qquad \hat{\theta}_j = -\hat{\overset{*}{\beta}}_{jn} / \hat{\overset{*}{\alpha}}_m, \; j = 1, \ldots, k,$$

the large sample variance of $\hat{\theta}_j$ can be estimated by

$$(12) \qquad \hat{\mathrm{var}}(\hat{\theta}_j) = (\hat{\alpha}_m^*)^{-2}[(\hat{\theta}_j)^2 \hat{\mathrm{var}}(\hat{\alpha}_m^*) + \hat{\mathrm{var}}(\hat{\beta}_{jn}^*) + 2\hat{\theta}_j \hat{\mathrm{cov}}(\hat{\alpha}_m^*, \hat{\beta}_{jn}^*)].$$

Full details of this derivation can be found in Bårdsen (1989).

So far the original dynamic linear regression model in equation (1) has only been reparameterized – if the cointegrating restrictions are true. So "problems" in (1) can also be present in (9). Any collinearity, say, in the dynamic linear regression model will only be absent in the error correction model if parameter sums are more precisely estimated than individual parameters; collinearity is a property of the chosen parameterization.

Let me elaborate. $\hat{\mathrm{Var}}(\hat{\beta}_{js}^*)$ is the variance of a sum of parameters, so the standard formula applies:

$$(13) \qquad \hat{\mathrm{var}}(\hat{\beta}_{js}^*) = \Sigma_{i=0}^{s} \hat{\mathrm{var}}(\hat{\beta}_{ji}) + 2\Sigma_{i=0}^{s-1}\Sigma_{g=i+1}^{s} \hat{\mathrm{cov}}(\hat{\beta}_{ji}, \hat{\beta}_{jg}),\ s = 0,\ldots,n,$$

but it can also be written

$$(14) \qquad \hat{\mathrm{var}}(\hat{\beta}_{js}^*) = \hat{\mathrm{var}}(\hat{\beta}_{js-1}^*) + \hat{\mathrm{var}}(\hat{\beta}_{js}) + 2\Sigma_{i=0}^{s-1} \hat{\mathrm{cov}}(\hat{\beta}_{ji}, \hat{\beta}_{js}).$$

If $\hat{\mathrm{cov}}(x_{jt-i}, x_{jt-s}) > 0$, which is likely with *I(1)* series, $\hat{\mathrm{cov}}(\hat{\beta}_{ji}, \hat{\beta}_{js}) < 0$.[6] Accordingly $\hat{\mathrm{var}}(\hat{\beta}_{js}^*)$ is adjusted for collinearity between individual variables.

The same line of reasoning applies to $\hat{\mathrm{var}}(\hat{\theta}_j)$ in equation (12) since $sign\{\hat{\mathrm{cov}}(y_{t-m}, x_{jt-n})\} = (-1) \cdot sign\{\hat{\mathrm{cov}}(\hat{\alpha}_m^*, \hat{\beta}_{jn}^*)\} = sign\{\hat{\theta}_j\} \Leftrightarrow 2\hat{\theta}\hat{\mathrm{cov}}(\hat{\beta}_{jn}^*, \hat{\alpha}_m^*) < 0$. So the covariance term will always be negative. It is also an illustration of cointegration:

6 See Johnston (1984), p. 240.

as $\hat{\text{cov}}(y_{t-m}, x_{jt-n})$ goes to infinity $\hat{\text{var}}(\hat{\theta}_j)$ goes to zero.[7]

Equation (9) has two main advantages. First, it shows both the long–run solution of the model and the adjustment towards long–run equilibrium. And second, it is a more efficient way of conducting a specification search for a parsimonious model if the null hypothesis is an error correction representation of the data generation process.

But equations (6) and (9) can be inconvenient to use in the early stages of a simplification search since a natural first step is to restrict lag lengths, which means testing $\hat{\beta}^*_{jn} = \hat{\beta}^*_{jn-1}$, say, and could consequently lead to a lot of reformulations.

The testing of lag lengths is easier with the implicit error correction mechanism on the first lag, as in the usual exposition of error correction models: Rewrite equation (2) as

$$\Delta y_t = \boldsymbol{a} + \boldsymbol{y}^{\dagger\prime}_{-1}\boldsymbol{\alpha}^{\dagger} + \Sigma^k_{j=1}\boldsymbol{x}^{\dagger\prime}_j\boldsymbol{\beta}^{\dagger}_j + u_t, \tag{15}$$

with $\boldsymbol{y}^{\dagger\prime}_{-1} = \boldsymbol{y}_{-1}'\boldsymbol{M}_1 = [y_{t-1}\ \Delta y_{t-1}\ \Delta y_{t-2}\cdots\Delta y_{t-m+1}]$, $\boldsymbol{\alpha}^{\dagger} = \boldsymbol{M}_1^{-1}\boldsymbol{\alpha}_{-1} = [\alpha^*_m\ \alpha^{\dagger}_2\cdots\alpha^{\dagger}_m]'$, $\boldsymbol{x}^{\dagger\prime}_j = \boldsymbol{x}_j'\boldsymbol{N}_1 = [\Delta x_{jt}\ x_{jt-1}\ \Delta x_{jt-1}\cdots\Delta x_{jt-n+1}]$, $\boldsymbol{\beta}^{\dagger}_j = \boldsymbol{N}_1^{-1}\boldsymbol{\beta}_j = [\beta^*_{j0}\ \beta^*_{jn}\ \beta^{\dagger}_{j1}\cdots\beta^{\dagger}_{jn}]'$,

$$\underset{(n\times n)}{\boldsymbol{N}_1} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ -1 & 1 & 1 & \ddots & \vdots \\ 0 & 0 & -1 & \ddots & 0 \\ \vdots & & \ddots & \ddots & 1 \\ 0 & \cdots & \cdots & 0 & -1 \end{bmatrix} \quad \text{and} \quad \boldsymbol{N}_1^{-1} = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ 1 & 1 & \cdots & \cdots & 1 \\ 0 & 0 & -1 & \cdots & -1 \\ \vdots & & \ddots & \ddots & \vdots \\ 0 & \cdots & \cdots & 0 & -1 \end{bmatrix},$$

and

$$\begin{Bmatrix} \alpha^{\dagger}_r = -\Sigma^m_{i=r+1}\alpha_i - 1, & r = 1,\dots, m-1, \\ \beta^{\dagger}_{js} = -\Sigma^n_{i=s+1}\beta_{ji}, & s = 0,\dots, n-1 \end{Bmatrix}. \tag{16}$$

[7] For further aspects of collinearity, see Hendry (1986, pp. 207 — 208), Hendry (1989, pp. 95 — 97), Hendry and Morgan (1989), Leamer (1983), Maddala (1988, ch.7), and Spanos (1986, ch. 20.5 — 20.6).

The matrices $\boldsymbol{M}_1$ and $\boldsymbol{M}_1^{-1}$ are obtained by deleting the first column of $\boldsymbol{N}_1$ and the first row of $\boldsymbol{N}_1^{-1}$. See also Harvey (1990, p. 281).

The consequence of moving the levels terms around in the unrestricted error correction model is clear from equations (7) and (16). In general, if the levels terms are on lag p, the coefficients of the differenced variables are increasing partial sums of the parameters of the dynamic linear regression model until lag $p-1$. From lag p onwards the coefficients of the differenced variables are decreasing partial sums multiplied by –1. The longest sum runs from lag $p+1$ to the final lag, while the shortest is the final lag. So in this form sequential testing of maximum lag orders are straightforward. As regards inference in general, the same points of caution apply as those noted in Bårdsen (1989).

The conditions for estimating both long–run and short–run dynamics within a standard statistical framework are now almost established. The question still remains if the mixture of normals constituting the limit distribution of $\hat{\boldsymbol{\theta}}$ can be approximated by a normal distribution.

2. A PILOT SIMULATION STUDY

Monte Carlo evidence on the performance of various estimators of cointegrating relationships are compiled by Hansen and Phillips (1989), Phillips and Hansen (1990) and Phillips and Loretan (1989). This section reports results on the performance of the Error Correction Model as represented above, using the variance formula of Bårdsen (1989) from equation (12).

The data generation process is

$$(17)\qquad \begin{Bmatrix} \Delta y_t = 1 - 0.4\Delta y_{t-1} + 0.6\Delta x_t - 0.3\Delta x_{t-1} - 0.5[y_{t-2} - 0.5x_{t-2}] + u_{yt} \\ \Delta x_t = 1 + \delta\Delta z_t + u_{xt} \\ \Delta z_t = 0.5 + u_{zt} \end{Bmatrix},$$

and

$$(18) \qquad \begin{bmatrix} u_{yt} \\ u_{xt} \\ u_{zt} \end{bmatrix} \sim N \left[\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \sigma_{yx} & 0 \\ \sigma_{yx} & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \right],$$

where σ_{yx} is either 0.75 or 0.

In each experiment the regression

$$(19) \qquad \Delta y_t = a + \alpha_1 \Delta y_{t-1} - \gamma_2 y_{t-2} + \beta_0 \Delta x_t + \beta_1 \Delta x_{t-1} + \gamma_2 \theta x_{t-2} + u_{yt}$$

is run. The estimates of θ and its variance are computed according to equations (11) and (12). I limit the attention to $\hat{\beta}_0$ and $\hat{\theta}$ and their "t–statistics" in the following.

With 1000 replications, 600 observations are generated and the first 100 are discarded. The 50 next are used in

a. OLS regression with $\sigma_{yx} = 0$,

b. OLS regression with $\sigma_{yx} = 0.75$,

c. IV regression with $\sigma_{yx} = 0.75$.

The variable Δz_t is used as instrument for Δx_t, together with the lagged regressors. In *a.* and *b.* $\delta = 0$; in c. $\gamma = 0.5$.

I finally repeat the procedure with the full sample of 500 observations. The same random numbers are used in all 6 experiments.

Biases in the parameter estimates and the corresponding standard errors are reported in Table I.[8] Evaluation by a "t–test" shows that while unbiasedness can be rejected for $\hat{\beta}_0$ in almost all instances, $\hat{\theta}$ is always unbiased and seems to be totally

[8] The standard errors are computed as the standard deviation of the bias divided by the root of the number of replications, following Hendry (1984b, p. 943).

unaffected by any simultaneity present, even in a sample size of 50.

(Tables I and II about here.)

Table II reports distributional results for the "t–statistics" evaluated at their true values. The "t–statistics" are generally unbiased, apart from the case of OLS(σ=.75). The IV version of $t(\hat{\beta}_0)$ does not fare too well in the small sample case, having both excess kurtosis and being skewed to the right. These anomalies disappear as the sample size increases, confirming that IV estimation is a large sample procedure.

(Figures 1 and 2 about here.)

The "t–statistic" of $\hat{\theta}$ seems to have a more peaked distribution than the standard normal in the small sample case, but approaches the latter for the sample size of 500. It remains unbiased and symmetric regardless of violations of exogeneity and is invariant to choice of estimation method. These impressions are confirmed by the histograms given in Figure 2.

The interesting question for applied research is whether critical values for the normal distribution can be used as an approximate guide for inference, and Table III gives the empirical fractiles of $t(\hat{\beta}_0)$ and $t(\hat{\theta})$.

(Table III about here.)

The $t(\hat{\theta})$ fares quite impressively in the small sample case, especially when its asymptotic justification is taken into consideration. The fat tails seem relatively invariant to choice of estimation method. When the sample size is 500, it performs at least as well as the OLS $t(\hat{\beta}_0)$, which is normally distributed asymptotically. An anomaly of this experiment is that this test statistic is actually closer to the normal distribution in the small sample case than when the number of observations is increased. This should be a clear indication of not putting too much weight on outcomes from one point in the parameter space only.

So the evidence presented should be regarded as provisional. Many experiments have to be conducted before the performance of the estimator of long–run coefficients is understood. Nevertheless it must be said that the experience so far looks promising. A particularly strange result is the absence of endogeneity bias in $\hat{\theta}$.

3. APPLICATION: THE DEMAND FOR NARROW MONEY IN NORWAY

3.1 *Finding a Base Line*

The Norwegian economy has undergone several changes in the last twenty years. Deregulation of credit markets and expanding income from the oil industry are particularly relevant for the demand for money.[9] Liberalization of the credit markets has taken place from 1984 onwards and the deregulation process is summarized in Table IV.[10] All the regulations were in force at the end of 1983. Note in particular the reintroductions of loan controls and loan guarantee limits in 1986:I.

(Table IV about here.)

The effect of a deregulation of credit rationing on money demand is uncertain. It will imply a less tight budget constraint for current consumption and money holding, but the availability of credit will make it a closer substitute for money – and therefore reduce the demand for money. Under the regime of rationing previous saving was required to obtain credit. This enforced money demand is probably diminished after the deregulation.[11]

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[9] Steffensen and Steigum (1990) give a detailed account of the deregulation process.

[10] Table IV is compiled by Jan Tore Klovland.

[11] This discussion draws on Steffensen and Steigum (1990).

A model estimated on data generated under rationing and controlled prices that predicts well under and after the abolition of these constraints means that the underlying model of the agents preferences is unchanged.[12] I estimate a money demand function for the period 1966:II to 1983:IV, while the data for 1984:I to 1989:I are retained for forecasting.

A long–run money demand function general enough to include most theoretical specifications is:

$$M = f(\underset{+}{P}, \underset{+}{X}, \underset{+}{RD1}, \underset{-}{\boldsymbol{R}}), \tag{20}$$

where M is demand for money; P is the price level; X is a measure of the volume of transactions, income, and/or wealth; $RD1$ is the own yield of holding money; and $\boldsymbol{R}$ is the vector of costs associated with money holding. The hypothesized signs of the partial derivatives are given below the variables.

Applied econometrics is about trying to find what is relevant in modelling the real world – by finding appropriate proxies for theoretical variables, determining their interrelationships and estimating relevant parameters. In order to give this task manageable proportions relative to a limited set of data, some simplifying assumptions have to be made. This typically implies a choice of functional form. Here the log–linear dynamic linear regression model is taken as a basis for an error correction model – building upon the work of Hendry (1979, 1985 and 1988).

In Norway $M1$ is roughly defined as coins, currency and demand deposits. Usually narrow money is taken to represent transactional and precautionary demand, but since it includes interest bearing deposits as well the speculative or portfolio aspect of money demand cannot be ruled out.

The choice of scale variable in a money demand function is not straightforward.

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[12] There is also the possibility that changes in deep parameters cancel out, but I don't find it very likely.

While the Fischer (1911) version of quantity theory would be consistent with a proxy for the volume of transactions, an income or wealth variable would be more in line with the Cambridge approach.

Keynes (1936, pp. 194 – 209) states the relevance of income (the income–motive), production (the business–motive) and expenditure (the precautionary–motive). Wealth is implicit in the speculative–motive. Keynesian refinements like the inventory approach clearly identifies income as the appropriate measure, while the portfolio approach of Tobin (1958) and the quantity theory restatement of Friedman (1956) advocate the role of wealth.

Laidler (1985, p. 119) recommends wealth as the appropriate scale variable although he points out that Keynesian theory has room for income and wealth in the same specification. This is explicit in Brainard and Tobin (1968), where demand for money is homogeneous in wealth while income reflects changes in transactions demand. Klovland (1990) finds a long–run wealth effect and a short–run influence from income in his study of Norwegian *M2* over 1968 – 1989.

On the other side of the fence McCallum and Goodfriend (1989, p. 121) argue that "...there is no separate room for wealth in a portfolio–balance relation if appropriate transaction and opportunity–cost variables are included".

Finally there is the absence of any volume of financial transactions in the ordinary approach using gross national product or related measures. This point is made by Field (1984) in his study of the United States 1919–1929.

I have simply tried out empirical proxies of these variables and chosen the ones with most satisfactory long–run properties in the general model (15). Models including various income measures, the volume of trading on the stock exchange and real wealth are all investigated. The possibility of income/expenditure and wealth in the same model has also been considered.

The scale variable preferred is a measure of real absorption – namely real gross domestic expenditure, investment in ships and off–shore industry excluded; its implicit deflator is the price variable. The choice of scale variable makes sense in modelling narrow money, since the impact from the oil sector would be more relevant using a broader definition of the money stock.

Money demand functions often exclude an own yield. Since Norwegian narrow money is interest bearing neglection of this fact implies a potential misspecification. The own yield is represented by the interest rate on demand deposits.

As regards alternative prices of money holding, the literature is at least as diverse as for scale variables. In this study several interest rates are included, while the real–wage rate as a measure of the brokerage fee – following Laidler (1985, p. 68) – was discarded at an early stage. The long term bond yield is available together with the average rate on time deposits in banks. But considering Norway's position as a small open economy, an interest rate reflecting international influence is required – as stressed by Hamburger (1977). A natural candidate is the three month eurokrone rate. Although a surrogate measure for the earlier part of the period, the variable represents both a shadow price on credit in domestic markets as well as a yield on foreign assets.

Given these considerations equation (20) is specified as

$$(21) \qquad M = A\cdot P^{\delta}\cdot X^{\zeta}\cdot(1+RD1)^{\eta}\cdot(1+RD2)^{\kappa}\cdot(1+RL)^{\mu}\cdot(1+RS)^{\xi},$$

while its empirical formulation is

$$(22) \gamma(L)m = \boldsymbol{a} + \delta(L)p + \zeta(L)x + \eta(L)RD1 + \kappa(L)RD2 + \mu(L)RL + \xi(L)RS + u_t.$$

where[13]

M = narrow money,

$\boldsymbol{a}$ = constant and seasonal dummies.

P = deflator of gross domestic expenditure X,

[13] Precise definitions and a listing of the series are given in Appendix B.

