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Long run equilibrium estimation and inference: a non-parametric application

V.B. Hall *

R.G. Trevor *

* Macarthy Professor of Economics
The Economics Group
Faculty of Commerce and Administration
Victoria University of Wellington

* Associate Professor
Australian Graduate School of Management

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V.B. Hall
Macarthy Professor of Economics
Victoria University of Wellington

R.G. Trevor
Associate Professor
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ABSTRACT

Phillips (1988a) has demonstrated that the long run parameters of a continuous time error correction model (ECM) involving non–stationary variables can be estimated from a corresponding discrete time ECM. He suggests Hannan efficient and band spectral frequency domain procedures for estimation and inference, anticipating they would provide significant advantages over the parametric methods traditionally used for continuous time models. A further advantage of Phillips' proposed methodology is that conventional asymptotic chi–squared hypothesis testing can be carried out.

This paper provides an early successful application of that methodology, using Australian consumption and income data. The spectral regression estimates are relatively straight forward to compute, with only a few iterations being required. The spectral estimates are not sensitive to alternative initial estimates. The application also highlights the potential importance of non–parametric estimators. Empirically, the long run consumption function estimates obtained are sufficiently realistic for it to be worthwhile exploring conditional short run dynamic relations and other macroeconomic data sets. Our hypothesis testing procedures are consistent across the aggregate and disaggregated data sets used, and between the unit root and cointegration stages of the investigation. A surprising result is that the null of no cointegration between aggregate real consumption and household disposable income cannot be rejected.

Keywords: Long run equilibria, Cointegration, Unit roots, Regression with non–stationary variables, Spectral regression, Continuous time, Australian consumption

LONG RUN EQUILIBRIUM ESTIMATION AND INFERENCE:

A Non–Parametric Application

V.B. Hall and R.G. Trevor*

1. Introduction

Phillips (1988a) has demonstrated that the long run parameters of a continuous time error correction model (ECM) involving non–stationary variables can be estimated from a corresponding discrete time ECM. He derives theoretical results for a first order stochastic differential equation system, driven by quite general stationary errors. The vector of variables is integrated of order one (an I(1) process), with the multiple long run relationships being given by the cointegrating vectors. This theoretical work is an extension of Phillips (1988c) results for a discrete time ECM with a single cointegrating relationship.

He suggests frequency domain procedures of the type due to Hannan (1963) for estimation and inference, anticipating they would provide significant computational advantages over methods traditionally used for continuous time models.[1] In particular, he considers the very significant problems associated with temporal aggregation (see, for example, Bergstrom (1984)), the problems of selecting short run dynamics, and the complexities of non–linear estimation would not arise. This is due to the generality afforded by the non–parametric treatment of regression errors in frequency domain procedures.

A further key element of Phillips' paper is that spectral estimates of the cointegrating parameters are asymptotically equivalent to the corresponding maximum likelihood estimates. Moreover, the nuisance parameters introduced into the limiting distributions by the presence of non–stationary processes have

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1 Major contributions to the continuous time literature have recently been reviewed in Phillips (1988a, Section 1) and Bergstrom (1988). The complexities of formulating and estimating empirical macroeconomic models have been illustrated for the United Kingdom, Australia, and New Zealand in Bergstrom and Wymer (1976), Jonson, Moses and Wymer (1977) and Bailey, Hall and Phillips (1987).

only scale effects. It is therefore possible to carry out conventional asymptotic chi-squared hypothesis testing.

In light of the above, the principal aim of this paper is to present some initial estimates and inferences based on Phillips' theoretical results and suggested empirical procedures. The innovative aspects are:

- it provides an early application of this methodology to macroeconomic time series data[2], thereby giving initial evidence on both the potential gains and difficulties relative to traditional methods;

- it extends the Engle and Granger (1987) type scalar cointegration methods to vector cases, in a way which is not conditional on the precise modelling of short run dynamics (as is required, for example, in the maximum likelihood procedure developed by Johansen (1988) and Johansen (1989)); and

- it illustrates the outcome of some simple hypothesis tests on the long run parameter values. This is possible because Wald test statistics involving coefficients on the I(1) regressors are not misleading. It therefore overcomes a major limitation of the Engle–Granger procedure.

More specifically, our application is to a vector of Australian data on household disposable income, and aggregate and disaggregated consumer expenditure. The long run consumer expenditure equations estimated could help to underpin a full continuous time or discrete time macroeconometric model, once satisfactory long term relationships have been developed in other key areas.

We have chosen a restricted vector of Australian data as suitable for this study, as it is not the purpose of this paper either to estimate a "best" long run (or short run) consumption function, or to test alternative forms of underlying consumption theory. Previous Australian studies, such as those undertaken by Freebairn (1976),

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2 During the revision stages of this paper, it was brought to our attention that Corbae (1990) has recently reported empirical results based on the techniques suggested in Phillips (1988c) for a single cointegrating vector ECM. Corbae examines a permanent income hypothesis consumption function, similar to that estimated by Campbell (1987) in the time domain. A principle result from Corbae's Monte Carlo work was the powerful support for "...the bias and efficiency gains from conducting [Phillips (1988c)] systems spectral estimation over [Engle (1974)] single equation estimation" (Corbae (1990, p. 176)).

Williams (1979), Anstie, Gray and Pagan (1983), Johnson (1983), and McKibbin and Richards (1988), have not focussed on long run cointegrating relationships.

Hence, the three stages in our empirical work involve:

- firstly, testing each variable for its order of integration and for the presence of any deterministic trend;
- secondly, testing for the number of cointegrating relationships amongst the variables; and
- thirdly, from the discrete data set, estimating and conducting tests on the coefficients of the appropriate cointegrated system. The two methods used are the Hannan efficient and band spectral estimators suggested by Phillips.

A fourth stage, that of estimating the corresponding short run dynamic equations conditional on these non–parametric estimates of the long run relationships, is left for future work.

From a methodological point of view, we have employed consistent hypothesis testing procedures whenever possible. At the first (unit root) stage, this involves checking to ensure results are consistent for the real, nominal and implicit deflator forms of each consumption and income variable. At the second (cointegration) stage, this means using non–univariate cointegration tests for both aggregate and disaggregated data sets, and relying on unit root test findings with respect to trend and drift.

Relevant aspects of the econometric theory and estimation procedures are the subject of Section 2, empirical results are presented in Section 3, and our concluding comments appear in the final section.

2. Econometric Theory and Estimation Procedures

Following the treatment in Phillips (1988a), let $y(t)$ be an n–vector I(1) process in continuous time and let $\mu(t)$ be an n-vector stationary time series. The vectors $y(t)$ and $\mu(t)$ are partitioned into the n_1 and n_2–subvectors as follows

$$(1) \qquad y(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix} \qquad \mu(t) = \begin{bmatrix} \mu_1(t) \\ \mu_2(t) \end{bmatrix}$$

On the assumption that there are n_1 cointegrating relationships between these n variables (that is, there are n_1 linearly independent linear combinations of the n elements of the y(t) vector which are stationary), the data generating mechanism for y(t) is therefore the cointegrated system

(2) $\quad y_1(t) = By_2(t) + \mu_1(t)$

(3) $\quad Dy_2(t) = \mu_2(t)$

Equation (2) gives the long–run relationship between the variables. This relationship is perturbed by stationary deviations, which may represent short–run (or stationary) dynamics, measurement error and temporal aggregation errors as well as the innovations. Differentiation of equation (2) (in the sense of Phillips (1988a, pp. 3-4)) leads to

$$Dy_1(t) = B\mu_2(t) + D\mu_1(t)$$

which may be combined with equations (2) and (3) to yield

(4) $\quad Dy(t) = -EAy(t) + \omega(t)$

where

$$E = \begin{bmatrix} I \\ 0 \end{bmatrix} \qquad A = [I, -B] \qquad \omega(t) = \begin{bmatrix} \mu_1(t) + B\mu_2(t) + D\mu_1(t) \\ \mu_2(t) \end{bmatrix}$$

and E is an $(n_1+n_2)xn_1$ array and A is $n_1x(n_1+n_2)$.

