THE EFFECTS OF SEASONAL ADJUSTMENT LINEAR FILTERS ON COINTEGRATING EQUATIONS: A MONTE CARLO INVESTIGATION

Jesus Otero and Jeremy Smith

No.456

WARWICK ECONOMIC RESEARCH PAPERS

THE UNIVERSITY OF WARWICK

DEPARTMENT OF ECONOMICS

THE EFFECTS OF SEASONAL ADJUSTMENT LINEAR FILTERS ON COINTEGRATING EQUATIONS: A MONTE CARLO INVESTIGATION

Jesus Otero and Jeremy Smith
Department of Economics
University of Warwick
Coventry CV4 7AL
England

No.456

March 1996

This paper is circulated for discussion purposes only and its contents should be considered preliminary.

THE EFFECTS OF SEASONAL ADJUSTMENT LINEAR FILTERS ON COINTEGRATING EQUATIONS: A MONTE CARLO INVESTIGATION

Jesús Otero
Department of Economics
University of Warwick

and

Jeremy Smith
Department of Economics
University of Warwick

March 1996

Abstract

In this paper we assess, via Monte Carlo simulations, the effects of some seasonal adjustment linear filters on cointegrating regressions. We find that the use of filters has adverse consequences in terms of the power of the Augmented Dickey and Fuller and Phillips and Perron tests for cointegration. As an empirical application, we re-examine the results of the money demand modelling exercise performed by Carrasquilla and Galindo (1994); we find that when one attempts to model the variables' seasonal pattern using simple methods, instead of removing it by filtering the data, the null hypothesis of non-cointegration is no longer accepted.

Contact Address:
Jesús Otero
Department of Economics
University of Warwick
Coventry CV4 7AL
United Kingdom
E-mail: J.G.Otero@warwick.ac.uk

The first author would like to thank the Fundación para el Futuro de Colombia - Colfuturo, the British Council and the Banco de la República for their financial assistance. The views expressed in the paper are those of the authors.

1. Introduction

The effects of seasonal adjustment filters on linear regression models have been analysed by Wallis (1974). He shows that as long as *all* the variables in a regression are adjusted with the *same* filter, the underlying relation among them is not altered, although the error term is no longer white noise but a high-order moving average process; nonetheless conducting inference may be problematic. If, on the other hand, the variables are adjusted using different filters, or if some of the explanatory variables are left unadjusted, then the estimated relationship among the variables will differ from the true relationship.

In the context of nonstationary series, Ghysels (1990) conducts a Monte Carlo investigation to assess the effects of the Henderson moving average filter and the linear approximation of the X-11 filter, in both their quarterly and monthly versions, on the power of the augmented Dickey and Fuller (ADF) and Phillips and Perron (PP) unit root tests. His main result is that these filters substantially reduce the power of the tests; additionally, he also reports that while the null hypothesis for the presence of a unit root in the series of post-war seasonally adjusted quarterly U.S. GNP is strongly accepted, the evidence is "far less conclusive" when seasonally unadjusted data is used. Ghysels and Perron (1993) explore, in more detail, the effects of seasonal adjustment filters from both analytical and simulation perspectives. They find that both the ADF and PP unit root tests exhibit a considerable reduction in power compared to the benchmark cases where the data is seasonally unadjusted.

Within the cointegration framework, Ericsson, Hendry and Tran (1994) and Hendry (1995, ch. 15) show that for a given I(d) variable y_t with $d \leq 2$, if the weights of a seasonal adjustment linear filter sum to unity, then the unadjusted and adjusted series cointegrate with cointegrating vector [1, -1]. They further show that if the filter satisfies the assumptions that it is symmetric and eliminates deterministic seasonals, then the number of cointegrating vectors and the cointegrating vectors themselves are invariant to the type of data; in the short run, however, the use of seasonally adjusted observations may not only distort the dynamics of the system but also whether or not a set of variables can be regarded as weakly exogenous.

Taking the above aspects into consideration, the purpose of this paper is to assess, via Monte Carlo simulations, the effects of some seasonal adjustment linear filters on static cointegrating regressions. The idea is then to examine whether the filters reduce the power of cointegration tests. The outline of the paper is as follows. In section 2 we first describe the way the Monte Carlo simulations were designed and then we report the main results. In section 3 we re-examine the results of the money demand modelling exercise performed by Carrasquilla and Galindo (1994); we find that when one attempts to model the variables' seasonal pattern using simple methods, instead of removing it by filtering the data, the null hypothesis of non-cointegration is no longer accepted. In section 4 we present some concluding remarks.

2. The Effects of Seasonal Adjustment Filters on Cointegrating Equations

2.1 Design of the Monte Carlo Simulations

As we indicated previously, we examine the effects of seasonal adjustment linear filters on static cointegrating regressions via Monte Carlo simulations. In particular, let us consider a data-generation process (DGP) defined by the following set of equations:

$$x_t = x_{t-1} + u_t \qquad [1]$$

$$y_t = x_t + v_t \qquad [2]$$

where u_t and v_t are initially assumed to be white noise.

As can be observed, equations [1] and [2] indicate that x_t and y_t follow a random walk, and that both series cointegrate with cointegrating vector [1, -1]. Put another way, the null hypothesis of a unit root in the error term v_t is rejected. The question is then, to what extent this null hypothesis is rejected when both x_t and y_t are subjected to a seasonal adjustment linear filter, or when only y_t is filtered? Ghysels and Perron (1993) argue that "...studying the effect of seasonal adjustment filtering procedures on series that have no seasonal components also has its advantages. Indeed, in this context, the issue concerning whether the seasonal part has been removed adequately does not occur. Hence, it permits a more specific investigation of the properties of the filters and their effects on the correlation structure of the data" (p. 63).

For the purpose of the Monte Carlo experiment, we generated 1,000 replications of the series $\{y_t\}$ and $\{x_t\}$ of length n = 64 as defined by equations [1] and [2], with the initial condition that x_1=0; the sample size was selected in order to match that of the empirical application. The innovation term u_t is assumed to be ~ i.i.d N(0,1), whereas v_t is assumed to be ~ i.i.d N(0,10). In a further set of experiments, v_t is given by the following seasonal autoregressive seasonal moving average SARSMA (0,1,1,0) process:

$$v_t = 0.6v_{t-1} + \varepsilon_t + 0.25\varepsilon_{t-4} \qquad [3]$$

where ε_t ~ i.i.d N(0,6); this is the form of the error term in the empirical application.

Within this framework, we analyse four linear filters:

- A moving average of fourth order which can be written as $B(L)=(0.25 + 0.25L + 0.25L^2 + 0.25L^3)$, where L denotes the lag operator.
- A filter that satisfies the three assumptions in Ericsson, Hendry and Tran (1994) which we referred to as the "simple filter", and is given by the following polynomial in the lag operator: $B(L)=0.25+0.125\sum_{j=-3}^{3}L^j$, for $j\neq 0$.
- The linear approximation of the quarterly version of the X-11 filter, as given by Laroque (1977, Table 1); see also Ghysels and Perron (1993, Table A.2).
- The quarterly version of the Henderson moving average filter, as given by Ghysels and Perron (1993, Equation 2.7). This filter is actually a sub-filter of the X-11 filter, and provides an estimate of the trend component of a series.

Before describing the results, it is worth mentioning the following aspects. Firstly, we refer to the case where the linear filter is applied on both sides of the cointegrating equation as 2-sided, whereas the 1-sided case corresponds to that where the filter is only applied to the dependent variable. Secondly, in order to obtain the sample size of 64 for the filtered series, it was necessary to generate additional data points before and after the actual sample; this is also important for reducing the impact of the initial condition. Consequently, both the unadjusted and adjusted versions of the series begin with the 101st observation[1].

2.2 Description of the Results

To begin with, we look at the effects of the seasonal adjustment filters on the cointegrating equation, by examining the t-ratio on the cointegrating parameter being equal to 1. Given that the filters introduce serial correlation in the error term of the

[1]All the simulations were performed using the econometrics software package RATS version 4.20; the routines are available on request.

cointegrating equation, we also use the fully modified estimation method (FM-OLS) of Phillips and Hansen (1990) and Hansen and Phillips (1990).[2]

Figure 1 plots the distributions of the t-ratio for OLS and FM-OLS on the filtered series, denoted OLSAdj and FM-OLS, respectively, as well as the distribution of the t-ratio on the unfiltered series, denoted OLS, which is close to that of a standard normal distribution. Table 1 reports summary statistics on the OLSAdj and FM-OLS t-ratios. In the 2-sided case the distributions of the OLS t-ratio are centred around zero, whereas in the 1-sided case the distributions are negatively biased for MA[4] and simple filters and, to a lesser extent, for the Henderson filter. The X-11 filter does not appear to seriously distort the distribution. The FM-OLS improves the distribution of the t-ratios for the MA[4] and simple filters, both partially correcting the bias and reducing the variance. Furthermore it does not appear to have a substantial effect in the case of the Henderson filter, although it actually produces a less normally distributed distribution for the X-11 filter, presumably because the number of lagged terms used in calculating the FM-OLS estimators, that is, 7, is excessive.

To examine the effects of the various filters on the power of cointegrating tests, we calculate the number of times the ADF and PP unit root tests correctly reject, at a 5% significance level, the null hypothesis of a unit root in the residuals of the cointegrating equation[3]. Both the ADF and PP tests are calculated for up to p=10 lags. For the ADF test, the optimal number of lags included in the test regression is chosen

[2]The number of covariances used in FM-OLS was set equal to 7. As it is known, this procedure relies on the fact that although OLS produces "superconsistent" estimates of the cointegrating parameters, in finite samples they may be severely biased, either because the static regression omits the short run dynamics, or because some of the series may be jointly determined. Thus, Phillips and Hansen's estimator aims to correct the bias originated from these two sources (see also Banerjee, et. al., 1993 ch.7; Davidson and MacKinnon, 1993 ch. 20).