X = real gross domestic expenditure,

$RD1$ = interest rate on demand deposits,

$RD2$ = interest rate on time deposits,

RL = long–term private bond yield,

RS = three–month eurokrone rate,

and

u_t = error term.

Lower case letters of the regressors denote natural logarithms of the corresponding uppercase variables. The choice of interest rates in levels follows Trundle (1982). The lag operator L is defined as $L^i x_t = x_{t-i}$ and the corresponding scalar polynomials as $f(L) = \Sigma_{i=m}^{n} f_i L^i$.

(Figures 3 and 4 about here.)

The time series of m, p, and x are plotted in Figure 3. A structural break in the m series in 1987:I is pointed out. It is due to changes in the definition of demand deposits. Disregarding this break, the change in trend in the money series compared to both prices and expenditure remains evident.

A changing trend can also be seen in the plot of the interest rates in Figure 4. Note especially how the series appear to move together towards the end of the forecast period.

The model as expressed in equation (22) is hopefully general enough to be an adequate statistical description of the data, but it is of less value as regards economic interpretation: Reformulations and restrictions are required. The earlier research as reported in Hendry (1979, 1985 and 1988), as well as the motivation provided by Goodhart (1989), makes the error correction model a natural starting point for a search for parsimony.

The claim of an error correction representation of the data generation process is a testable proposition in several ways, all of which rely upon the one–to–one mapping between cointegration and error correction models given by the Granger representation theorem. Some tests of the individual time series properties and their long–run co–variation are given in Appendix A. It appears that all of the series, with the possible exception of *RS*, are *I(1)*. In addition the linear combination of *m*, *p*, *x*, *RD1* and *RL* seem to constitute a *I(0)* series, i. e. they appear to be cointegrated. This result is clear when using the static regression set–up from Engle and Granger (1987), but not when the vector autoregression approach of Johansen (1988) is employed.

3.2 *Modelling* [14]

Table V displays the result from estimating the general model in the form of equation (15). The period 1984:I to 1989:I is used for forecasting.

(Table V about here.)

The diagnostic testing procedures follow Hendry (1989), but a brief description might be warranted for the sake of completeness. "*Normality* $\chi^2(2)$" refers to the Jarque–Bera (1980) test for normality of the residuals, with a correction for degrees of freedom. The "*AR 1–df1 F(df1,df2)*" is the test for autoregression performed by testing the significance of augmenting the original model by *df1* lagged residuals. The *F*–form of the test is used, as recommended by Kiviet (1986). "*ARCH df1 F(df1,df2)*" refers to the test for ARCH–errors introduced by Engle (1982), while "*RESET F(1,df2)*" is Ramsey's test for correct specification – performed by testing the relevance of adding the squared predicted values to the original model. A more detailed account of these

[14] The estimation of the general models in Tables V — VIII utilizes a RATS procedure written by the author, while the testing sequence to a parsimonious model is performed in PC–GIVE.

tests can be found in Hendry (1989), Spanos (1986), and Godfrey (1988).

(Table VI about here.)

Although the model is well determined according to the diagnostics, the one–step forecasts are horrendous, as Figure 5 illustrates. One possible explanation is overparameterization. A quicker reaction to changes in interest rates than in the remaining variables seems natural. Deleting the longest lag on interest rates produces the model in Table VI. The long–run estimates of *RD1* and *RL* are about half as big as in Table V, while Figure 6 shows a drastic improvement in the forecasting ability. Whether this instability is a general consequence of overparameterization or few degrees of freedom remains to be established.

(Figures 5 and 6 about here.)

The assumption of weakly exogenous regressors is always controversial. While Cooley and LeRoy (1981) argue that simultaneity bias is important, Laidler (1985) takes the opposite view. Bias is seldom significant when tested for – see for example Poloz (1980), Gregory and McAleer (1981), and Klovland (1983, 1990) – but the possibility has to be taken into consideration.

I test for independence between regressors and error term by the variant of the Hausman–test proposed by Holly (1983). The advantage of this approach lies in the ability of testing exogeneity in any subset of regressors within the same regression.

Write the equation under investigation $\boldsymbol{y} = \boldsymbol{Y\alpha} + \boldsymbol{X_1\beta_1} + \mathbf{u}$, where $\boldsymbol{Y} = [\boldsymbol{Y_1}\ \boldsymbol{Y_2}]$ are the possibly endogenous variables and $\boldsymbol{X_1}$ are the known weakly exogenous regressors. Write also the reduced forms $\boldsymbol{Y} = \boldsymbol{\Pi X} + \boldsymbol{V}$, $\boldsymbol{X} = [\boldsymbol{X_1}\ \boldsymbol{X_2}]$, $\boldsymbol{X_2}$ being the matrix of instruments, and make $\hat{\boldsymbol{V}} = [\boldsymbol{I} - \boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}']\boldsymbol{Y}$ the matrix of residuals of the reduced form regressions. The test is performed by running the regression $\boldsymbol{y} = \boldsymbol{Y\alpha} +$

$X_1\beta_1 + \hat{V}(\hat{V}'\hat{V})^{-1}\delta + \varepsilon$, and test whether $\boldsymbol{\delta} = \mathbf{0}$. If Y_1 are endogenous and the test only concerns Y_2, partition δ conformably with Y as $\boldsymbol{\delta}' = [\boldsymbol{\delta}_1{}' \ \boldsymbol{\delta}_2{}']$ and test if $\boldsymbol{\delta}_2 = \mathbf{0}$. For further details see Holly (1983) or Maddala (1988, pp 439 – 441).

The instruments used, in addition to the lagged variables, are differences of *REUR*, *RBN*, *po*, *imp*, *cg*, and *ig*, all with one lag. The definitions of the variables are:

REUR = the eurodollar rate

RBN = the marginal lending rate of the central bank

po = the price of oil exports

imp = the volume of imports of the main trading partners of Norway weighted using the weights of the basket of currencies.

cg = real public expenditure

ig = real public investment.

Testing all the regressors produces a test statistic of $F(6,19) = 0.60$, while the t–value for $\Delta RS_t = 1.80$. If ΔRBN is dropped from the set of instruments the test statistic for ΔRS_t falls drastically. When all the other variables are treated as weakly exogenous, and $\Delta REUR_t$, $\Delta REUR_{t-1}$ and $\Delta REUR_{t-2}$ are used as the set of instruments for ΔRS_t, the t–value = – 0.53. The conflicting results are probably due to the invalid assumption of ΔRBN as an instrument, since estimation with this variable in the instrument set tends to result in a rejected test of independence between residuals and instruments. Accordingly, the regressors are taken to be weakly exogenous in the following.

As pointed out in section 1 the regressors have to be strongly exogenous in order for the asymptotic theory to be valid. But since the validity of testing for Granger non–causality is heavily questioned no attempt has been made in that direction.

It might also be worth emphasizing that the results reported in Hansen and Phillips (1989) and Phillips and Hansen (1990) indicate that bias in the estimates of the long–run coefficients due to endogeneity cannot be eliminated by means of ordinary instrumental variables techniques. This invariance is consistent with the Monte Carlo results reported in section 2, but here the estimates remain unbiased regardless of the method of estimation.[15]

The next step is to test and impose restrictions on the cointegrating vector, which from equations (7), (10), and (22) is:

$$(23) \qquad m = [-\overset{*}{\delta}_5/\overset{*}{\gamma}_5]p + [-\overset{*}{\zeta}_5/\overset{*}{\gamma}_5]x + [-\overset{*}{\eta}_4/\overset{*}{\gamma}_5]RD1 + [-\overset{*}{\kappa}_4/\overset{*}{\gamma}_5]RD2 + [-\overset{*}{\mu}_4/\overset{*}{\gamma}_5]RL + [-\overset{*}{\xi}_4/\overset{*}{\gamma}_5]RS.$$

A natural question at this point is what the testing sequence should be. A purely statistical answer would probably be to impose all the restrictions and use an F–test. The strategy followed is a pragmatic mixture of statistical criteria and economic theory. First, the parameters with lowest precision and least theoretical justification are deleted. Next, the highest ranking theoretical restriction of a long–run unit price elasticity is tested, and so on.

(Table VII about here.)

The restrictions on the cointegrating vector are all easily accepted, as Table VII shows.[16] In the long run real money is homogeneous in real income. There are considerable costs in adjusting the portfolio between money and bonds, since a percentage point change in the own yield must be set off by at least two percentage points change in RL, the alternative yield on bonds, if adjustment is to take place. Note how close the restricted cointegrating vector is to the Engle–Granger estimates in

[15] Instrumental variables estimation produced the same set of long–run coefficients as well as the same preferred model.

[16] Bårdsen and Klovland (1990) investigate the cointegration properties of money, credit and income in Norway using the techniques of appendix A.

regression *d* of Table A2 in Appendix A.

(Table VIII about here.)

Next, the Error Correction Mechanism is moved back to the longest lag in order to preserve the interim multiplier interpretation. This restricted general model is reported in Table VIII and is the starting point of the "General–to–Specific" search. The changes compared to table VI illustrate the effect of moving the Error Correction Mechanism.

The building of the short run dynamics to obtain a parsimonious model with interpretable parameters is the most difficult part. The general approach is that of Hendry and Richard (1982, 1983), but the most important guidelines used are parsimony, robustness, and an economic interpretation. I have also opted for short lags and simple restrictions. The strive for parsimony has for instance resulted in the exclusion of seasonal dummies, since they are unnecessary.

These considerations have reduced Table VIII to equation (24):

$$\text{(24)}\quad \Delta\hat{m}_t = \underset{(0.025)}{0.283}\Delta(p+x)_t - \underset{(0.029)}{0.190}\Delta(m-p-x)_{t-1} - \underset{(1.254)}{4.828}\Delta RD2_{t-1} - \underset{(0.055)}{0.227}\Delta_2 RS_t - \underset{(0.049)}{0.183}(m-p-x-7.5RD1+3RL)_{t-5} + \underset{(0.348)}{1.322}$$

$R^2 = 0.75$, $\sigma = 0.0118$, $DW = 2.03$, $RSS = 0.0084$, *Normality* $\chi^2(2) = 0.43$, *AR 1–5* $F(5,55) = 0.90$, *ARCH 4* $F(4,52) = 0.63$, *Hetero* $F(10,49) = 0.52$, *RESET* $F(1,59) = 1.52$, *Func. form* $F(20,39) = 0.60$.

"*Hetero F(df1,df2)*" is White's test for heteroscedasticity and tests the joint significance in a regression of the squared residuals on the regressors and their squares. The validity of the chosen functional form is assessed through the "*Func. form*

F(df1,df2)" test due to White: The squared residuals are regressed against all the squares and cross products of the regressors.

Whether one estimates real or nominal demand for money as long as prices are included in the specification is a matter of preference, as re–estimation demonstrates:

$$(25) \quad \widehat{\Delta(m-p)}_t = \underset{(0.155)}{-0.816}\Delta p_t + \underset{(0.025)}{0.281}\Delta x_t - \underset{(0.029)}{0.190}\Delta(m-p-x)_{t-1} - \underset{(1.359)}{4.495}\Delta RD2_{t-1}$$
$$- \underset{(0.056)}{0.230}\Delta_2 RS_t - \underset{(0.052)}{0.174}(m-p-x-7.5RD1+3RL)_{t-5} + \underset{(0.365)}{1.256}$$
$$R^2 = 0.84,\ \sigma = 0.0119,\ DW = 2.01,\ RSS = 0.0083,\ Normality\ \chi^2(2) = 0.27,$$
$$AR\ 1\text{–}5\ F(5,54) = 0.83,\ ARCH\ 4\ F(4,51) = 0.58,\ Hetero\ F(12,46) = 0.54,$$
$$RESET\ F(1,58) = 0.53.$$

In the following I will continue to use the nominal version, since this gives a more parsimonious model.

According to equation (24), the demand for nominal money growth pr. quarter depends negatively upon the half year change in the money market rate and the quarterly change in the alternative yield of time deposits. There is an immediate positive effect from nominal income growth, while there is a smaller adjustment of changes in money income ratio the previous quarter. Finally there is the adjustment of deviations from the long–run desired relation between real money, real income, the own yield and the maximum alternative yield for long term investments. At least twice as large a yield on bonds over money is required before it is considered worth the cost of adjusting the portfolio in the long–run. So in the short–run the agents speculate in the money market and change their money holdings between demand and savings deposits, while in the long–run the the portfolio is adjusted between money and bonds.

While the actual and fitted values together with forecasts for 1984:1 to 1989:1 are given in Figure 7, a closer examination of the forecasting performance is provided in

Figure 10. The forecasts show how the model underpredicts the increased demand in 1984 and 1985. The peak in 1987:I is the structural break mentioned earlier.

(Figures 7 – 10 about here.)

Estimation with recursive least squares facilitates stability analysis. Figure 9 provides a graphical account of *Break–point F –* tests: Chow–tests where the model at each period is tested for stability against the end period of 83:IV. The horizontal line represents the critical values at the 5 % level. The test sequence fail to reject parameter stability of the model throughout the estimation period, even though the one–step residuals can be taken to be non–zero on some occasions in Figure 8.[17]

Concentrating on the period before the break in 1987:I, the model forecasts reasonably well apart from the underpredictions in 1984:IV and 1986:II. It is interesting to note that Klovland (1990) reports a similar finding for the first period in his study of *M2*. Klovland links this to a possible speculative capital inflow and points to a similar effect in the Danish study of Juselius (1989).

As regards 1986:II, the prediction error could linked with the reintroduction of credit restrictions in the previous quarter, as pointed out in the discussion of Table IV.

Nevertheless, the Chow test for stability of the coefficients over 1984:I – 1986:IV gives as result: *CHOW F(12,60)* = 1.70. Consequently the model suggests that no structural change in agent behaviour has taken place as a result of the credit liberalization.

[17] *Forecast F* –tests, Chow–tests for predictive ability where the model is evaluated against the earliest date by increasing the sample size sequentially, are never rejected. They are not reported in order to save space.

This conclusion is reinforced when the sample size is extended to 1986:I:

$$\text{(26)}\quad \Delta\hat{m}_t = \underset{(0.024)}{0.302}\Delta(p+x)_t - \underset{(0.028)}{0.176}\Delta(m-p-x)_{t-1} - \underset{(1.269)}{4.958}\Delta RD2_{t-1} - \underset{(0.057)}{0.239}\Delta_2 RS_t$$
$$- \underset{(0.045)}{0.224}(m-p-x-7.5RD1+3RL)_{t-5} + \underset{(0.318)}{1.608}$$

$R^2 = 0.73$, $\sigma = 0.0124$, $DW = 2.02$, $RSS = 0.0111$, *Normality* $\chi^2(2) = 0.00$, *AR 1–5* $F(5,67) = 0.32$, *ARCH 4* $F(4,64) = 0.29$, *Hetero* $F(10,61) = 0.68$, *RESET* $F(1,71) = 0.44$, *Func. form* $F(20,51) = 0.67$.

Hardly any coefficients have changed. Any instability is likely to have occurred in the mid–seventies and not after the credit liberalization, judging from Figures 11 – 13.

(Figures 11 – 13 about here.)

Finally, the model is re–estimated over the whole sample. A shift dummy *D87* which takes the value *1* from 1987:I onwards is introduced to take account of the break. It appears in three different forms to correct the corresponding money terms:

$$\text{(27)}\quad \Delta\hat{m}_t = \underset{(0.037)}{0.302}\Delta(p+x)_t - \underset{(0.027)}{0.185}\Delta(m-p-x)_{t-1} - \underset{(1.199)}{5.389}\Delta RD2_{t-1} - \underset{(0.058)}{0.234}\Delta_2 RS_t$$
$$- \underset{(0.039)}{0.214}(m-p-x-7.5RD1+3RL)_{t-5} + \underset{(0.276)}{1.538} + \underset{(0.014)}{0.157}\Delta D87_t$$
$$+ \underset{(0.016)}{0.100}\Delta D87_{t-1} + \underset{(0.007)}{0.010}D87_{t-5}$$

$R^2 = 0.79$, $\sigma = 0.0127$, $DW = 2.03$, $RSS = 0.0126$, *Normality* $\chi^2(2) = 0.01$, *AR 1–5* $F(5,73) = 0.73$, *ARCH 4* $F(4,70) = 0.69$, *Hetero* $F(13,64) = 0.50$, *RESET* $F(1,77) = 0.00$, *Func. form* $F(21,58) = 0.64$.

In order to exploit the recursive least squares option of PC–GIVE, the dummies are incorporated in the constant term. Figures 14 – 16 are from this estimation.

(Figures 14 –16 about here.)

The model is reasonably stable over the sample period. The *Break–point F*–tests in Figure 16 show only show signs of instability around 1976. Judging from the residual plot in Figure 15 the model seems to cope with the expansion in 1984, while it takes some periods to get in line again after the break in 1987. But the model cannot be properly evaluated until more data are available, so the influence of the re–definition of demand deposits in 1987:I can be better controlled.

4. CONCLUSION

The paper illustrates one way to obtain an interpretable and parsimonious representation of a general statistical model. The focal point has been to tie down the long–run properties of the model through imposing data tested restrictions. Although the theoretical justification for the procedures are derived under strong exogeneity assumptions, the pilot simulation study indicates a surprising robustness of the method. One explanation can be the experimental design. More evidence is needed – for instance comparing different estimators and the importance of overparameterization – before any judgment can be made of the merits of the method compared to alternative strategies.

The empirical model especially highlights the role of several prices of money holding. In the long–run the relevant interest rates are the own rate and the alternative yield on bonds, and considerable adjustment costs are associated with adjusting the portfolio. In the short–run the agents respond to changes in the alternative yield of time deposits as well as to changes in the money market rate.