Equation (4) is a continuous time analogue of a triangular format ECM. In this formulation, the matrix E is known; it is only the B submatrix of the coefficient matrix A which is to be estimated.

Phillips proves that every continuous time ECM of the form of equation (4) generates an exact discrete model that may be written in the discrete time triangular ECM format

(5) $\quad \Delta y_t = -EAy_{t-1} + \varepsilon_t$

where the discrete data are recordings of the instantaneous data at equispaced points in time, and Δ is the difference operator.[3]

The long run equilibrium coefficients B, incorporated in the matrix A, are the same in both the continuous time and discrete time ECM's. There are no identification or aliasing problems. The only requirements on the error processes are stationarity and the existence of a continuous spectral density matrix. In particular, any short–run dynamics are absorbed into these error processes.

Equation (5) could be estimated by maximum likelihood or instrumental variables. Both of these techniques would require a precise formulation of the residual processes. However, given the quite general conditions placed on these processes, a non–parametric treatment of the residuals is appropriate. Hence, spectral regression methods provide a suitable estimation strategy.

Two such estimators are suggested in Phillips (1988a). These are the Hannan efficient and band spectral estimators. Equation (5) may be reduced to

$$(6) \qquad z_t = EBx_t + \varepsilon_t$$

where

$$z_t = \begin{bmatrix} y_{1t} \\ \Delta y_{2t} \end{bmatrix} \qquad x_t = y_{2t-1}$$

Now if β is defined as the column vector containing the stacked rows of B, then the Hannan efficient estimators are

$$(7) \qquad \tilde{\beta} = \left[\frac{1}{2M} \sum_{k=-M+1}^{M} E'F_{\varepsilon\varepsilon}^{-1}\left(\frac{\pi k}{M}\right) E \otimes F_{xx}\left(\frac{-\pi k}{M}\right) \right]^{-1} \left[\frac{1}{2M} \sum_{k=-M+1}^{M} \left\{ E'F_{\varepsilon\varepsilon}^{-1}\left(\frac{\pi k}{M}\right) \otimes I_{n_2} \right\} f_{zx}\left(\frac{\pi k}{M}\right) \right]$$

3 The proposition also has a converse. For every discrete time cointegrated system such as equation (5), there is an underlying continuous system such as equations (2) and (3) which gives rise to it. Phillips (1988b) shows that all that is required for optimal estimation of the long run coefficients is consistent estimation of the long run covariance matrix of the system residuals. Hence, given the estimation technique used here, it matters little for the estimation of the long run parameters whether the underlying dynamics are continuous or discrete. However, everything depends on the estimation procedure used.

$$\text{(8)}\qquad \operatorname{var}(\tilde{\beta}) = \frac{1}{T}\left[\frac{1}{2M}\sum_{k=-M+1}^{M} E'F_{\varepsilon\varepsilon}^{-1}\left(\frac{\pi k}{M}\right)E\otimes F_{xx}\left(\frac{-\pi k}{M}\right)\right]^{-1}$$

In these equations, the F(•) functions denote smoothed periodogram estimates of the respective spectral density matrices, using a rectangular window and a band of width π/M for M integer. Correspondingly, f(•) is the vectorisation of F(•) obtained by stacking the rows of F(•) into a column vector.

This estimator is essentially generalised least squares (GLS) applied in the frequency domain; the 'covariance matrices' of the variables are adjusted for the 'covariance matrix' of the residuals. This is done by averaging over the whole spectrum. The role of the E matrix is simply to pick out the relevant rows and columns of equation (6) which correspond to the long run coefficients in the B matrix.

Asymptotically, the important parts of the GLS weighting scheme are those that incorporate the long run behaviour of the data. Accordingly, band spectral estimators based on spectral estimates at the origin may be used, and can be written as

$$\text{(9)}\qquad \tilde{\beta}_0 = \left[E'F_{\varepsilon\varepsilon}^{-1}(0)E\otimes F_{xx}(0)\right]^{-1}\cdot\left[\left\{E'F_{\varepsilon\varepsilon}^{-1}(0)\otimes I_{n_2}\right\}f_{zx}(0)\right]$$

$$\text{(10)}\qquad \operatorname{var}(\tilde{\beta}_0) = \frac{2M}{T}\left[E'F_{\varepsilon\varepsilon}^{-1}(0)E\otimes F_{xx}(0)\right]^{-1}$$

Phillips (1988a) shows that these estimators are asymptotically equivalent to the maximum likelihood estimator of B in equation (5). They therefore share all the advantages of maximum likelihood, with one major additional advantage. Maximum likelihood requires explicit modeling of the error process in equation (5). In particular the estimates would be conditional on a specific parameterisation of the short run dynamics—a subject on which economic theory is often silent.

The limit distributions of these two spectral regression estimators involve nuisance parameters due to the presence of integrated processes. However, the nuisance parameters involve only scale effects, so conventional asymptotic Wald tests may be constructed.

The null hypothesis $R\beta=r$ may be tested by the statistics

$$\text{(11)} \quad S = (R\tilde{\beta}-r)'[R\text{var}(\tilde{\beta})R']^{-1}(R\tilde{\beta}-r) \quad \text{or} \quad S_0 = (R\tilde{\beta}_0-r)'[R\text{var}(\tilde{\beta}_0)R']^{-1}(R\tilde{\beta}_0-r)$$

corresponding to the two estimators. Each statistic has a χ^2 distribution with rank(R) degrees of freedom.

Three additional issues are of particular importance for the implementation of this approach. These involve: establishing effective procedures for computation of the spectral regressions; determining the order of cointegration; and choosing initial estimates of the residuals for the GLS procedure.

Hannan (1970) provides formulae for spectral regression which are computationally more tractable than equations (7) through (10). For instance, the Hannan efficient estimator in equation (7) may be more conveniently computed by

$$\text{(12)} \quad \tilde{\beta} = \left[\frac{1}{M}\sum_{k=0}^{M}\delta_k\left\{E'u_{\varepsilon\varepsilon}(\bullet)E\otimes c_{xx}(\bullet) - E'v_{\varepsilon\varepsilon}(\bullet)E\otimes q_{xx}(\bullet)\right\}\right]^{-1} \times$$

$$\text{vec}\left[\frac{1}{M}\sum_{k=0}^{M}\delta_k\left\{E'u_{\varepsilon\varepsilon}(\bullet)c_{zx}(\bullet) - E'v_{\varepsilon\varepsilon}(\bullet)q_{zx}(\bullet)\right\}\right]$$

where

$$F(\bullet) = \frac{1}{2}(c(\bullet) - iq(\bullet))$$

$$u = (c + qc^{-1}q)^{-1}$$

$$v = -c^{-1}q(c + qc^{-1}q)^{-1}$$

$$\delta_k = \begin{cases} 1 & k\neq 0,M \\ 0.5 & k=0,M \end{cases}$$

On the issue of the number of cointegrating vectors, Johansen (1988) and Johansen (1989) provide a likelihood ratio test capable of determining the order of cointegration. His method can also provide estimates of, and hypothesis tests on, both long run and short run parameters. A potentially important limitation of his procedure is that the maximum likelihood estimates produced are conditional on the specific parameterisation of the model. For instance, Johansen's theory allows only for VAR–type dynamics. However, in the absence of a well developed non–parametric test for *multiple* cointegrating relationships, in this study we have relied on Johansen's cointegration tests.

