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Documento de trabajo

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No.9501 Marzo 1995

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COINTEGRATION, ERROR CORRECTION MODELS AND FORECASTING: THE U.K. DEMAND FOR MONEY*

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ABSTRACT

We analyze the ability of recent methods proposed for the specification and estimation of relationships among nonstationary variables, to overcome the traditional instability of empirical money demand functions. We use a 1964-1982 sample for the UK which has been widely used in the literature. The forecasting ability of the resulting model is then compared with that of alternative, reduced form specifications.

· RESUMEN

Con objeto de resolver la tradicional inestabilidad mostrada por las funciones de demanda de dinero estimadas, en este artículo se analiza la capacidad de algunos métodos recientemente propuestos para la especificación y estimación de relaciones entre variables no estacionarias. Se utiliza una muestra de datos de la economía del Reino Unido, período 1964-1982, ampliamente utilizada en esta literatura. La capacidad predictiva del modelo resultante se compara con la de

*We aknowledge comments and suggestions received from T.Pérez-Amaral and J.Vallés. Any possible remaining errors are our only responsability. Research financed by CICYT, program PB90-0188.

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1. INTRODUCTION

There has been in the last years an spectacular expansion of research on the integration and cointegration properties of economic time series, and their relevance in the specification and estimation of econometric models. Hundreds of papers have appeared in many important journals and most international meetings in economics tend to offer both invited lectures and several sections devoted to this topic. Following the Granger Representation Theorem that linked cointegration to a variety of other dynamic representations, the new approach has also meant a significant reevaluation of the statistical foundations of the econometric methodology applied to nonstationary economic time series data.

That has fueled a similar growth of the related central research topics within the field. Data transformations, unit roots testing, estimation methods and comparative Monte Carlo studies have received abundant treatment in the cointegration literature. Researchers have also studied problems like long-run exogeneity, causality, the encompassing hypothesis, measurement errors, parameter stability, the influence of the lag length of the multivariate representation of a set of variables on the resulting number of cointegration vectors, etc.[2]

Given the significance of economic forecasting in today's world, it seems odd that this question has received scant (theoretical and empirical) coverage in this research line[3]. In spite of Friedman's statement that 'the ultimate goal of a positive science is the development of a "theory" or "hypothesis" that yields valid and meaningful predictions about phenomena not yet observed', there is a long tradition among some econometricians who tend to concentrate their attention on modeling and testing procedures, and view the forecasting problem as one of secondary importance. Even though recognizing that this is a controversial issue, this paper is written from the point of view that the previous is a fully meaningful requirement for econometric work. Many other authors, have also shown considerably skepticism towards this absence of real time economic prediction, and contend that cointegration does not necessarily provide the applied economist with easy short-cuts in coping with the problems of forecasting economic time series.

In order to analyze some of the practical issues related to the use of cointegration procedures

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[2] Banerjee *et al.* (1993) provides an exhaustive summary of the present state of recent research on these topics. Other excellent surveys on the theoretical aspects of cointegration are Hylleberg and Mizon (1989), and Dolado *et al.* (1991).

[3] Banerjee *et al.* (1993) provides a good proof of this statement. Out of 200 references in the book, only 9 have some connection with forecasting.

in structural model specification, as well as on their resulting forecasting performance, we have chosen the quarterly data corresponding to the largely analyzed demand for money in the U.K., reproduced in the appendix of Muscatelli and Hurn (1992) over the sample period 1963(1) - 1984(4). We begin by considering in the next section some of the problems related to the use of unit root tests (both seasonal and non-seasonal) in order to appraise the orders of integration of the individual variables. In this regard, some comparisons with the traditional Box and Jenkins (1970) identification tools (acf's and pacf's) are presented in order to verify the possibility of alternative integration orders. In section 3, we use the Johansen (1988) procedure to determine the cointegration rank and to construct a dynamic econometric model for the demand for M1 using an error correction term with the (restricted) cointegration vector obtained before. In section 4 we discuss the dangers of being too emphatic on the interpretation of the obtained ECM as being a demand for money function, suitable for optimal economic policy design. In section 5, the eight quarters *ex ante* forecasting, as well as the repeated one-period ahead perfomance of the resulting *Error Correction Model* (ECM) is assesed and compared with alternative specification strategies. The paper closes with some conclusions.

2. INTEGRATION AND COINTEGRATION TESTS

2.1 Unit Root Tests and Other Procedures

The variables used in our demand for money analysis, taken from Muscatelli and Hurn(1992), are: the narrow money stock M1 (*M*), either in nominal or real terms, as the dependent variable, and total final expenditures on goods and services (TFE) at constant prices as a real income variable (*Y*), the implicit TFE deflator as a price variable (*P*), and the treasury bill rate as a measure of the opportunity cost of holding money (*R*) as potential explanatory variables[4]. Plots of these variables for the period 1963(1) to 1984(4) are shown in Figure 1, where both nonstationarity as well as strong seasonality are evident. In all cases, the series exhibit a clear trend that constitutes a classic example of *nonstationarity of the mean.* The nature of seasonality varies over the different series. In some cases there are signs of steadily growing amplitude, indicating *nonstationarity in the seasonality* about the trend.

** Insert Figure 1*

[4] All series are quarterly and seasonally unadjusted. Log values are used, except in the case of the interest rate.

This first visual impression has to be confirmed by using other statistical tools in order to verify not only the nonstationarity property, but also to determine the integration order of the individual series. In the non-seasonal case, the most widely used integration test is the Augmented Dickey-Fuller (ADF) t-ratio test. [Said and Dickey (1984)]. The ADF statistic to test for the order of integration of an individual series x_t is based on the regression:

$$\Delta x_t = \mu + \beta\ t + (\alpha - 1)\ x_{t-1} + \sum_{i=1}^{n} \gamma_i\ \Delta x_{t-i} + u_t \quad (1)$$

where n is chosen so as to ensure that the resulting residuals are white noise. Although there are several other integration and cointegration tests [Phillips (1987), Phillips and Perron (1988), Stock and Watson (1988), Sargan and Bhargava (1983), Phillips and Ouliaris (1990), etc.], we use just variants of the ADF test in order to maintain this exercise as simple as possible. Moreover, a recent, comprehensive Monte Carlo analysis by Gregory (1994) has found that no test dominates in terms of size and power and hence, disparate implications would make difficult to reach a clear-cut conclusion.

Table 1: Summary Statistics for the Original Series and its First Differences (Estimation Period: 1963:1 to 1983:4).

Variable	*Mean*	*S.E./S.E.(Mean)*	*Maximum*	*Minimum*
M	9.681	0.606 / 0.064	10.862	8.888
(M-P)	10.471	0.095 / 0.010	10.626	10.273
P	-0.790	0.665 / 0.071	0.298	-1.635
R	0.087	0.033 / 0.004	0.170	0.035
Y	11.042	0.156 / 0.017	11.317	10.678
Δ*M*	2.269	2.890 / 0.309	9.900	-5.510
Δ*(M-P)*	0.047	3.207 / 0.342	8.196	-8.973
Δ*P*	2.222	1.500 / 0.160	3.520	-3.480
Δ*R*	0.067	1.222 / 0.130	8.786	-0.170
Δ*Y*	0.734	3.527 / 0.376	3.000	-7.900

Note: S.E. denotes the sample standard deviation.
S.E.(Mean) is the standard deviation of the mean.

In the case of the ADF tests, decisions over the integration orders may depend upon: i) the presence of the intercept μ; ii) the existence of a deterministic trend t; and iii) the number of lags n.

Some basic computations may be helpful in deciding over the first two questions. If the sample mean of x_t is different from zero, this may be an indication that an intercept is needed. Also, if the sample mean of Δx_t is different from zero, the possibility of a deterministic trend may be explored[5]. The decision over n is conditioned by the type of data used in the analysis. In Table 1 we have included some basic information to give us an idea about the expected outcomes. Including *a constant is necessary for all the variables*, while there is the *need for a deterministic trend just for M, P and Y*, at a variance with the conclusion in Muscatelli and Hurn (1992), where a deterministic trend is included in the equations for Y and ΔM. These authors apply not only the ADF, but the Perron Z-tests as well. They report the different conclusions reached for a possible unit root in income, depending on whether or not the deterministic trend is incorporated into the model when applying the Z-tests [see also Cochrane (1988) for a discussion on this ambiguity]. Contradictory evidence is also obtained from the Z-tests and the ADF tests for unit roots in interest rates and for ΔM and $\Delta(M\text{-}P)$.