[3]See Fuller (1976) and Dickey and Fuller (1979, 1981) for the ADF test and Phillips (1987) and Phillips and Perron (1988) for the PP test

in two alternative ways; (i) estimating the test regression for a given maximum lag length, say p, and testing whether the last coefficient of the augmented part is statistically different from zero; if this coefficient is not significant, then the order of the autoregression is reduced by one until the last coefficient is significant (this procedure is suggested by Campbell and Perron (1991), and will be referred to as the significance of the last coefficient (SLC); (ii) using the model selection procedure based on the minimisation of the Akaike information criterion (AIC).

Table 2 reports the power of the ADF and PP tests for cointegration for 1-sided and 2-sided filters, for all lags, p = 1 ,..., 10, as well as the proportion of times each of the ADF tests is selected according to the SLC and AIC criteria described above.[4] For the ADF test, in five out of eight cases both the SLC and AIC yield the same number of optimal lags to include in the test regression; when they do not coincide, the latter procedure is more parsimonious.[5] When the MA[4] and simple filters are applied to both the dependent and explanatory variables there is a low probability of finding a cointegrating relationship, at 8.2% and 11.2% for the MA[4] and simple filter, respectively, at their optimal lag length. When these filters are applied to just the dependent variable there is an increase in power. For the Henderson and X11 filters there is a loss in power for p>3, although only for SLC for the X-11 filter (1-sided and 2-sided) is a value of p>3 actually selected. The power of the PP test is high and robust to changes in p for both the X-11 and Henderson filters; this is expected as the PP test is able to model the MA error structure more precisely.[6] For

---

[4]When the variables are not filtered, results not reported here indicate that the power of the DF and the PP tests is 100%.

[5] For p < 4 an LM(4) test for serially correlated errors rejects the null hypothesis of no serial correlation, a fact which yield size distortions in the ADF test.

[6] This is a highly idealistic scenario where the residuals of the cointegrating regression are white noise.

the MA[4] and simple filters the power of the test is highly dependent on p, although, in general, power does not fall by as much as the results ADF for p>3.[7]

Turning to the more realistic scenario that the residuals of the cointegrating regression are not white noise but, for example, a SARSMA (0,1,1,0) process. The distributions of the t-ratio that the cointegrating parameter is equal to 1 are plotted in Figure 2; this time we include the density function of a standard normal random variable to facilitate comparison. Table 1 reports summary statistics on these distributions. Again there is only a bias in the mean of the distribution when the filter is applied to the dependent variable. All distributions are markedly fatter than the standard normal distribution. For the Henderson and X-11 filters all distributions are reasonably similar, although perhaps that of FM-OLS is closer to normality. For the MA[4] and simple filters, OLS on the adjusted series yields serious distortions, although the use of FM-OLS partially corrects these distortions.

With reference to the power of the tests for cointegration, results not reported here indicate that both the ADF and the PP tests exhibit reasonable power when none of the variables have been filtered, for small p. In particular, for a DF test the probability of correctly rejecting the null hypothesis of noncointegration is 86.2%, and the probability of rejecting a LM[4] test for residual serial correlation is slightly greater than the nominal size of 5%; in the case of the PP test, the power is always above 85% and the statistic does not appear to be sensitive to the number of autocovariances considered when constructing it.

---

[7] In practice the use of the X-11 filter is very limited because its long tails lead to the lost of 22 observations at every end of the sample period.The lost of observations can be overcome by using the actual X-11 filter instead of its linear approximation. In the context of univariate unit root tests, Ghysels and Perron (1993) find that "...filtering with the actual X-11 filter reduces the power of the ADF test more than the linear X-11 filter does" (p.86). It might be therefore interesting to assess the power of the tests for cointegration when the series are filtered with the actual X-11 filter and not with its linear approximation.

The results presented in Table 3 indicate that when the filters are applied to both sides of the cointegrating equation, or only on the left hand side, the power performance of the ADF and PP tests for the existence of a unit root is very low; for example, the MA[4] and simple filters at best correctly find cointegration on 18.5% and 14.3% of occasions when both the dependent variable and the explanatory variable are filtered.[8] The power of the ADF test is markedly lower than that observed in Table 2 for both the X-11 and Henderson filters. The power of the PP test is extremely low when the MA[4] and simple filters are used and is also much worse than those observed in Table 2 for the X-11 and Henderson filters.

The basic conclusion of the Monte Carlo simulations is that the use of linear filters for seasonal adjustment in cointegrating equations has adverse consequences in terms of the power of the ADF and PP tests for cointegration. In this sense, our results suggest that the findings of Ghysels (1990) and Ghysels and Perron (1993), in the context of univariate unit root tests, are also applicable for the residuals of static cointegrating equations. Thus, considerable care must be exercised when using linear filters for seasonal adjustment, as one may wrongly conclude that a static regression between nonstationary series is spurious.

3. Empirical Application: A Money Demand Modelling Exercise

In this section we look at the effects of linear filters for seasonal adjustment in cointegrating equations, by re-examining the results of the money demand modelling exercise performed by Carrasquilla and Galindo (1994). It is important to highlight that it is our interest to assess if the results of their cointegration analysis change when

[8] Again for $p<4$ there exists substantial serial correlation problems and hence the size of the tests will be severely distorted.

one attempts to model the variables' seasonal pattern using simple methods, instead of removing it by filtering the data.

Carrasquilla and Galindo estimate a long-run money demand equation of the form:

$$\frac{m^d}{p} = f\,(y, \mathbf{R}) \qquad [4]$$

where m^d is money in nominal terms, p is an appropriate price level, y is a measure of the volume of real transactions[9], and **R** is a vector of interest rates on the alternatives of money. The f function is expected to be increasing in y as well as decreasing in the elements of **R**; however, if some of the components of the monetary aggregate bear interest, their interest rate should also be present in **R** and the f function should be increasing in these elements.

For their analysis, Carrasquilla and Galindo utilise quarterly information for the sample period 1978:1-1993:4[10]. The monetary aggregate corresponds to the traditional definition of M1, that is currency plus demand deposits, which is then deflated by the consumer price index to produce real money balances; the scale variable corresponds to the GDP series constructed by the Departamento Nacional de Planeación[11]; and the proxy for the opportunity cost of holding money is constructed by combining two different interest rate series: from 1978:1 to 1980:1 the yield of 120-day CAT (certificados de abono tributario) certificates, and from 1980:2 to

---

[9]The variables commonly used as proxies are real GNP (see e.g. Goldfeld and Sichel, 1990; and Hendry and Ericsson, 1991), real total final expenditure (see e.g. Hendry and Ericsson, 1991 and Hendry, 1995 ch. 16), and real consumer expenditure (see e.g. Mankiw and Summers, 1986).

[10]We thank Arturo Galindo for having provided the data set used in the aforementioned paper. It is worth indicating that our results do not exactly coincide with theirs because the series of M1 and GDP were updated. Nonetheless, our results are qualitatively the same.

[11]See Cubillos and Valderrama (1993) for a presentation of the methodology as well as of the results for the period 1980-1992.

1993:4 the yield of 90-day CDT (certificado de depósito a término) certificates offered by banks and financial corporations. All series are considered in logarithms and denoted LRM1, LGDP and LR, respectively[12].

In Figure 3, we plot LRM1, LGDP and LR for the period 1978:1-1993:4. As can be noticed from the figures, both LRM1 and LGDP exhibit a clear seasonal pattern consisting of peaks during the fourth quarter, and in the case of LGDP it is also possible to distinguish that after 1985:4, a peak in the second quarter is also present; the interest rate series, on the other hand, does not present any kind of seasonality. Instead of modelling the seasonal behaviour of LRM1 and LGDP, Carrasquilla and Galindo choose to adjust *all* series using a moving average of fourth order which, although unnecessary in the case of the interest rate series, can be justified on the grounds that as long as *all* the variables in a regression are adjusted with the *same* filter, the underlying relation among them is not altered, although the error term is no longer white noise but a high-order moving average process (see Wallis, 1974)[13]. Accordingly, we apply the same filter to the series under consideration, and the resulting adjusted series are denoted LRM1A, LGDPA and LRA (see Figure 3)[14].

---

[12]For previous money demand modelling exercises for Colombia see e.g. Clavijo (1987, 1988), Steiner (1988), Lora (1990), Carrasquilla and Rentería (1990), Herrera and Julio (1993), Misas, Oliveros and Uribe (1994) and Misas and Suescún (1993).

[13]It is possible to show that Carrasquilla and Galindo's suggested filter transform a white noise error term into a MA(3) process, whose theoretical autocorrelation function is given by ρ_1=0.75, ρ_2=0.5, ρ_3=0.25 and ρ_k=0 for all k>3.

[14]The moving average is calculated since 1977:2 in order to avoid the loss of the first three observations.

3.1 Testing for Unit Roots

The order of integration of the series under consideration is investigated by means of the ADF tests for unit roots, which we apply as indicated by Perron (1988)[15]. The number of lags of the dependent variable to include in the test regressions is selected following Campbell and Perron (1991), starting with an upper bound of 5 lags, and then we perform the LM[4] test for serial correlation on the residuals of the test regressions. Lastly, when dealing with the unadjusted versions of LRM1 and LGDP we also include centred seasonal dummies to capture some of the seasonal pattern[16]; Dickey, Bell and Miller (1986) show that this procedure does not have any effect on the limiting distributions of the unit root tests statistics.

In the top half of Table 4 we summarise the results of the ADF unit root tests for LRM1, LGDP and LR, whereas in the bottom half we report those for the filtered series. Regardless of the type of data, the results suggest that LGDP seems to contain a unit root and a non-zero drift term, whereas LRM1 and LR may also contain a unit root with a zero drift term; in the case of LR, however, this conclusion seems to contradict what the correlogram of the series (not reported here) shows[17].

3.2 Cointegration Analysis for Pairs of Unadjusted and Adjusted Series

One important property of seasonal adjustment filters is that they should only remove the seasonal behaviour of a series, without affecting its long-run properties.

[15]Given that our interest is to discuss the modelling of cointegrated variables at the zero, or long-run, frequency, we do not perform tests for seasonal unit roots nor tests for cointegration at seasonal frequencies. On these issues see e.g. Dickey, Hasza and Fuller (1984), Hylleberg, Engle, Granger and Yoo (1990) and Engle, Granger, Hylleberg and Lee (1993).