Finally, both spectral estimators require an initial estimate of B in order to construct the residual spectral density estimate $F_{\varepsilon\varepsilon}(\bullet)$. This also raises the question of iterating on the estimate of B. Such choices, together with the choice of method to calculate the spectral density matrices, may affect the finite sample performance of the estimators. They will not, however, affect the asymptotic properties of the estimators. For the purposes of this application, it was decided to use both OLS and Johansen estimates as initial values for B, and to examine the implications of multiple iterations.[4]

3. Empirical Results

3.1 Data

It seemed appropriate to commence with estimating some long run relationships between consumption expenditure and income. This was not only because it could reasonably be expected from recent work by Engle and Granger (1987) (and by a number of others) for the United States that such series would be I(1), but also because it is widely believed that long run relationships exist between consumption and income variables. The general long run equations (13) and (14) specified below are consistent with a variety of economic theoretic specifications, including forms of Keynesian and permanent income hypotheses.[5]

Some theoretical models postulate a long run relationship between real permanent income, and real consumption of non–durables and service flows from durables.[6] As no official measures of these variables exist for Australia, household disposable income and consumption expenditure series were used. This choice will not affect

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4 We do not explicitly examine differing methods of constructing the spectral density matrices. Nevertheless, we do control for some of the choices available by using both the Hannan efficient and band spectral estimators.

5 For example, equation (13) is consistent with the long run equilibrium of the continuous time consumption function specified in Bergstrom and Wymer (1976, pp. 269-72).

6 See, for example, Hall (1978), Flavin (1981) and Campbell (1987). Note that the error correction modelling structure we use is consistent both with present value models and with models that postulate adjustment to long run equilibrium. See, for example, Campbell and Shiller (1987) and Campbell and Shiller (1988).

our parameter estimates, given the non-parametric nature of our estimator and provided the measurement errors are stationary.

The fourteen variables we consider are defined in Table 1. Each series consists of 118 quarterly (seasonally adjusted) observations in logarithmic form, from 1959(3) to 1988(4). The constant price series are at average 1984/85 prices.[7]

Table 1
Variable Descriptions

Variable	Description
C	Aggregate real private final consumption expenditure
CHD	Real private consumption expenditure on household durables
CMV	Real private consumption expenditure on motor vehicles
CND	Real private consumption expenditure on non–durables
YHD	Real household disposable income (= YHD$/PC)
C$	Aggregate nominal private final consumption expenditure
CHD$	Nominal private consumption expenditure on household durables
CMV$	Nominal private consumption expenditure on motor vehicles
CND$	Nominal private consumption expenditure on non–durables
YHD$	Nominal household disposable income
PC	Implicit deflator for aggregate private final consumption expenditure
PCHD	Implicit deflator for private consumption expenditure on household durables
PCMV	Implicit deflator for private consumption expenditure on motor vehicles
PCND	Implicit deflator for private consumption expenditure on non–durables

Possible long run relations amongst our variables at the aggregate level would include

(13) $C = \beta_1 YHD$

and its nominal equivalent.

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7 The data are taken from the dX NIF data set supplied by EconData. The non–durables series are the sums of the series for food, rent and other non–durables. The real, nominal and implicit price deflator series were double checked for consistency with each other, as were the aggregate and disaggregated consumption expenditure series. All the econometric calculations were carried out on a microcomputer using the programming facilities of the RATS package.

The corresponding vector form for real disaggregated consumption would be

$$(14)\quad \begin{bmatrix} CHD \\ CMV \\ CND \end{bmatrix} = \begin{bmatrix} \beta_2 \\ \beta_3 \\ \beta_4 \end{bmatrix} [YHD]$$

Two particular advantages of equation (14) for our purposes are that it provides a useful illustration for the Phillips estimation procedures in multivariate form, and allows for the testing of a range of restrictions on the parameter values (e.g., $\beta_1=1$; $\beta_2=\beta_3=\beta_4$; and $\beta_2=\beta_3=\beta_4=1$).

3.2 Unit Root Tests for Stationarity

Testing for the order of integration of individual data series is seldom a straight forward exercise (see, for example, Pagan and Wickens (1989, s. I.2.1)). Broadly speaking, it is known that the tests are sensitive to the presence of deterministic drift or time trends, and to departures from residuals which are independently and identically distributed (iid).

Based on a general equation of the form

$$(15)\quad w_t = \delta + \gamma t + \alpha w_{t-1} + \upsilon_t$$

our procedure was to test each series (and their first and second differences) for a unit root, with and without drift and linear time trends, under a sequence of nested hypotheses. Particular care was taken to ensure our unit root test results were consistent for the real, nominal, and implicit deflator forms of each consumption and income variable, as this kind of consistency check seldom seems to have been reported in previous empirical work.

Many of the tests available in the literature are modifications to the original Dickey–Fuller (Dickey and Fuller (1979) and Dickey and Fuller (1981)) tests, for situations where the residuals are not iid.[8]

However, consistent with the non–parametric approach adopted in this paper, we employed initially the tests as modified by Phillips and Perron (Phillips and Perron (1988) and Perron (1988)). To test a given order of integration, say one unit root

8 These include extensions to adjust for seasonality. See, for example Dickey, Hasza and Fuller (1984), Engle, Granger and Hallman (1989) and Hylleberg, Engle, Granger and Yoo (1990). Because our quarterly data are seasonally adjusted, conventional unit root tests are employed.

versus none, we start by estimating equation (15). First the hypothesis that $\alpha=1$ is tested by the $Z(\alpha)$ and $Z(t_\alpha)$ statistics; it would be rejected if the statistic were more negative than the critical value. If this hypothesis is not rejected, the joint hypothesis that $\alpha=1$ and $\gamma=0$ is tested by the $Z(\Phi_3)$ statistic; it is rejected if it exceeds the critical value. In the event that this hypothesis is not rejected, the joint hypothesis that $\alpha=1$, $\gamma=0$ and $\delta=0$ is tested by the $Z(\Phi_2)$ statistic; it is rejected if it exceeds the critical value. If this hypothesis also is not rejected, equation (15) is re-estimated under the constraint that $\gamma=0$. Based on the constrained estimates, the hypothesis that $\alpha=1$ is again tested by $Z(\alpha)$ and $Z(t_\alpha)$ statistics (with different critical values). If this hypothesis is not rejected, the joint hypothesis that $\alpha=1$ and $\delta=0$ would be tested using the $Z(\Phi_1)$ statistic.

In all cases the hypotheses of two or more unit roots were unambiguously rejected by the Phillips–Perron (PP) tests. Under the conditions of equation (15), empirical results for the single unit root case are therefore presented in Table 2. The lags reflect the number of terms in the Newey and West (1987) variance calculation used in the PP adjustments. At lag zero, the statistics are essentially the unadjusted Dickey–Fuller statistics.

Table 2

Phillips–Perron Unit Root Test Statistics

Test	Lag	C	CHD	CMV	CND	YHD	C$	CHD$	CMV$	CND$	YHD$
α		.9955	.9659	.9423	.9956	.9701	.9652	.9543	.8425	.9674	.9622
$Z(\alpha)$	0	-.47	-3.82	-6.46	-.45	-3.35	-3.99	-5.21	-17.68	-3.74	-4.30
	5	-.67	-7.09	-6.51	-.35	-2.52	-5.12	-7.45	-19.15	-4.78	-4.90
	10	-.43	-7.79	-5.73	-.25	-2.62	-5.90	-8.81	-18.44	-5.50	-5.83
	15	-.28	-7.74	-4.54	-.24	-2.64	-6.33	-9.15	-16.21	-5.94	-6.40
$Z(t_\alpha)$	0	-.25	-1.32	-1.82	-.24	-1.31	-4.12	-2.98	-3.12	-4.31	-2.38
	5	-.33	-1.84	-1.83	-.19	-1.14	-2.86	-2.71	-3.23	-2.84	-2.32
	10	-.23	-1.93	-1.72	-.14	-1.17	-2.70	-2.75	-3.18	-2.66	-2.32
	15	-.15	-1.93	-1.54	-.13	-1.17	-2.67	-2.77	-3.00	-2.62	-2.34
$Z(\Phi_3)$	0	2.68	.87	2.68	2.79	2.13	17.36	6.90	4.80	20.03	4.76
	5	2.45	1.69	2.68	2.95	2.35	6.69	4.68	5.17	6.89	4.10
	10	2.74	1.86	2.63	3.12	2.31	5.41	4.52	4.99	5.44	3.68
	15	2.98	1.85	2.64	3.14	2.31	5.04	4.52	4.43	5.00	3.59
$Z(\Phi_2)$	0	47.59	11.62	2.26	58.09	14.11	307.20	49.82	7.86	383.91	103.92
	5	42.92	7.30	2.26	61.71	18.60	90.99	21.46	7.72	103.19	76.41
	10	48.64	6.89	2.29	65.38	17.93	61.89	16.49	7.78	68.98	54.51
	15	53.19	6.91	2.45	65.85	17.80	52.69	15.67	8.09	57.60	46.54

Critical values are given in Fuller (1976) and Dickey and Fuller (1981). At the 1% level they are -29.50, -3.96, 8.27 and 6.09 for $Z(\alpha)$, $Z(t_\alpha)$, $Z(\Phi_3)$ and $Z(\Phi_2)$ respectively.

