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Source: *The Economic Journal*, Vol. 101, No. 407 (Jul., 1991), pp. 887-901
Published by: Wiley on behalf of the Royal Economic Society
Stable URL: http://www.jstor.org/stable/2233861

The Economic Journal, **101** (*July* 1991), 887–901
Printed in Great Britain

DATA REVISIONS AND THE EXPENDITURE COMPONENTS OF GDP*

K. D. Patterson and S. M. Heravi

It is well known that a great deal of the data which is published by official statistical sources undergoes a process of revision as new information comes to light. The official source typically has to balance the need for timeliness, which relates to pressures for information on the state of the economy to be made available as quickly as possible, with the knowledge that the process of data gathering itself takes time. This results in several *vintages* of an observation relating to a specific time period being available. For example, a first ever value for a component of GDP will be published in a particular issue of *Economic Trends*, which will then be updated one quarter later in the same publication; these and further updates give rise to a sequence of vintages of observation for a particular variable. This process can result in substantial revisions to the preliminary estimates; for example, the 1970 Q1 figure for constant price fixed investment was subject to a revision of +7·6% between vintages 1 and 15, a change of base then affected subsequent vintages, with a further revision of +2·2% between vintages 16 and 25.

It is not surprising that the nature of revisions has been studied to see if, for example, the earliest published preliminary data are an unbiased predictor of subsequent vintages of the same series; whether preliminary vintages can be regarded as efficient forecasts of other vintages; and if time series models are sensitive to the use of data from different vintages. Zellner (1958) and Morgenstern (1963) were amongst the earliest studies in the general area of data revisions, and more recent studies include those by Harvey *et al.* (1983), Mankiw *et al.* (1984), and Mork (1987). The CSO itself has indicated the general nature of the revision's process – see Kenny (1987). However, to our knowledge, two of the concerns of this study, that is the construction of consistent, rebased series and the stationarity of the revisions resulting from different vintages, have not been considered in any depth. The third aspect of this study, that is an assessment of whether a particular vintage efficiently incorporates information available at the time of its construction, could not be undertaken until the consistent, rebased series on the different vintages have been constructed. Further, we have at our disposal an extensive data set on different vintages made available by the CSO; this comprises 25 vintages of the components of the expenditure measure of Gross Domestic Product (GDPE). As the vintages are on a quarterly basis the last vintage thus becomes available

* The authors would like to thank the CSO for providing data and advice at an early stage in this project. Financial support from the ESRC Macromodelling Consortium is gratefully acknowledged. Constructive comments from the editor and two referees led to improvements in earlier versions of this paper. Remaining errors and the views expressed herein are the responsibility of the authors.

6 years on from the first vintage. For practical purposes the twenty-fifth vintage is regarded as the 'final' vintage, though occasional revisions may take place thereafter.

An emphasis on the need for long runs of time series data is common in both theoretical and empirical work. *Ceteris paribus* more data is better; but the changes which occur through systematic rebasing can create a problem in meeting this emphasis. A typical procedure to overcome this problem is the 'overlap' method which splices together a series by applying a conversion factor based on a comparison of the series under the new and old bases. This procedure, however, confuses the *rebasing* and *vintage* effects of new data. The series of economic interest are those on a single consistent base, but to obtain them seems to require what is not generally known: that is, the relationship between the data for the *same* vintage but under *different* bases. Since this is not generally available it may seem harsh to criticise those who use the 'overlap' method. We do, however, suggest and apply a method, which uses information on all of the available vintages of a particular series, to retrieve the conversion or rescaling coefficients, which does not confuse the vintage and rebasing effects. Once this is done it is then possible to construct a data matrix for each time series, with dimensions given by the number of observations (rows) and the number of vintages (columns), on a single, consistent basis. It should be clear from the context below whether we are referring to an un-rebased vintage or a rebased (consistent) vintage.

The construction of a consistent data matrix for each series allows us to analyse the stationarity of the revisions and co-integration properties of the preliminary and final vintages. A finding of non-co-integration between, for example, the initial and final vintages of a particular variable, implies that regression models which rely on the initial data alone to predict the final data will be flawed. It might be of interest to anticipate briefly the results we report below. When comparing the initial and final vintages we do find some limited evidence that we cannot reject the non-co-integration hypothesis. However, we have to be cautious in our interpretation of this evidence because we necessarily lose observations from our overall sample size in order to obtain the final vintage. We are on firmer ground in saying that several of the series considered have a long memory characteristic, in which shocks have a persistent though not necessarily infinitely lived effect – as would occur with a random walk.