APPENDIX A

PROPERTIES OF THE TIME SERIES

A1. *Properties of the individual time series*

Hylleberg et al. (1990) note that the usual definition of integrated processes takes account of a stochastic trend while nonstationarity might also be due to stochastic seasonals, i.e. there might be unit roots at the seasonal frequencies. A series with a unit root of order d at frequency ω is denoted $x_t \sim I_\omega(d)$. If x_t is a quarterly series generated according to $(1 - L^4)x_t$, it can be factorized as $(1 - L)(1 + L)(1 + iL)(1 - iL)x_t = \mu_t + e_t$, where $i \equiv \sqrt{-1}$. This series has the four unit roots 1, –1, i and $-i$ which correspond to the zero, or long–run, frequency, the half–year cycle and two roots at the annual cycle. A test for seasonal integration is based on the polynomial expansion $\varphi(L)$ about these roots:

(A1)
$$\varphi(L) = -\pi_1 L(1 + L + L^2 + L^3) - \pi_2(-L)(1 - L + L^2 - L^3) \\ - (\pi_3 L + \pi_4)(-L)(1 - L^2) + \varphi^*(L)(1 - L^4),$$

where $\varphi^*(L)$ is a remainder. It follows that $\varphi(1) = 0$ only if $\pi_1 = 0$, $\varphi(-1) = 0$ only if $\pi_2 = 0$, and $\varphi(|i|) = 0$ only if $\pi_3 \cap \pi_4 = 0$. So if x_t is generated as $\varphi(L)x_t = \mu_t + e_t$, it can be written:

(A2)
$$\varphi^*(L)y_{4t} = \pi_1 y_{1(t-1)} + \pi_2 y_{2(t-1)} + \pi_3 y_{3(t-2)} + \pi_4 y_{3(t-1)} + \mu_t + e_t,$$

where

(A3)
$$\left\{ \begin{array}{l} y_{1t} = (1 + L + L^2 + L^3)x_t \\ y_{2t} = -(1 - L + L^2 - L^3)x_t \\ y_{3t} = -(1 - L^2)\, x_t \\ y_{4t} = (1 - L^4)\, x_t \end{array} \right\}.$$

Ordinary t – tests of the π's are used to test the hypotheses of unit roots at the different frequencies, together with an $F-$ test for $\pi_3 \cap \pi_4 = 0$. The critical values are given in Hylleberg et al. (1990).

As seen in Figures 3 and 4, the series seem to be nonstationary, with the possible exception of *RS*. Furthermore, x has a very strong seasonal pattern. As mentioned in the main text, the shift in m from 1987:I is due to a re–definition of demand deposits. Accordingly, the tests below exclude this latter period for that variable.

The results from applying the test are displayed in Table A1, Panels A and B.

(Table A1 about here.)

The tests basically confirm the graphic investigation as far as the long–run frequency is concerned. All variables except *RS* seem to be nonstationary. The eurokrone rate can be interpreted as stationary if a linear trend is taken into account. As for the seasonal frequencies, all the series except the deposit rate *RD2* seem to have a nonchanging seasonal pattern when the deterministic part is taken account of.

A2. *Cointegration techniques*

The success of the static regressions of Engle and Granger (1987) in estimating long–run coefficients depends upon all variables being stationary at the seasonal frequencies, as the estimates might otherwise not be unique, as argued in Hylleberg et al. (1990). But according to the tests above, cointegrating regressions should be a valid procedure for most of the variables. Stationarity of the residuals from the cointegrating regressions is tested by Dickey–Fuller (DF and ADF) and Sargan–Bhargava (CRDW) tests. See Engle and Granger (1987) for details.

There could be problems with this approach if the data contain deterministic components, as in the present case. First, the critical values of Engle and Granger (1987) and Engle and Yoo (1987) are derived with no deterministic components in the series. So the values will not be appropriate if any deterministics are not adjusted for in using the tests – unless the components cancel out. It also follows that the CRDW and DF statistics are more likely to exhibit upward bias than the ADF statistic, which will correct for induced autoregression in the residuals through the augmentation. And second, if any deterministic terms do not cancel out, one should expect this to induce bias in the estimate of the cointegrating vector from that part of the deterministics that is not represented in the regression, since the effects will vanish asymptotically.

The natural solution to these problems should be to correct for any deterministic components present. This is the solution adopted in testing for unit roots in individual series not only by Hylleberg et al. (1990), but also by Dickey, Hasza and Fuller (1984), Dickey, Bell and Miller (1986), and Osborn et al. (1988). Following Lovell (1963), theorem 4.1, this is equivalent to include seasonal dummies in the cointegrating regression.[18] A small simulation study by the author indicates that the critical values of the DF–statistic will be smaller than tabulated if no seasonal effects are present and seasonal dummies are included. A conservative strategy should therefore be to adopt the usual critical values and include seasonal dummies in the regression. The results of applying the Engle–Granger (1987) tests are given in table A2.

(Table A2 about here.)

The change in both the parameter estimates and the test–statistics when seasonal dummies are included is quite spectacular. While long–run homogeneity is clearly rejected in regression *a* without seasonal dummies, the estimated long–run elasticities of prices and expenditure jump to 0.98 when seasonal dummies are included in regression *b*. If *RS* is excluded – since it is probably stationary – and if *RD2* is deleted – relying upon its relative unimportance in regression *b* – the parameter space is reduced so the critical values of Engle and Yoo (1987) can be used. The preferred cointegrating vector is given by equation *d* as a relation between the ratio of real money to real

[18] See Hendry (1984a) for an example of such an approach.

expenditure and the own yield and alternative cost of holding money.

The problem of establishing the number of cointegrating vectors has been solved by Johansen (1988) and exemplified in Johansen and Juselius (1990). Although the apparatus developed by Johansen is impressive in its complexity, the underlying idea is intuitive.

The method relies upon the concept of canonical correlations from the theory of multivariate analysis. The data is divided into a differenced and a levels part. Under the assumption of $I(1)$ processes the differenced data are stationary. The technique of canonical correlations is used to find linear combinations of the data in levels that maximize the correlation with the differences. It follows that these linear combinations must be stationary, or cointegrated.

Another appealing aspect of the Johansen set–up is its completeness in providing tests of linear restrictions on $\boldsymbol{\theta}$ as well as estimates of its elements and information about its rank. Finally, the method also takes account of the short–run dynamics and any simultaneity in the estimation process.

Since the purpose of the procedure in the present context will be to establish a benchmark, the reader is referred to Johansen (1988, 1989) and Johansen and Juselius (1990) for details.

Being a full information method, a correct information set is an assumption. Strict fulfillment would make the problem quite unmanageable from the viewpoint of traditional simultaneous equations modelling. For example, in the present data set one can maybe claim to be modelling a demand for money function but hardly the process of price formation, let alone expenditure demand.

The results of applying the Johansen procedure to the present information set can be seen in table A3.[19]

(Table A3 about here.)

Panel A displays the results of using all variables. The first eigenvector cannot be taken as a demand for money function, possibly a relationship between the interest rates. The second eigenvector normalized with respect to m bears some resemblance to the results of Table A2, although the long–run homogeneity with respect to expenditure seems more dubious. It seems clear that at least two cointegrating vectors are present. One possibility is of course that the first one simply is *RS*, provided this is a stationary series.

Next, *RD2* and *RS* are excluded from the information set. The results in panel B clearly indicate the dependence of the estimates upon the information supplied. The test statistics indicate that two cointegrating vectors are still present.

APPENDIX B

THE DATA[20]

M = Coins and currency notes, unutilized bank overdrafts and building loans and demand deposits held by the domestic non–bank public. The bank deposits included in this aggregate comprise deposits in domestic and foreign currency with domestic commercial and savings banks and postal institutions, excluding all deposits held by non–residents. The definition of demand deposits was widened from 1987:I. Quarterly average of end–of–month data. Source: Bank of Norway.

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19 Panel A was computed by a SHAZAM–program written by the author, while panel B was obtained by means of a RATS–program written by Søren Johansen, Katarina Juselius and Henrik Hansen. I would like to thank Kenneth F. Wallis for giving me access to the latter software.

20 All the series in this appendix have been compiled by Jan Tore Klovland.

X = Real gross domestic expenditure, excluding investment in the following sectors: petroleum and natural gas, pipeline transport, oil platforms, and ships. Quarterly average of end–of–month data. Sources: Various issues of Quarterly National Accounts.

P = Implicit deflator of *X*. Quarterly average of end–of–month data. Source: as for *X*.

RD1 = Average interest rate paid on banks' demand deposits. Quarterly data prior to 1978 are obtained by interpolation between end–of–year figures. Between 1978:I and 1985:III the series is a weighted average of lowest (weight = 1/3) and highest (weight = 2/3) interest rates paid on demand deposits by commercial and savings banks. As from 1985:IV properly averaged data is compiled by the Bank of Norway. End–of–quarter estimates averaged over periods t and $t-1$. Sources: Various issues of *Credit Market Statistics* and *Penger and Kreditt.*

RD2 = Average interest rate paid on banks' total deposits denominated in domestic currency (NOK). Methods of calculation and sources as for *RD1*.

RL = Yield to average life of long term bonds (more than six years to expected maturity date) issued by private mortgage loan associations. Quarterly average of end–of–month data. Source: Yield calculations based on bond prices quoted at the Oslo Stock Exchange.

RS = Three–month eurocurrency interest rate on NOK computed from the covered interest parity relationship using middle quotations on spot and three–month forward exchange rates (NOK against USD) and the three–month eurodollar interest rate. Quarterly average of end–of–month data. Source: Data on exchange rates and the eurodollar interest rate obtained from *International Financial Statistics* tapes and some private banks; as from 1988:I interest data as quoted in *Penger and Kreditt.*

(Table B1.)

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TABLE I

THE BIASES AND THEIR STANDARD ERRORS FOR $\hat{\beta}_0$ AND $\hat{\theta}$.

		T=50 OLS	T=50 OLS(σ=.75)	T=50 IV(σ=.75)	T=500 OLS	T=500 OLS(σ=.75)	T=500 IV(σ=.75)
$\hat{\beta}_0$	Bias	–0.00155	0.74762	–0.25985	–0.00541	0.74638	–0.01349
	St.err	0.00461	0.00304	0.12529	0.00130	0.00086	0.00273
$\hat{\theta}$	Bias	–0.00089	–0.00053	–0.00143	–0.00001	0.00000	–0.00003
	St.err.	0.00063	0.00042	0.00176	0.00002	0.00001	0.00002

TABLE II

DISTRIBUTIONS OF THE t–VALUES $t(\hat{\beta}_0)$ and $t(\hat{\theta})$

		T=50 OLS	T=50 OLS(σ=.75)	T=50 IV(σ=.75)	T=500 OLS	T=500 OLS(σ=.75)	T=500 IV(σ=.75)
$t(\hat{\beta}_0)$	Mean	–0.0198	7.6080	0.1633	–0.1234	25.1110	–0.0353
	St.dev.	0.9677	1.4169	0.9193	0.9132	1.3815	0.9107
	Skewn.	–0.0928	0.1816	0.9557	–0.1230	–0.0740	0.2532
	Kurt.	0.1044	0.2064	0.9394	0.0816	–0.0049	0.1125
$t(\hat{\theta})$	Mean	–0.0806	–0.0568	–0.1581	–0.0088	–0.0039	–0.0362
	st.dev.	1.2106	1.2211	1.0366	0.9848	0.9865	1.0183
	Skewn.	–0.1618	–0.0688	–0.0540	–0.0863	–0.0523	–0.0958
	kurt.	1.0873	1.2395	1.0904	0.3266	0.3393	0.0621

TABLE III

EMPIRICAL FRACTILES OF $t(\hat{\beta}_0)$ AND $t(\hat{\theta})$

			2.5 %	5 %	50 %	95 %	97.5 %
$t(\hat{\beta}_0)$	T=50	OLS	–1.93	–1.62	–0.02	1.57	1.86
		OLS(σ=.75)	4.99	5.34	7.55	10.04	10.36
		IV(σ=.75)	–1.11	–1.01	0.01	1.92	2.32
	T=500	OLS	–2.06	–1.70	–0.12	1.34	1.66
		OLS(σ=.75)	22.35	22.80	25.13	27.27	27.64
		IV(σ=.75)	–1.72	–1.44	–0.06	1.53	1.99
$t(\hat{\theta})$	T=50	OLS	–2.53	–2.09	–0.07	1.91	2.16
		OLS(σ=.75)	–2.60	–2.02	–0.05	1.91	2.33
		IV(σ=.75)	–2.39	–1.88	–0.13	1.49	1.84
	T=500	OLS	–2.11	–1.68	0.01	1.61	1.94
		OLS(σ=.75)	–2.04	–1.67	0.00	1.65	1.93
		IV(σ=.75)	–2.12	–1.80	0.01	1.53	1.99

TABLE IV
CREDIT MARKET REGULATIONS IN NORWAY, 1983 – 1989

Type of regulation	Dates when abolished (A) or reintroduced (R)				
	BANKS	FINANCE COMP.	LOAN ASS.	LIFE INSUR.	NON–LIFE INSUR.
Direct loan controls[a]	A1984:I R1986:I A1987:III	A1988:III	A1988:III		A1988:III
Primary reserve req.	A1987:II	A1987:III		A1987:II	
Bond investment quota[b]	A1984:I			A1985:I	
Loan guarantee limits	A1984:III R1986:I A1988:III	A1984:III R1986:I A1988:III	A1984:III R1986:I A1988:III	A1984:III R1986:I A1988:III	A1984:III R1986:I A1988:III
Max int. rate on loans	A1985:III			A1985:III	

[a] Credit extended by the finance companies in the form of factoring and leasing contracts was exempted as from 1984:IV. The regulations concerning mortgage loan associations only applied to loans to households and selected industries.

[b] The dates refer to the point in time when the required percentage of growth was set equal to zero, viz. net additions to the bond portfolio were no longer required. The regulation was completely removed in 1985:I for banks and in 1985:III for life insurance companies.

General notes. If no date is specified, no regulation applies. In all other cases the regulation was in operation at the end of 1983. The information is compiled from *Annual reports of the Norges Bank* 1984 — 1988 and various issues of *Penger og Kreditt* in the same period. The table is taken from Bårdsen and Klovland (1990).

TABLE V
THE GENERAL MODEL
Ordinary least squares estimates of the general model in the form of (15). The sample is 1967:III to 1983:IV; 66 observations, 45 parameters

	Differences: $(\alpha^\dagger_i, \beta^\dagger_{ji})$					Levels: $(\alpha^*_m, \beta^*_{jn})$
lags:	0	1	2	3	4	1
$\gamma(L)m$	–	−0.028 (0.268)	0.296 (0.226)	0.356 (0.243)	0.559 (0.242)	−0.335 (0.221)
$\delta(L)p$	0.240 (0.306)	0.171 (0.256)	0.118 (0.273)	0.025 (0.242)	−0.129 (0.269)	0.261 (0.251)
$\zeta(L)x$	0.082 (0.158)	−0.410 (0.210)	−0.382 (0.221)	−0.202 (0.225)	−0.202 (0.213)	0.373 (0.302)
$\eta(L)RD1$	2.424 (4.457)	−3.346 (5.780)	−10.936 (6.151)	−0.804 (5.092)	−6.174 (5.400)	6.895 (4.633)
$\kappa(L)RD2$	−2.600 (4.783)	−4.801 (4.015)	−1.436 (4.140)	−5.068 (3.003)	−0.969 (3.120)	−0.323 (2.121)
$\mu(L)RL$	−1.142 (1.095)	1.559 (1.393)	0.848 (1.072)	0.419 (0.923)	0.864 (0.930)	−2.492 (1.448)
$\xi(L)RS$	−0.150 (0.117)	−0.607 (0.187)	−0.317 (0.194)	−0.316 (0.171)	−0.048 (0.127)	0.510 (0.228)
a	2.171 (2.056)	0.006 (0.036)	0.044 (0.040)	0.022 (0.044)	–	–

Long run solution:

$$m = \underset{(0.422)}{0.779p} + \underset{(0.748)}{1.113x} + \underset{(12.224)}{20.601RD1} - \underset{(6.504)}{0.966RD2} - \underset{(3.385)}{7.445RL} \quad \underset{(1.365)}{1.524RS}$$

Diagnostics:

$R^2 = 0.92$, $\sigma = 0.0114$, $DW = 2.09$, $RSS = 0.0027$, *Normality* $\chi^2(2) = 0.02$, *AR 1–5* $F(5,16) = 1.25$, *ARCH 4* $F(4,13) = 0.08$, *RESET* $F(1,20) = 1.22$.