Results in Table 2 show that all the series are I(1) with drift (and no time trend), except for the CMV series which is I(1) with no drift. The latter result is confirmed by the statistics derived from the restricted version of equation (15), the point estimate of the root from the constrained model being 0.9556. As a consistency check, tests were conducted on the (log–levels) of the implicit price deflator series. In all cases these were found to be I(1).[9]

Further consistency checks, involving the augmented Dickey–Fuller (ADF), Dickey–Pantula (ADP), and Stock–Watson (SW) tests were then undertaken.[10] These tests are parametric extensions to the original Dickey–Fuller tests. Each of these tests requires an autoregressive (AR) parametric adjustment in order to adjust for serial

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9 For the series PCMV, the outcome was I(1) with a time trend.

10 See Said and Dickey (1984) and Dickey, Bell and Miller (1986); Dickey and Pantula (1987); and Stock and Watson (1988).

dependency in the residuals of equation (15). Following Schwert (1987) we used AR adjustments of length four and twelve.[11]

The ADF and ADP results show our variables to be I(2) in almost all cases for an AR correction of 12, and in about half of the cases for an AR correction of 4. However, there was a marked lack of consistency in the inferences drawn from these tests applied to each set of real, nominal and implicit deflator measures. For example, the ADF tests with an AR correction of 4 suggest that the logs of nominal and real consumption of household durables are I(1), but that the log of the implicit price deflator is I(2). Since these variables are related by a simple identity, at least one of these inferences must be erroneous.[12]

Given this outcome, results from a univariate version of the SW q_f test were then examined. For AR corrections of both 4 and 12, variables were consistently I(1), thereby confirming the outcomes from the PP tests.

It can therefore be said with reasonable confidence that all the real, nominal and implicit deflator variables of interest to us are I(1).[13] For the second stage of our empirical work, this meant that the following groupings of variables were then examined:

- real aggregate consumption C YHD;
- real disaggregated consumption CHD CMV CND YHD;
- nominal aggregate consumption C$ YHD$; and
- nominal disaggregated consumption CHD$ CMV$ CND$ YHD$.

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11 Based on a Monte Carlo analysis, Schwert suggests correcting for an AR of order k, where $k=\text{int}\{4(T/100)^{1/4}\}$ or $k=\text{int}\{12(T/100)^{1/4}\}$, and T is the number of observations.

12 The inconsistency of the inferences from ADF tests on the components of identities between (the logs of) aggregate nominal, real and implicit price deflator data for Australia may be found in other studies also. (See, for example, the results reported in Table 2 of Hargreaves (1990).) This is a puzzling result, and the stochastic properties of the Australian data are worthy of further investigation. Peter Phillips has suggested a possible explanation, based on Phillips and Ouliaris (1990). The ADF test is asymptotically equivalent to the PP $Z(t_\alpha)$ statistic. Both have less power than the $Z(\alpha)$ test, as the rate of divergence under the alternative is greater for $Z(\alpha)$ than the ADF.

13 All further calculations were performed on data in demeaned form.

3.3 Testing for the Number of Cointegrating Vectors

For a long run relationship to exist between a set of variables which are I(1), there must be one or more cointegrating vectors. In the context of our application, failure to find one cointegrating vector for C and YHD (or C$ and YHD$) would mean a simple aggregate long run consumer expenditure equation is not estimable. On the other hand, the finding of one cointegrating vector allows estimation to proceed legitimately. Similarly, establishing the existence of three cointegrating vectors for either the real or nominal disaggregated groups of variables would support the estimation of three equations.

Johansen's (Johansen (1988) and Johansen (1989)) trace and maximum eigenvalue likelihood ratio tests were used to establish the number of cointegrating vectors, and the corresponding estimates of the cointegrating vectors were also used as one set of starting values for the spectral estimation procedure results reported in sub-section 3.4.

As was done in Johansen's empirical work (Johansen and Juselius (1988) and Johansen and Juselius (1990)), we first determined the order of the VAR model for each group of variables, using a likelihood ratio test.[14] For the four cases above, the outcomes were VAR(1), VAR(3), VAR(2) and VAR(3) respectively. In line with our research strategy of conducting the same hypothesis tests consistently across our aggregate and disaggregate data sets, non-univariate cointegration tests were used in the two aggregate cases where there could at most be a single cointegrating vector.

Johansen's tests for the number of cointegrating vectors were applied to each of these VAR models. Initially one uses the trace statistic to test the null hypothesis that there are at most zero cointegrating relationships. Should that be rejected, tests for successively higher orders of cointegration are applied until an acceptance occurs.[15] Maximum eigenvalue tests are used in conjunction with this sequence of trace tests. Each maximum eigenvalue statistic is used to test the null hypothesis that there are P cointegrating vectors against the alternative that there are P+1 cointegrating vectors.

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[14] We considered a maximum of six lags and applied the small sample correction of Sims (1980).

[15] The maximum number of cointegrating relationships within a group of I(1) variables is one less than the number of variables. Should no acceptance be found in the sequence of tests, the inference would be that the variables are I(0). This would call into question the results of earlier unit root tests.

Results are presented in Table 3. Each order of cointegration statistic presented in the table is the value of the trace statistic for the null hypothesis of at most P cointegrating vectors. The difference between the values at P and P+1 gives the value of the maximum eigenvalue statistic for the null hypothesis of P cointegrating vectors.

Table 3
Johansen's Order of Cointegration Statistic

	Aggregate			Disaggregated		Critical Values			
						Trace		Max. Eigenvalue	
P	Real	Nominal	P	Real	Nominal	2.5%	5%	2.5%	5%
-			0	60.08	79.60	50.4	47.2	29.3	27.2
-			1	35.45	32.90	32.3	29.5	23.0	20.8
0	10.21	31.57	2	17.22	13.45	17.3	15.2	15.8	14.0
1	4.68	.02	3	3.65	.05	5.3	4.0	5.3	4.0

Critical values are given in Johansen (1989) and Johansen and Juselius (1990). The statistic tests the hypothesis that there are *at most* P cointegrating vectors.

Conditional on the particular VAR corrections for serial dependence, the outcomes of these tests at the 5 per cent level of significance are[16]:

- there is no evidence against no cointegration between aggregate real consumption and household disposable income;
- for the real disaggregated group of variables, there are three cointegrating vectors;
- aggregate nominal consumption is cointegrated with household disposable income; and
- for the nominal disaggregated group of variables, the evidence is less clear cut. There are either two or three cointegrating vectors. For the maximum eigenvalue statistic of 13.4, the null hypothesis of two cointegrating vectors is narrowly unable to be rejected, the critical value

[16] We followed the convention that tests can only reject or fail to reject null hypotheses. Evidence against a null hypothesis need only be provided by either of the two tests.

being 14.0. However, both test statistics clearly fail to provide evidence against three cointegrating vectors.

Consequently, for *real* consumer expenditure an aggregate equation should not be estimated, but a vector equation including three disaggregated components should be estimated.

In contrast, results for the *nominal* variables suggest that it would be appropriate to estimate the aggregate model. A disaggregated model including either two or three cointegrating vectors could be estimated. We proceeded with three cointegrating vectors.[17]

However, before turning to the spectral estimates and tests of long run coefficients work in sub-section 3.4, it is necessary to comment further on what is perhaps our major surprising result—the finding of no cointegration between aggregate real consumption and household disposable income.[18] There are *two* main puzzles: whether this result is consistent with that for the aggregate nominal variables; and whether it is consistent with economic theoretic notions of a long run relationship between consumption and income.