[16]These centred seasonal dummy are defined as $CSD_{i,t} = 0.75$ if t is the ith quarter of the year and -0.25 otherwise.

[17]It shall be remembered that these results must be interpreted with caution due to the low power of the tests (Schwert, 1989); in addition, it is important to bear in mind that the order of integratedness is not an inherent property of a time series, that is the order of integration of a time series may differ for different sample periods (see Hendry, 1995).

Ericsson, Hendry and Tran (1994) and Hendry (1995, ch. 15) show that for a given I(d) variable y_t with $d \leq 2$, if the weights of the seasonal filter sum to unity, then the pair of unadjusted and adjusted series cointegrate with cointegrating vector [1, -1]. Accordingly, it is of particular interest to test whether this result holds for the adjusted and unadjusted versions of LRM1, LGDP and LR.

In order to do this, we test for cointegration between the pairs of series LRM1-LRM1A, LGDP-LGDPA and LR-LRA, using Johansen's maximum likelihood procedure (see Johansen, 1988 and Johansen and Juselius, 1990). The advantage of this procedure is that it allows us to estimate all possible cointegrating vectors between a set of variables, and perform likelihood ratio tests of hypotheses about cointegrating vectors.

On this basis, we consider the following two-dimensional VAR models: i) LMR1-LMR1A (VAR model 1); ii) LGDP-LGDPA (VAR model 2); iii) LR-LRA (VAR model 3). All VAR models include a μ_t vector of constant terms, and the first two also include a 3x1 D_t matrix containing centred seasonal dummy variables. Both the centred seasonal dummy variables and the constant terms are entered unrestricted. It is worth indicating that given the nature of the filter for seasonal adjustment, we use a lag length of two for the estimations, as longer lags yield perfect multicollinearity.

In Table 5 we report the main diagnostic tests for the three models as well as the cointegration analysis results. With regard to VAR model 1, the regression for LRM1A fails the LM[4] test for serial correlation at the 5% significance level; the other tests for misspecification are easily passed. Under other circumstances, it would have been desirable to include additional lags to remove the autocorrelation; however, as it is not possible to do this because of perfect multicollinearity, we proceed with the cointegration analysis. Both the trace and maximal-eigenvalue test statistics indicate the presence of one cointegrating vector. Moreover, the null hypothesis that LRM1 and LRM1A cointegrate with a unit coefficient is easily accepted (χ^2_1=0.014).

Concerning VAR model 2, both the regressions for LGDP and LGDPA fail the LM[4] test for serial correlation at the 5% significance level; in addition, LGDP fails White's test for heteroscedasticity at the 1% level. Similar to VAR model 1, the outcome of the cointegration analysis not only indicates the presence of one cointegrating vector, but also that LGDP and LGDPA cointegrate with a unit coefficient (χ^2_1=0.002).

Lastly, the estimation of VAR model 3 is very disappointing. To begin with, the two regressions fail *all* misspecification tests. Additionally, if one tests for cointegration, both the trace and maximal-eigenvalue test statistics indicate that there are two cointegrating vectors. Put another way, both LR and LRA seem to be I(0) variables for the period under review.

3.3 A Long-Run Money Demand Equation using the Seasonally Adjusted Series

The results of estimating the long-run money demand equation using the seasonally adjusted series are presented below:

$$\text{LRM1A} = 8.799 + 0.493\ \text{LGDPA} - 0.228\ \text{LRA} + \hat{\hat{u}}_t \qquad [5]$$

It is important to recall that the seasonally adjusted and unadjusted versions of LRM1 and LGDP may contain a unit root, and that the interest rate may be an I(0) variable for the period under review. Thus, it may seem peculiar that for estimating the long-run money demand equation we are combining variables of different order of integration. The reason is that even if asymptotically the inclusion of I(0) variables does not make any difference, in finite samples, as in our case, they may significantly affect the outcome.

Returning to the cointegrating equation, the signs of the estimated coefficients correspond to those of a money demand equation, with the coefficient associated to LGDPA suggesting scale economies in the holding of money.

The residuals of [5] were then tested for a unit root using the ADF and PP tests. When we use the first method, it is necessary to introduce 5 lags of the dependent variable in order to whiten the residuals, as indicated by the LM[4] test for serial correlation; the following results are obtained:

$$\Delta\hat{\tilde{u}} = -0.118\hat{\tilde{u}}_{t-1} + \sum_{i=1}^{5}\alpha_i \Delta\hat{\tilde{u}}_{t-i} \qquad [6]$$

t-Stat (-2.781)

Thus, it is not possible to reject the null hypothesis of non-cointegration at traditional significance levels (critical value of -3.552 at the 10% significance level). On the basis of this outcome, Carrasquilla and Galindo conclude that the demand equation for real balances is spurious, and proceed to formulate it in first differences[18].

With regard to the Phillips and Perron test, we use different truncation lag parameters, that determine the number of autocovariances to be considered when constructing the statistic; however, regardless of this the null hypothesis of non-cointegration cannot be rejected.

Lastly, regression [5] is estimated using Phillips and Hansen's fully modified estimator, for selected truncation lag parameters. The results, which are reported

[18]The null hypothesis of noncointegration is also accepted when the series are adjusted using the "simple filter" defined in the Monte Carlo simulations; these results, however, will not be reported. The series were not adjusted with the linear version of the X-11 filter because a significant number of observations is lost.

below, indicate that the estimated coefficient on LGDPA does not change markedly in comparison to the OLS estimate in equation [5], although the same cannot be said about the estimated coefficient on LRA.

Trunc. Lag	Const.	LGDPA	LRA	ADF(5)	PP(4)	PP(6)	PP(8)
3	8.503	0.527	-0.258	-2.902	-2.296	-2.337	-2.387
4	8.536	0.528	-0.271	-2.845	-2.329	-2.368	-2.416
6	8.473	0.532	-0.266	-2.870	-2.289	-2.329	-2.378
8	8.415	0.534	-0.258	-2.914	-2.248	-2.290	-2.339
10	8.308	0.535	-0.232	-3.043	-2.161	-2.208	-2.260
12	8.156	0.539	-0.200	-3.185	-2.049	-2.102	-2.157

The residuals of the fully modified regressions are then tested for a unit root using the ADF(5) test, and the PP test for selected truncation lag parameters; regardless of the test, the null hypothesis of non-cointegration is not rejected at traditional significance levels.

It shall be remembered from the Monte Carlo simulations reported previously, that both the ADF and PP tests for cointegration suffer of low power when the variables have been previously filtered.

3.4 A Long-Run Money Demand Equation using the Seasonally Unadjusted Series

Let us now consider the results when one attempts to model the seasonal pattern of LRM1 and LGDP by including a set of centred seasonal dummy variables in the cointegrating equation. Firstly, the estimated cointegrating equation is:

$$\text{LRM1} = 9.080 + 0.478\ \text{LGDP} - 0.256\ \text{LR} + \text{CSD} + \hat{u}_t \qquad [7]$$

where CSD indicates the set of centred seasonal dummies. As can be seen, the estimated coefficients change little with respect to those obtained using the adjusted variables.

The residuals of [7] were then tested for a unit root using the Dickey and Fuller and Phillips and Perron tests. With regard to the former, we begin by including 5 lags of the dependent variable, although none of them proved significant. Thus, we end up with the following regression:

$$\Delta\hat{u} = -0.372\hat{u}_{t-1} \qquad [8]$$

t-Stat (-3.662)

which easily passes the LM[4] test for residual serial correlation ($F_{4,58}$=1.093). Unlike the previous case, the null hypothesis of non-cointegration can be rejected at a 10% significance level[19]. In the case of the PP test, the statistics are not greatly affected by the selection of the truncation parameter, and the hypothesis of non-cointegration can be rejected at the 10% significance level.

4. Concluding Remarks

In this paper we assess, via Monte Carlo simulations, the effects of some seasonal adjustment filters on static cointegrating regressions. We find that the use of filters has adverse consequences in terms of the power of the ADF and PP tests for cointegration, so that they are not likely to correctly reject the null hypothesis of the existence of a unit root in the residuals of a cointegrating equation. In this sense, our results suggest that the findings of Ghysels (1990) and Ghysels and Perron (1993), in the context of univariate unit root tests, are also applicable for the residuals of static cointegrating equations. Consequently, considerable care must be exercised when using filters for seasonal adjustment, as one may wrongly conclude that a static regression between nonstationary series is spurious.

[19]After examining the autocorrelation and partial autocorrelation functions of the residuals of [7], we end up with the SARSMA (0,1,1,0) specification utilised in the Monte Carlo simulations.

As an empirical application, we re-examine the results of the money demand modelling exercise performed by Carrasquilla and Galindo (1994); we find that when one attempts to model the variables' seasonal pattern using simple methods, instead of removing it by filtering the data, the null hypothesis of non-cointegration is no longer accepted.