Test of lag lengths:

$$H_0\colon \eta^\dagger_4 = \kappa^\dagger_4 = \mu^\dagger_4 = \xi^\dagger_4 = 0;\ F(4,21) = 0.58.$$

TABLE VI

THE REDUCED GENERAL MODEL

Ordinary least squares estimates of the general model in the form of (15). The sample is 1967:III to 1983:IV; 66 observations, 41 parameters

	Differences: $(\alpha^{\dagger}_{i}, \beta^{\dagger}_{ji})$					Levels: $(\alpha^{*}_{m}, \beta^{*}_{jn})$
lags:	0	1	2	3	4	1
$\gamma(L)m$	–	−0.127 (0.196)	0.287 (0.199)	0.363 (0.220)	0.453 (0.206)	−0.277 (0.190)
$\delta(L)p$	0.298 (0.280)	0.336 (0.216)	0.168 (0.257)	−0.074 (0.205)	−0.179 (0.245)	0.212 (0.225)
$\zeta(L)x$	0.097 (0.147)	−0.337 (0.185)	−0.399 (0.195)	−0.248 (0.198)	−0.135 (0.199)	0.338 (0.270)
$\eta(L)RD1$	2.767 (4.221)	−0.923 (5.258)	−7.921 (3.658)	−1.197 (4.764)	–	3.201 (2.973)
$\kappa(L)RD2$	−1.746 (4.332)	−6.449 (3.454)	−1.159 (3.132)	−4.533 (2.556)	–	0.209 (1.635)
$\mu(L)RL$	−0.493 (0.943)	0.568 (1.015)	0.106 (0.841)	−0.103 (0.783)	–	−1.362 (1.004)
$\xi(L)RS$	−0.145 (0.107)	−0.528 (0.164)	−0.242 (0.149)	−0.216 (0.129)	–	0.425 (0.202)
a	1.625 (1.808)	0.004 (0.032)	0.040 (0.035)	0.035 (0.041)	–	–

Long run solution:

$$m = \underset{(0.476)}{0.766p} + \underset{(0.850)}{1.222x} + \underset{(9.305)}{11.559RD1} + \underset{(5.741)}{0.755RD2} - \underset{(2.525)}{4.917RL} \quad \underset{(1.481)}{1.534RS}$$

Diagnostics:

$R^2 = 0.91$, $\sigma = 0.0110$, $DW = 2.20$, $RSS = 0.0030$, *Normality* $\chi^2(2) = 0.31$,
AR 1−5 $F(5,20) = 1.61$, *ARCH 5* $F(4,17) = 0.22$, *RESET* $F(1,24) = 1.11$.

TABLE VII
TESTING LONG–RUN RESTRICTIONS

Restricting the model: $m = [-\overset{*}{\delta}_5/\overset{*}{\gamma}_5]p + [-\overset{*}{\zeta}_5/\overset{*}{\gamma}_5]x + [-\overset{*}{\eta}_4/\overset{*}{\gamma}_5]RD1 + [-\overset{*}{\kappa}_4/\overset{*}{\gamma}_5]RD2 + [-\overset{*}{\mu}_4/\overset{*}{\gamma}_5]RL + [-\overset{*}{\xi}_4/\overset{*}{\gamma}_5]RS$ from Table VI. The sample is 1967:III to 1983:IV, 66 observations

Panel A

Restricting $[-\overset{*}{\kappa}_4/\overset{*}{\gamma}_5] = [-\overset{*}{\xi}_4/\overset{*}{\gamma}_5] = 0$

Level terms on lag 1:

$-\,0.409m$	$+\,0.422p$	$+\,0.350x$	$+\,4.248RD1$	$-\,1.734RL$
(0.172)	(0.184)	(0.281)	(2.782)	(0.997)

Long run solution:

$m\ =$	$1.032p$	$+\,0.855x$	$+\,10.376RD1$	$-\,4.235RL$
	(0.300)	(0.513)	(4.083)	(1.702)

Diagnostics, 39 parameters:

$R^2 = 0.89$, $\sigma = 0.0115$, $DW = 2.20$, $RSS = 0.0036$, *Normality* $\chi^2(2) = 0.08$, *AR 1–5* $F(5,22) = 1.68$, *ARCH 5* $F(4,19) = 0.29$, *RESET* $F(1,26) = 2.30$.

Panel B

Restricting $[-\overset{*}{\delta}_5/\overset{*}{\gamma}_5] = 1$, testing $[-\overset{*}{\zeta}_5/\overset{*}{\gamma}_5] = 1$

Level terms on lag 1:

$-\,0.414(m-p-x)$	$-\,0.038x$	$+\,4.306RD1$	$-\,1.707RL$
(0.164)	(0.051)	(2.682)	(0.948)

Long run solution:

$(m-p-x) =$	$-\,0.092x$	$+\,10.396RD1$	$-\,4.122RL$
	(0.104)	(3.958)	(1.299)

Diagnostics, 38 parameters:

$R^2 = 0.89$, $\sigma = 0.0113$, $DW = 2.20$, $RSS = 0.0036$, *Normality* $\chi^2(2) = 0.07$, *AR 1–5* $F(5,23) = 1.68$, *ARCH 4* $F(4,20) = 0.31$, *RESET* $F(1,27) = 2.38$.

TABLE VII, CONTINUED
TESTING LONG–RUN RESTRICTIONS

Restricting the model: $m = [-\overset{*}{\delta}_5/\overset{*}{\gamma}_5]p + [-\overset{*}{\zeta}_5/\overset{*}{\gamma}_5]x + [-\overset{*}{\eta}_4/\overset{*}{\gamma}_5]RD1 + [-\overset{*}{\kappa}_4/\overset{*}{\gamma}_5]RD2 + [-\overset{*}{\mu}_4/\overset{*}{\gamma}_5]RL + [-\overset{*}{\xi}_4/\overset{*}{\gamma}_5]RS$ from Table VI. The sample is 1967:III to 1983:IV, 66 observations

Panel C

Restricting $[-\overset{*}{\zeta}_5/\overset{*}{\gamma}_5] = 1$

Level terms on lag 1:

$$\underset{(0.132)}{-0.340(m-p-x)} + \underset{(1.105)}{2.469RD1} \quad \underset{(0.481)}{-1.096RL}$$

Long run solution:

$$(m-p-x) = \underset{(2.050)}{+7.281RD1} \quad \underset{(0.930)}{-3.225RL}$$

Diagnostics, 37 parameters:

$R^2 = 0.89$, $\sigma = 0.0112$, $DW = 2.16$, $RSS = 0.0036$, *Normality* $\chi^2(2) = 0.05$, *AR 1–5* $F(5,24) = 1.23$, *ARCH 5* $F(4,21) = 0.38$, *RESET* $F(1,28) = 3.05$.

Panel D

Testing the long–run restrictions $m = p + x + 7.5RD1 - 3RL$

Level terms on lag 1:

$$\underset{(0.190)}{-0.277(m-p-x-7.5RD1+3RL)} \quad \underset{(0.125)}{-0.065p} \quad \underset{(0.225)}{+0.061x}$$

$$\underset{(2.511)}{+1.124RD1} \quad \underset{(1.635)}{+0.209RD2} \quad \underset{(0.694)}{-0.531RL} \quad \underset{(0.202)}{+0.425RS}$$

Long run solution:

$$(m-p-x-7.5RD1+3RL) = \underset{(0.476)}{-0.234p} \quad \underset{(0.850)}{+0.222x}$$

$$\underset{(9.305)}{+4.059RD1} \quad \underset{(5.741)}{+0.755RD2} \quad \underset{(2.525)}{-1.917RL} \quad \underset{(1.481)}{1.534RS}$$

Testing H_0: $m - p - x - 7.5RD1 + 3RL = 0$:
$F(6,25) = 1.06$.

TABLE VIII
THE RESTRICTED GENERAL MODEL
Ordinary least squares estimates of the general model in the form of (9). The sample is 1967:III to 1983:IV; 66 observations, 35 parameters

lags (i):	0	1	2	3	4	5
$\gamma_i^* \Delta m$	–	–0.410	0.014	0.002	–0.079	–
		(0.206)	(0.196)	(0.173)	(0.178)	
$\delta_i^* \Delta p$	0.236	0.409	0.467	0.243	–0.033	–
	(0.226)	(0.205)	(0.247)	(0.190)	(0.193)	
$\zeta_i^* \Delta x$	0.118	0.123	0.092	0.127	0.054	–
	(0.116)	(0.124)	(0.137)	(0.134)	(0.131)	
$\eta_i^* \Delta RD1$	–1.861	5.915	–6.144	3.217	–	–
	(3.340)	(4.219)	(3.607)	(3.169)		
$\kappa_i^* \Delta RD2$	2.695	–7.358	2.936	–4.963	–	–
	(3.042)	(3.075)	(2.792)	(2.299)		
$\mu_i^* \Delta RL$	–0.207	–0.856	–0.707	–1.058	–	–
	(0.753)	(0.707)	(0.672)	(0.768)		
$\xi_i^* \Delta RS$	–0.232	–0.334	–0.095	–0.071	–	–
	(0.091)	(0.121)	(0.126)	(0.103)		
$(m-p-x-7.5RD1+3RL)$	–	–	–	–	–0.242 (0.105)	
a	1.718 (0.741)	0.002 (0.037)	0.018 (0.031)	0.043 (0.038)	–	–

Diagnostics:

$R^2 = 0.88$, $\sigma = 0.0112$, $DW = 2.09$, $RSS = 0.0039$, *Normality* $\chi^2(2) = 0.03$, *AR 1–5* $F(5,26) = 0.63$, *ARCH 4* $F(4,23) = 0.30$, *RESET* $F(1,30) = 1.84$.

TABLE A1
TESTS FOR UNIT ROOTS

Panel A

Var.	Aux. regr.	"t" π_1	"t" π_2	"t" π_3	"t" π_4	"F" $\pi_3 \cap \pi_4$	Lag augm.	sample
	–	2.74	–1.81	–1.36	–0.83	1.30	1,3,4,5	68:3–86:4
	C	0.26	–1.75	–1.36	–0.83	1.30	1,3,4,5	68:3–86:4
m	C,Q	0.29	–5.37*	–6.62**	–4.30**	58.73**	–	67:2–86:4
	C,T	–2.99	–1.68	–1.38	–0.68	1.20	1,3,4,5	68:3–86:4
	C,Q,T	–3.03	–3.04*	–4.25*	–0.27	9.47**	1,4,5	68:3–86:4
	–	2.74	–3.92**	–3.00**	–4.63**	15.53**	1	67:3–89:1
	C	–0.57	–3.86**	–3.09**	–4.50**	15.32**	1	67:3–89:1
p	C,Q	–0.44	–5.34**	–5.32**	–6.79**	60.26	–	67:2–89:1
	C,T	–2.79	–3.79**	–3.09**	–4.08**	13.32**	1	67:3–89:1
	C,Q,T	–2.11	–5.33**	–5.64**	–6.26**	59.11**	–	67:2–89:1
	–	1.70	–0.38	–0.68	–0.58	0.40	1,4,5	68:3–89:1
	C	–1.56	–0.37	–0.74	–0.56	0.43	1,4,5	68:3–89:1
x	C,Q	–1.52	–4.99**	–6.01**	–3.82**	34.93**	–	67:2–89:1
	C,T	–2.35	–0.44	–0.42	–0.59	0.27	1,2,4,5	68:3–89:1
	C,Q,T	–1.80	–5.11**	–6.26**	–3.80	36.84**	–	67:2–89:1

C = constant, Q = seasonal dummies, T = time trend.

$* = \begin{cases} \text{For } \pi_1, \pi_2, \pi_3, \text{ and } \pi_3 \cap \pi_4\text{: greater than the 5 \% critical value for 100 observations;} \\ \text{for } \pi_4\text{: greater than the 2.5 \% critical value for 100 observations.} \end{cases}$

$** = \begin{cases} \text{For } \pi_1, \pi_2, \pi_3, \text{ and } \pi_3 \cap \pi_4\text{: greater than the 1 \% critical value for 100 observations;} \\ \text{for } \pi_4\text{: greater than the 1 \% critical value for 100 observations.} \end{cases}$

The critical values are taken from Hylleberg *et al.* (1988).

TABLE A1, CONTINUED
TESTS FOR UNIT ROOTS

Panel B

Var.	Aux. regr.	"t" π_1	"t" π_2	"t" π_3	"t" π_4	"F" $\pi_3 \cap \pi_4$	Lag augm.	sample
	–	4.17	-7.13^{**}	-3.62^{**}	-2.46^{**}	10.52^{**}	1–8,10	69:4–89:1
	C	3.82	-7.20^{**}	-3.77^{**}	-2.41^{**}	10.97^{**}	1–8,10	69:4–89:1
RD1	C,Q	3.76	-7.00^{**}	-3.59^{*}	-2.29	9.96^{**}	1–8,10	69:4–89:1
	C,T	1.48	-7.15^{**}	-3.68^{**}	-2.34^{*}	10.33^{**}	1–8,10	69:4–89:1
	C,Q,T	1.46	-6.96^{**}	-3.48^{**}	-2.23	9.35^{**}	1–8,10	69:4–89:1
	–	2.01	-5.26^{**}	-0.92	-3.80^{**}	7.66^{**}	1–5	68:3–89:1
	C	0.24	-5.24^{**}	-0.95	-3.75^{**}	7.50^{**}	1–5	68:3–89:1
RD2	C,Q	0.26	-7.67^{**}	-1.10	-5.95^{**}	18.03^{**}	1,4,5	68:3–89:1
	C,T	-2.18	-5.11^{**}	-1.00	-3.59^{**}	6.97^{**}	1–5	68:3–89:1
	C,Q,T	-2.19	-7.51^{**}	-1.19	-5.65^{**}	16.14^{**}	1,4,5	68:3–89:1
	–	0.34	-5.99^{**}	-3.70^{**}	-6.05^{**}	36.11^{**}	–	67:2–89:1
	C	-1.14	-5.96^{**}	-3.77^{**}	-5.96^{**}	35.88^{**}	–	67:2–89:1
RL	C,Q	-1.18	-5.83^{**}	-3.59^{*}	-5.83	33.78^{**}	–	67:2–89:1
	C,T	-1.49	-5.98^{**}	-3.87^{**}	-5.76^{*}	35.33^{**}	–	67:2–89:1
	C,Q,T	1.41	-5.85^{**}	-3.68^{**}	-5.60	33.12^{**}	–	67:2–89:1
	–	-0.08	-5.51^{**}	-6.02^{**}	-2.89^{**}	26.83^{**}	–	67:2–89:1
	C	-2.32	-5.60^{**}	-6.26^{**}	-2.78^{**}	28.12^{**}	–	67:2–89:1
RS	C,Q	-2.31	-6.14^{**}	-6.23^{*}	-2.64^{*}	27.33^{**}	–	67:2–89:1
	C,T	-3.52^{*}	-5.84^{**}	-6.74^{**}	-2.64^{**}	31.31^{**}	–	67:2–89:1
	C,Q,T	3.66^{*}	-6.47^{**}	-6.77^{**}	-2.51^{*}	30.96^{**}	–	67:2–89:1

C = constant, Q = seasonal dummies, T = time trend.

* = For π_1, π_2, π_3, and $\pi_3 \cap \pi_4$: greater than the 5 % critical value for 100 observations; for π_4: greater than the 2.5 % critical value for 100 observations.

** = For π_1, π_2, π_3, and $\pi_3 \cap \pi_4$: greater than the 1 % critical value for 100 observations; for π_4: greater than the 1 % critical value for 100 observations.

The critical values are taken from Hylleberg *et al.* (1988).

TABLE A2
COINTEGRATING REGRESSIONS
Dependent variable: m. The sample is 1966:II to 1983:IV, 71 observations

	Regressions			
var.	*a*	*b*	*c*	*d*
p	1.39	0.98	1.44	0.99
x	0.36	0.98	0.35	0.99
RD1	1.01	6.36	3.21	7.40
RD2	2.86	1.09	–	–
RDL	–3.31	–2.99	–3.27	–3.03
RS	–0.11	–0.08	–	–
C	10.01	7.18	10.16	7.18
Q1	–	–0.08	–	–0.08
Q2	–	–0.06	–	–0.07
Q3	–	–0.11	–	–0.11
CRDW	1.20	0.89	1.16	0.88
DF	–6.29	–4.64	–6.08***	–4.56*
ADF(4)	–4.07	–4.65	–3.62	–4.46**

C = constant, (*Q1*, *Q2*, *Q3*) = seasonal dummies.

$\begin{Bmatrix} * \\ ** \\ *** \end{Bmatrix} = \begin{Bmatrix} \text{greater than the 10 \% critical value for 50 observations;} \\ \text{greater than the 5 \% critical value for 50 observations;} \\ \text{greater than the 1 \% critical value for 50 observations.} \end{Bmatrix}$

The critical values are taken from Engle and Yoo (1987).

TABLE A3
THE JOHANSEN PROCEDURE
VAR with 5 lags, seasonal dummies included. The sample is 1967:III to 1983:IV, 66 observations.

Panel A
The whole information set

The eigenvalues:

	0.705	0.616	0.476	0.355	0.333	0.186	0.011

The test statistics:

	Testing the number of cointegrating vectors						
Test type	$r = 0$	$r \leq 1$	$r \leq 2$	$r \leq 3$	$r \leq 4$	$r \leq 5$	$r \leq 6$
trace	256.374	175.788	112.672	69.992	41.045	14.315	0.748
λ_{max}	80.586	63.116	42.680	28.947	26.731	13.567	0.748

The eigenvectors:

m	–1.318	–93.717	–23.783	19.646	7.634	37.512	–34.697
p	–0.235	94.598	–27.384	–15.690	39.260	–67.654	23.257
x	–12.938	69.446	102.901	–8.156	–101.849	9.892	25.395
RD1	545.522	1193.370	–579.091	–480.238	–1664.848	–450.782	1383.401
RD2	158.398	140.206	504.164	–304.310	999.875	48.186	–143.337
RL	–293.973	–487.192	185.036	217.198	76.796	234.738	–298.180
RS	75.762	–11.232	43.822	72.747	–14.100	22.202	13.036

Normalization by m of the second eigenvector:
$m = 1.01p + 0.74x + 12.74RD1 + 1.50\ RD2 - 5.20\ RL - 0.12\ RS$

TABLE A3, CONTINUED
THE JOHANSEN PROCEDURE
VAR with 5 lags, seasonal dummies included. The sample is 1967:III to 1983:IV, 66 observations.