In spite of the suggestions of Dickey and Pantula (1987) regarding testing order procedures, we will start considering the null hypothesis that the variables are I(1) against the alternative that they are I(0). Results for the ADF tests for different values are presented in Table 2. The following points are worth mentioning:

1. Both the choice of n as well as the use of the different ADF alternatives (A,B or C) provide distinct results when checking for the existence of unit roots. We would maintain the null of a unit root for M and R, with independence of the choice of n and type of ADF test. The presence of a unit root in P is also maintained, except if we did not include constant or trend in the regression. However, our previous discussion suggests the presence of both of them. With the suggested constant and trend in the model, we would reject H_0 for Y for short lags. There seems to be evidence on the non-stationarity of $M\text{-}P$, except precisely for n=4.

2. The plots in Figure 1 as well as most of the evidence in Table 2, lead us to reject the I(0) hypothesis in favour of the I(1) alternative in all cases. This result can be clearly confirmed if we look at the graphs of the *acf* and *pacf* of the original variables shown in Figure 2. Following the

[5] In this regard, however, MacKinnon (1994) has shown that the asymptotic distributions of the tests without an intercept are quite different from those that include one, so we might expect that the finite-sample results on relative test perfomance would also be sensitive to the inclusion of the constant in the model.

traditional identification criteria of Box and Jenkins (1970), the *original series are unequivocally nonstationary*.

** Insert Figure 2*

Table 2: DF and ADF Unit Root Tests. H_0: I(1). Equation 1.

		Number of Lags. n					
Variable	*Model*	0	1	2	3	4	8
M	A	2.272	2.802	2.525	3.510	1.538	1.700
	B	-1.163	-1.462	-1.580	-2.001	-2.098	-1.904
	C	7.379	6.772	4.895	5.218	2.363	2.462
M-P	A	-1.491	-1.471	-1.701	-1.562	-2.681^a	-1.812
	B	-1.168	-1.135	-1.436	-0.875	-2.957	-2.170
	C	0.085	0.086	0.029	-0.102	0.087	0.103
P	A	2.481	0.635	-0.297	-0.315	-0.782	-0.240
	B	-2.971	-2.264	-2.086	-2.401	-2.346	-2.422
	C	-5.990^c	-1.667^a	-1.672^a	-1.468	-1.733^a	-1.444
R	A	-2.077	-2.411	-2.402	-2.169	-2.099	-1.751
	B	-2.325	-3.033	-3.089	-2.607	-2.562	-2.924
	C	-0.265	-0.467	-0.429	-0.268	-0.232	-0.202
Y	A	-1.244	-1.222	-1.205	-1.860	-0.893	-0.999
	B	-4.554^c	-3.347^a	-2.812	-1.629	-2.193	-2.040
	C	1.738	2.574	2.970	5.797	2.609	2.357

Notes: Model A: Model with a constant;
Model B: Model with a constant and a deterministic trend;
Model C: ADF model, that does not include a constant or a deterministic trend;
^{a}: Significant at 10%;
^{b}: Significant at 5%;
^{c}: Significant at 1%;
The critical levels used can be found in MacKinnon (1991).

We have also tried to verify the possibility of I(2) variables against the I(1) case, the results from the ADF tests being reported in Table 3. Although some of the previous comments are still valid in this case, the empirical evidence consistently leads to rejecting the I(2) hypothesis, except for the case of P . The estimated acf and pacf of ΔP_t (not shown in the paper) suggest that P_t is unambiguously I(2). This last feature may be important later on, since all variables entering in a cointegration vector must have the same degree of differencing[6].

Table 3: DF and ADF Unit Root Tests. H_0: I(2). Equation 1.

		Number of Lags, n					
Variable	*Model*	0	1	2	3	4	8
ΔM	A	-10,482^{c}	-6,031^{c}	-5,954^{c}	-2,392	-2,553	-2,042
	B	-11,499^{c}	-6,966^{c}	-7,708^{c}	-3,205^{a}	-3,396^{a}	-3,044
	C	-6,779^{c}	-3,446^{c}	-3,072^{c}	-0,938	-0,930	-0,421
$\Delta(M\text{-}P)$	A	-9,308^{c}	-5,785^{c}	-5,735^{c}	-2,484	-2,856^{a}	-3,340^{b}
	B	-9,369^{c}	-5,856^{c}	-5,880^{c}	-2,623	-2,964	-3,180^{a}
	C	-9,364^{c}	-5,820^{c}	-5,770^{c}	-2,504	-2,882^{c}	-3,099^{c}
ΔP	A	-3,947^{c}	-2,395	-2,061	-1,824	-1,840	-2,031
	B	-3,968^{b}	-2,235	-1,934	-1,503	-1,664	-1,866
	C	-1,984	-1,140	-1,037	-0,772	-0,890	-0,887
ΔR	A	-7,526^{c}	-5,996^{c}	-5,893^{c}	-5,110^{c}	-4,663^{c}	-3,943^{c}
	B	-7,519^{c}	-6,006^{c}	-5,299^{c}	-5,157^{c}	-4,720^{c}	-4,010^{b}
	C	-7,554^{c}	-6,013^{c}	-5,903^{c}	-5,115^{c}	-4,664^{c}	-3,936^{c}
ΔY	A	-13,718^{c}	-9,282^{c}	-13,656^{c}	-4,155^{c}	-3,922^{c}	-2,616^{a}
	B	-13,646^{c}	-9,244^{c}	-13,825^{c}	-4,099^{c}	-3,888^{b}	-2,575
	C	-13,071^{c}	-8,395^{c}	-10,402^{c}	-3,108^{c}	-2,800^{c}	-1,780^{a}

Notes: Model A: Model with a constant; Model B: Model with a constant and a deterministic trend;
Model C: ADF model, that does not include a constant or a deterministic trend;
^{a}: Significant at 10%; ^{b}: Significant at 5%; ^{c}: Significant at 1% ;
The critical levels used can be found in MacKinnon (1991).

[6] Note, however, as Muscatelli and Hurn (1992) point out, that as M-P appears to be I(1), it should be used as one of the variables in a cointegration vector, jointly with other I(1) variables, in preference to entering M and P separately. It is nevertheless somewhat surprising that M-P can be accepted to be I(1) with M being I(1) and P being I(2).

2.2 Seasonal Integration

So far, we have focused our attention on testing for unit roots at the zero frequency. However, the presence of seasonality in our data series complicates the estimation and testing procedures of models with cointegrated variables. Accordingly, the definition of integration must be generalized to allow for the possibility of nonstationary seasonality. Engle *et al.* (1988) define a variable x to be seasonally integrated of orders d and D, SI(d,D), if the series is stationary after first differencing d times and seasonal differencing D times. Seasonal integration testing procedures are discussed by Engle *et al.* (1988), Ghysels (1990), Hylleberg *et al.* (1990), Osborn *et al.* (1988) and Osborn (1990), among others. The existence of a seasonal unit root would imply, in particular, the presence of a unit root at the zero frequency[7], so the previous evidence might also be an indication of nonstationary seasonality, even without stochastic nonstationarity of the mean. However, the evidence of nonstationarity in the mean is so overwhelming, that in order for the seasonality to be non-stationary, we would need a second unit root. The tests for H_0: I(2) vs. H_1: I(1) suggests the contrary, although by ignoring the presence of seasonality it cannot be taken as a serious test of that hypothesis. A direct test for a seasonal unit root is needed.

For our U.K. data set, Muscatelli and Hurn (1992, p.19) have tested for the possible presence of seasonal unit roots using two of the procedures mentioned above, with mixed results. The Osborn test for the null H_0: $y_t \sim$ SI(1,1), versus the alternatives: H_1: $y_t \sim$ SI(1,0) or SI(0,1) examines the regression:

$$\Delta \Delta_4 y_t = \sum_{1}^{4} \alpha_i Q_{it} + \beta_1 \Delta_4 y_{t-1} + \beta_2 \Delta y_{t-4} + \sum_{1}^{p} \phi_i \Delta \Delta_4 y_{t-i} + \varepsilon_{1t}$$

A non-significant t statistic on β_1 would be evidence in favor of $y_t \sim$ SI(1,0), while a non-significant β_2 would constitute evidence in favor of $y_t \sim$ SI(0,1). If an F-test reveals the joint lack of significance of both coefficients, H_0 would not be rejected.

Muscatelli and Hurn found that the Osborn test leads to rejecting the hypothesis of SI(1,1) at the 5% level for all series and only in the cases of M and Y is rejection at the 1% level not indicated[8] [Muscatelli and Hurn (1992), p.19]. That is evidence in favor of stationary seasonality. On the other hand, the results from the HEGY tests [Hylleberg et al.(1990)] are not as conclusive. This

[7] Since the polynomial $1\text{-}L^4$ can be decomposed as: $1\text{-}L^4 = (1\text{-}L)(1+L)(1+L^2)$.