Table 1
Distribution of t-ratios : Summary Statistics

Filter	v_t is white noise				v_t is SARSMA (0,1,1,0)			
	2-sided		1-sided		2-sided		1-sided	
	OLS	FM-OLS	OLS	FM-OLS	OLS	FM-OLS	OLS	FM-OLS
MA[4] Filter								
Mean	0.032	0.017	-1.296	-0.694	0.017	0.002	-1.001	-0.403
Variance	4.419	2.793	3.660	2.297	10.381	3.966	8.667	3.327
Skewness	-0.078	-0.030	-0.193	-0.198	-0.035	-0.039	-0.188	-0.098
Excess Kurtosis	0.102	0.273	0.113	0.221	0.297	0.396	0.491	0.412
Simple Filter								
Mean	0.042	0.013	-1.808	-0.109	0.031	0.008	-1.231	-0.072
Variance	7.635	3.371	5.870	2.902	14.454	4.574	11.584	4.136
Skewness	-0.062	-0.062	-0.292	-0.254	-0.070	-0.082	-0.342	-0.200
Excess Kurtosis	0.178	0.498	0.203	0.417	0.686	0.763	0.719	0.795
X-11 Filter								
Mean	0.017	0.021	-0.054	-0.012	0.019	0.000	-0.058	-0.019
Variance	1.240	2.260	1.220	2.244	5.876	3.491	5.762	3.460
Skewness	-0.022	-0.004	-0.032	-0.016	-0.029	-0.045	-0.040	-0.050
Excess Kurtosis	-0.092	0.142	-0.123	0.126	0.089	0.409	0.090	0.418
Henderson Filter								
Mean	0.018	0.007	-0.199	-0.052	0.022	0.000	-0.168	-0.034
Variance	2.117	2.454	2.040	2.411	6.754	3.593	6.440	3.522
Skewness	-0.054	-0.055	-0.080	-0.077	-0.031	-0.052	-0.068	-0.059
Excess Kurtosis	-0.028	0.140	-0.058	0.118	0.140	0.366	0.138	0.385

Table 2: Power of Tests for Cointegration (v_t is white noise)

Filter and Lag	2-sided				1-sided			
	ADF			PP	ADF			PP
	AIC	SLC	Power	Power	AIC	SLC	Power	Power
MA[4]								
0	0.7	1.1	34.5		**19.8**	**24.6**	48.2	
1	1.0	1.1	56.3	50.4	12.3	10.3	65.3	64.3
2	1.2	0.4	71.5	58.9	9.4	6.6	68.6	70.0
3	2.1	5.4	86.6	64.3	9.1	10.6	70.5	70.6
4	**23.6**	**26.1**	8.2	47.7	14.9	17.5	15.6	58.5
5	11.1	8.0	13.0	36.8	10.8	8.3	18.0	49.3
6	6.2	5.6	18.4	29.1	5.9	4.6	15.4	41.7
7	12.2	14.9	27.2	25.0	5.6	4.9	16.1	39.4
8	18.0	21.9	2.8	22.7	4.4	4.1	5.9	36.2
9	13.0	10.1	4.3	20.9	4.1	4.3	5.9	34.3
10	10.9	5.4	5.2	20.1	3.7	4.2	3.8	32.0
Simple								
0	0.0	0.0	26.3		**35.0**	31.7	63.3	
1	0.0	0.0	3.2	24.0	6.5	1.5	29.1	64.5
2	0.0	0.0	3.3	24.5	2.7	1.0	11.7	65.7
3	5.6	7.2	86.0	39.2	21.9	**33.7**	38.1	70.8
4	3.9	4.0	43.1	38.8	7.6	3.8	16.0	69.4
5	0.8	0.5	14.6	37.8	8.7	7.0	15.8	69.2
6	6.9	12.6	0.6	36.3	4.9	4.8	13.4	69.3
7	**39.6**	**47.5**	11.2	30.9	2.9	3.5	8.7	67.0
8	8.5	3.1	7.2	27.7	3.5	3.9	5.6	64.3
9	16.1	13.5	11.6	26.3	2.3	4.2	3.3	62.0
10	18.6	11.6	3.4	25.4	4.0	4.9	3.3	60.1
X-11								
0	**22.2**	10.4	100.0		**24.3**	13.7	100.0	
1	2.8	0.4	99.8	100.0	3.4	0.4	100.0	100.0
2	2.0	1.1	86.3	100.0	2.2	1.4	87.3	100.0
3	19.4	22.5	94.5	100.0	21.1	23.3	94.2	100.0
4	7.7	4.8	58.6	100.0	7.0	5.1	58.4	100.0
5	2.8	1.0	32.0	100.0	3.1	0.9	32.9	100.0
6	2.6	4.0	13.9	100.0	2.8	3.5	14.7	100.0
7	18.4	**39.8**	38.6	100.0	17.4	**37.4**	37.4	100.0
8	10.6	8.6	11.3	100.0	8.5	7.7	11.5	100.0
9	5.6	2.5	4.9	100.0	5.7	2.3	5.5	100.0
10	5.9	4.9	2.1	100.0	4.5	4.3	2.8	100.0
Henderson								
0	0.0	0.0	95.6		0.8	1.1	98.0	
1	2.9	3.8	99.9	99.5	**26.0**	**35.5**	99.8	99.9
2	8.8	9.2	53.1	99.1	21.2	14.3	79.2	99.7
3	**25.5**	**21.2**	80.0	97.6	12.7	7.7	66.6	99.3
4	7.7	3.9	49.4	95.8	9.7	9.7	59.9	98.5
5	5.1	4.8	21.4	90.9	5.6	4.7	24.6	95.7
6	10.9	18.0	37.3	87.4	8.4	9.7	27.5	93.6
7	7.8	9.7	6.2	84.3	4.9	4.2	12.7	91.9
8	14.1	19.6	16.2	81.1	4.3	4.2	9.4	90.1
9	9.3	4.5	5.6	78.9	4.0	5.6	8.2	88.5
10	7.9	5.3	4.8	77.7	2.4	3.3	4.7	87.5

Table 3: Power of Tests for Cointegration (v_t is SARSMA(0,1,1,0))

Filter and Lag	2-sided ADF AIC	2-sided ADF SLC	2-sided ADF Power	2-sided PP Power	1-sided ADF AIC	1-sided ADF SLC	1-sided ADF Power	1-sided PP Power
MA[4]								
0	0.0	0.0	0.2		7.6	11.7	2.3	
1	19.9	11.3	44.7	0.7	**40.3**	**41.6**	28.3	4.1
2	4.9	1.2	36.6	1.1	17.7	7.9	30.2	5.4
3	1.7	0.6	24.0	1.2	6.5	2.8	16.9	4.6
4	6.0	8.5	2.4	0.9	4.7	3.0	10.7	3.2
5	**21.4**	26.5	18.5	0.7	7.3	10.1	14.1	2.6
6	6.1	2.5	13.7	0.6	3.9	4.9	11.0	2.2
7	3.9	2.1	8.0	0.5	3.5	4.1	8.9	2.0
8	6.2	10.3	1.5	0.4	1.8	2.9	4.7	1.8
9	19.7	**31.5**	6.6	0.4	3.4	6.9	4.9	1.9
10	10.2	5.5	4.9	0.4	3.3	4.1	3.4	1.6
Simple								
0	0.0	0.0	0.4		**25.3**	**30.0**	3.3	
1	0.0	0.0	9.0	0.4	16.3	12.5	5.5	4.4
2	0.0	0.0	34.7	0.6	11.6	9.0	9.6	4.3
3	1.0	1.8	78.4	0.8	12.7	13.3	18.6	4.3
4	15.3	14.1	7.4	0.8	9.9	8.1	15.3	4.3
5	3.1	1.1	2.1	0.8	5.6	6.2	12.8	4.6
6	1.6	1.1	1.1	0.8	4.6	3.1	10.9	4.3
7	**37.2**	**55.2**	14.3	0.7	4.3	4.2	6.9	4.2
8	13.2	4.5	4.8	0.6	2.1	2.4	4.4	3.8
9	16.3	15.9	10.0	0.6	3.3	6.4	3.6	3.6
10	12.3	6.3	3.5	0.6	4.3	4.8	2.7	3.4
X-11								
0	**35.5**	23.0	61.7		**43.4**	**31.4**	63.5	
1	7.6	1.4	45.3	66.6	9.5	2.0	45.2	68.8
2	3.6	0.8	27.6	67.5	3.4	1.0	27.6	69.0
3	6.3	4.7	25.8	68.0	5.6	4.7	23.9	69.9
4	2.4	2.1	6.4	66.0	2.4	2.4	6.9	67.7
5	2.6	4.7	9.6	66.2	2.8	5.3	9.9	68.2
6	2.6	3.7	13.2	67.2	2.7	4.6	12.6	68.7
7	8.4	22.5	25.4	66.4	7.6	20.6	23.4	68.4
8	13.4	**23.3**	2.8	61.9	9.1	16.8	3.4	65.1
9	11.0	9.8	4.3	60.0	8.3	7.1	4.1	62.3
10	6.6	4.0	4.0	58.8	5.2	4.1	3.9	60.4
Henderson								
0	0.0	0.0	10.2		2.1	5.3	19.5	
1	0.0	0.0	87.8	31.9	15.1	18.3	75.5	37.1
2	1.1	1.7	1.9	25.7	**20.5**	16.4	13.8	31.9
3	19.6	17.2	37.0	14.3	8.4	6.2	11.2	24.0
4	5.0	3.2	16.0	11.9	20.3	**21.8**	24.6	20.9
5	4.8	3.8	7.7	12.2	5.4	4.1	11.8	20.9
6	12.2	21.2	23.2	9.7	8.6	8.9	12.0	19.1
7	12.5	14.2	2.8	8.1	7.3	5.9	9.2	16.3
8	**21.0**	**25.6**	10.7	6.6	5.3	4.3	4.9	15.1
9	12.0	6.7	4.1	6.5	3.9	5.4	5.9	13.9
10	11.8	6.4	2.9	6.0	3.1	3.4	3.6	12.8

Table 4
Dickey and Fuller Unit Root Tests

Variable	Lags of Dep. Var.	Model	LM[4]	t Statistic Ho: $\gamma_2=0$	Φ_3 Statistic Ho: $\gamma_1=\gamma_2=0$	Φ_2 Statistic Ho: $\gamma_0=\gamma_1=\gamma_2=0$	t Statistic Ho: $\beta_1=0$	Φ_1 Statistic Ho: $\beta_0=\beta_1=0$
LRM1	1	A	$F_{4,52}$ 0.632	-1.776	2.189	2.180		
LRM1	1	B	$F_{4,53}$ 0.656				-0.013	1.020
LGDP	3	A	$F_{4,48}$ 1.108	-1.440	1.078	**11.988		
LR	1	A	$F_{4,55}$ 0.781	-3.070	5.648	3.766		
LR	1	B	$F_{4,56}$ 0.691				-2.750	3.782
LRM1A	5	A	$F_{4,46}$ 0.564	-2.765	5.260	3.961		
LRM1A	5	B	$F_{4,47}$ 0.207				0.186	0.591
LGDPA	5	A	$F_{4,46}$ 0.972	-2.099	3.191	*5.311		
LRA	4	A	$F_{4,48}$ 0.697	-2.106	4.666	3.153		
LRA	4	B	$F_{4,49}$ 0.686				-1.556	1.269

MODEL A: $\Delta y_t = \gamma_0 + \gamma_1 t + \gamma_2 y_{t-1}$ + lags of the dependent variable
MODEL B: $\Delta y_t = \beta_0 + \beta_1 y_{t-1}$ + lags of the dependent variable

* Indicates that the null hypothesis is rejected at the 5% significance level, but not at the 1%.
** Indicates that the null hypothesis is rejected at the 1% significance level.
The critical values for the t statistics are reported in MacKinnon (1991).
The critical values for the Φ_1, Φ_2 and Φ_3 statistics are reported in Dickey and Fuller (1981).