There would seem at least the following possible explanations:

- the real variables, as measured, are in fact not cointegrated over the sample period;
- despite substantial progress having occurred in recent years, existing tests are still inadequate to cover all situations;
- the long run relationship between consumption and income depends on other non-stationary variables; and
- there are sizeable (non-stationary) measurement errors in the real data set. These could be in the deflators for consumer durables during periods of rapid technological change, and/or in the household disposable income variable during periods of significant inflation.

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[17] Johansen and Juselius (1990), when analysing their Finish data, were faced with a similar situation. They also chose the higher order of cointegration.

[18] The result continues to hold when our aggregate data are expressed in per capita terms. This finding is not inconsistent with the conclusion cautiously expressed in McKibbin and Richards (1988, pp. 11, 25-26).

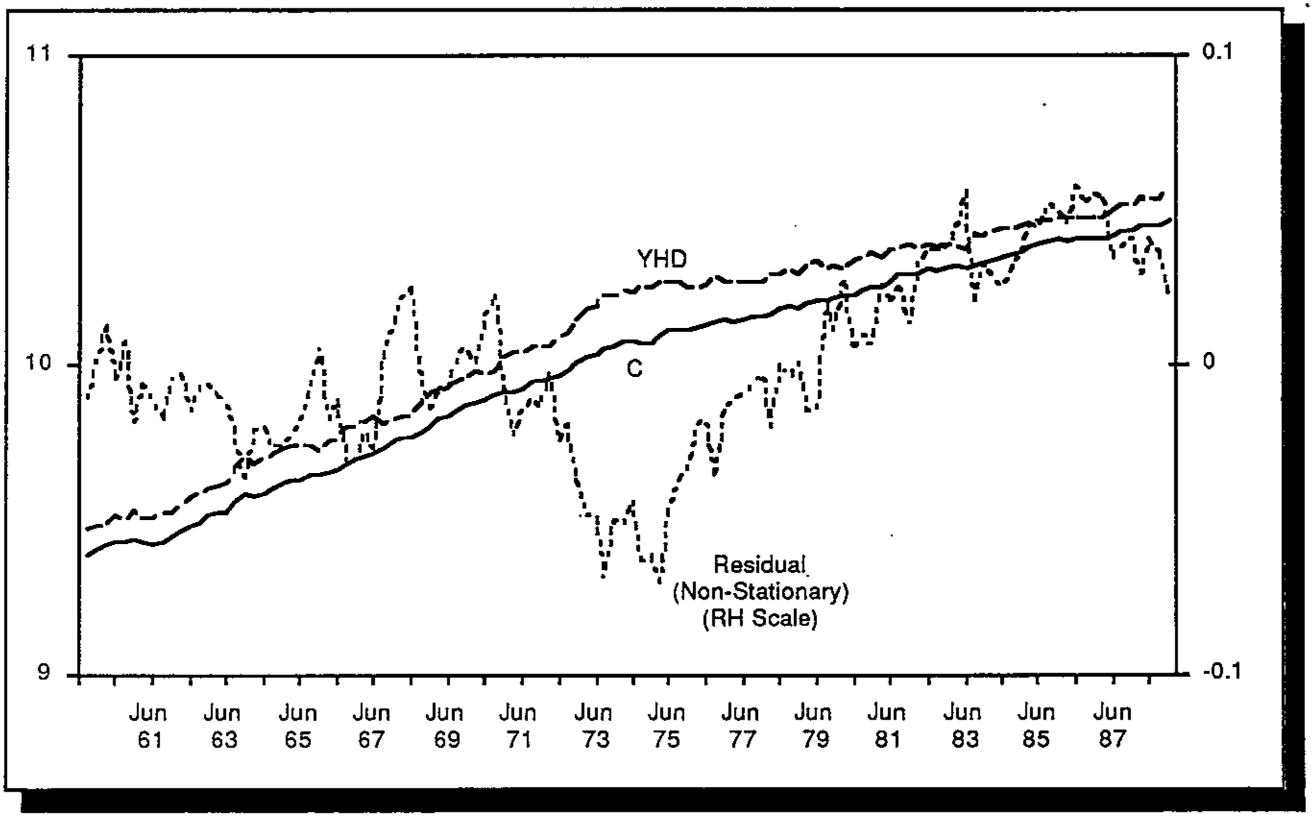
The deflator for durable goods view is based on there having been substantial technological innovation in consumer durables. For example, technological innovations in household durables over our estimation period include: clothes washers and dryers; dish washing machines; microwave ovens; home entertainment centres; video machines and computers; and central heating and air conditioning. There are likely to have been significant changes in the degree of durability of some items. Perhaps more importantly, there are likely to be severe problems in measuring the real expenditures on these goods—the same constant dollar amount buys a much higher quality item today than it did previously. The latter case has been argued in principle and demonstrated empirically by Baily and Gordon in the context of measurement of investment in computers. For example, as expressed in Baily and Gordon (1988, p. 386): *"Goods where technological progress has been rapid have falling relative prices and increasing sales volumes. The use of base–period prices overweights the growth of these dynamic commodities in years following the base year and underweights them in years preceding the base year.* ...*Constant–dollar base–weighted investment series imply that the computer industry disappears as you go back a few years, and it explodes and takes over the total as you go forward in time."*

The income based view of mis–measurement has been argued and illustrated empirically for Australia by Anstie, Gray and Pagan (1983). Real "economic" income is defined by them as that income which may be consumed while leaving real wealth intact. In essence, they argue that the Australian Statistician's definition of household disposable income is inadequate in the face of inflation and that it should be modified by an inflation adjusted wealth measure. That is, measured income needs to be adjusted downwards by the value of the inflation tax on nominal assets. However, our unit root results suggest that the log of the implicit price deflator is I(1), so inflation will be a stationary variable and an unlikely explanation for the lack of cointegration between the real aggregate variables.

Unfortunately, neither of these two sources of mis–measurement are unique to the Australian data. Moreover, any complete explanation of our no cointegration result also needs to resolve the puzzle of the inconsistent aggregate real and nominal outcomes. These outcomes of no cointegration in the real case, and cointegration in the nominal case, would only be consistent if the nominal long run income elasticity is not unity.[19] However, all the estimates of this elasticity presented in Table 4 are unambiguously unity, and cointegration of the real variables is also rejected when a unitary elasticity is imposed.

Our finding in sub–section 3.2 of inconsistent inferences arising from parametric ADF unit root tests on the components of identities between (the logs of) aggregate nominal, real and implicit price deflator data, suggests that a similar problem may be occurring with the parametric Johansen tests for the number of cointegrating vectors in the aggregate real and nominal data sets. Figure 1 shows the log levels of real aggregate consumption and real disposable income, as well as the estimated (non–stationary) residual from the Johansen 'cointegrating' relationship. Figure 2 shows the analogous variables from the nominal aggregate data set, where the cointegrating residual is stationary. The two residuals are compared in Figure 3.

Figure 1
Cointegrating Equation: Real Aggregate Data



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19 The nominal cointegrating equation may be written as

$$(C + PC) = \beta(YHD + PC) + \xi$$

and may be rearranged as a real cointegrating equation of the form

$$C = \beta YHD + (\beta\text{-}1)PC + \xi$$

with the additional I(1) term (β-1)PC.