[8] One important drawback of the Osborn *et al.* (1988) procedure is that it does not test for all possible unit roots in a seasonal process.

test is based on the regression:

$$\Delta\Delta_4 y_t = \alpha_0 + \alpha_1(Q_{1,t}-Q_{4t}) + \alpha_2(Q_{2t}-Q_{4t}) + \alpha_3(Q_{3t}-Q_{4t}) +$$

$$+ \pi_1 Z_1 y_{t-1} + \pi_2 Z_2 y_{t-1} + \pi_3 Z_3 y_{t-1} + \pi_4 Z_4 y_{t-2} + \sum_{1}^{p} \psi_i \Delta\Delta_4 y_{t-i} + e_{2t}$$

where Z_1, Z_2 and Z_3 are the lag operators: $Z_1 = 1+L+L^2+L^3$, $Z_2 = -(1-L+L^2-L^3)$, $Z_3 = -(1-L^2)$, and tests for H_0: I(1,1) vs. the alternatives H_1: I(2,0) or I(1,0). While all the variables show evidence of a unit root at the nonseasonal frequency in terms of the t-statistic for π_1 not being significant, Muscatelli and Hurn found some contradictions between the rejection of seasonal roots in terms of the individuals t-statistic on π_2 , and the rejection of complex unit roots by the joint F-test on π_3 and π_4 .

Although the practical applications of these seasonal integration tests are still very few, some authors tend to infer (from such a fragile evidence as the one presented here) that seasonal unit roots are found infrequently in quarterly U.K. macroeconomic data and consequently that this type of data does not seem to exhibit nonstationary seasonality [Osborn (1988),(1990)]. For our same variables and sample, Muscatelli and Hurn maintain the non significance of π_2, but reject the null of joint non-significance of π_3 and π_4. On the basis of both tests, they seem to agree with Osborn's statement that these variables (as almost any other macroeconomic U.K. variable) are all SI(1,0).

** Insert Figures 3, 4 and 5*

A comparison of the plots in Figures 3, 4 and 5 suggests that *M* is I(1,1), *P* is I(2,0), *M-P* is either I(1,0) or I(1,1), *R* is I(1,0) and *Y* is I(1,1), the evidence on the seasonal root in *Y* coming from the notorious changes in the amplitude of seasonal fluctuations in ΔY in Figure 3. This is not to imply that the shape of the plots is a proof of the existence or absence of unit roots at different frequencies, but a clear suggestion that, at least in this application, a quite tight *a priori* opinion can be formed previous to any formal testing. We believe that it is only then that statistical testing can be safely implemented.

** Insert Figure 6*

The estimated acf and pacf of the first differences of the series shown in Figure 6, provide

a picture very different from the one suggested by the Osborn test[9]. These functions *clearly indicate the presence of a nonstationary seasonal component for M, (M-P) and Y.* On the contrary (as we might have expected) there is no such seasonal evidence either for *R* and *P* , which seem to be I(1,0) and I(2,0), respectively. Interestingly enough, this statistical evidence is in all consistent with our more informal inspection of the plots of the different transformations of the variables. If anything, the seasonal unit root in *M-P* is now more evident.

As a summary, *the fragility of inferences drawn from the degree of regular and seasonal integration tests* should be emphasized. This situation (often found when testing for unit roots in practice) is the reflection of problems associated with the power of the tests, confidence levels fixed *a priori*, sample sizes different from those tabulated in different publications, and even the potential influence of outliers, not explored in our time series data. In summary, the accumulated empirical evidence suggests the following integration orders:

Variable	*Integration Orders*	*Representation*
M	I(1,1)	$\Delta\ \Delta_4$
M-P	I(1,1) or I(1,0)	$\Delta\ \Delta_4$ or Δ
Y	I(1,1)	$\Delta\ \Delta_4$
P	I(2,0)	Δ^2
R	I(1,0)	Δ

The orders of integration seem to differ considerably among the variables in our demand for money equation. The reader must be aware of this important piece of information when considering advancing one more step and checking the existence of cointegration relationships and their associated error correction models.

[9] For the case of *P*, the acf and pacf are those corresponding to $\Delta^2 P$, given the previous unit root tests for this variable.

3. ESTIMATION OF THE DEMAND FOR MONEY IN THE U.K.

A stable demand for money function is the central piece in the design of optimal monetary policy. It is hence not surprising that the U.K. demand for money has received considerable attention in the literature of cointegrated systems, a good part of which has emerged in that country [Hendry and Ericsson (1991), Johansen (1992), Muscatelli and Hurn (1992), Drake and Chrystal (1993), among others]. The long-run determinants of the money demand equation are a subset of the variables we have been considering in previous sections, and the first issue to deal with is related to whether or not these variables are cointegrated.

One standard test for cointegration is attributable to Engle and Granger (1987). There are, however, a number of potential problems associated with their approach: small sample biases [Banerjee *et al.* (1986)] since it relies on a super-convergence result, the use of simple OLS to estimate the cointegrating vector as well as the possibility, not considered in their approach, of multiple (r) cointegration vectors[10]. In contrast, the maximum likelihood estimation technique developed by Johansen (1988) allows for the existence of several cointegrating vectors and has become the standard procedure in a multivariate setting.

In implementing the Johansen procedure on (M-P), Y and R following the strategy in Muscatelli and Hurn (1992), we have made the following assumptions: i) in spite of the ambiguous evidence on seasonal integration discussed in the previous section, it is now assumed that *the data for these variables does not exhibit non-stationary seasonality*, since the method does not accomodate that possibility; ii) Y and R are *weakly exogenous* in the conditional money demand model, so their contemporaneous values can appear as explanatory variables; and iii) we include a constant in the cointegration vectors. Also, four lags of $\Delta(M\text{-}P)$, ΔP, ΔY and ΔR variables were included in order to capture the short run dynamics of the model[11].

The test values in Muscatelli and Hurn (1992) show that, while the null hypothesis of $r = 0$ can be rejected in favour of the alternative that $r = 1$, the null that $r = 1$ cannot be rejected in favor of $r = 2$. Since the null hypothesis of a unit income elasticity is not rejected when the Johansen methodology is applied, these authors interpret the estimated, restricted, single cointegration vector: $(M\text{-}P\text{-}Y)_t = 1.3625 - 15.071\ R_t$ as the long-run demand for money. The residuals of this long term relation, with and without imposing the unit elasticity of income are shown in Figure 7, which

[10] The inappropriateness of the Engle-Granger procedure for our particular data set is shown in Muscatelli and Hurn (1992).

[11] Again, these are precisely the assumptions made in Muscatelli and Hurn (1992).

suggests disturbing evidence on nonstationarity of the mean and the variance of these residuals.

It is shocking that the stationarity of the residuals of the cointegrating relation estimated in Muscatelli and Hurn(1992) by the one-step Engle-Granger method is much more evident and, in particular, their range of sample variation (-0.4,0.3) is much tighter than that for the first set of residuals (-1.4,0.4). This one-step method is despised in the more recent literature on cointegration on the basis of its statistical properties in small samples.

We are now ready to construct a dynamic model for the money demand where the deviation from long term equilibrium, the lagged residual Z_t in the previous long-run relation is included. The *general* money demand model is of the form:

$$\Delta(M-P)_t = c + \sum_{i=1}^{3} \phi_i Q_{it} + \alpha(L)\,\Delta(M-P)_{-1} + \beta(L)\,\Delta X_t + \gamma Z_{t-1} + u_t \qquad (2)$$

$$X_t \equiv (P_t\ Y_t\ R_t)$$

where Q_{it} i=1,2,3 represents the dummies, and $\alpha(L)$ and $\beta(L)$ are polynomials in the lag operator. Initially 4 lags were considered for each regressor (except Z_t, the dummies and the constant) and the model was estimated by OLS over the period 1963(1)-1982(4) leaving aside 8 periods to assess the model's *ex ante* forecasting perfomance, as well as its time stability.

Applying OLS to equation (2) implies the estimation of 24 parameters. According to this methodology, such a number has to be reduced following the well known '*general-to-specific*' modelling procedure [Hendry (1986)]. However, reading many applied papers that emphasize this approach leaves only puzzlement about how the simplification did actually take place. Instead of an adequate documentation of the path followed during the simplification process, what we tend to get are vague statements about..."*successful elimination of insignificant regressors*" or "*imposing data-acceptable restrictions on the regression parameters*" [Muscatelli and Hurn (1992), p.33]. Although some authors have pointed out the difficulties on this simplification stage [Pagan (1987) and Hill (1986), among others] a broader discussion of this topic is out of the scope of this paper. Taken the final equation from Muscatelli and Hurn (1992, p.33) as our simplified demand for money model, our OLS estimates (using *EVIEWS*) are shown in Table 4.

Although there are small numerical differences in some of the coefficients with those in Muscatelli and Hurn (probably due to the software used), their results are approximately reproduced by those on Table 4. Also, in our case all the diagnostics are satisfactory, except for the Chow test over the forecast period[12], which seems to indicate the possibility of a structural break. It is somewhat worrisome that we get a very significant seasonal dummy for the first quarter, which may reflect the in-sample effect of some omitted variable, and could have some negative consequences for out of sample forecasting.