Table 5
Cointegration Analysis for pairs of Adjusted and Unadjusted series

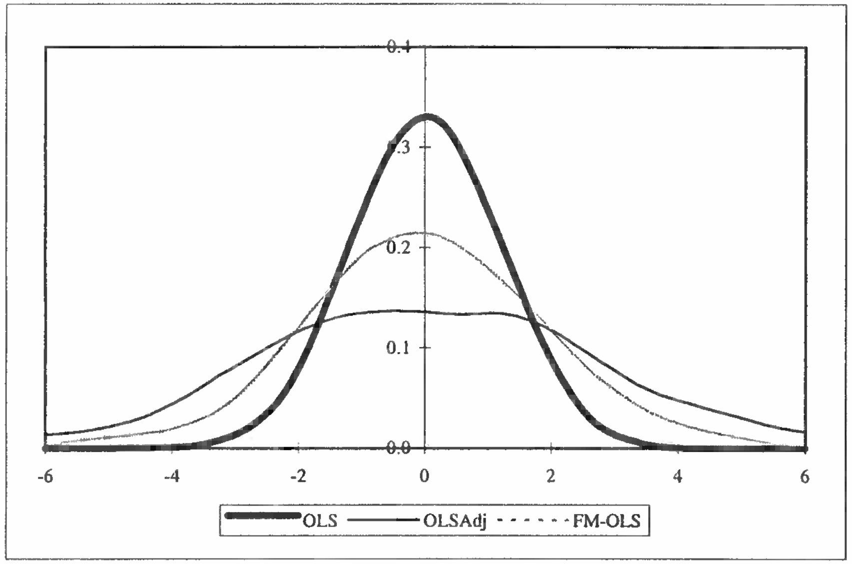
	VAR Model 1		VAR Model 2		VAR Model 3	
	LRM1	LRM1A	LGDP	LGDPA	LR	LRA
LM [4]	0.495	*2.740	*3.375	*3.490	**6.018	**8.851
ARCH [4] [1/]	1.544	1.868	1.381	0.370	**4.958	**4.640
Normality [2/]	0.363	1.900	0.034	1.867	**10.287	*8.245
Heteroscedasticity [3/]	0.535	0.425	3.379	1.368	*2.598	**3.757
Maximal Eigenvalue Test [4/]						
Null Hypothesis	r = 0	r <= 1	r = 0	r <= 1	r = 0	r <= 1
Alternative Hypothesis	r = 1	r = 2	r = 1	r = 2	r = 1	r = 2
Statistic	**63.850	0.043	**71.120	0.042	**89.190	*6.043
Trace Test [4/]						
Null Hypothesis	r = 0	r <= 1	r = 0	r <= 1	r = 0	r <= 1
Alternative Hypothesis	r >= 1	r = 2	r >= 1	r = 2	r >= 1	r = 2
Statistic	**63.900	0.043	**71.160	0.042	**95.240	*6.043
β' Eigenvectors	1.000	-1.002	1.000	-1.000	1.000	-0.979
(Standarised)	2.550	1.000	-0.572	1.000	0.225	1.000

* Indicates that the null hypothesis is rejected at the 5% significance level, but not at the 1% significance level.
** Indicates that the null hypothesis is rejected at the 1% significance level.
r denotes the number of cointegrating vectors.

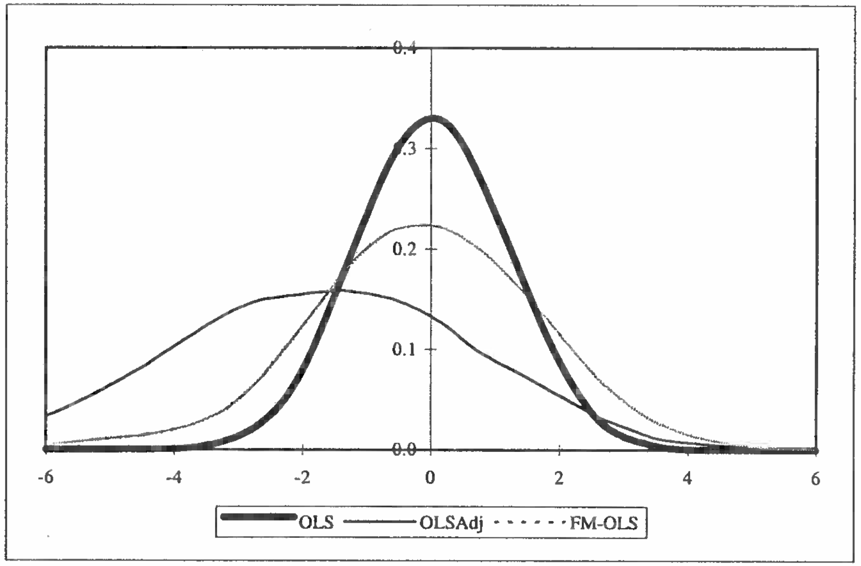
[1/] ARCH[4] stands for Engle's LM[4] test for AutoRegressive Conditional Heteroscedasticity (F version).
[2/] Shenton and Bowman test (F version).
[3/] White's test based on the regression of squared residuals on original regressors and all their squares (F version).
[4/] The critical values for both the maximal eigenvalue and trace tests are reported in Osterwald-Lenum (1992).

Figure 1: Distribution of t-ratios
Vt is White Noise

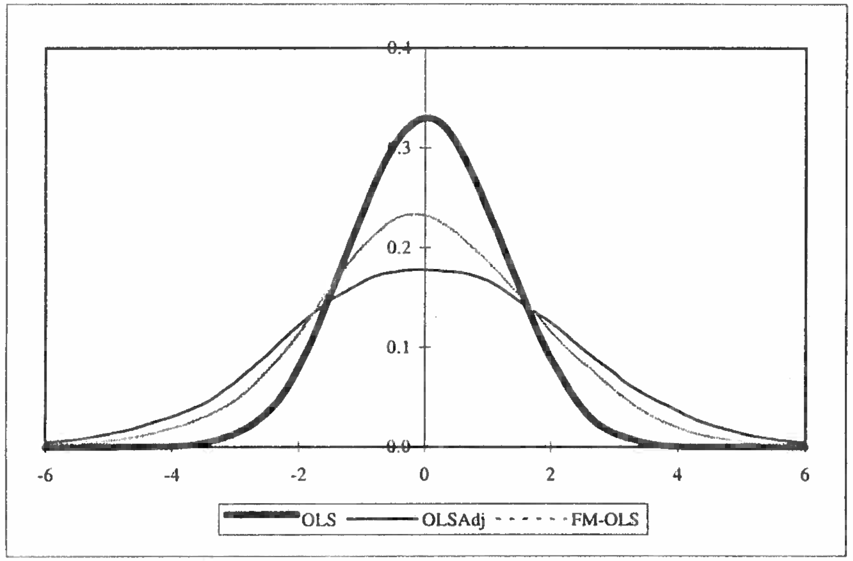
Simple Filter (2-sided)



Simple Filter (1-sided)



MA[4] Filter (2-sided)



MA[4] Filter (1-sided)

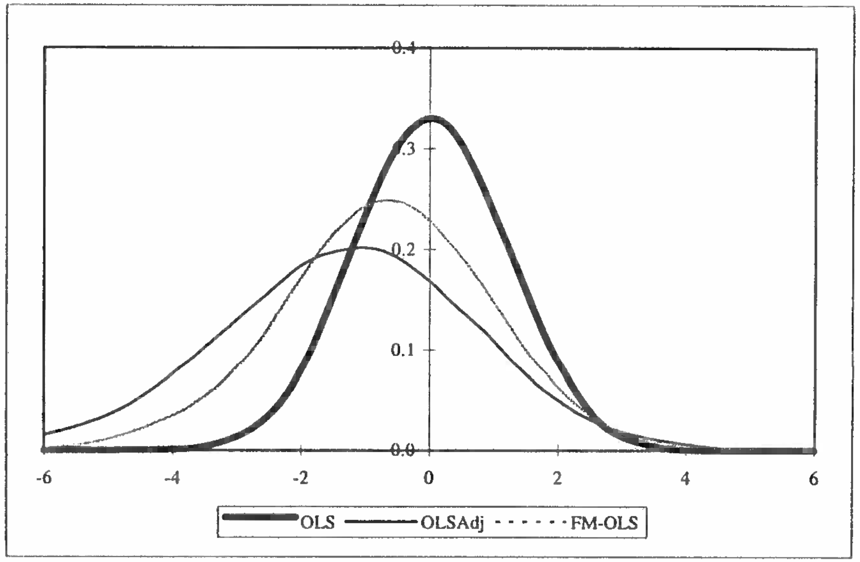
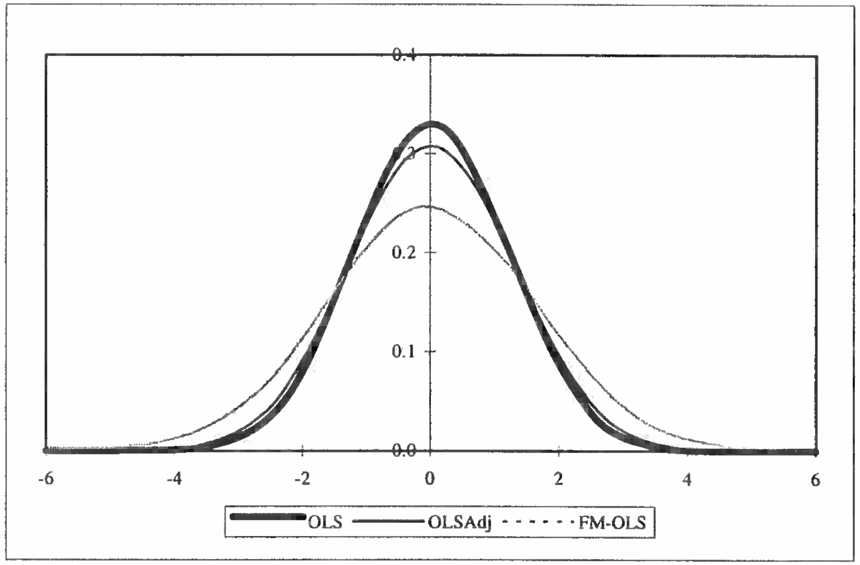
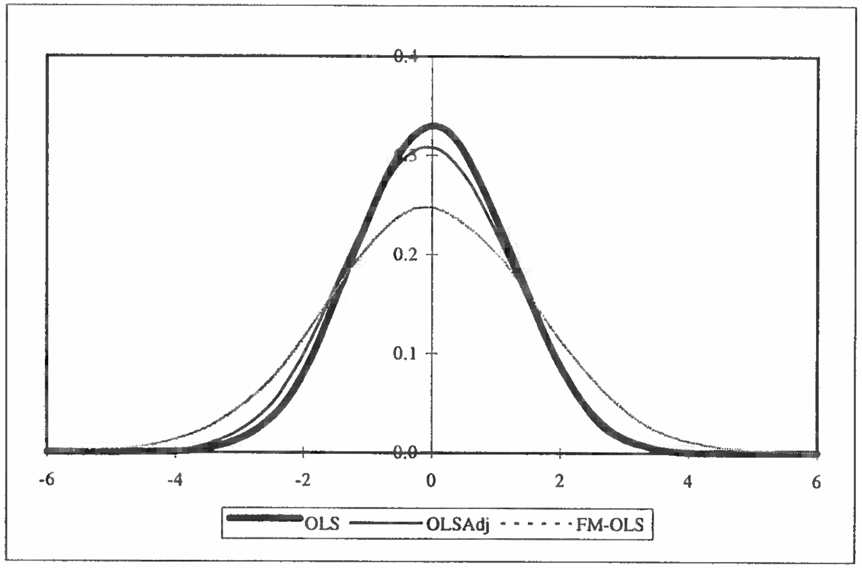