Figure 2
Cointegrating Equation: Nominal Aggregate Data

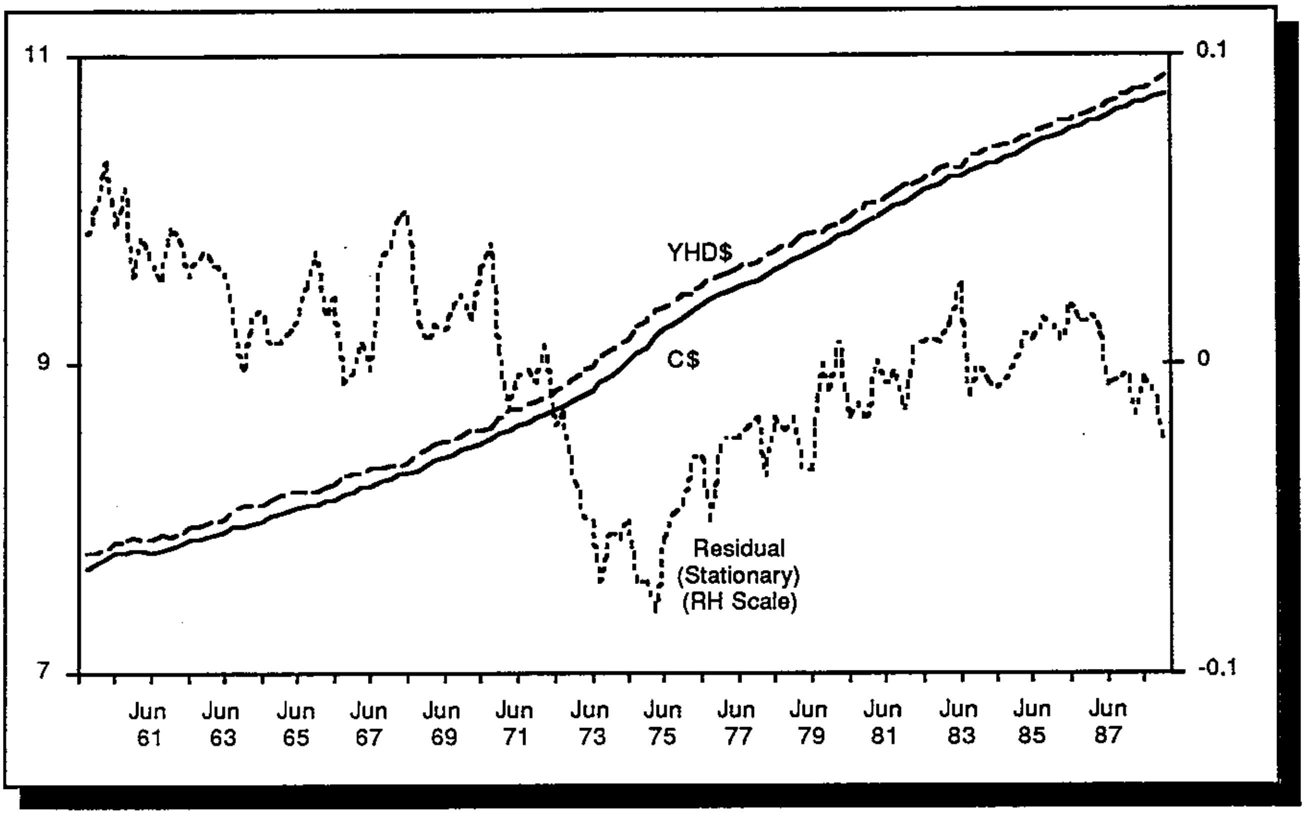
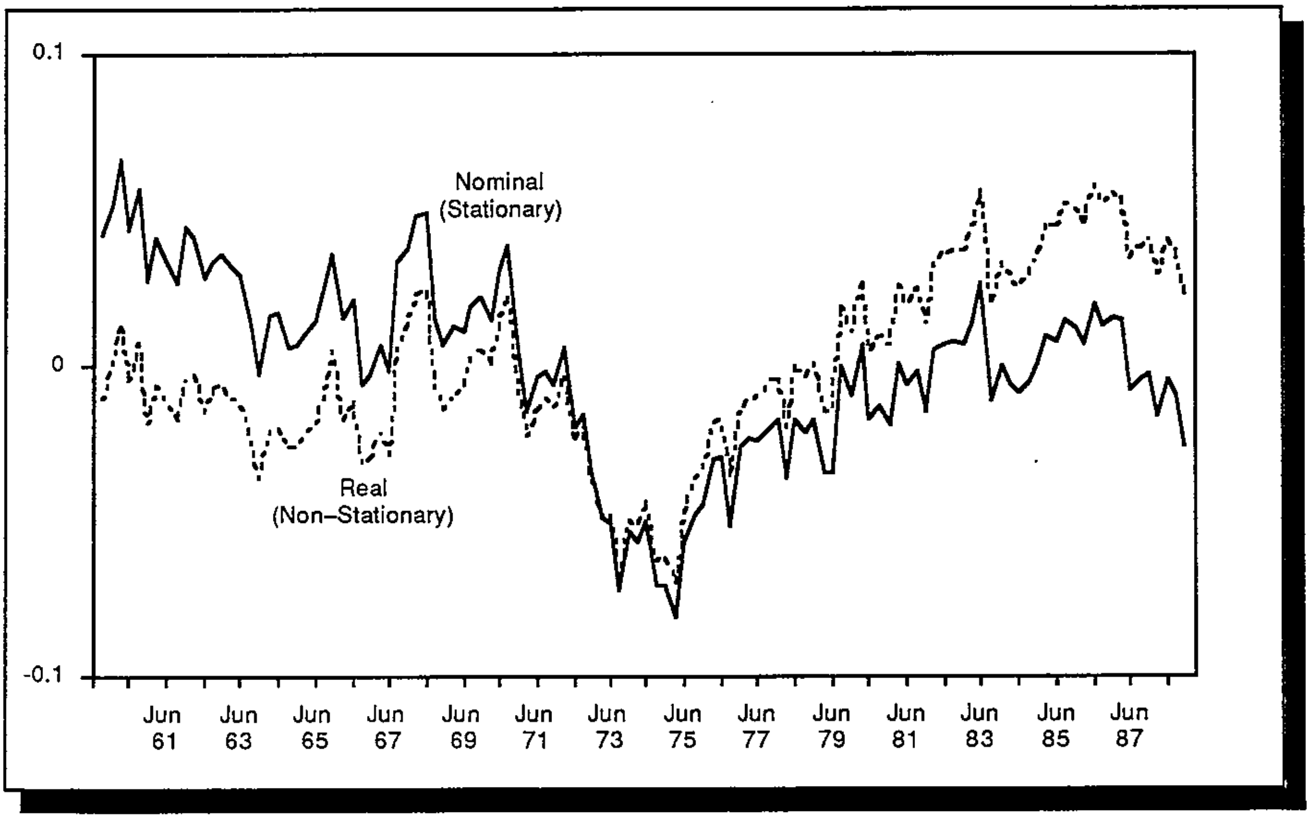


Figure 3
Cointegration Residuals: Aggregate Data



Visually, there appears to be little difference in the stationarity of the two residuals, yet the Johansen test results infer otherwise. This suggests that some parametric adjustment (such as introducing a polynomial in time) to the VAR model of the real aggregate data underlying the Johansen procedure may produce different inferences. Yet such adjustments would not satisfy the criteria of internal consistency—there is no evidence of time trends in our unit root tests, and the existence of a deterministic trend in the real cointegrating relationship would imply that a similar trend existed in the nominal cointegrating relationship.

Consequently, for the purposes of this paper, these puzzles have to remain unresolved. For the sake of completeness, however, we will present the estimation and hypothesis testing results from the 'non–cointegrated' real aggregate data set along with the results from the cointegrated real disaggregated and nominal aggregate and disaggregated data sets.

3.4 Spectral Estimates and Tests of Long Run Coefficients

Given the number of cointegrating vectors established in the previous sub–section, it is now necessary to make a normalisation of these in order to write models in the form of equations (2) and (3). Since the spectral estimates are not maximum likelihood, they will not be invariant to normalisation—this, of course, is a feature shared with other potential estimators. It seemed sensible in our application to make the standard normalisation that consumption is a function of income, as illustrated in equations (13) and (14). The disaggregated cointegration vectors can be written with each disaggregated consumption component as a function of the other two components and income. These can be solved for the 'reduced form' in which each consumption component is a function of income only.