Table 4: Estimation of the Simplified General Dynamic Model of $\Delta(M\text{-}P)$: 1964.2 - 1982.4

Variable	*Coefficient*	*S.E.*	*t-ratios*
c	0.013	0.009	1.365
Q_1	-0.052	0.010	-5.098
Q_2	-0.001	0.012	-0.604
Q_3	0.000	0.011	0.039
$\Delta(M\text{-}P)_{t-2}$	0.345	0.085	4.049
ΔP_t	-1.003	0.199	-5.045
ΔP_{t-1}	0.692	0.201	3.447
ΔY_{t-1}	0.250	0.107	2.332
ΔY_{t-3}	-0.246	0.114	-2.161
ΔR_t	-0.826	0.167	-4.931
Z_{t-1}	-0.014	0.007	-2.099

R^2:	0.790	$\eta_1(8,64)$:	2.12
Adj. R^2:	0.757	$\eta_2(5,64)$:	0.40
R.S.S.:	0.018	*RESET(1)* :	0.28
S.E. of Reg.:	0.017	*ARCH(4,67)*	0.27
Log-Like.:	207.160	$\eta_6(17,46)$:	0.47
D.W.:	1.793		

The Ljung-Box statistic for the residuals of the estimated model was 2,79, so that we can reject the existence of some autocorrelation scheme. η_1 is the statistic for the Chow's test. η_2 is the Breusch-Godfrey 5th order serial correlation tests, the ARCH statistic tests for 4th order arch structure in the residuals, and η_6 is White's heteroscedasticity test.

[12] The 95% critical value for (8,60) degrees of freedom is 2.10 .

4. THE COINTEGRATING RELATION AS A LONG RUN EQUILIBRIUM CONDITION

In the empirical analysis of a demand function for money, a set of questions need to be addressed in relation with the theoretical framework underlying that single equation econometric specification. First of all, unless we admit the possibility of monetary illusion, it should be a *demand for real balances*, which could nevertheless accomodate a negative effect from the rate of inflation. Besides, there is an open question as to whether or not real income enters that equation with a unit coefficient, i.e., whether the *income elasticity* of the so-called demand for money function, is equal to one.

Furthermore, to be exploitable for policy purposes, *the relationship should be stable over time*. If not, we should analyze the reasons for the time evolution and if it is smooth, discuss whether it is still appropriate for policy design.

A widespread approach to macroeconometric modeling relies on the existence of cointegrating relationships among variables as a necessary condition to believe that a long-run equilibrium condition exists. The cointegration relations are then the candidates to be interpreted as such equilibrium conditions. From that point of view, and maintaining the assumption that coefficients are stable over time, if a relationship in the form of a money demand equation is to be used for policy design, it needs to be an equilibrium condition and hence, a cointegrating relation, i.e., the resulting residuals must be stationary.

For this analysis we multiply the log of P_t, by 100 to make its values more readable as a price index, and used the log R_t rather than $\log(1+R_t)$. We apply to our variable set the methodology developped by Johansen (1988),(1991).

We started with a VAR in the first differences of the logs of M/P, R and Y:

$$\Delta X_t = C + \sum_{1}^{k-1} \Gamma_i \, \Delta X_{t-i} + \Pi \, X_{t-k} + \varepsilon_t$$

where $X_t = [(M\text{-}P)_t, R_t, Y_t]$, always in logs of the original variables. The first choice to be made concerns the number of cointegrating relationships (r) among the three variables. Since they all have a unit root, that number must be either one or two. Testing for the value of r may yield different results depending on the choice of lag length for the VAR, the inclusion of seasonal dummies in the short run money demand equation and the presence of a constant term in either the long-run or the short-run relationships. Seasonal dummies are needed to produce white noise residuals. The maximum eigenvalue and trace statistics [see Johansen(1988)] for k=5 clearly suggest a single cointegrating relation.

4.1 The time stability of the cointegrating relation.

Special attention must be paid to the stability of the cointegrating relation over time. To that end, we estimated both the cointegrating relation between the logs of real balances, interest rates and income, as well as the short run relationship, for different annual horizons, again with *$(M-P)_t$, R_t* and *Y_t* as the vector of variables[13]. Using the whole sample 1963(1)-84(4), the income elasticity was estimated at .79, not rejecting the constraint that it is equal to 1, although there was some autocorrelation left in the restricted income equation.

Table 5

Estimated Error Correction Term and its relative importance in each short-run equation

	Coefficient of the ECM term in the short-run equation for:			*Estimated Cointegration relation: $(M-P)_t = \beta_0 + \beta_1 R_t + \beta_2 Y_t$*		
Last observation	*M-P*	*R*	*Y*	β_1	β_2	β_0
1982(4)	-.021	-.049	-.041	-.882	.788	-.591
1981(4)	-.046	-.105	-.072	-.591	.460	2.222
1980(4)	-.080	-.110	-.103	-.459	.252	4.165
19794)	-.065	-.079	-.090	-.457	.228	4.460
1978(4)	-.153	-.067	-.113	-.535	.442	2.152
1977(4)	-.081	-.102	-.097	-.581	.516	1.504
1976(4)	-.056	-.057	-.082	-.616	.622	.494

[13] That is, we use an interest rate variable different to that in Muscatelli and Hurn.

There are two striking facts in Table 5. On the one hand, the crucial long run income elasticity is estimated at a high .79 with the whole sample, but its value drastically changes by just dropping one or two years, providing a completely different picture of the money-income relation. In particular, in 1979 and 1980, the estimated elasticity would have been extremely low. These results are damaging for the use of the estimated equation as a tool for the optimal design of monetary policy. In that planning exercise, the estimated demand for money plays a crucial role, since the coefficient of income will determine the rate of growth of the money supply which is consistent with a target growth for real income[14].

On the other hand, we see in the table how the estimates of the short-run adjustment coefficient in the equation for real balances changes a great deal over the sample. Figure 9 shows the estimated values of the ECM coefficient γ in equation (2) at the end of each year in our sample, which indicates the strength of the short run adjustment to deviations from the long run equilibrium path. As can be seen, it not only moves widely over time, difficulting the forecasting of income, but it also comes very close to being zero in the last years of the sample[15]. That would reflect a null adjustment to those deviations, weakening the structural interpretation of the estimates of the dynamic econometric model (DEM) (2).

4.2 The unit income elasticity of the demand for money.

Given the theoretical relevance of the unit income elasticity in the demand for money equation, we tested for alternative hypothesis on the estimated model in the first row of Table 5, i.e. using the sample 1963(1)-1982(4). Figure 10 shows the values of the likelihood ratio statistic to test for the null hypothesis of a given income elasticity value, which appears in the horizontal axis[16]. As it was to be expected, the lowest value corresponds to the estimated coefficient, .788, increasing slowly when we move across the positive elasticities, but very quickly when we hypothesize low positive or negative income elasticities. That in itself is not too bad, except for what it implies as a less than perfect identification of the elasticity of income in the range of positive values.

Figure 11, which presents the p-values for each of the possible income elasticity values, is

[14] That is because we have estimated the equation in terms of real balances. Alternatively, the monetary authority might want to consider nominal income as its target, and the rate of growth of the nominal supply of money as its policy instrument.

[15] Notice that the alternative of plotting the estimates of the ECM coefficient in the equation for *M-P* as derived from the Johansen(1988) procedure in Table 5 is still more obvious.

[16] Against the alternative of being different from that value.

rather more worrisome, since it shows that on the model estimated with the whole sample, *we would not be able to reject any hypothesized value of the income elasticity in the interval (-1.3, +4.0)*, at least at the standard confidence levels of 90%, 95% or 99%. That is just a reflection of the low power of the test, which leads to the inability of rejecting any false null hypothesis. Even though the justification of the test is asymptotic, the fact that even with 22 years of data we get such a poor inference is very surprising. A possible time instability of the equation would of course add to the small sample loss of power, explaining our results. But using the estimated money demand function for policy design in this context would be a very risky proposition.

Another way of interpreting these results is that if one insists on using the estimated error correction model (DEM) for structural economic analysis, then a fixed confidence level of 95% would be too low to be used for inference, not allowing for discrimination among alternative values of the elasticity of income. Since so much emphasis has been placed on the cointegrating properties of variables as a necessary condition for the existence of long-term equilibrium relationships, and given the dependence of the critical values of the tests on different model specifications, it is rather amazing that so little questioning has been made of the standard practice of testing at a fixed confidence level, with independence of the amount of sample information [see Leamer (1978)].