Figure 1 (Cont.): Distribution of t-ratios
Vt is White Noise

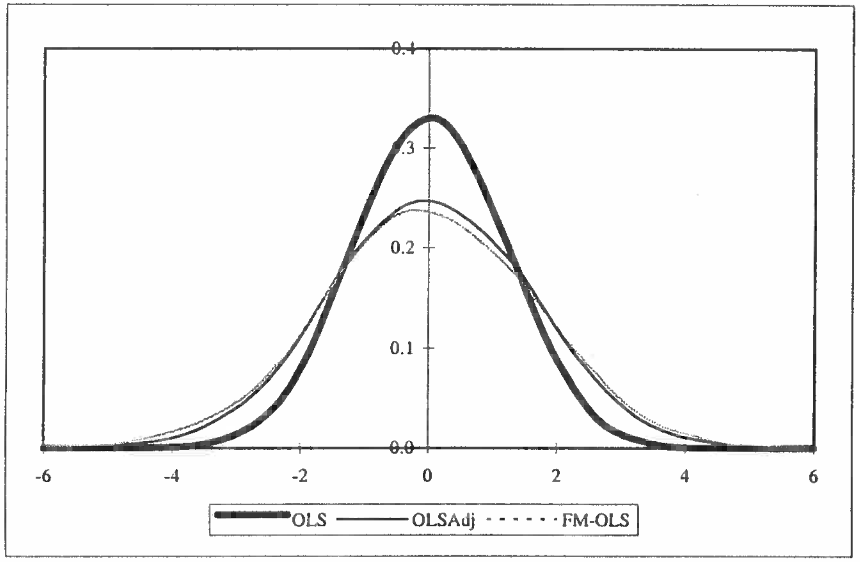
X-11 Filter (2-sided)



X-11 Filter (1-sided)



Henderson Filter (2-sided)



Henderson Filter (1-sided)

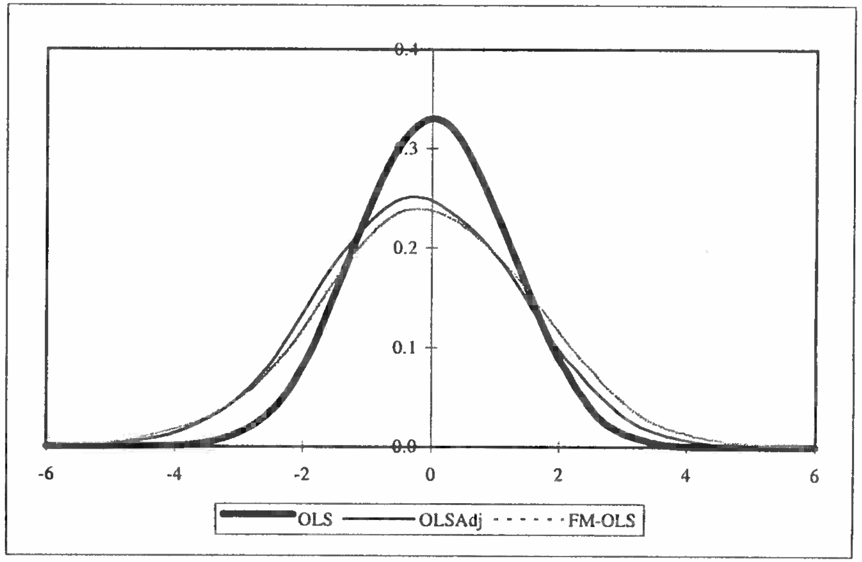
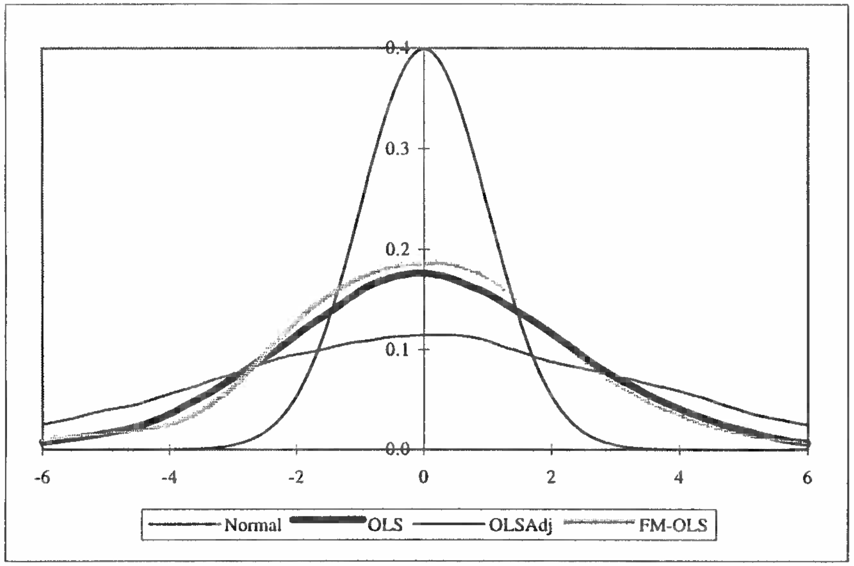
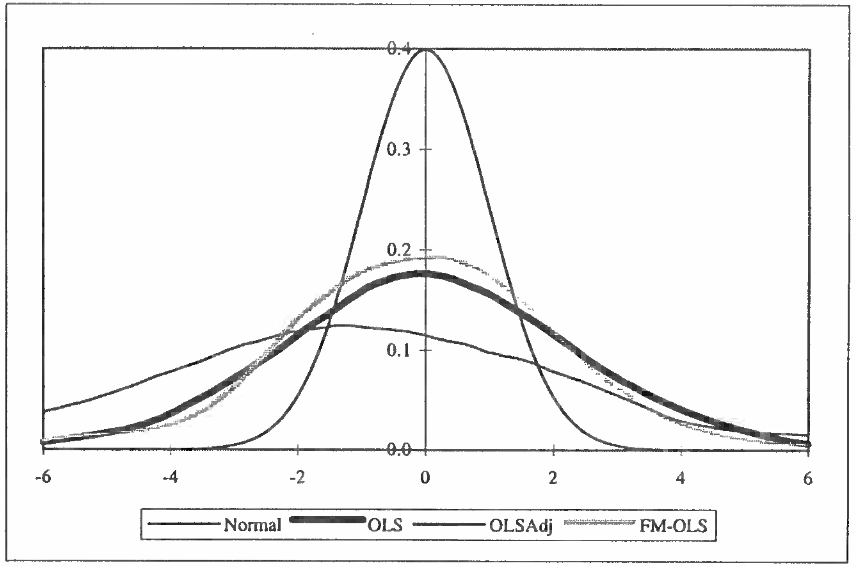


Figure 2: Distribution of t-ratios
V_t is SARSMA(0,1,1,0)

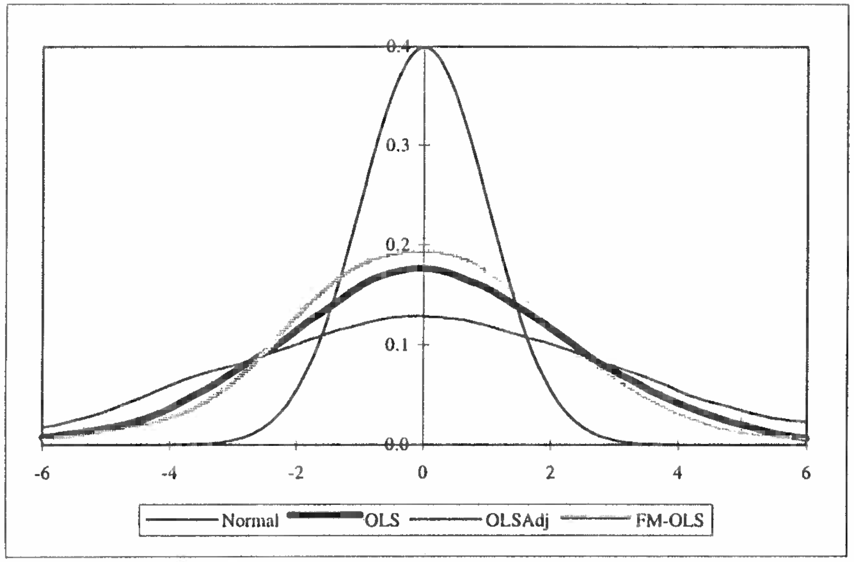
Simple Filter (2-sided)