For each model, two obvious restrictions that we test are that the income elasticities of consumption expenditure are jointly unity and that they are jointly equal.

As indicated in section 2, both spectral techniques require an initial estimate of the coefficients. Two sets of initial values are used: one being the OLS estimates of equation (6)[20]; the other being the Johansen estimates of the cointegrating vector (appropriately normalised). In each case, the effects of multiple iterations were evaluated by taking the number of iterations to nine. Empirical results from the final iteration are presented in Tables 4 and 5. Table 4 provides the band spectral and Hannan efficient parameter estimates and relevant standard errors, for each of

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[20] These estimates will differ slightly from those of Engle and Granger (1987) since our regressors are lagged.

the two sets of initial values. Wald test statistics for the two types of restrictions are presented in Table 5.

Table 4
Long Run Parameter Estimates

Equation	OLS Initial Values			Johansen Initial Values		
	OLS Estimate	Band Spectral	Hannan Efficient	Johansen Estimate	Band Spectral	Hannan Efficient
C	.9841	.9890 (.0790)	.9649 (.0134)	.9527	.9890 (.0790)	.9649 (.0134)
CHD	1.4008	1.4008 (.1752)	1.2999 (.0295)	1.4160	1.4008 (.1752)	1.3000 (.0295)
CMV	.8970	.9127 (.3889)	.9251 (.0706)	.7785	.9127 (.3889)	.9252 (.0706)
CND	.9580	.9630 (.0901)	.9582 (.0130)	1.1075	.9630 (.0901)	.9583 (.0130)
C$	1.0057	1.0054 (.0225)	1.0011 (.0048)	1.0151	1.0054 (.0225)	1.0011 (.0048)
CHD$	.9756	.9758 (.0539)	.9472 (.0080)	.9596	.9758 (.0539)	.9472 (.0080)
CMV$	.8047	.8045 (.0536)	.8177 (.0172)	.7981	.8045 (.0536)	.8177 (.0172)
CND$	1.0180	1.0176 (.0290)	1.0209 (.0045)	1.0314	1.0176 (.0290)	1.0209 (.0045)

Each entry is the point estimate of the coefficient on household disposable income in the relevant equation. Where Wald test statistics are asymptotically χ^2, estimated standard errors are given in parentheses. For the spectral methods, the estimates are from the ninth iteration.

On methodological issues, it can be concluded that:

- our estimates are not substantially affected by iterations beyond the first. For example, for the Hannan efficient estimates based on OLS initial values, there was only one parameter which changed by more than one percent between the first and ninth iterations—the change was actually less than two percent;

- even though two of the three initial values given by the Johansen and OLS estimators differ substantially in the real disaggregated case, this has negligible effect on the frequency domain estimates;

- the band spectral estimates appear less precise, in the sense that they have larger standard errors. This is because an adjustment has been made to take into account that there are effectively 'fewer' observations used in their estimation[21]; and

- the VAR parameterisation inherent in the Johansen estimator can have significant impacts on the estimates of long run parameters. There are, for example, a number of non–trivial differences between the (parametric) Johansen and the (non–parametric) spectral estimates in Table 4.

Table 5
Wald Tests of Restrictions

	All Coefficients Unity				All Coefficients Equal			
	OLS		Johansen		OLS		Johansen	
	Band Spectral	Hannan Efficient	Band Spectral	Hannan Efficient	Band Spectral	Hannan Efficient	Band Spectral	Hannan Efficient
Real agg.	.8892	.0089	.8892	.0089	-	-	-	-
Real disagg.	.0339	.0000	.0339	.0000	.0267	.0000	.0267	.0000
Nominal agg.	.8101	.8181	.8101	.8181	-	-	-	-
Nominal disagg.	.0006	.0000	.0006	.0000	.0066	.0000	.0066	.0000

Each entry is the marginal significance level of the test statistic. At the 5% level of significance, a hypothesis with a marginal level of significance less than .0500 would be rejected.

With respect to the economic implications of our results:

- it is generally the case that the estimated long run income elasticities of consumption are sensible in magnitude, ranging from around 0.8 to about 1.0;

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21 Fewer is in the sense that only a small part of each observation is used, namely that part which corresponds to the long run trend. In our case this adjustment increases the standard errors approximately tenfold.

- in the case of real disaggregated consumption, the various estimates of the income elasticity for expenditure on household durables are all substantially larger than unity. This is consistent with the view in sub-section 3.3 that the lack of cointegration between the real aggregate variables could be due to measurement errors in the deflators for consumer durables during periods of rapid technological change. Perhaps not surprisingly, both the hypotheses of equality and of unity of the coefficients are rejected by the joint tests. When these two tests are redone on the non-durables and motor vehicles coefficients alone, the hypothesis of equality cannot be rejected for either set of estimates, but that of unity can be rejected for the Hannan efficient estimates[22];

- the long run nominal income elasticity of consumption is unambiguously unity; and

- the nominal income elasticity estimates for disaggregated consumption are distinctively different from those for their real counterparts. The two of most interest are for household durables and motor vehicles. The lower nominal estimates are consistent with our comments about possible measurement problems in the real durables data. In each case the hypotheses of equality and of unity of the coefficients are unambiguously rejected.

4. Concluding Comments

We have taken an important first step towards evaluating empirically whether the theoretical framework and methods suggested by Phillips (1988a) should be used to estimate long run relations (in continuous time).

In terms of statistical procedures adopted, it has been demonstrated that the spectral regression estimates were relatively straight forward to compute, that a few iterations of the spectral estimators may be all that is required, and that the spectral estimates have not been sensitive to alternative initial estimates.

Our application has also highlighted the potential importance of non-parametric estimators. In the univariate case, for parametric (autoregressive) based corrections,

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[22] For the band spectral and Hannan efficient estimators, the marginal significance levels for the hypothesis of unity of the two coefficients are .8002 and .0010 respectively, while those for the hypothesis of equality are .9097 and .6579.

the unit root test results were somewhat confusing and internally inconsistent. This is in complete contrast to the results from the (Phillips–Perron) tests with non-parametric corrections, which were internally consistent. In the multivariate area also, a number of the non–parametric (spectral regression) estimates of the long run coefficients were markedly different from the parametric (vector autoregressive) Johansen estimates. Monte Carlo work, building on the contributions of Schwert (1987), Phillips and Ouliaris (1990) and Corbae (1990), would allow an evaluation of conditions under which the non–parametric methods might be more generally superior.

Empirically, the long run consumption function estimates obtained are sufficiently realistic for it to be worthwhile exploring conditional short run dynamic relations. A number of cautionary comments about data measurement had to be made along the way, and careful judgement had to be exercised during the course of several of the test procedures. The test procedures we used were consistent across our aggregate and disaggregated data sets, and between the unit root and cointegration stages of our investigation. This methodological stance could have contributed to our major surprising result, namely that the null of no cointegration between aggregate real consumer expenditure and household disposable income cannot be rejected. Some unresolved empirical issues relating to aggregate *real* consumer expenditure have been referred to in sub–section 3.3. However, overall the outcomes have certainly been sufficiently encouraging for the examination of other macroeconomic and financial data sets to be justified, and for the testing of long run relationships more rigorously grounded in economic theory. Setting such relations more explicitly into a fuller macroeconomic model with either discrete or continuous dynamics could also be considered.

REFERENCES

Anstie, R. K., M. R. Gray and A. R. Pagan. (1983). "Inflation and the Consumption Ratio". In A. R. Pagan and P. K. Trivedi (ed.). *The Effects of Inflation: Theoretical Investigations and Australian Evidence.* Canberra: Centre for Economic Policy Research, ANU.

Bailey, R. W., V. B. Hall and P. C. B. Phillips. (1987). "A Model of Output, Employment, Capital Formation and Inflation". In G. Gandolfo and F. Marzano (ed.). *Keynesian Theory, Planning Models and Quantitative Economics.* Giuffrè–Editore.

Baily, M. N. and R. J. Gordon. (1988). "The Productivity Slowdown, Measurement Issues, and the Explosion of Computer Power." *Brookings Papers on Economic Activity.* Vol. 2. pp. 347-431.