A rigid interpretation of the structural money demand function that for the U.K. emerges from the application of the cointegration methodology would then be subject to two major drawbacks: the important time instability of the relevant coefficients in the model, as well as the lack of statistical power to test for fundamental hypotheses, which are crucial in implementing the practical use of the demand function for the design of monetary policy.

5. FORECASTING PERFORMANCE

5.1 One step ahead predictions

One of the main tests that any macroeconometric model must face concerns its forecasting performance. Given the *ad-hoc* procedure followed to reach the final specification in Table 5, it is only logical to verify how that *dynamic econometric model* (DEM) for the money demand behaves in terms of forecasting, in comparison with alternative, simpler specifications. The first difficulty in using multivariate models like the DEM for forecasting real balances is the fact that future values of the explanatory variables are unknown. Without information on future changes in prices, income and interest rates, we would not be able to use the DEM to forecast even one period ahead unless we

added forecasting models for those variables. That is one of the reasons behind the use of alternative, univariate models for forecasting purposes.

After using the 1963(1)-1982(4) sample for estimation, we report in this section the forecasting performance of the DEM for the 1983(1)-1984(4) period, relative to other alternatives. These are one-step-ahead predictions, so that the model was reestimated eight times, starting with the 1963-82 sample, and including each time one more quarter in the sample, to obtain the next quarter prediction. Since we did not want to incorporate to the DEM model any subjective analysis, in the form of predictive models for the explanatory variables, we took the rather extreme choice of using their actual, observed, future values, to compute predicted rates of change for real balances[17].

The first column in Table 6 shows the actual rates of change of real balances, computed as first differences of the natural logarithm of the series, while the second column presents the rates predicted by the DEM. The last three rows show the percent annual mean square errors for the rates of change, being of the order of 2,5% for this model for both, 1983 and 1984.

The next three columns show *three naive models*, labelled Naive I through Naive III, characterized by not requiring any sophisticated specification technique, although having some theoretical foundation. The first one assumes that the rates of change are constant over time, the prediction that would emerge from a random walk process for them. The second is more restrictive, based on the expectation that the rate of change is zero every quarter, with independence of past sample information. Hence, the underlying model is a random walk in the levels of real balances. The third naive model takes the 'seasonal' rate of change as prediction, as if that growth rate had a seasonal unit root with no further stochastic structure. Having proved the existence of a zero frequency unit root, we should not expect the Naive II model to do too well. For the same reason, the Naive I model might be expected *a priori* to perform better than the Naive III model.

The three naive models do better than the dynamic econometric model (DEM) for the 1983-84 period, which outperforms just the Naive I model for the first year. Among them, the seasonal unit root model does best over the two years. Even though the seasonal unit root (DFA) tests in section 2 did not detect seasonal non-stationarity, just imposing such a unit root produces an excelent one-step-ahead forecasting performance. That is in correspondence with the ARIMA models specified in that section. The regular unit root model does very well for 1984. As expected, the forecasting results for the random walk model for the levels of the variable (Naive II) are not so good.

[17] This practice, that we consider to be just a model's adjustment test, rather than a truly forecasting practice, is nevertheless sometimes used to check a model's adequacy. We use it here just to be conservative when evaluating the forecasting performance of the dynamic structural model (DEM).

Table 6

FORECASTING RESULTS FROM ALTERNATIVE MODELS

Predicted rates of change of real balances and RMSE's : one step ahead

Observation	*Data*	*DEM*	*Naive I* $y_t = y_{t-1}$	*Naive II* $y_t = 0$	*Naive III* $y_t = y_{t-4}$	*AR(2): Δ*	*AR(2): Δ4*	*VAR Levels: k=5*	*VAR Δ : k=2*	*UCM*
1983:1	0.64	-3.44	5.18	0	-1.92	-0.79	0.06	0.59	-1.21	0.02
1983:2	1.35	3.26	0.64	0	0.13	-0.07	-4.61	1.23	0.84	0.62
1983:3	0.11	1.70	1.35	0	1.24	-0.25	-0.63	0.95	-0.92	1.47
1983:4	3.53	3.92	0.11	0	5.18	2.48	4.94	5.07	4.88	4.98
1984:1	2.05	-1.67	3.53	0	0.64	0.19	0.28	0.20	-2.57	0.61
1984:2	2.67	-0.56	2.05	0	1.35	0.78	-1.93	1.13	0.78	0.44
1984:3	1.69	1.21	2.67	0	0.11	-0.44	-2.25	-0.52	-0.57	1.32
1984:4	2.40	4.63	1.69	0	3.53	1.52	0.61	1.44	2.87	4.94
%RMSE(83)		2.39	2.93	1.92	1.73	1.15	2.56	0.88	1.28	1.10
%RMSE(84)		2.71	1.00	2.23	1.37	1.76	2.50	1.70	2.75	1.84
%RMSE(83/84)		2.56	2.19	2.08	1.56	1.49	2.53	1.36	2.15	1.52

Note: In columns 3 to 5, y_t denotes the rate of change of real balances.

Columns 6 and 7 present the predicted rates of change from autoregressive models for both, regular and seasonal differences. In spite of the good results obtained from the Naive III model, the seasonal autoregression does not work very well over these two years, being uniformly dominated by the autoregression on first differences. The latter produces the best overall results of the models we have so far described.

The next two columns show the predictions from *vector autoregressions* (VAR) on the same variables included in the structural model: real balances, income, interest rates and prices. Including variables other than real balances, these models use more information than the previous univariate ones, but less than the DEM, since in obtaining their forecasts, we used them to obtain predictions for all the included variables. Quarterly dummies as well as a constant term, but no trend, were included in all equations.

The VAR model in levels with 5 lags has an excelent forecasting performance over the two years, and specially so in 1983. Its overall RMSE is the best in the table. The VAR(2) for the quarterly differences works well for 1983, but not so well for 1984, and it does not beat the VAR in levels.

The last column corresponds to an *unobserved component model* (UCM), of the type developed by Young(1984,1994), which has been shown to produce good forecasting results for international GNP data [García-Ferrer et al. (1993,1994)]. The UCM model does very well for 1983, and has an excelent performance over the 1983-84 period, beating the three naive models. Its results are quite similar to the autoregression for the quarterly differences. It is important to emphasize that no subjective element entered this UCM model, and that no sample information beyond 1982(4) was used for its initial specification.

Our analysis in section 2 suggested that, while real balances have a clear unit root at the regular frequencies, the evidence in favor of a seasonal unit root, i.e., non-stationary seasonality, is much less clear. Table 6 shows that four models stand well in front of the rest in terms of forecasting performance: the VAR in levels, the AR in first differences, the unobserved components model, and the seasonal random walk model. That a VAR model in levels can do well in terms of forecasting, so long as enough lags have been included so that residuals are stationary, has already been pointed out by Sims, Stock and Watson (1990). Something similar applies to the UCM model, which is fitted to the levels of the single variable considered, real balances, and has the form of a long autoregression. The AR(2) for first order differences may incorporate most of the stochastic structure underlying a transformation of the series which is close to stationary. The good performance of the random walk for the seasonal differences, may be surprising from the point of view of the seasonal unit root tests, but not from the ARIMA specifications.

Table 7

RANKING OF MODELS

According to forecasting performance : one step ahead

	DEM	Naive I	Naive II	Naive III	AR Δ	AR Δ_4	VAR Levels k=5	VAR Δ	UCM
Over 1983	7	9	6	5	3	8	1	4	2
Over 1984	8	1	6	2	4	7	3	9	5
Overall: 1983-84	9	7	5	4	2	8	1	6	3

5.2 Long-term predictions

One could argue that structural models incorporate the true underlying nature of the joint stochastic process of the relevant economic variables. From that point of view, one could accept that univariate models might be an interesting alternative for capturing the short-run inertia in the variable of interest, hence producing potentially better short run forecasts, but a noticeable deterioration when forecasting over the longer run.

Table 8

FORECASTING RESULTS OF ALTERNATIVE MODELS

Predicted rates of change of real balances and RMSE's : eight quarters ahead

Observation	DEM	Naive I $y_t = y_{t-1}$	Naive II $y_t = 0$	Naive III $y_t = y_{t-4}$	AR(2): Δ	AR(2): Δ_4	VAR Levels k=5	VAR Δ: k=2	UCM
%RMSE(83)	2.39	3.99	1.92	1.73	1.15	1.85	3.16	1.16	0.98
%RMSE(84)	2.73	2.99	2.23	2.74	2.26	2.12	5.10	3.22	2.22
%RMSE(83/84)	2.57	3.53	2.08	2.29	1.80	1.99	4.24	2.42	1.72

To analyze this issue, we also conducted the forecasting exercise for the eight 1983-84 quarters. Table 8 shows the results for the same models considered in the one step ahead forecasting exercise. We have only excluded the VAR in levels of the variables, which showed a considerable deterioration after one year. Model specifications were the same as in the previous exercise.