Simple Filter (1-sided)



MA[4] Filter (2-sided)



MA[4] Filter (1-sided)

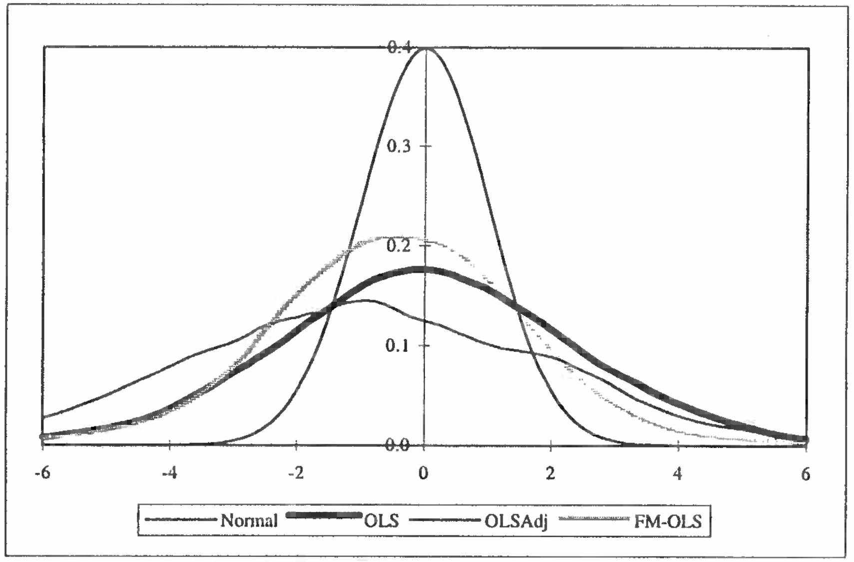
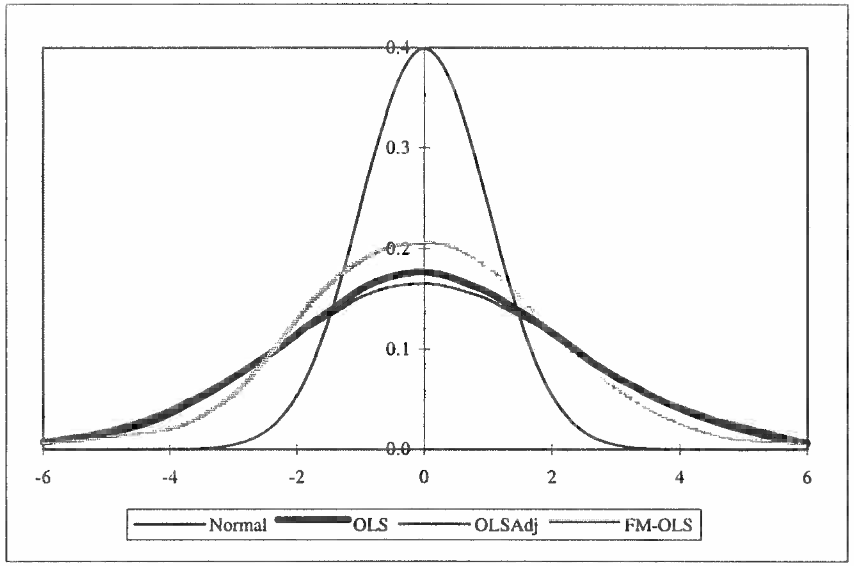
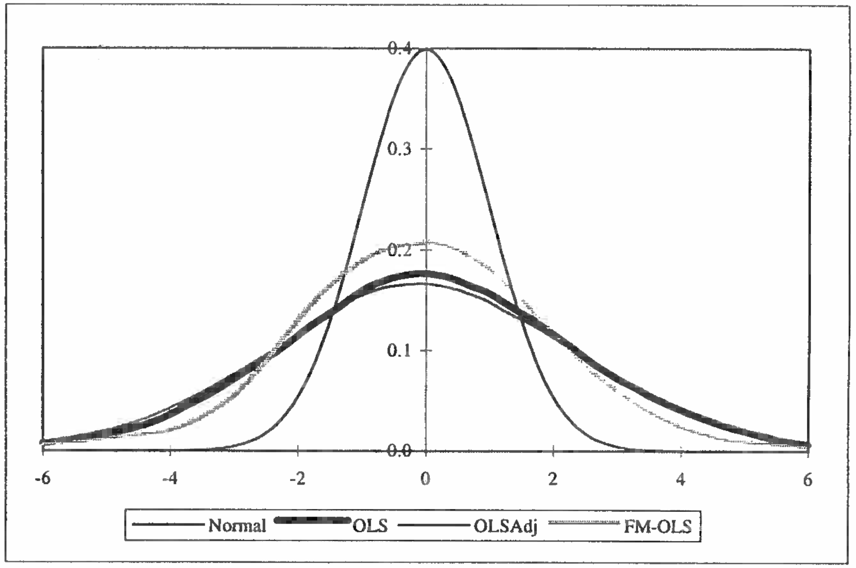


Figure 2 (Cont.): Distribution of t-ratios
Vt is SARSMA(0,1,1,0)

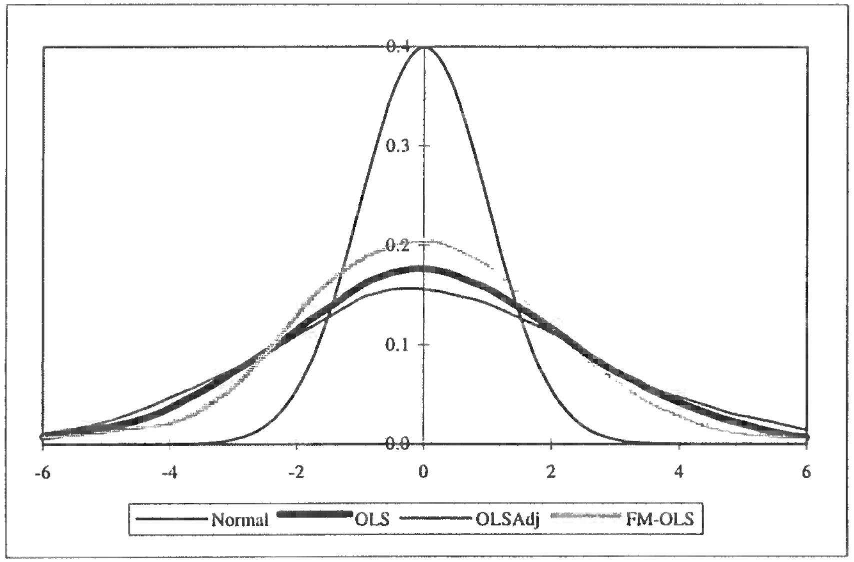
X-11 Filter (2-sided)



X-11 Filter (1-sided)



Henderson Filter (2-sided)



Henderson Filter (1-sided)