Panel B
The restricted information set

The eigenvalues:

0.548	0.475	0.275	0.093	0.006

The test statistics:

Test type	Testing the number of cointegrating vectors				
	$r=0$	$r\leq 1$	$r\leq 2$	$r\leq 3$	$r\leq 4$
trace	122.957***	70.494***	28.000	6.810	0.368
λ_{max}	52.464***	42.494***	21.195*	6.441	0.368

The eigenvectors:

m	−39.430	−85.844	13.862	24.820	13.664
p	70.656	43.794	−36.811	−59.193	−12.829
x	−34.330	140.969	20.169	24.639	4.128
$RD1$	1216.925	1231.409	449.989	6.304	−608.804
RDL	−553.410	−283.536	−70.945	127.733	121.275

Normalization by m of the second eigenvector:
$m = 0.51p + 1.64x + 14.35RD1 - 3.30\ RL$

$\begin{Bmatrix} * \\ ** \\ *** \end{Bmatrix} = \begin{Bmatrix} \text{greater than the 10 \% critical value;} \\ \text{greater than the 5 \% critical value;} \\ \text{greater than the 1 \% critical value.} \end{Bmatrix}$

The critical values are taken from Johansen and Juselius (1989).

TABLE B1
THE DATA

	m	p	x	$RD1$	$RD2$	RL	RS
66:II	9.421314	–1.264924	3.811867	0.00095	0.02585	0.0540	0.0556
66:III	9.474037	–1.252152	3.847332	0.00105	0.02595	0.0556	0.0681
66:IV	9.532960	–1.241873	3.907295	0.00115	0.02605	0.0555	0.0661
67:I	9.520767	–1.260685	3.806295	0.00120	0.02625	0.0575	0.0489
67:II	9.524734	–1.241531	3.898780	0.00120	0.02655	0.0577	0.0494
67:III	9.550200	–1.230950	3.906064	0.00125	0.02685	0.0565	0.0486
67:IV	9.599669	–1.222152	3.951572	0.00130	0.02715	0.0559	0.0840
68:I	9.577368	–1.228341	3.837307	0.00155	0.02740	0.0548	0.0916
68:II	9.589261	–1.218399	3.905566	0.00205	0.02760	0.0537	0.0962
68:III	9.634259	–1.205953	3.913269	0.00255	0.02780	0.0533	0.0721
68:IV	9.702588	–1.196533	3.961909	0.00310	0.02800	0.0534	0.0758
69:I	9.708348	–1.178278	3.888326	0.00360	0.02820	0.0535	0.0822
69:II	9.715632	–1.170212	3.940799	0.00400	0.02840	0.0537	0.1035
69:III	9.766523	–1.154264	3.963245	0.00440	0.02860	0.0575	0.1154
69:IV	9.819044	–1.139390	4.083302	0.00480	0.03170	0.0670	0.1062
70:I	9.818140	–1.077037	3.915296	0.00530	0.03520	0.0639	0.0958
70:II	9.853150	–1.061747	4.014728	0.00595	0.03615	0.0640	0.0899
70:III	9.898319	–1.049073	4.019488	0.00665	0.03705	0.0642	0.0832
70:IV	9.951563	–1.026452	4.107306	0.00735	0.03795	0.0643	0.0757
71:I	9.967747	–1.013746	3.976129	0.00790	0.03840	0.0644	0.0555
71:II	9.985293	–0.991185	4.051440	0.00825	0.03840	0.0644	0.0631
71:III	10.030630	–0.984540	4.069336	0.00855	0.03835	0.0641	0.0534
71:IV	10.076100	–0.970004	4.139353	0.00885	0.03830	0.0641	0.0447
72:I	10.083370	–0.948303	4.001455	0.00910	0.03830	0.0647	0.0343
72:II	10.099700	–0.925120	4.052187	0.00925	0.03825	0.0645	0.0598
72:III	10.147250	–0.923986	4.078771	0.00940	0.03820	0.0635	0.0533
72:IV	10.185260	–0.917403	4.158588	0.00960	0.03815	0.0632	0.0795
73:I	10.185170	–0.889898	4.038051	0.00965	0.03835	0.0637	0.0691
73:II	10.202860	–0.854436	4.090366	0.00955	0.03890	0.0642	0.0707
73:III	10.241370	–0.842284	4.114245	0.00950	0.03945	0.0639	0.0894
73:IV	10.280490	–0.814281	4.188347	0.00945	0.04000	0.0639	0.1080
74:I	10.301880	–0.793655	4.083324	0.00970	0.04055	0.0640	0.0664
74:II	10.298980	–0.766890	4.178598	0.01020	0.04110	0.0740	0.1487
74:III	10.333740	–0.740222	4.190242	0.01085	0.04170	0.0748	0.1253
74:IV	10.406810	–0.700548	4.246134	0.01165	0.04230	0.0748	0.0791
75:I	10.427930	–0.689123	4.140411	0.01230	0.04290	0.0756	0.1192
75:II	10.451220	–0.651025	4.226036	0.01295	0.04350	0.0756	0.0971
75:III	10.526640	–0.634048	4.221670	0.01360	0.04410	0.0762	0.0595
75:IV	10.583910	–0.618186	4.316669	0.01425	0.04470	0.0750	0.0674
76:I	10.628070	–0.605006	4.206283	0.01480	0.04550	0.0745	0.0651
76:II	10.642940	–0.561932	4.265233	0.01515	0.04655	0.0744	0.0812
76:III	10.687510	–0.546009	4.285534	0.01550	0.04760	0.0748	0.1184
76:IV	10.744740	–0.531066	4.365819	0.01585	0.04865	0.0750	0.0981
77:I	10.779050	–0.505782	4.249671	0.01625	0.04960	0.0752	0.0843
77:II	10.773320	–0.475017	4.332119	0.01680	0.05035	0.0758	0.0981
77:III	10.819830	–0.465651	4.347503	0.01735	0.05110	0.0759	0.1157
77:IV	10.869500	–0.456358	4.427725	0.01790	0.05185	0.0796	0.1713

TABLE B1, CONTINUED
THE DATA

	m	p	x	$RD1$	$RD2$	RL	RS
78:I	10.868630	−0.431265	4.279709	0.01910	0.05720	0.0865	0.1411
78:II	10.853480	−0.408070	4.317450	0.02100	0.06295	0.0862	0.1275
78:III	10.895040	−0.386065	4.312070	0.02250	0.06335	0.0864	0.1070
78:IV	10.941700	−0.378812	4.410075	0.02350	0.06315	0.0855	0.1330
79:I	10.944970	−0.377137	4.274574	0.02300	0.06275	0.0845	0.0838
79:II	10.956600	−0.365107	4.344246	0.02350	0.06185	0.0844	0.0929
79:III	11.023420	−0.362517	4.351372	0.02550	0.06325	0.0844	0.1255
79:IV	11.052840	−0.343897	4.448654	0.02600	0.06690	0.0919	0.1413
80:I	11.055870	−0.319116	4.372761	0.02700	0.06965	0.1068	0.1340
80:II	11.058550	−0.272592	4.381366	0.02950	0.07110	0.1070	0.1143
80:III	11.097780	−0.247967	4.403548	0.03200	0.07210	0.1103	0.1202
80:IV	11.147920	−0.224979	4.498529	0.03400	0.07285	0.1085	0.1196
81:I	11.159850	−0.197342	4.345243	0.03650	0.07325	0.1174	0.1247
81:II	11.168130	−0.167546	4.393927	0.03900	0.07330	0.1271	0.1222
81:III	11.228090	−0.145765	4.404917	0.03800	0.07355	0.1313	0.1319
81:IV	11.257720	−0.128672	4.503472	0.03500	0.07550	0.1313	0.1431
82:I	11.275940	−0.104328	4.386078	0.03550	0.07795	0.1402	0.1449
82:II	11.287180	−0.075348	4.430427	0.03800	0.07920	0.1416	0.1626
82:III	11.325760	−0.048949	4.432178	0.04000	0.07995	0.1418	0.1562
82:IV	11.363380	−0.036239	4.502607	0.04250	0.08195	0.1414	0.1491
83:I	11.371040	−0.017751	4.382733	0.04450	0.08320	0.1402	0.1362
83:II	11.375110	−0.003369	4.410929	0.04700	0.08285	0.1396	0.1334
83:III	11.425420	0.006071	4.440842	0.04800	0.08250	0.1381	0.1300
83:IV	11.466630	0.014758	4.504582	0.04750	0.08250	0.1346	0.1303
84:I	11.475590	0.021854	4.438060	0.04850	0.08385	0.1327	0.1315
84:II	11.499340	0.032418	4.489360	0.05000	0.08400	0.1320	0.1276
84:III	11.561950	0.047538	4.511442	0.05100	0.08455	0.1319	0.1275
84:IV	11.636030	0.062906	4.587735	0.05050	0.08575	0.1315	0.1306
85:I	11.675830	0.078969	4.507558	0.05250	0.08610	0.1314	0.1231
85:II	11.698990	0.100530	4.543697	0.05600	0.08625	0.1333	0.1276
85:III	11.769840	0.111782	4.577076	0.05650	0.08665	0.1366	0.1258
85:IV	11.842090	0.123808	4.663826	0.06050	0.08815	0.1389	0.1245
86:I	11.846480	0.134598	4.586051	0.06550	0.08975	0.1465	0.1306
86:II	11.898090	0.158688	4.660529	0.06700	0.09125	0.1452	0.1393
86:III	11.922190	0.185026	4.652239	0.06900	0.09350	0.1451	0.1452
86:IV	11.956790	0.203370	4.743658	0.07550	0.09950	0.1483	0.1511
87:I	12.096110	0.249754	4.581220	0.08450	0.10650	0.1512	0.1490
87:II	12.151870	0.262509	4.615067	0.08800	0.10850	0.1473	0.1444
87:III	12.164370	0.269270	4.642238	0.08950	0.10900	0.1450	0.1403
87:IV	12.230420	0.280140	4.737014	0.09400	0.11150	0.1440	0.1495
88:I	12.260860	0.301317	4.588318	0.09850	0.11350	0.1466	0.1440
88:II	12.253900	0.317361	4.597835	0.10000	0.11300	0.1420	0.1350
88:III	12.312010	0.325422	4.599866	0.09850	0.11050	0.1420	0.1340
88:IV	12.404500	0.335867	4.656516	0.09750	0.10800	0.1350	0.1280
89:I	12.439010	0.345138	4.548312	0.09300	0.10200	0.1220	0.1140

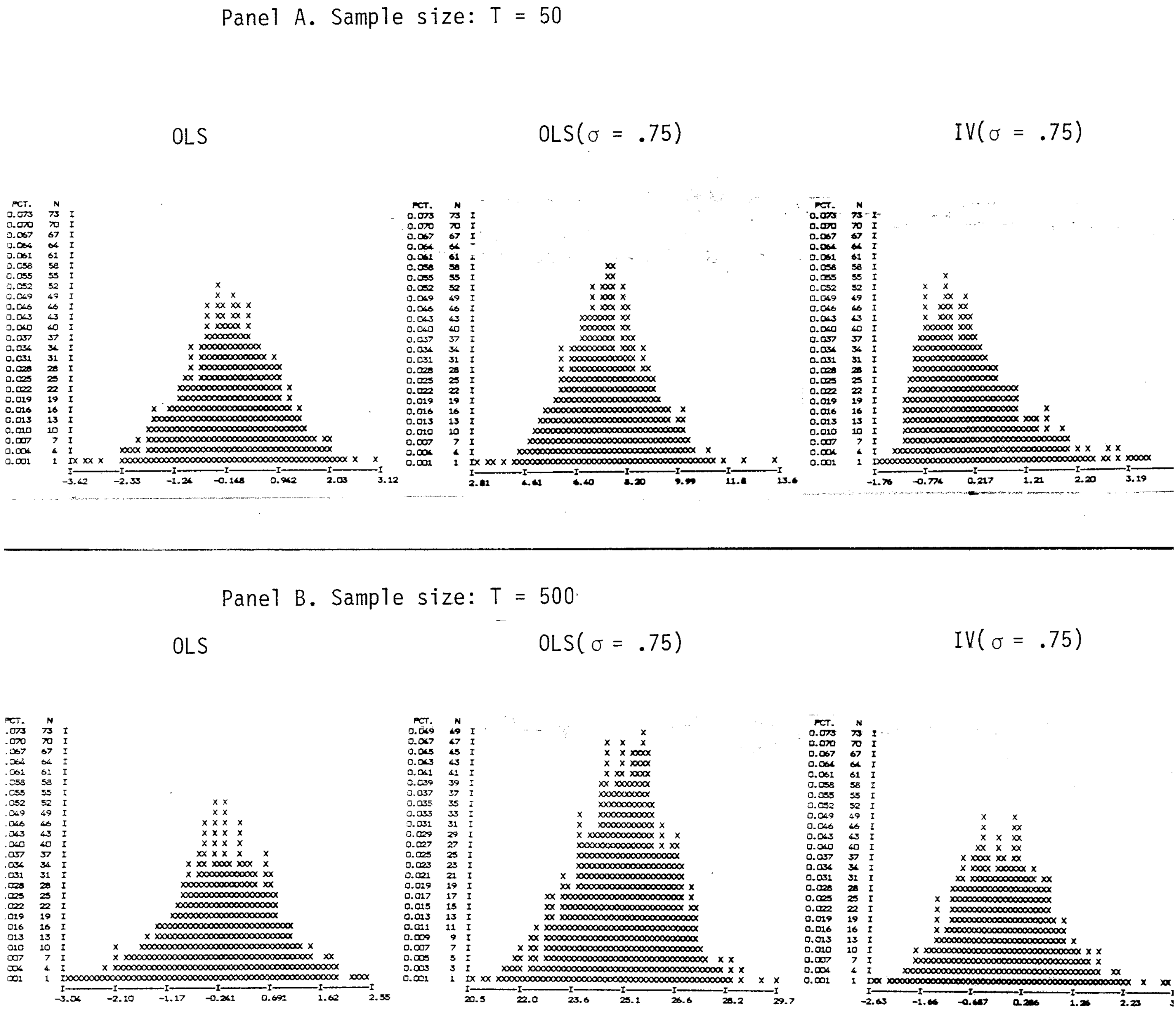
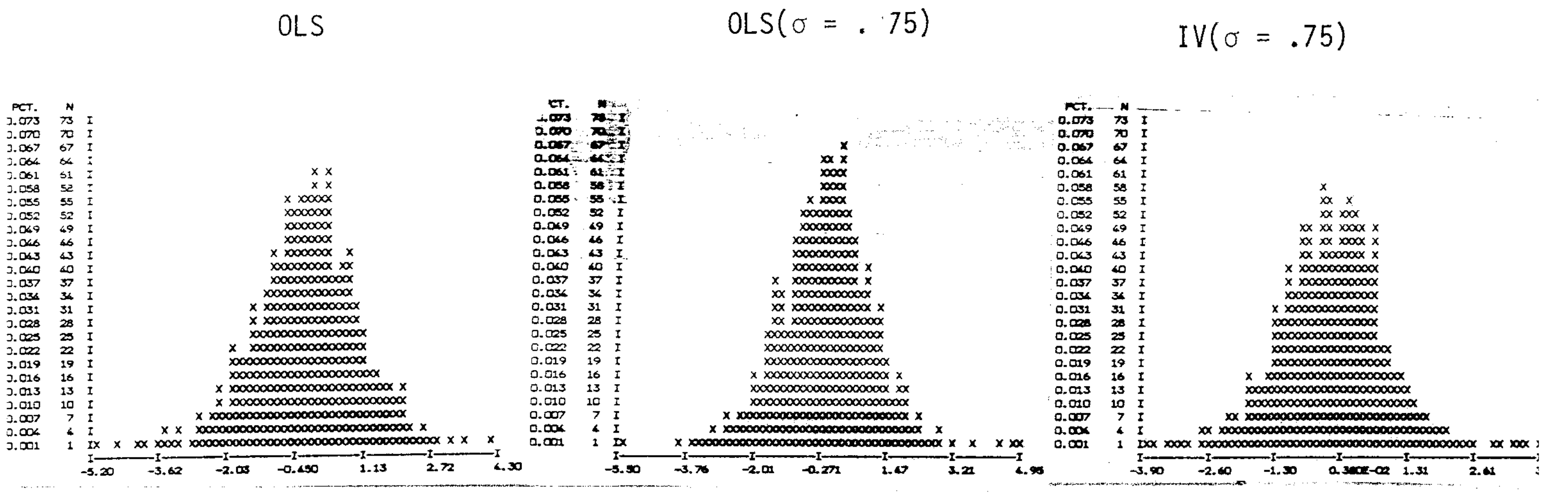


Figure 1. Histograms of $t(\hat{\beta}_0)$.

Panel A. Sample size: T = 50



Panel B. Sample size: T = 500

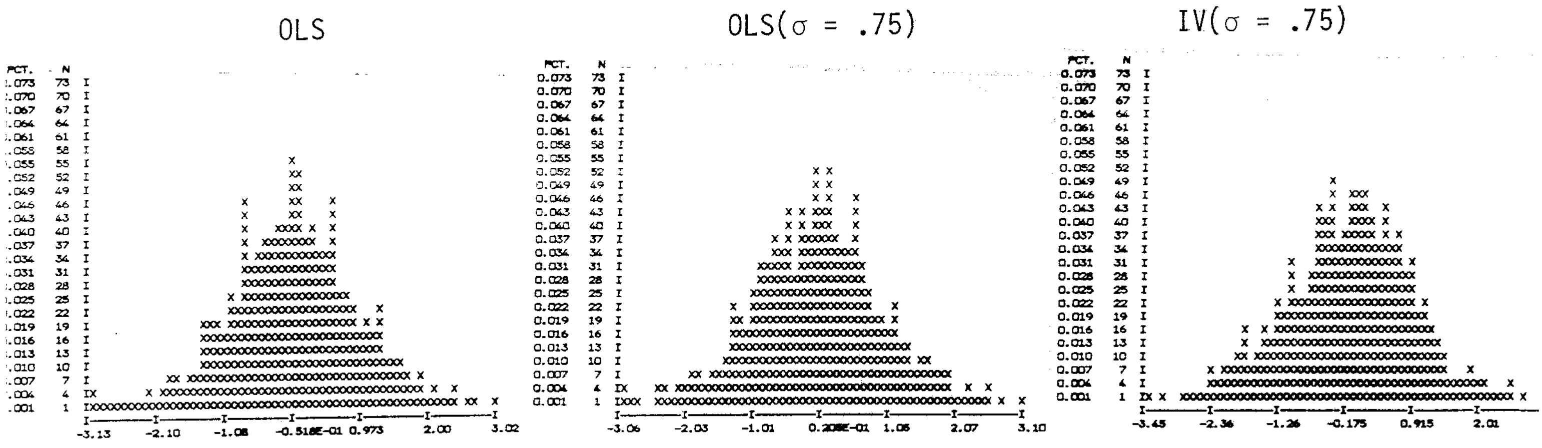


Figure 2. Histograms of $t(\hat{\theta})$.