Even though tests for co-integration are in widespread use, one problem with them is their probable lack of power against a stationary alternative close to the unit circle. This can be protected against in part by assessing the sensitivity of the results to an increase in the size of the test. In addition, when there is doubt about the conclusion to be drawn, we supplement the tests by estimating the order of (fractional) differencing necessary to induce stationarity. This is an idea due to Granger and Joyeux (1980), and put into operational form by Geweke and Porter-Hudak (1983), in which the differencing parameter is not restricted to be an integer (usually 1 or 2).

A further aspect of data revisions is the extent to which they incorporate information available at the time of their compilation. Mork (1987) analysed revisions to constant price GNP for the United States and found some evidence that these were not fully efficient. We carry out similar 'orthogonality' tests on a much wider range of vintages for the components of GDPE, and find that in some cases the history of revisions to the series and inflation have predictive ability for the final vintage.

This paper is organised as follows. In Section I we consider the problem of base changes in greater detail. In Section II we describe some characteristics of the data. In Section III we report the results of applying a unit root and co-integration analysis to our data set. In Section IV we report the results of our efficiency tests and in Section V offer some concluding remarks.

I. THE IMPORTANCE OF BASE CHANGES

I.1 The Effects of Changing the Base

The analysis of constant price series is complicated by the need to account for the various changes in base period which have occurred during the sample period. The relevant changes in base first have an effect on our data set in 1973Q2, 1978Q2 and 1983Q2. It is important to note the implications of a base change not just for the discontinuity it implies for the first vintage of a series, but also for the higher order vintages. To illustrate some of the salient points consider Table 1 which extracts some quarterly data for fixed investment in £million at constant prices but on *three* different bases. In this Table 1970Q1 corresponds to $t = 1$ and 1978Q2 to $t = 34$. These data are part of a data set provided to us by the CSO, which has been consistently extracted by them from successive quarterly issues of *Economic Trends* for the period 1970Q1 to 1986Q4.

The construction of Table 1 is as follows. The first un-rebased vintage for $t = 1$ is 1,613 (£million at 1963 prices) which was published in *Economic Trends* (ET), July 1970. In the October 1970 issue of ET this was revised to 1,614, which is thus the second vintage for $t = 1$. Also published in that issue was the first vintage for $t = 2$. The January 1971 issue of ET would then provide us with the third vintage of $t = 1$, the second vintage of $t = 2$ and the first vintage of $t = 3$.

Note also that when a new base period occurs, as in 1973Q2, the newly published data represent the first vintage for the 1973Q2 value, the second vintage for the 1973Q1 value, the third vintage for the 1972Q4 value and so on. These data are on the new rather than the old base, creating a diagonal effect in the data matrix which we term the *trace-back* effect. This implies that in comparing, for example, the first and twenty-fifth vintage of data relating to a particular time period there are at least one, and sometimes two, changes of base. It is important to note that when a base change occurs then, in general, all new data is issued on that base until the next base change. For further details on this point see, for example, Rushbrook (1979). There is no overlapping in the sense that the different vintages are *not* generally available on the new and the old base – or bases when considering a longer run of data. A typical practice in empirical work is to ignore the vintage effect, through necessity, and

Table 1

Fixed Investment on Different Bases (£mm)

Un-rebased vintage =		1	2	3		12	13	1st base change ↓ 14		25	
$t =$	1	1,613	1,614	1,619	...	1,729	1,735	2,236	...	2,285	
	2	1,714	1,740	1,736	...	1,821	2,317	2,317	...	2,372	
	.	.	.	.	...	.	.	.	...	.	
	.	.	.	.	...	.	.	.	...	.	
	.	.	.	.	...	.	.	.	...	.	
	9	1,755	1,809	1,814	...	2,431	2,431	2,424	...	2,376	
	10	1,804	1,803	1,809	...	2,438	2,436	2,436	...	5,019	← 2nd base change
	11	1,757	1,745	1,756	...	2,423	2,423	2,423	...	4,985	
	12	1,799	1,821	2,354	...	2,471	2,471	2,471	...	5,094	
	13	1,916	2,507	2,525	...	2,555	2,555	2,617	...	5,534	
1st base change →	14	2,355	2,374	2,358	...	2,434	2,516	2,516	...	5,331	
	.	.	.	.	...	.	.	.	...	.	
	.	.	.	.	...	.	.	.	...	.	
	.	.	.	.	...	.	.	.	...	.	
	32	2,254	2,271	4,954	...	5,144	5,156	5,156	...	10,115	
	33	2,245	5,015	5,030	...	5,299	5,299	5,271	...	10,378	
2nd base change →	34	5,024	5,056	5,161	...	5,298	5,327	5,327	...	10,963	
	.	.	.	.	...	.	.	.	...	.	
	.	.	.	.	...	.	.	.	...	.	
	.	.	.	.	...	.	.	.	...	.	

obtain a conversion or rescaling factor based on comparing data pertaining to the same time period but of a different vintage. Note, however, that even if vintage adjacent observations are used, there is still a confusion of vintage and rebasing effects in this 'overlap' method.