The main result is the excelent performance of the UCM model, uniformly over the two years. The univariate autoregressions did also quite well, whereas VAR's deteriorate. As it was to be expected, the Naive models performed much worse than in one period ahead forecasting, and are no longer a plausible alternative in this longer term forecasting exercise.

Table 9

RANKING OF MODELS

According to forecasting performance : eight quarters ahead

	DEM	Naive I	Naive II	Naive III	AR Δ	AR Δ_4	VAR Levels k=5	VAR Δ	UCM
Over 1983	7	9	6	4	2	5	8	3	1
Over 1984	5	7	3	6	4	1	9	8	2
Overall: 1983-84	7	8	4	5	2	3	9	6	1

In short, the results of this section show that the forecasting performance of the DEM is rather poor, being beaten by much simpler, non-structural specifications both in short and long-term forecasting. It is widely recognized that the goodness of fit of *structural econometric models* is by no means a guarantee of good forecasting, and this is just an example of such observation. We have shown clear evidence of time instability and that in itself may explain these forecasting results, provided one admits that reduced form models are more appropriate in such an environment. More important, this poor forecasting performance undermines the case for the use of structural econometric modeling of a demand for money, based on cointegration principles (at least in the U.K. during 1963-1984) to be used for optimal monetary policy design.

6. CONCLUSIONS

We have taken in this paper a close look to the practical relevance of the cointegration methodology. As a starting example, we have considered the U.K. demand for money for 1963-1984, which has been studied by a variety of authors using this methodology, and discussed the use of cointegration testing and estimation techniques to specify and estimate a money demand function that can be exploitable for optimal policy design. Our conclusions are, for this particular application, mainly negative. The unit roots tests do not conform with the evidence that we get from more basic practices and statistics used in standard ARIMA specifications. These, as well as more ad-hoc simple reduced form models used as baseline references, perform better in out of sample forecasting. The estimated Error Correction model has proven to be rather unstable, which might explain its poor forecasting performance once we accept that reduced form models are less affected by time varying parameters. Lastly, the unit income elasticity that has been tested and not rejected by some authors, to be then imposed in a restricted estimation strategy, seems to be a consequence of lack of power when making inferences for this estimated money demand function.

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APPENDIX

As an alternative, we have considered an univariate unobserved components (UC) model of the type developed by Young (1989,1994), where any observed time series y_t can be written as:

$$y_t = t_t + p_t + \epsilon_t \tag{3}$$

where t_t is a low frequency or *trend* component, p_t is a perturbational component around the trend and ϵ_t is a zero mean, serially uncorrelated white noise component with variance σ^2_ϵ. It is assumed that the low frequency component can be represented by a local linear trend model of the form:

$$\begin{aligned} t_t &= t_{t-1} + s_{t-1} + \eta_t \\ s_t &= s_{t-1} + \xi_t \end{aligned} \tag{4}$$

where s_t denotes the local slope or derivative of the trend, and η_t and ξ_t are zero mean, serially and mutually uncorrelated white noise inputs with variances σ^2_η and σ^2_ξ, respectively.

In most cases of interest, η_t can be safely constrained to be zero. [Young and Ng (1989)], which we do in what follows. Then the variance of ξ_t is the only unknown in (4) and it can be defined by the *Noise Variance Ratio* (NVR), which is the relation between σ^2_ξ and the variance of the observational noise σ^2_ϵ, that is NVR $= \sigma^2_\xi / \sigma^2_\epsilon$.

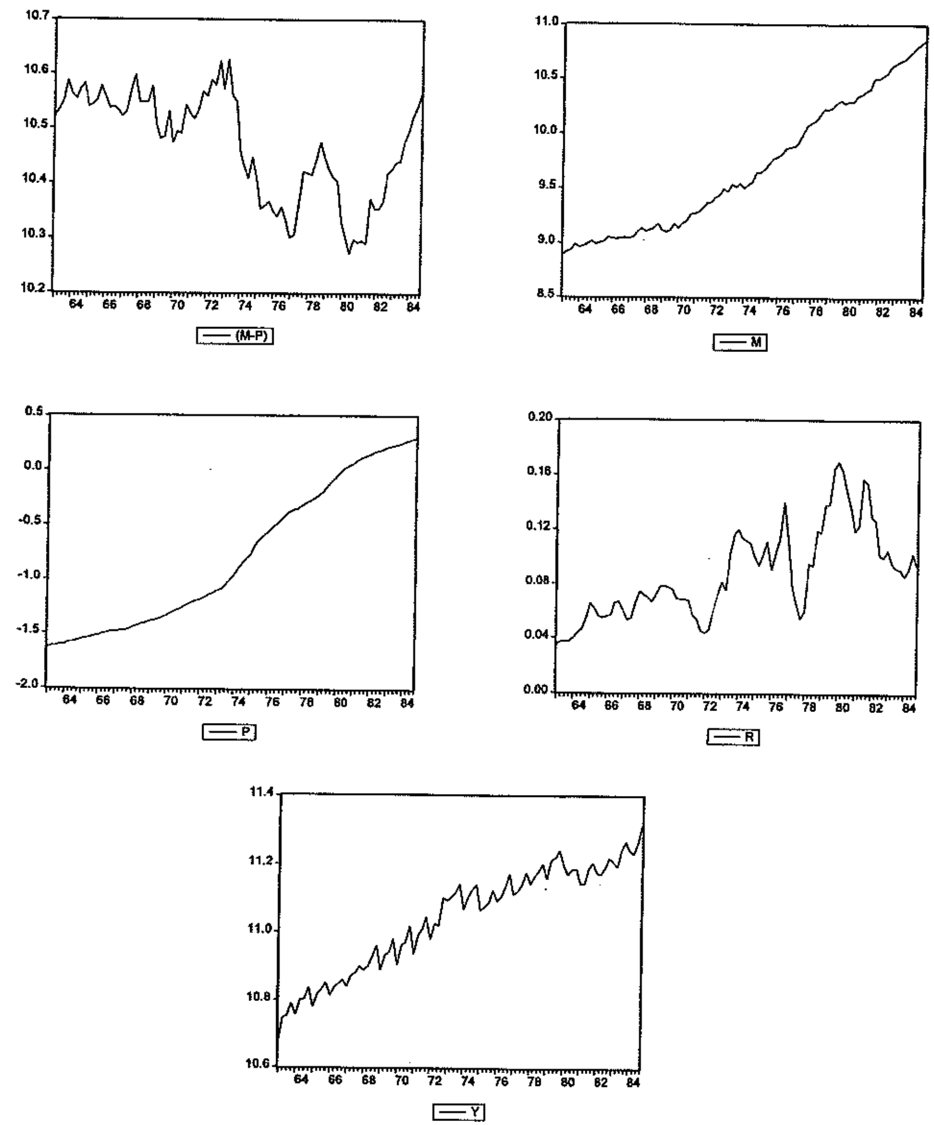
It is also assumed that the sum of the stochastic perturbation p_t and the white noise component ϵ_t allows an ARMA representation of the form:

$$p_t + \epsilon_t = \frac{\gamma(L)}{\phi(L)} a_t \tag{5}$$

where $\gamma(L)$ and $\phi(L)$ are polynomials of different orders in the lag operator L. No stationary restrictions are necessarily imposed in (5) and in the empirical application we will concentrate on the use of the purely autoregressive (AR) form of (5). In this case, an AR or subset AR model is identified for the perturbations using the Akaike Information Criterion (AIC).

Once we have defined the model structures for all the components, it is then straightforward to assemble them into an aggregate state space form [Young (1989)]. As regards identification and subsequent parameter estimation, the choice of the NVR value plays a crucial role. So far, we are faced with two alternatives. The first one can be considered half the way between the *objective optimisation* approach and the *objective bayesian* one: selecting an NVR value for the trend so that its estimate does not contain higher frequency components associated with the perturbational behavior [García-Ferrer *et al.* (1993)]. This alternative implies *manual tuning* of the NVR that can be dangerous, so a more objective option would be preferably in this case. The second alternative, recently developed by Tych and Young (1993) is based on *optimising* the NVR values based upon the spectral properties of the random walk family of models used to describe the nonstationary parameters, so that the logarithm of the pseudospectrum matches the logarithm of either the AR spectrum or the periodogram of the data in a least squares sense [García-Ferrer *et al.* (1994)]. Allowing for the use of the whole sample 1962-84 in choosing the resulting *optimal* NVR value of .456, rather than the .350 which was actually chosen on the basis of the 1962-82 sample, one obtains even better forecasting results, with an overall RMSE of 1.57.