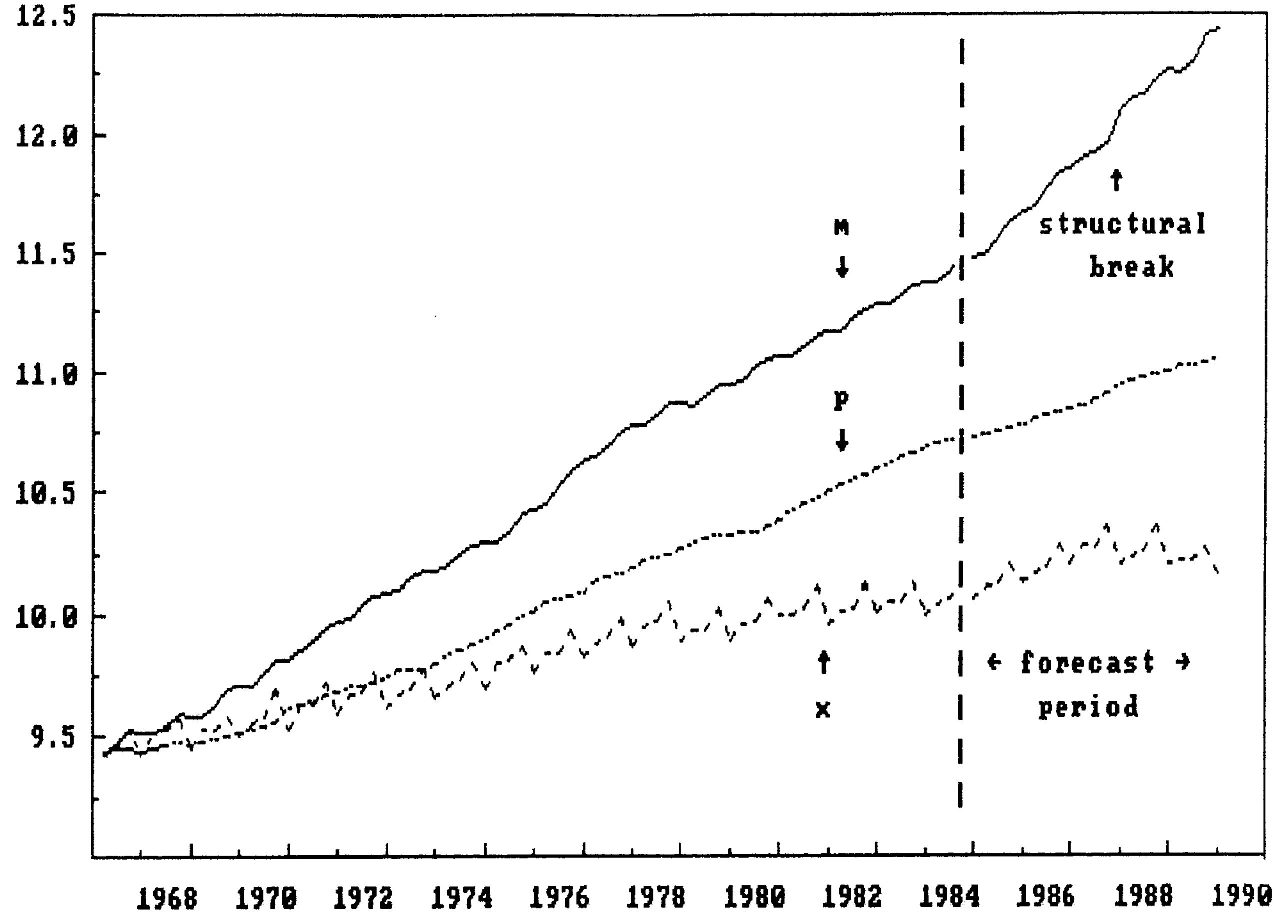


Figure 3. The series of m, p, and x with means adjusted.

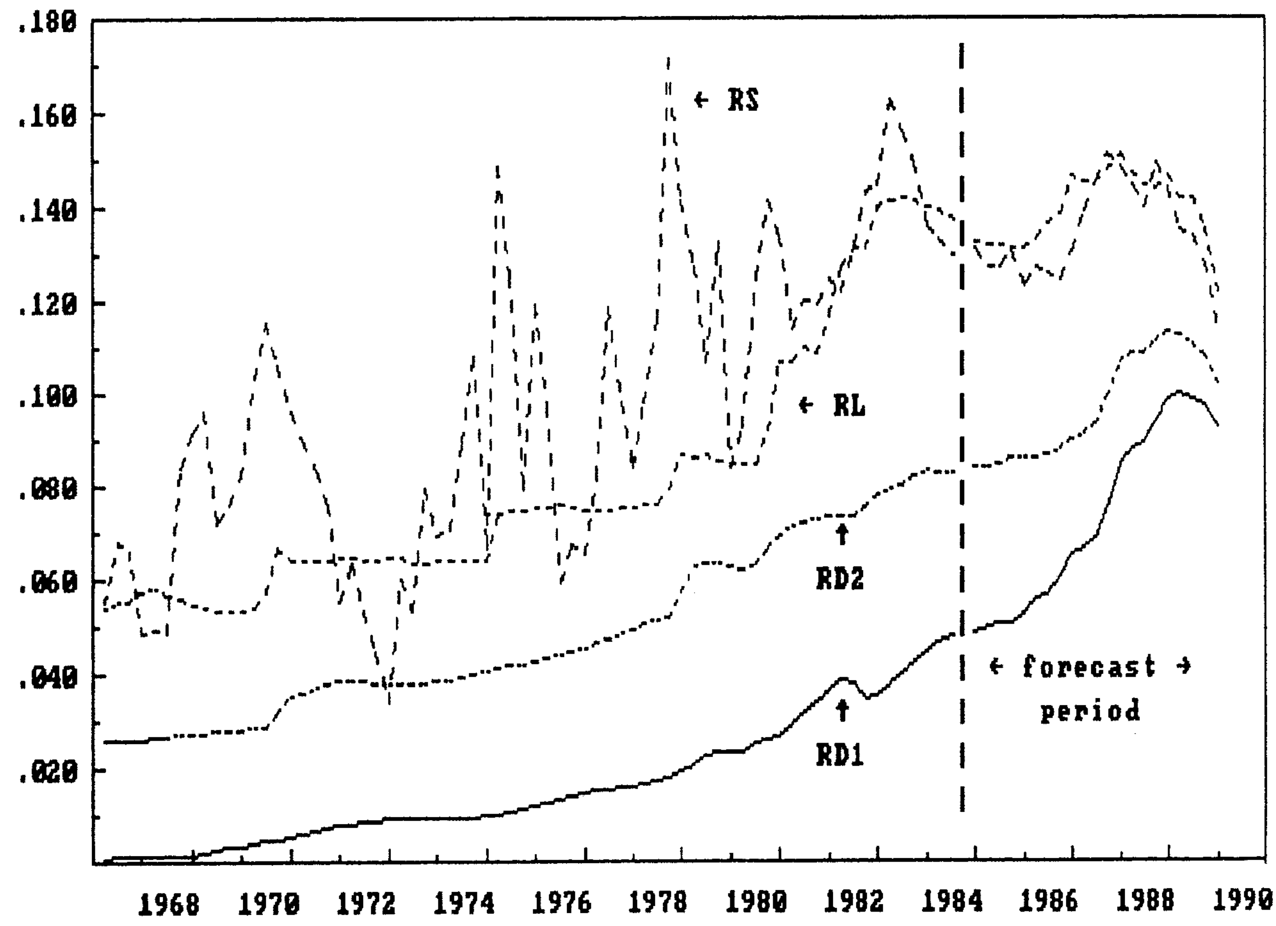


Figure 4. The series of *RD1*, *RD2*, *RL*, and *RS*.

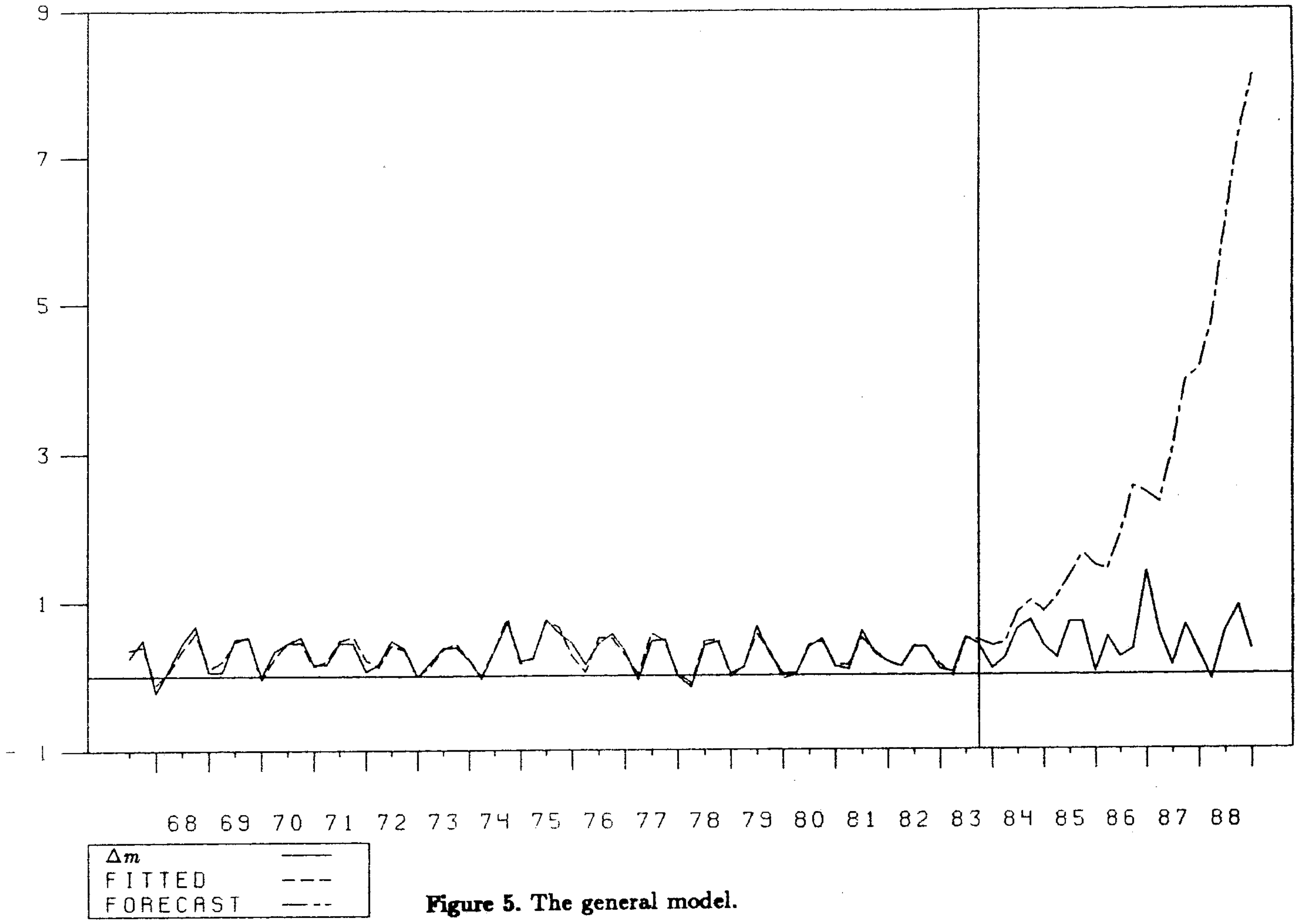


Figure 5. The general model.

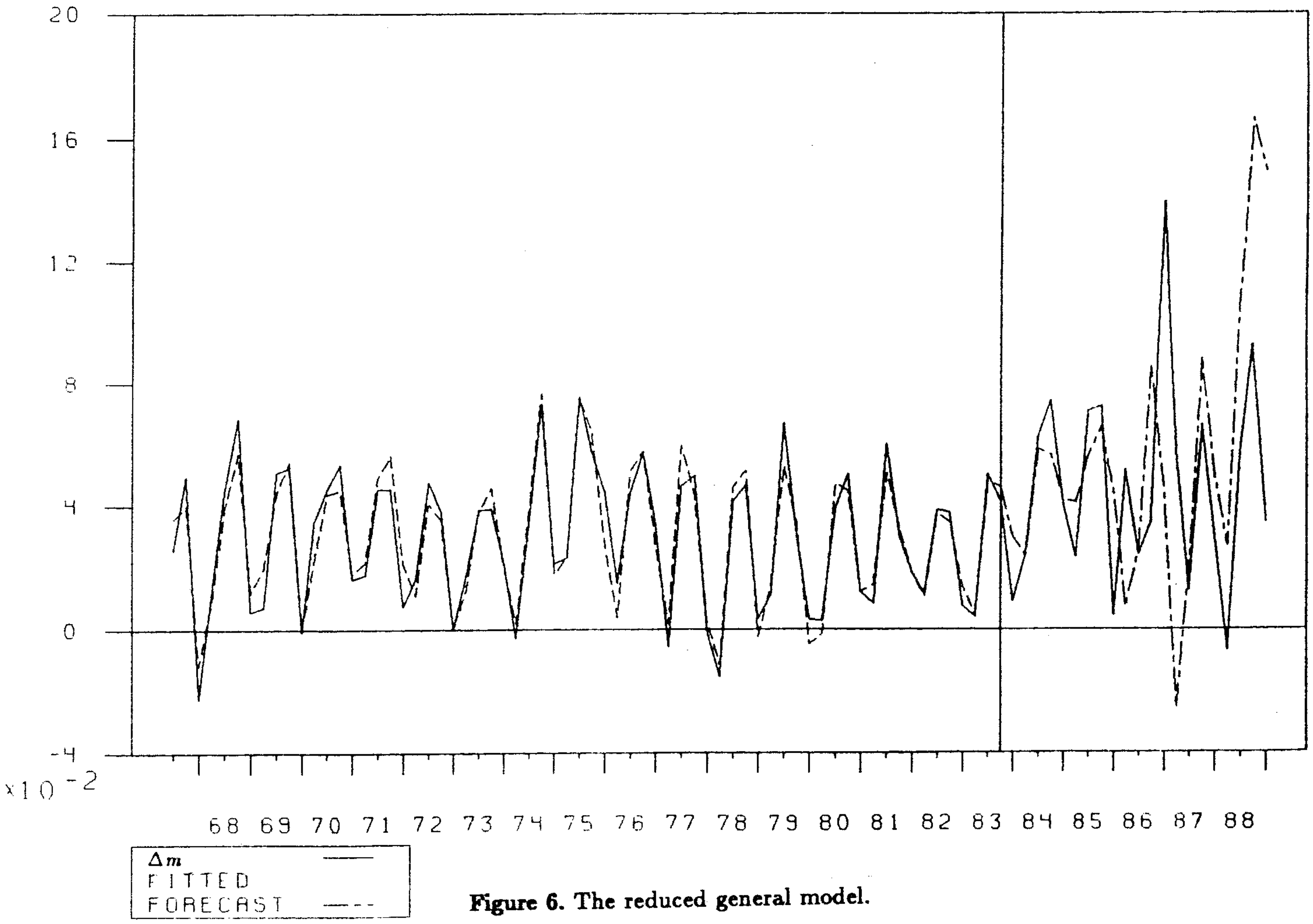


Figure 6. The reduced general model.