We need first to establish some notation. Let $Y^v_{t,i}$ be the v-th vintage of data on variable Y, on the i-th basis, for the t-th period. A sequence of vintages for the same variable in the t-th period on the i-th base is $Y^1_{t,i}, Y^2_{t,i}, \ldots, Y^{25}_{t,i}$; and a sequence of observations for the same variable on the i-th base and the v-th vintage is $Y^v_{1,i}, Y^v_{2,i}, \ldots, Y^v_{44,i}$. In general let m denote the final vintage of the data. The regression given by,

$$Y^m_{t,i} = a^v_{01} + a^v_{11} Y^v_{t,i} + \epsilon^v_t \quad v = 1, \ldots, m-1 \tag{1}$$

for $m > v$, can be interpreted as the co-integrating regression between different vintages of the data. As Engle and Granger (1987) establish, in a general context, if $Y^m_{t,i}$ and $Y^v_{t,i}$ are both integrated of order 1, that is I(1), an equilibrium relationship exists if (and only if) ϵ^v_t is I(0); and in such a case $Y^m_{t,i}$ and $Y^v_{t,i}$ are said to be co-integrated. Notice that for ϵ^v_t to be stationary it may be necessary to introduce a 'co-integrating coefficient', a^v_{11}, which could be other than unity; thus $Y^v_{t,i}$ could be a biased predictor of $Y^m_{t,i}$. Stock (1987) has shown that applying least squares methods to obtain the regression coefficients

Table 2
*Rebasing Coefficients**

	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
Consumers' expenditure (*C*)	1·3369	1·7995	1·9245	0·9888
	(881·9)	(2787·8)	(4562·6)	(4348·3)
Gross domestic fixed capital	1·2950	2·0926	1·9819	1·0492
formation (*I*)	(192·5)	(964·3)	(1775·2)	(1757·6)
Central government	1·5454	2·1107	1·9874	—
expenditure (*G*)	(631·3)	(1976·9)	(3092·2)	—
Export of goods and	1·3079	1·8735	1·9061	—
services (*X*)	(292·8)	(1413·8)	(3000·8)	—
Imports of goods and	1·3082	2·1397	1·7004	—
services (*M*)	(271·2)	(1932·2)	(3577·6)	—
Factor cost adjustment (*FCA*)	1·7091	1·2072	2·5886	—
	(569·4)	(1450·9)	(2855·4)	—
Stocks and work in progress	0·9834	2·2247	1·5512	—
(*SWIP*)	(7·681)	(668·231)	(98·80)	—

* Effective sample period 1970Q1 to 1980Q4, sample size = 1,056 (= 44 × 24). Estimated method: nonlinear (within and across equations) SURE. Estimated t statistics are shown in parentheses.

in (1) leads to estimators with the desirable property of 'superconsistency' if the regression variables are I(1).

The problem with estimating equation (1) is that because of rebasing we do not have long runs of consistent data on the same base. Indeed, the diagonal trace-back effect of rebasing implies that we do not have any observations for many of the cases which are of interest. To overcome this problem we formalise the 'overlap' method which is used frequently at an informal level. We note that whilst the opportunity is taken at times of rebasing to alter the weights in the various indices for which the CSO is responsible – see Rushbrook (1978) – the primary effect of a rebasing is one of rescaling the constant price indices. A simple model for the relationship between data for the same period and vintage but on a different base is –

$$Y^v_{t,i} = \beta_{i-1} Y^v_{t,i-1} \quad i = 2, 3, 4, \text{ and } v = 1, \dots, 25 \qquad (2)$$

There are 3 rescaling coefficients, corresponding to the different base changes in our sample, which serve to convert the v-th vintage of $Y_{t,i}$ on base $i-1$ to base i. Equation (2) could in principle be extended to include a constant and a stochastic element. In earlier work, however, we found that the rebasing constants were generally small and insignificant and have omitted them. Although introducing a disturbance term in (2) could be motivated from practical considerations, the rebasing relationship is not a directly estimable equation – because the CSO do not issue the 'same' data on both new and old bases – and we cannot, therefore, separately identify a variance component due to (2).