Figure 1: Plots of the original variables in UK Demand for Money: 1963.1 - 1984.4



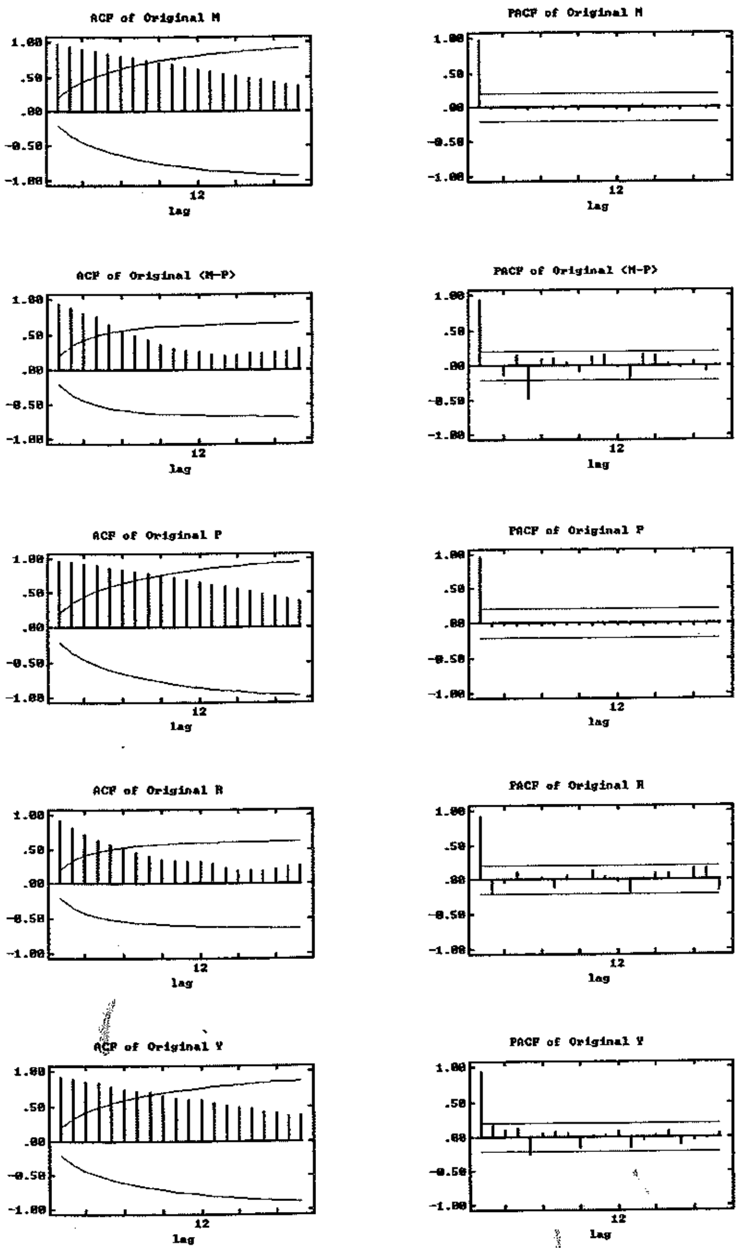


Figure 2: Estimated ACF and PACF of the original variables

Figure 3: Quarterly rates of growth
First differences of logged variables

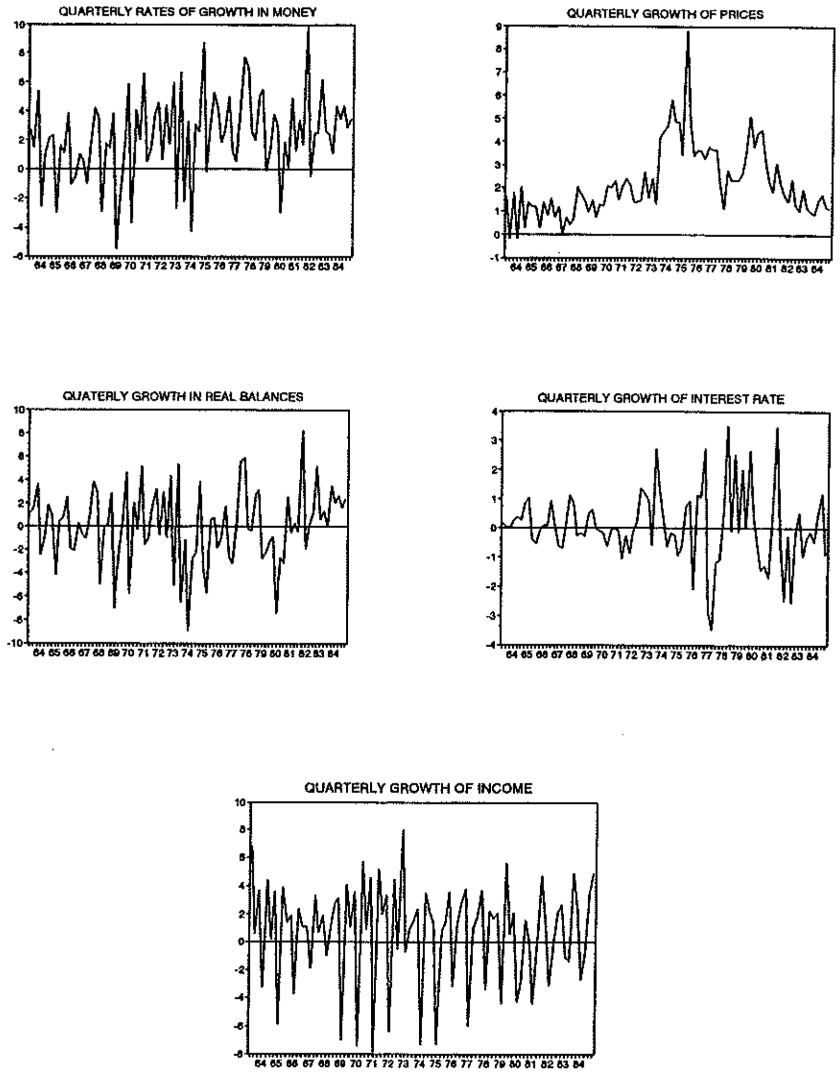


Figure 4 : Annual rates of growth
Fourth order diferences of logged variables

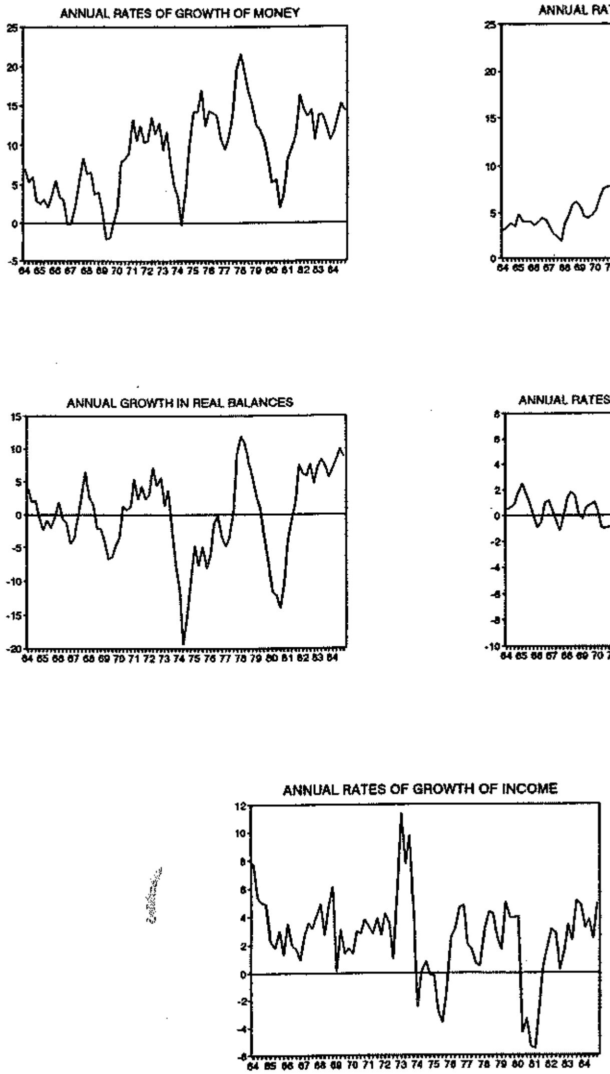
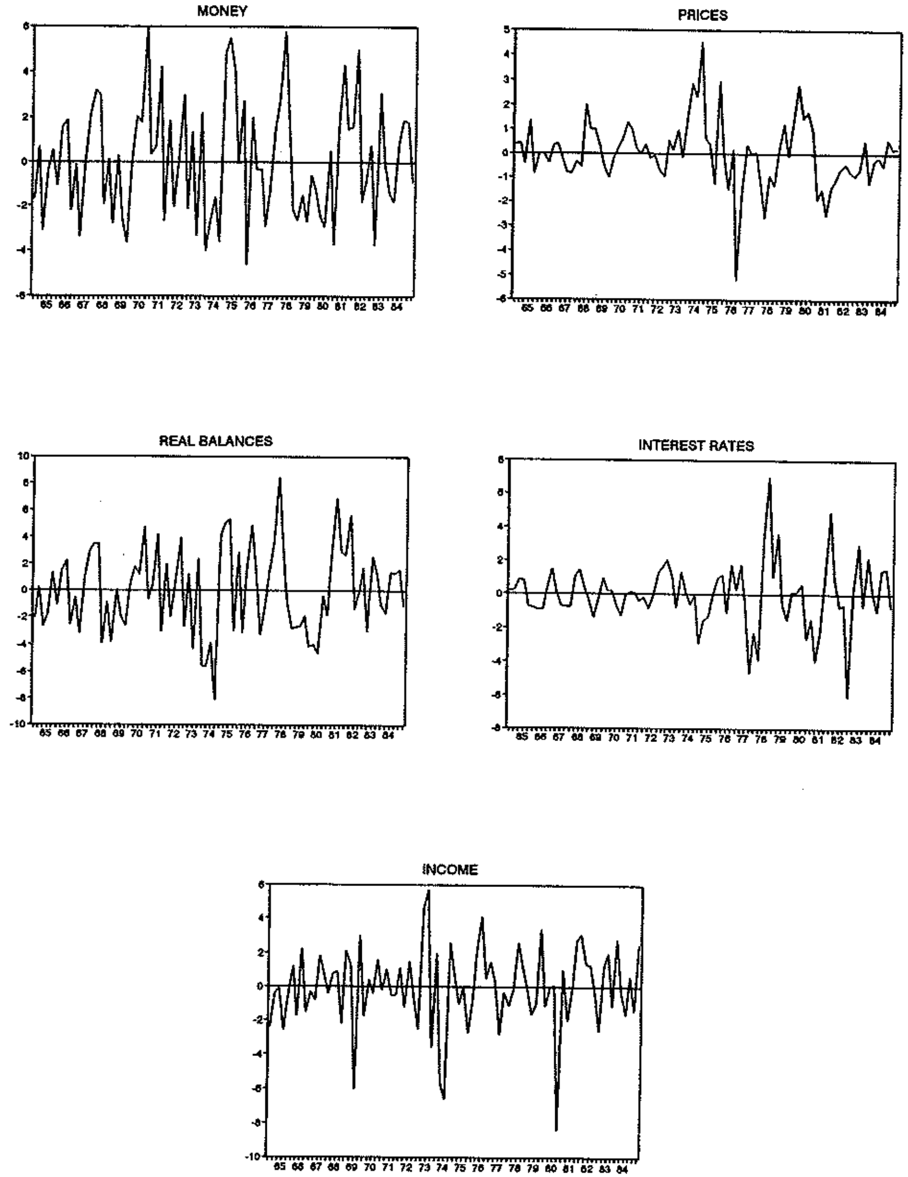