Bergstrom, A. R. (1984). "Continuous Time Stochastic Models and Issues of Aggregation Over Time". In Z. Griliches and M. D. Intriligator (ed.). *Handbook of Econometrics.* Amsterdam: North Holland. Volume II. pp. 1145-212.

Bergstrom, A. R. (1988). "The History of Continuous Time Econometric Models." *Econometric Theory.* Vol. 4. pp. 365-83.

Bergstrom, A. R. and C. R. Wymer. (1976). "A Model of Disequilibrium Neoclassical Growth and its Application to the United Kingdom". In A. R. Bergstrom (ed.). *Statistical Inference in Continuous Time Economic Models.* Amsterdam: North Holland.

Campbell, J. Y. (1987). "Does Saving Anticipate Declining Labor Income? An Alternative Test of the Permanent Income Hypothesis." *Econometrica.* Vol. 55. pp. 1249–73.

Campbell, J. Y. and R. J. Shiller. (1987). "Cointegration and Tests of Present Value Models." *Journal of Political Economy.* Vol. 95. pp. 1062–88.

Campbell, J. Y. and R. J. Shiller. (1988). "Interpreting Cointegrated Models." *Journal of Economic Dynamics and Control*. Vol. 12. pp. 505–522.

Corbae, D. (1990). "A Reexamination of the Consumption Function Using Frequency Domain Regressions". In *Essays in Dynamic Macroeconomics*. Yale University PhD Dissertation. Chapter IV.

Dickey, D. A., W. R. Bell and R. B. Miller. (1986). "Unit Roots in Time Series Models." *American Statistician*. Vol. 40. pp. 12–26.

Dickey, D. A. and W. A. Fuller. (1979). "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." *Journal of the American Statistical Association*. Vol. 74. pp. 427–31.

Dickey, D. A. and W. A. Fuller. (1981). "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root." *Econometrica*. Vol. 49 (4). pp. 1057–72.

Dickey, D. A., D. P. Hasza and W. A. Fuller. (1984). "Testing for Unit Roots in Seasonal Time Series." *Journal of the American Statistical Association*. Vol. 79 (386). pp. 355-367.

Dickey, D. A. and S. G. Pantula. (1987). "Determining the Order of Differencing in Autoregressive Processes." *Journal of Business and Economic Statistics*. Vol. 5 (4). pp. 455–61.

Engle, R. F. (1974). "Band Spectrum Regression." *International Economic Review*. Vol. 15. pp. 1–11.

Engle, R. F. and C. W. J. Granger. (1987). "Co–integration and Error Correction: Representation, Estimation and Testing." *Econometrica*. Vol. 55 (2). pp. 251–76.

Engle, R. F., C. W. J. Granger and J. J. Hallman. (1989). "Merging Short- and Long-Run Forecasts: An Application of Seasonal Cointegration to Monthly Electricity Sales Forecasting." *Journal of Econometrics*. Vol. 40. pp. 45-82.

Flavin, M. A. (1981). "The Adjustment of Consumption to Changing Expectations About Future Income." *Journal of Political Economy*. Vol. 89. pp. 974–1009.

Freebairn, J. W. (1976). "Determinants of Consumption". In W. E. Norton and D. W. Stammer (ed.). *Conference in Applied Economic Research: Papers and Proceedings*. Sydney: Reserve Bank of Australia.

Fuller, W. A. (1976). *Introduction to Statistical Time Series.* New York: Wiley.

Hall, R. E. (1978). "Stochastic Implications of the Life Cycle–Permanent Income Hypothesis: Theory and Evidence." *Journal of Political Economy.* Vol. 86. pp. 971–87.

Hannan, E. J. (1963). "Regression for Time Series". In M. Rosenblatt (ed.). *Time Series Analysis.* New York: John Wiley and Sons. pp. 17–37.

Hannan, E. J. (1970). *Multiple Time Series.* New York: John Wiley and Sons.

Hargreaves, C. (1990). "Money Demand Modelling in Australian Economy–Wide Models: Some Preliminary Analyses". Department of Economics, University of New England. Presented to Economic Modelling Bureau of Australia June 1990 Conference.

Hylleberg, S., R. F. Engle, C. W. J. Granger and B. S. Yoo. (1990). "Seasonal Integration and Cointegration." *Journal of Econometrics.* Vol. 44 (1/2). pp. 215-238.

Johansen, S. (1988). "Statistical Analysis of Cointegration Vectors." *Journal of Economic Dynamics and Control.* Vol. 12. pp. 231–54.

Johansen, S. (1989). "Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models". University of Copenhagen. Forthcoming in *Econometrica.*

Johansen, S. and K. Juselius. (1988). "Hypothesis Testing for Cointegration Vectors—With an Application to the Demand for Money in Denmark and Finland". Institute of Economics, University of Copenhagen.

Johansen, S. and K. Juselius. (1990). "Maximum Likelihood Estimation and Inference on Cointegration—with Applications to the Demand for Money." *Oxford Bulletin of Economics and Statistics.* Vol. 52 (2). pp. 169-210.

Johnson, P. (1983). "Life-Cycle Consumption under Rational Expectations: Some Australian Evidence." *Economic Record.* Vol. 59 (167). pp. 345-350.

Jonson, P. D., E. R. Moses and C. R. Wymer. (1977). "The RBA76 Model of the Australian Economy". In W. E. Norton (ed.). *Conference in Applied Economic Research.* Sydney: Reserve Bank of Australia.

McKibbin, W. J. and A. J. Richards. (1988). "Consumption and Permanent Income: The Australian Case". Research Discussion Paper Number 8808. Reserve Bank of Australia. October.

Newey, W. K. and K. D. West. (1987). "A Simple Positive Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica.* Vol. 55. pp. 703–08.

Pagan, A. R. and M. R. Wickens. (1989). "A Survey of Some Recent Econometric Methods." *Economic Journal.* Vol. 99. pp. 962-1025.

Perron, P. (1988). "Trends and Random Walks in Macroeconomic Time Series." *Journal of Economic Dynamics and Control.* Vol. 12. pp. 297–332.

Phillips, P. C. B. (1988a). "Error Correction and Long Run Equilibria in Continuous Time". Cowles Foundation Discussion Paper Number 882R. Yale University. Forthcoming in *Econometrica.*

Phillips, P. C. B. (1988b). "Optimal Inference in Cointegrated Systems". Cowles Foundation Discussion Paper Number 866R. Yale University. Forthcoming in *Econometrica.*

Phillips, P. C. B. (1988c). "Spectral Regression for Cointegrated Time Series". Cowles Foundation Discussion Paper Number 872R. Yale University. Forthcoming in W. Barnett (ed.). *Nonparametric and Semiparametric Methods in Economics and Statistics.* Cambridge: Cambridge University Press.

Phillips, P. C. B. and S. Ouliaris. (1990). "Asymptotic Properties of Residual Based Tests for Cointegration." *Econometrica.* Vol. 58 (1). pp. 165-193.

Phillips, P. C. B. and P. Perron. (1988). "Testing for a Unit Root in Time–Series Regression." *Biometrika.* Vol. 75. pp. 335–46.

Said, S. E. and D. A. Dickey. (1984). "Testing for Unit Roots in Autoregressive Moving Average Models of Unknown Order." *Biometrika*. Vol. 71. pp. 599–608.

Schwert, G. W. (1987). "Effects of Model Misspecification on Tests for Unit Roots in Macroeconomic Data." *Journal of Monetary Economics*. Vol. 20. pp. 73–103.

Sims, C. A. (1980). "Macroeconomics and Reality." *Econometrica*. Vol. 48. pp. 1–48.

Stock, J. H. and M. W. Watson. (1988). "Testing for Common Trends." *Journal of the American Statistical Association*. Vol. 83 (404). pp. 1097–1107.

Williams, R. A. (1979). "Household Saving and Consumption". In W. E. Norton and I. W. Little (ed.). *Conference in Applied Economic Research*. Sydney: Reserve Bank of Australia.

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