Substituting (2) into (1) for a particular choice of v results in a regression model with observable variables but which is, in general, nonlinear in the coefficients. Considering the equations for the same series but for different values of $v = 1, \dots, 24$, then results in a system of 24 nonlinear equations, with nonlinear cross equation restrictions, and 1,056 observations (= sample size times number of vintages). The initial data set comprises 68 observations from 1970Q1 to 1986Q4; however, because the 'final' vintage is not available until 6 years after the first vintage the effective sample period is 1970Q1 to 1980Q4. The nonlinear restrictions arise because the base linking coefficients appear in each of the equations. The estimation method we use generalises Zellner's (1962) method for seemingly unrelated regression equations – see Patterson and Heravi (1989) – to a system with nonlinear within and cross equation restrictions.

I.2 Estimates of the rebasing coefficients

The quarterly (seasonally adjusted) data series which form the basis of our analysis are those for the components of the expenditure estimate of GDP; that is, Consumers' Expenditure, (C), Gross Domestic Fixed Capital Formation, i.e. fixed investment, (I), Central Government Expenditure, (G), Exports of Goods and Services, (X), Imports of Goods and Services, (M), Stockbuilding and Work in Progress, ($SWIP$), and the Factor Cost Adjustment, (FCA).

We note here an important complication to the model outlined above which applies to the series for C and I (and hence GDP). An initial analysis with 3 rescaling coefficients for each series revealed that there was a further systematic revision of the data unconnected with rebasing. The first effect was noted in the vintage 1 data for 1984Q1, with a traceback effect to 1978Q2; thus, all 25 vintages of data were affected for the series in question. Further investigation revealed that there had been an important definitional change to consumption and private investment – see Jones (1984) and CSO (1984) – with the effect that some expenditures on housing improvement which had previously been classified as consumption were reclassified as private investment, although the net effect on GDP was not zero. From a modelling point of view, we treat these definitional changes using the method for changes due to rebasing. In generic terms this introduces a coefficient, denoted β_4, which serves to capture the rescaling effect of the definitional change.

The resulting estimates of the β_i coefficients are reported in Table 2. For each component we report the estimated standard error and conventional t statistic, but note that following Engle and Granger (1987) these may be biased in co-integrating regressions. Nevertheless, these coefficients do seem well-determined and are based on 1,056 observations for each series. Note that the rebasing, or rescaling, coefficients are generally greater than (and different from) 1; this pattern is as expected as the sample period has been one of generally increasing prices.

II. SOME CHARACTERISTICS OF THE DATA SERIES

The estimates of the rebasing coefficients given in Table 2 were used to construct a data matrix, with dimensions given by the number of observations and vintages, for each series on a single consistent basis. Some of the characteristics of these series are reported in Table 3. Column 1 gives the mean

Table 3

Some Characteristics of the Data Series (using the Rebased, Consistent Series)

			Cumulative revisions*		Successive revisions†	
	Vintage	Mean	%MAE‡	U§	%MAE‖	U§
Consumers'	1	8,860	2·04	2·41	0·74	1·10
expenditure (*C*)	13	8,933	1·20	1·32	0·46	0·61
Final mean = 9,042	21	9,002	0·48	0·58	0·48	0·58
Gross domestic	1	2,350	4·10	4·96	2·18	2·96
fixed capital	13	2,444	1·83	2·24	0·96	1·25
formation (*I*)	21	2,454	0·83	1·26	0·83	1·26
Final mean = 2,443						
Central government	1	2,632	0·87	0·80	0·78	0·99
expenditure (*G*)	13	2,626	1·09	1·28	0·62	0·87
Final mean = 2,629	21	2,626	0·45	0·69	0·45	0·69
Exports of goods	1	3,644	2·60	2·99	1·47	1·86
and services (*X*)	13	3,720	0·73	0·92	0·57	0·87
Final mean = 3,733	21	3,735	0·44	0·59	0·44	0·59
Imports of goods	1	3,478	2·43	3·12	1·90	2·48
and services (*M*)	13	3,483	0·96	1·39	0·56	0·92
Final mean = 3,496	21	3,487	0·42	0·75	0·42	0·75
Factor cost	1	2,239	2·30	3·05	1·79	2·46
adjustment (*FCA*)	13	2,236	1·03	1·36	0·84	1·26
Final mean = 2,229	21	2,225	0·71	1·04	0·71	1·04
Value of physical	1	18	57·52	55·63	33·09	36·62
increase in	13	52	22·14	25·02	19·35	19·71
stocks and work	21	79	10·09	10·94	10·00	10·93
in progress (*SWIP*)						
Final mean = 75						
GDPE	1	11,787	3·50	3·80	1·37	1·90
Final mean = 12,197	13	12,057	1·21	1·36	0·73	0·87
	21	12,184	0·35	0·43	0·35	0·43