Figure 5
First differences of annual rates of growth



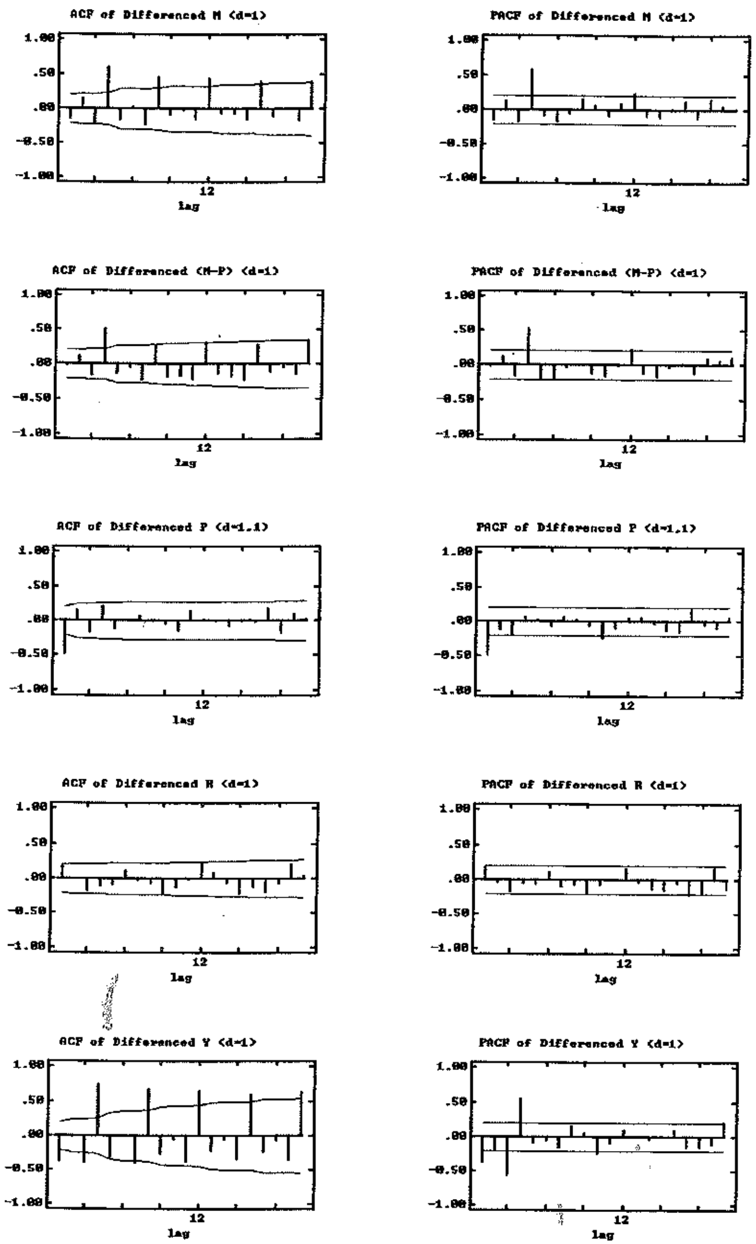


Figure 6: Estimated ACF and PACF of the differenced variables

Figure 7

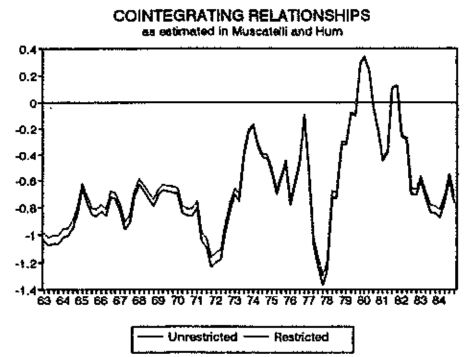


Figure 8

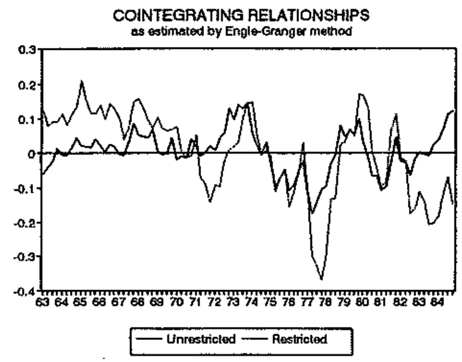


Figure 9

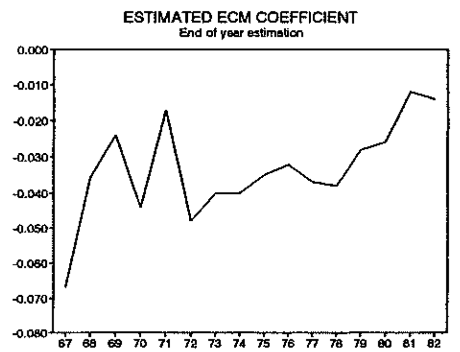


Figure 10

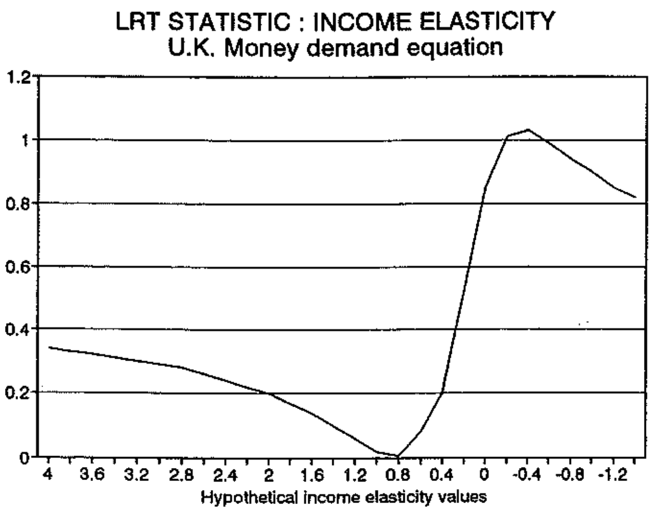


Figure 11