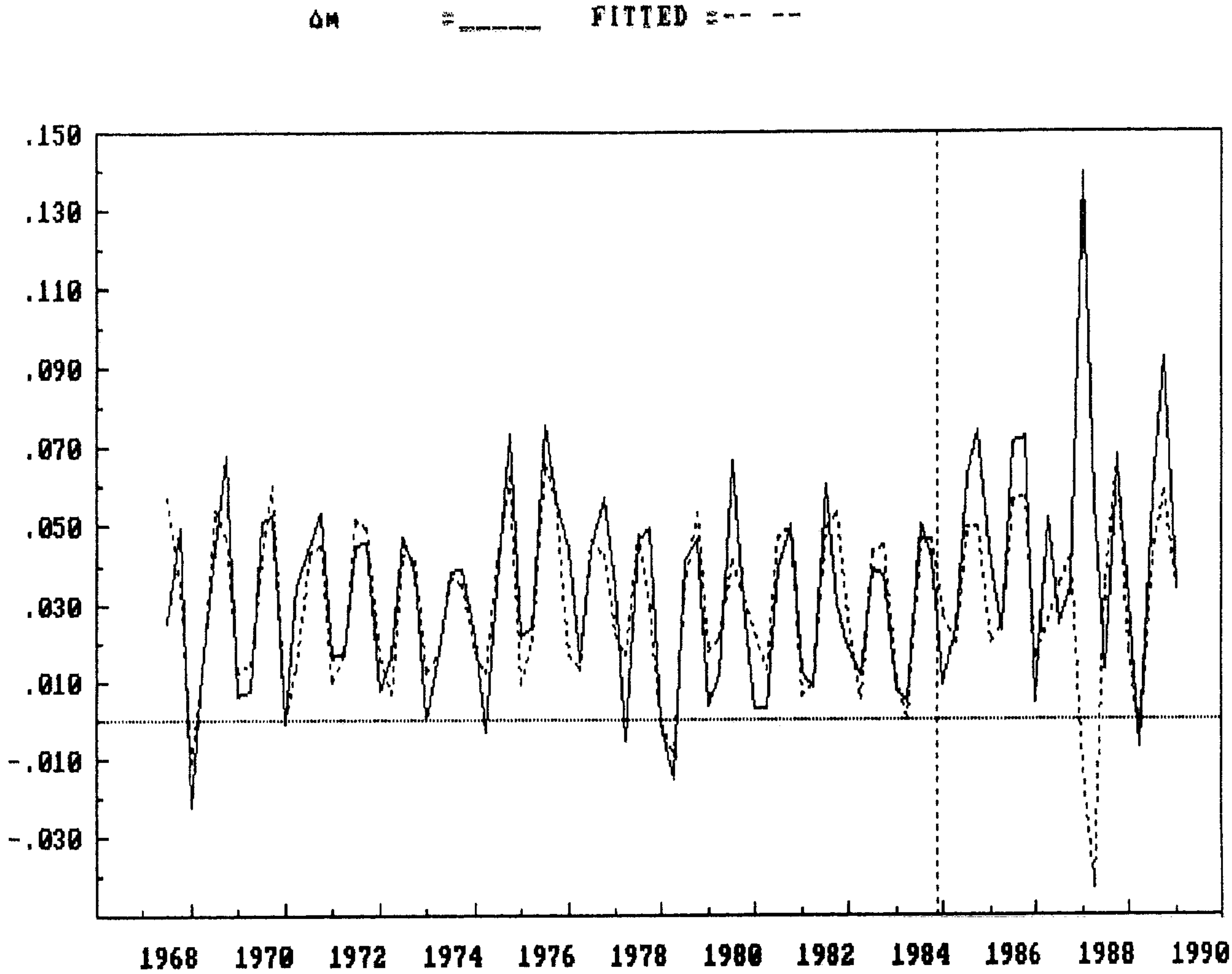


Figure 7. Fitted and forecasted values from equation (24), together with Δm.

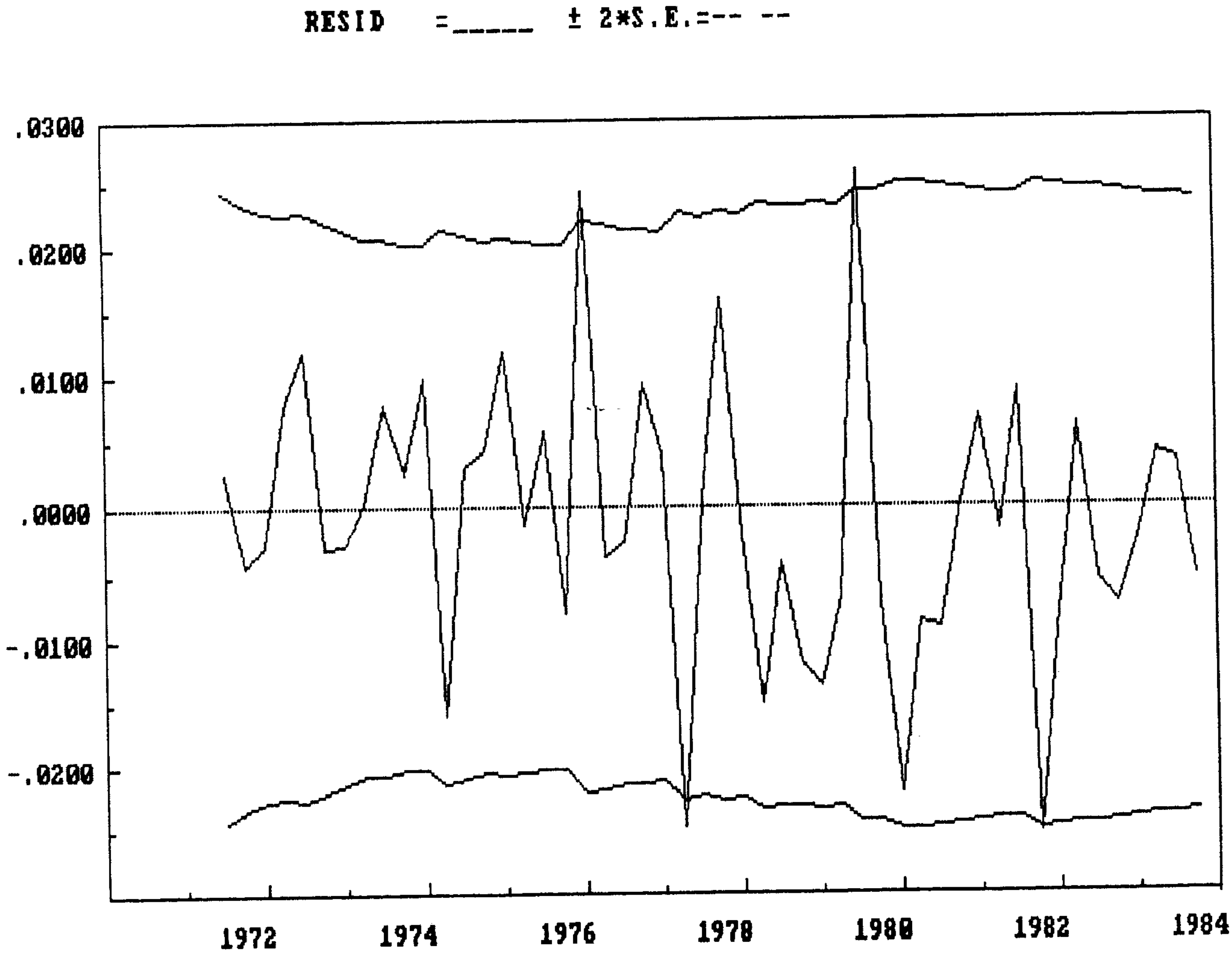


Figure 8. One–step residuals $\pm$ two standard errors from equation (24).

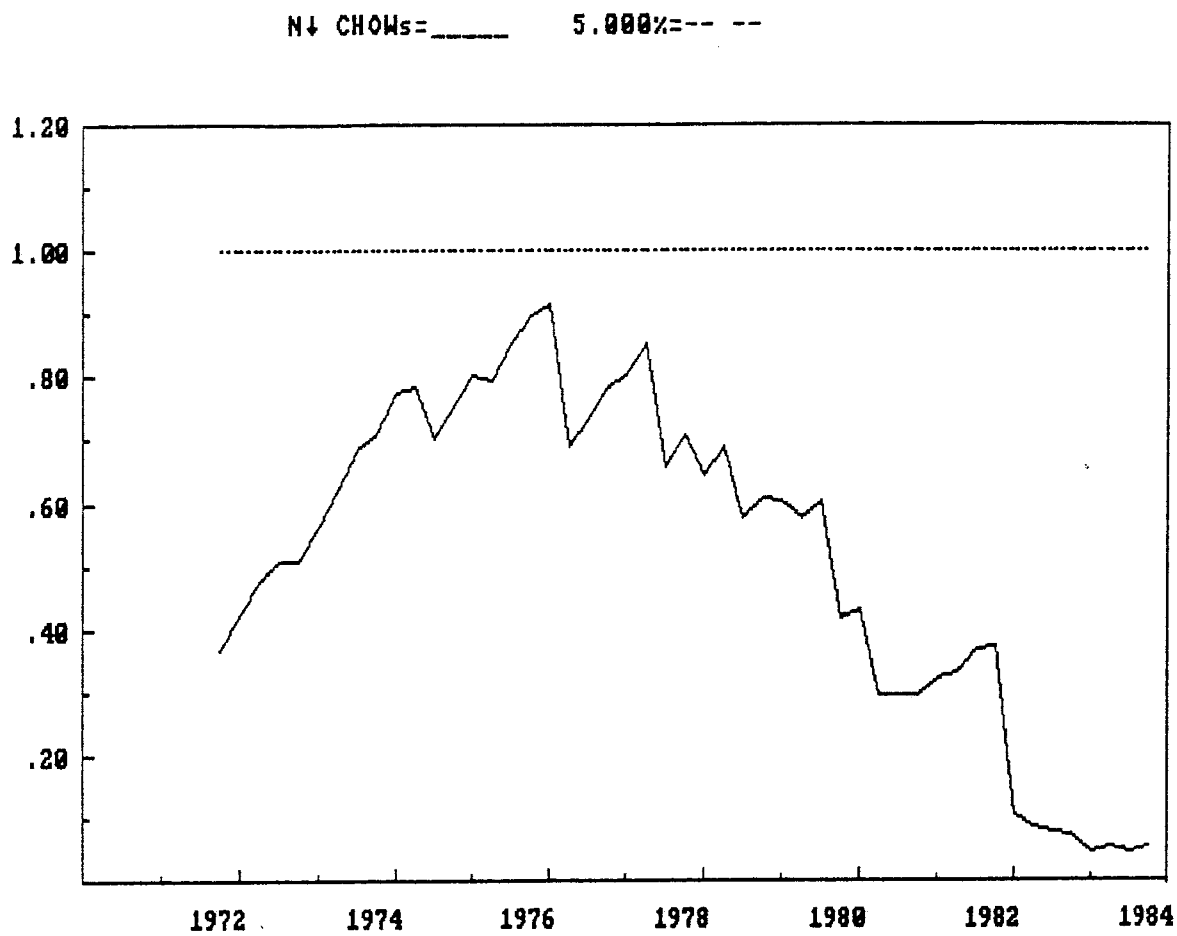


Figure 9. Break–point F–tests, scaled by degrees of freedom, for equation (24).

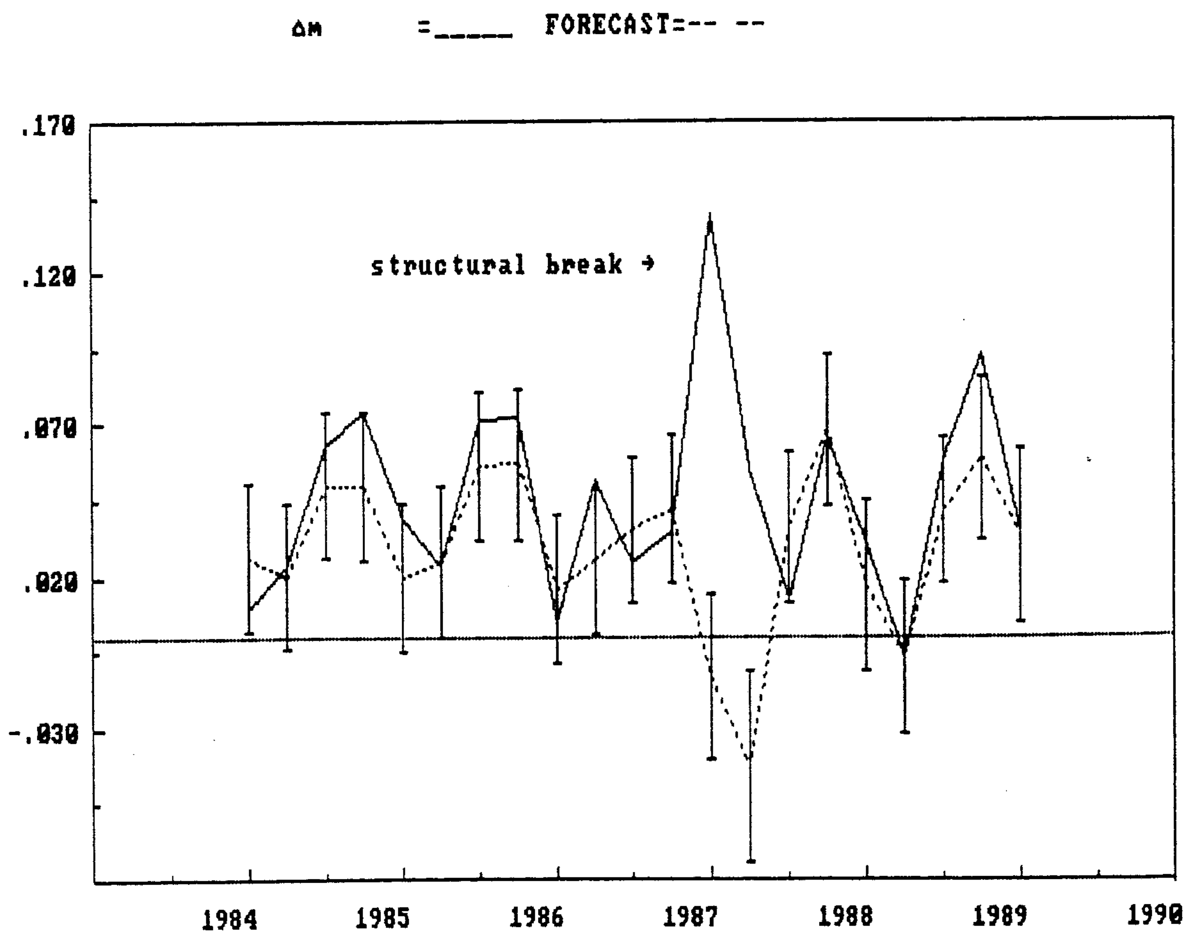


Figure 10. Forecasts, $\pm$ two standard errors, over 1984:I — 1989:I from equation (24).

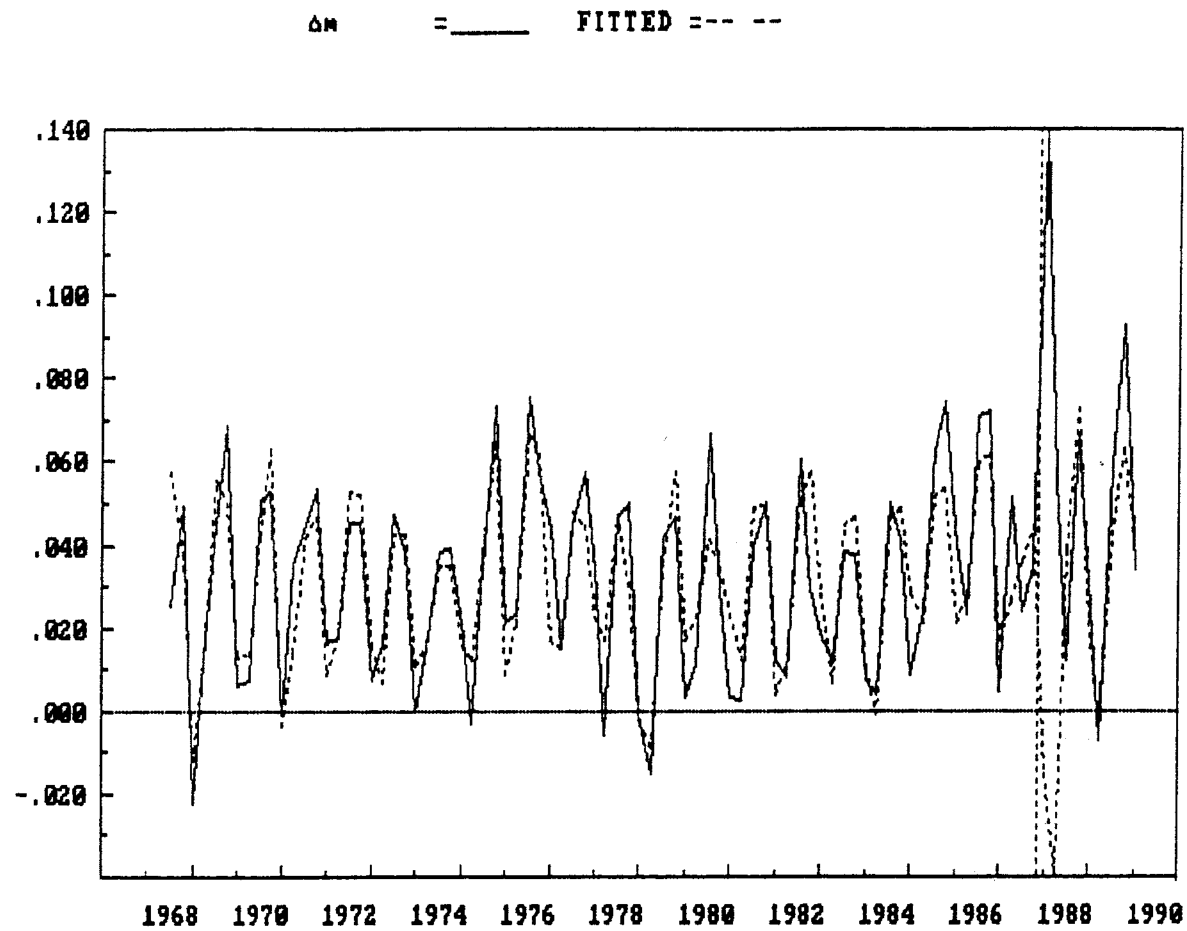


Figure 11. Fitted and forecasted values from equation (26), together with Δm.