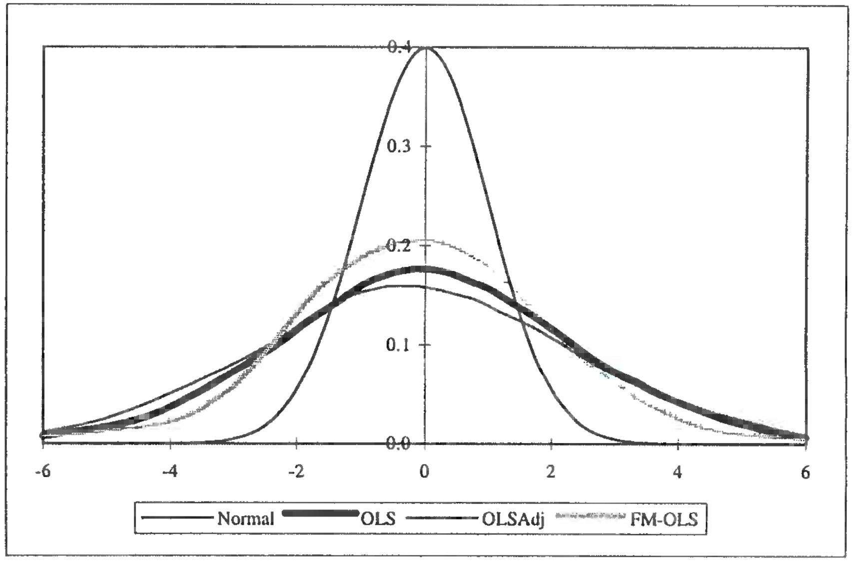
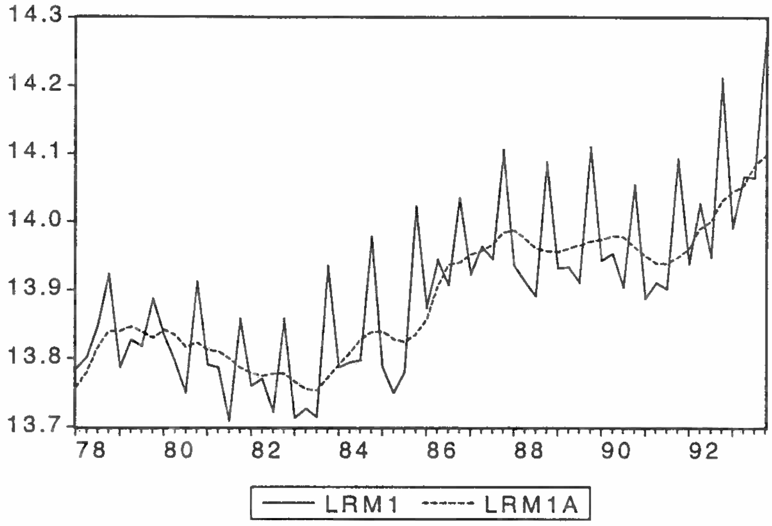
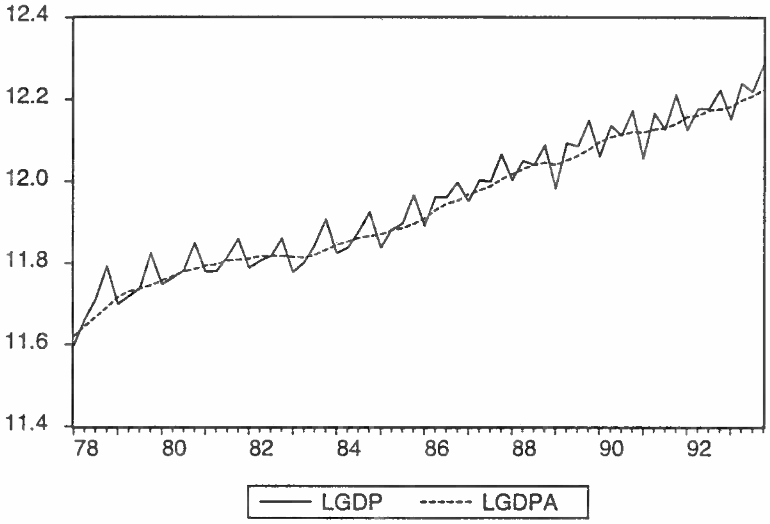
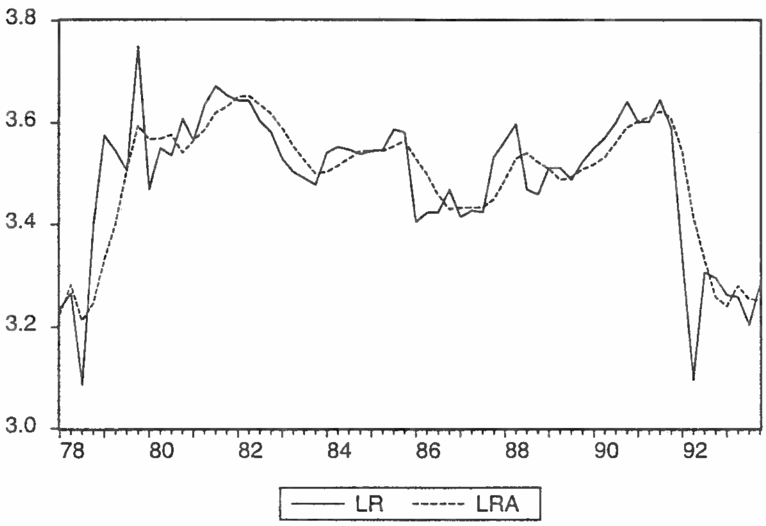


Figure 3


14.3
14.2
14.1
14.0
13.9
13.8
13.7
78
80
82
84
86
88
90
92
LRM1
LRM1A


12.4
12.2
12.0
11.8
11.6
11.4
78
80
82
84
86
88
90
92
LGDP
LGDPA


3.8
3.6
3.4
3.2
3.0
78
80
82
84
86
88
90
92
LR
LRA

References

Banerjee, A., Dolado, J., Galbraith, J. and Hendry, D. (1993), **Co-Integration, Error-Correction, and the Econometric Analysis of Non-Stationary Data**. Oxford University Press. Oxford.

Campbell, J. and Perron, P. (1991), "Pitfalls and opportunities: what macroeconomists should know about unit roots". **NBER Economics Annual 1991** Blanchard, O. and Fischer, S. (eds.). MIT Press.

Carrasquilla, A. and Galindo A. (1994), "El comportamiento monetario en Colombia: 1980-1993. Una hipótesis cambiaria". **Coyuntura Económica** 24 (No.1), 135-42.

Carrasquilla, A. and Rentería, C. (1990). "¿Es inestable la demanda por dinero en Colombia?" **Ensayos Sobre Política Económica** 17, 21-37.

Clavijo, S. (1987), "Hacia una caracterización del comportamiento de la velocidad de circulación del dinero: El caso Colombiano 1959-1986". **Ensayos Sobre Política Económica** 12, 59-79.

Clavijo, S. (1988), "Comparación de demandas reales por diferentes agregados monetarios. Política Monetaria". **Revista del Banco de la República** 61 (No.730), 14-9.

Cubillos, R. and Valderrama, F. (1993), "Estimación del PIB trimestral según los componentes del gasto". **Archivos de Macroeconomía Documento 13**. Unidad de Análisis Macroeconómico. Departamento Nacional de Planeación. República de Colombia.

Davidson, R. and MacKinnon, J. (1993), **Estimation and Inference in Econometrics**. Oxford University Press. Oxford.

Dickey, D., Bell. W. and Miller, R. (1986), "Unit roots in time series models". **American Statistician** 40, 12-26.

Dickey, D. and Fuller, W. (1979), "Distribution of the estimators for autoregressive time series with a unit root". **Journal of the American Statistical Association** 74, 427-31.

Dickey, D. and Fuller, W. (1981), "Likelihood ratio statistics for autoregressive time series with a unit root". **Econometrica** 49, 1057-72.

Dickey, D., Hasza, D. and Fuller, W. (1984), "Testing for a unit root in seasonal time series". **Journal of the American Statistical Association** 79, 355-67.

Engle, R. and Granger, C. (1987), "Co-Integration and error correction: Representation, estimation, and testing". **Econometrica** 55, 251-76.

Engle, R., Granger, C., Hylleberg, S. and Lee, H. (1993), "Seasonal co-integration: The Japanese consumption function". **Journal of Econometrics** 55, 275-98.

Ericsson, N, and Hendry, D. and Tran, H. (1994), "Cointegration, seasonality, encompassing, and the demand for money in the UK". In C. Hargreaves (ed.), **Nonstationary Time Series Analysis and Cointegration**. Oxford University Press. Oxford.

Fuller, W. (1976), **Introduction to Statistical Time Series**. John Wiley and Sons, New York.

Ghysels, E. (1990), "Unit root tests and the statistical pitfalls of seasonal adjustment: The case of U.S post war real GNP". **Journal of Business and Economic Statistics** 8, 145-152.

Ghysels, E. and Perron, P. (1993), "The effects of seasonal adjustment filters on tests for a unit root". **Journal of Econometrics** 55, 57-98.

Goldfeld, S. and Sichel, D. (1990), "The demand for money". In B. Friedman and F. Hahn (eds.), **Handbook of Monetary Economics**. Vol 1. North-Holland. Amsterdam.

Hansen, B. and Phillips P. (1990), "Estimation and inference in models of cointegration: A simulation study". In T. Fomby and G. Rhodes (eds.) **Advances in Econometrics**. Vol 8. JAI Press. Greenwich, Conn.

Hendry, D. (1995), **Dynamic Econometrics**. Oxford University Press. Oxford.

Hendry, D. and Ericsson, N. (1991), "Modelling the demand for narrow money in the United Kingdom and the United States". **European Economic Review** 35, 833-81.

Herrera, S. and Julio, J. (1993), "La demanda de dinero en el corto y largo plazo en Colombia". **Coyuntura Económica** 23 (No.1), 91-107.

Hylleberg, S., Engle, R., Granger, C. and Yoo, B. (1990), "Seasonal integration and cointegration". **Journal of Econometrics** 99, 215-38.

Johansen, S. (1988), "Statistical analysis of cointegration vectors". **Journal of Economic Dynamics and Control** 12, 231-54.

Johansen, S. and Juselius, K. (1990), "Maximum likelihood estimation and inference on cointegration - With applications to the demand for money". **Oxford Bulletin of Economics and Statistics** 52, 169-210.

Laroque, G. (1977), "Analyse d'une méthode de desaisonnalisation: Le programme X-11 du U.S Bureau of the Census version trimestrielle". **Annales de l'INSEE** 88, 105-27.

Lora, E. (1990), "La velocidad de circulación y la demanda de dinero en el corto y en largo plazo en Colombia". **Ensayos Sobre Política Económica** 18, 193-219.

MacKinnon, J. (1991), "Critical values for co-integration Tests". In R. Engle and C. Granger (eds.), **Long-Run Economic Relationships: Readings in Cointegration**. Oxford University Press. Oxford.

Mankiw, G. and Summers, L. (1986), "Money demand and the effects of fiscal policies". **Journal of Money, Credit, and Banking** 18, 415-29.

Misas, M. Oliveros, H. and Uribe, J. (1994), "Especificación y estabilidad de la demanda por dinero en Colombia". **Ensayos Sobre Política Económica** 25, 97-120.

Misas, M. and Suescún, R. (1993), "Funciones de demanda de dinero y el comportamiento estacional del mercado monetario". **Ensayos Sobre Política Económica** 23, 55-79.

Osterwald-Lenum, M. (1992), "A note with quantiles of the asymptotic distribution of the ML cointegration rank tests statistics". **Oxford Bulletin of Economics and Statistics** 54, 461-72.

Perron, P. (1988), "Trends and random walks in macroeconomic time series". **Journal of Economics Dynamics and Control** 12, 297-332.

Phillips, P. (1987), "Time series regression with a unit root". **Econometrica** 55, 277-301.

Phillips, P. and Hansen, B. (1990), "Statistical inference in instrumental variables regression with I(1) processes". **Review of Economic Studies** 57, 99-125.

Phillips, P. and Perron, P. (1988), "Testing for a unit root in time series regression". **Biometrika** 75, 335-46.

Schwert, G. (1989), "Tests for unit roots: A Monte Carlo investigation". **Journal of Business and Economic Statistics** 7, 147-159.

Steiner, R. (1988), "La demanda por medios de pago, Efectivo y depósitos en cuenta corriente: 1967-1986". **Ensayos Sobre Política Económica** 13, 69-85.

Wallis, K. (1974), "Seasonal adjustment and relations between variables". **Journal of the American Statistical Association** 69, 18-31.