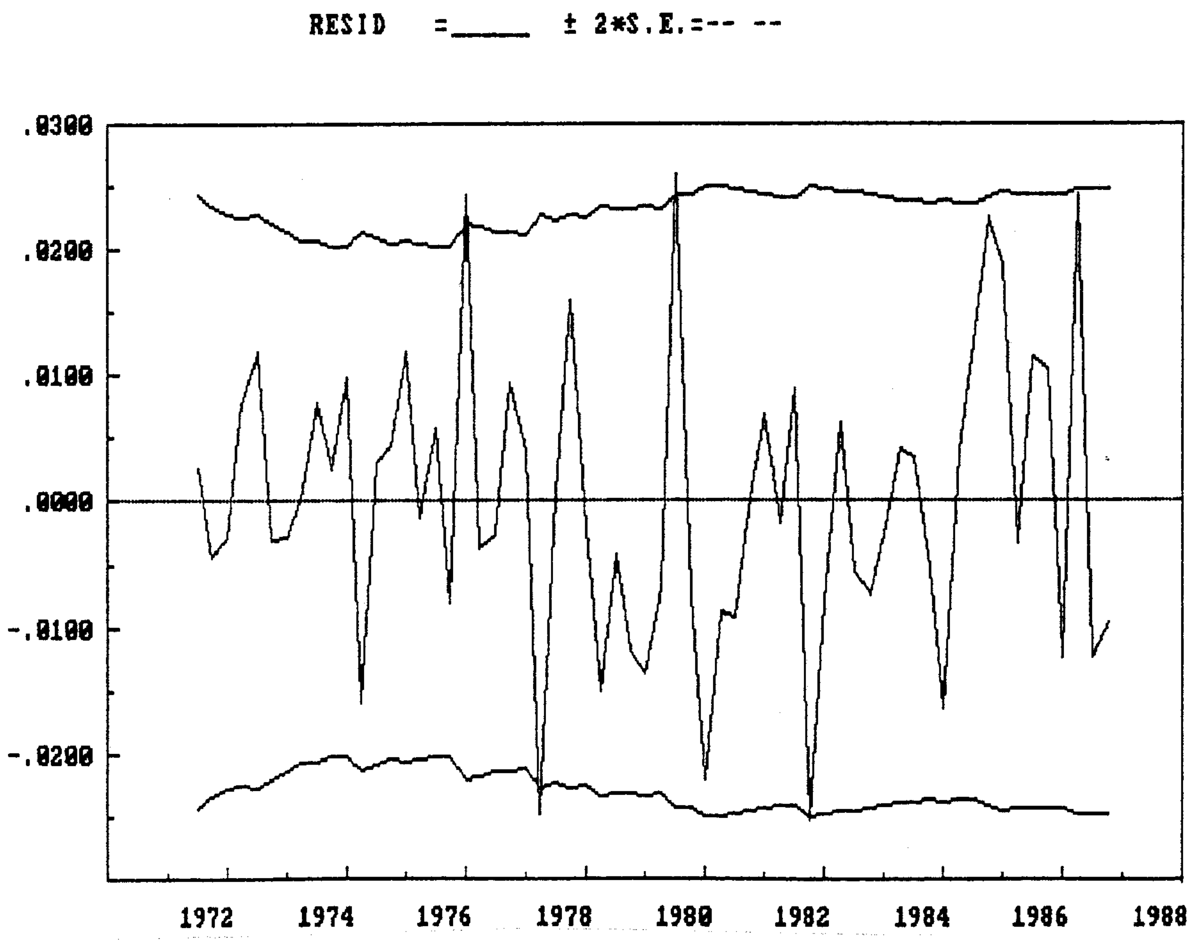


Figure 12. One–step residuals ± two standard errors from equation (26).

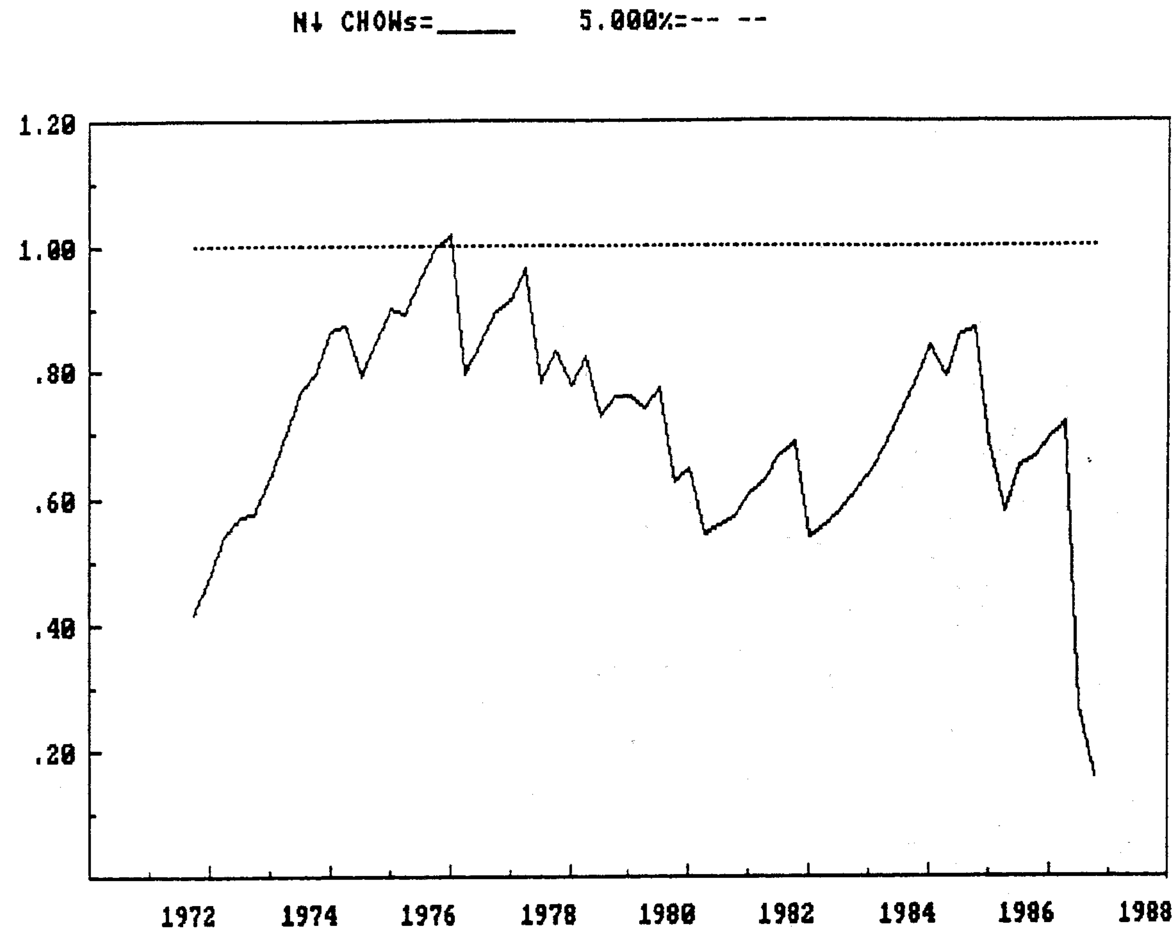


Figure 13. Break—point F—tests for equation (26).

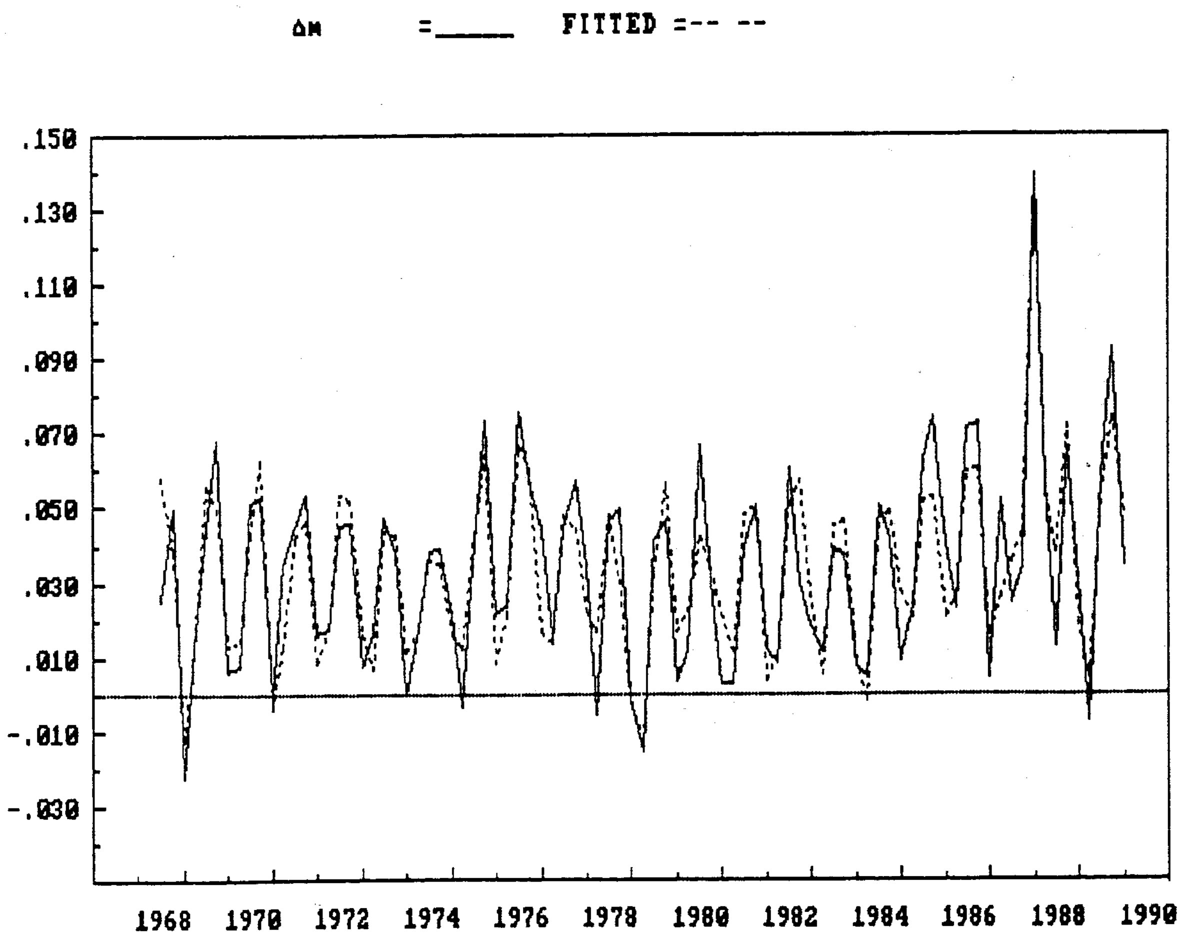


Figure 14. Actual and fitted values from equation (27).

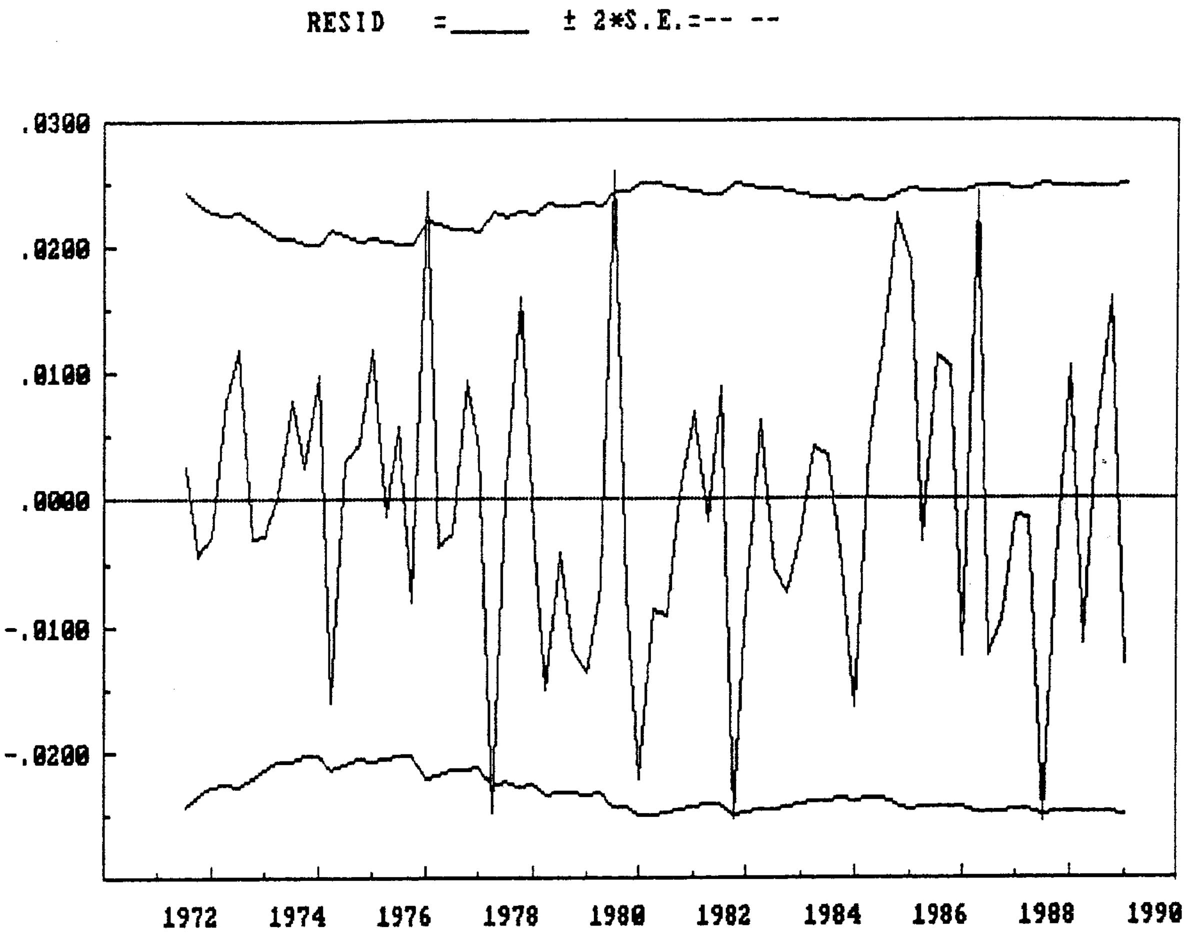


Figure 15. One–step residuals ± two standard errors from equation (27).

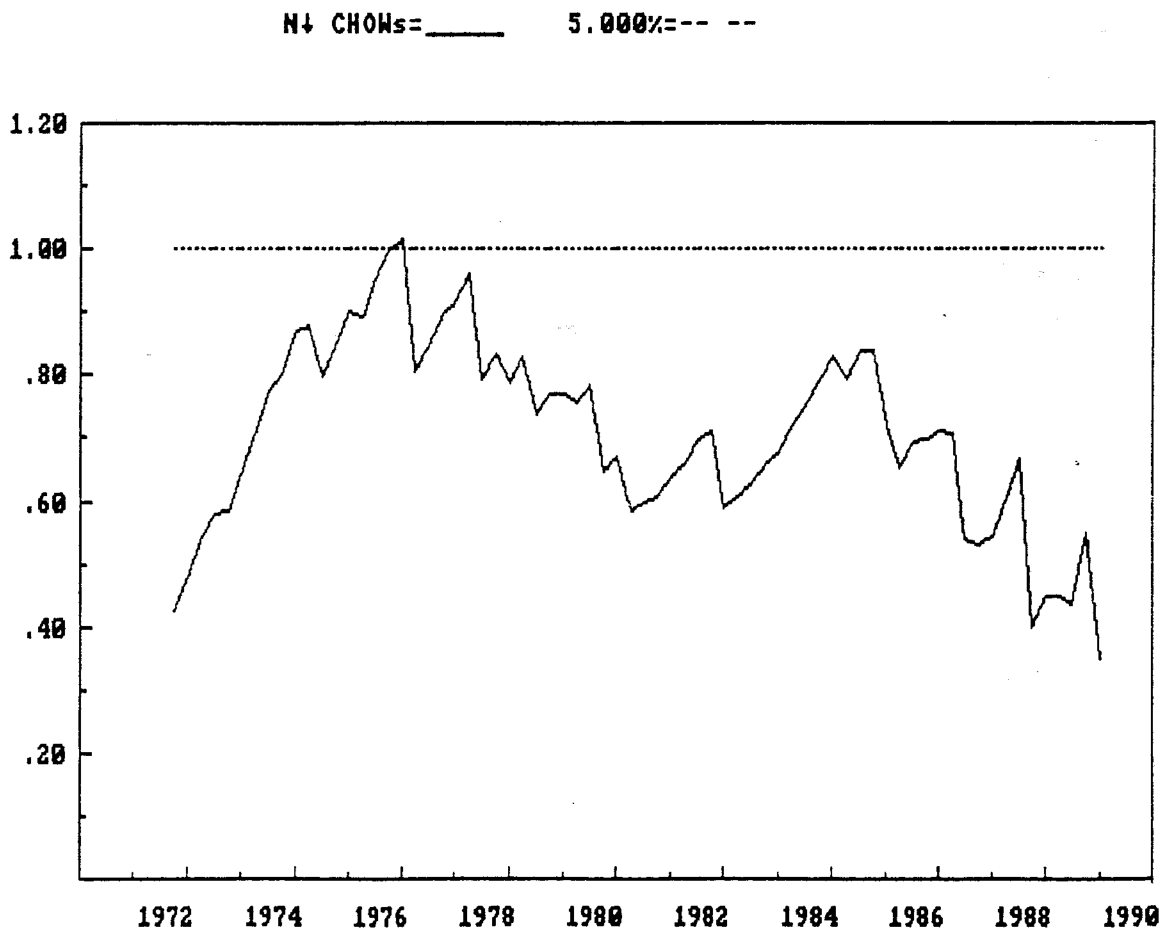


Figure 16. Break–point F–tests for equation (27).