* Final vintage minus vintage v for $v = 1, 13, 21$.
† Vintage $v+4$ minus vintage v for $v = 1, 13, 21$.
‡ Percentage mean absolute error compared to final vintage.
§ 100 times Theil's inequality coefficient.
‖ Percentage mean absolute error compared to vintage v, see †.

of each series for $v = 1, 13, 21$. Note that GDP tends on average to be revised up with an overall average revision between vintages 1 and 25 of the order of 3% of the final vintage. Comparing initial ($v = 1$) and final ($v = 25$) vintages we find that the largest proportionate mean revisions, in order, are to *I*, *X*, *C*, *M*, *FCA* and *G*; and in terms of the variability of revisions, the order is *I*, *X/M/FCA*, *C* and *G*. The series for *SWIP* has been excluded from this last comparison as its characteristics deserve special mention. It is by far the most variable of the series and although the numerical increase in the means of the different vintages is not of much importance, when compared with the other components of GDP, the magnitude of some of the revisions which have occurred is proportionately very large. For example, compare some of the following figures for the initial and final vintages of this series: 138 and 339 (1973Q3), 86 and 248 (1976Q4), 114 and 271 (1979Q3).

The last two columns of Table 3 give some summary statistics when the cumulative revisions are taken 4 vintages apart. This gives a further indication of which stages in the revisions process generally lead to the largest revisions. The general pattern is for later revisions to be less substantial than the earlier revisions. Whilst this is to be expected it is worth noting that there are, nevertheless, still some later revisions which do not appear to be negligible.

Fig. 1 illustrates the nature, and in particular the variability, of the cumulative revisions in greater detail. Note just how substantial the revisions have been at particular times. Also illustrated in Fig. 1 is the cumulative revision taken as the difference between the twenty-first and final vintages of the data series. Although, as we might expect, the revisions are now not so substantial they do still occur. The individual figures show a common pattern for some of the variables. For example, C and I (and to a lesser extent FCA) show peaks around 1973 and 1977/9 and there are two noticeable peaks around 1974/5 and 1978/9 for G. These peaks and troughs correspond quite closely to different stages in the business cycle; in particular, both peaks are associated with similar peaks in the inflation rate – a variable which Kenny (1987) has suggested is influential in the revisions process. We consider this further below when assessing whether information available at the time the preliminary vintages are compiled is fully incorporated into these vintages.

III. CO-INTEGRATION TESTING

Having obtained the rebasing coefficients we concentrate, in this section, on the question of whether different vintages of data on the same variable are co-integrated. This question is important for, at least, two reasons. If we accept the hypothesis that the residuals from a co-integrating regression between, say, a preliminary vintage and the final vintage of a data series are I(1) rather than I(0), it implies that a I(1) variable, or combination of variables, has been omitted. (This is considered again in Section IV below on orthogonality tests.) If the residuals from a co-integrating regression of Y_t^m on Y_t^v are consistent with an I(1) process, then the associated revision $Y_t^m - Y_t^v$ must also be non-stationary since it corresponds to the joint restrictions on the corresponding co-integrating regression that the constant is zero and the co-integrating coefficient is unity. We use the estimated rebasing coefficients, $\hat{\beta}_i$, to construct the data on a single, consistent base and then generate residuals from the individual co-integrating regressions. (As an alternative, we could use the residuals which result from system estimation and as a check we also calculated the corresponding test statistics, but there were no differences of note.) Estimation of the rebasing coefficients implies a loss of 4 degrees of freedom for C and I and 3 for the other series.

Our original sample size was 68, of necessity we lose 24 observations for which 'finals' were not available giving an effective sample of 44. In our opinion this is worth considering, even if it implies some caution in interpreting the results, for our initial data analysis revealed revisions of some numerical importance. Our data can be re-analysed in due course as more 'final' observations become available. We also take advantage of a recent paper by

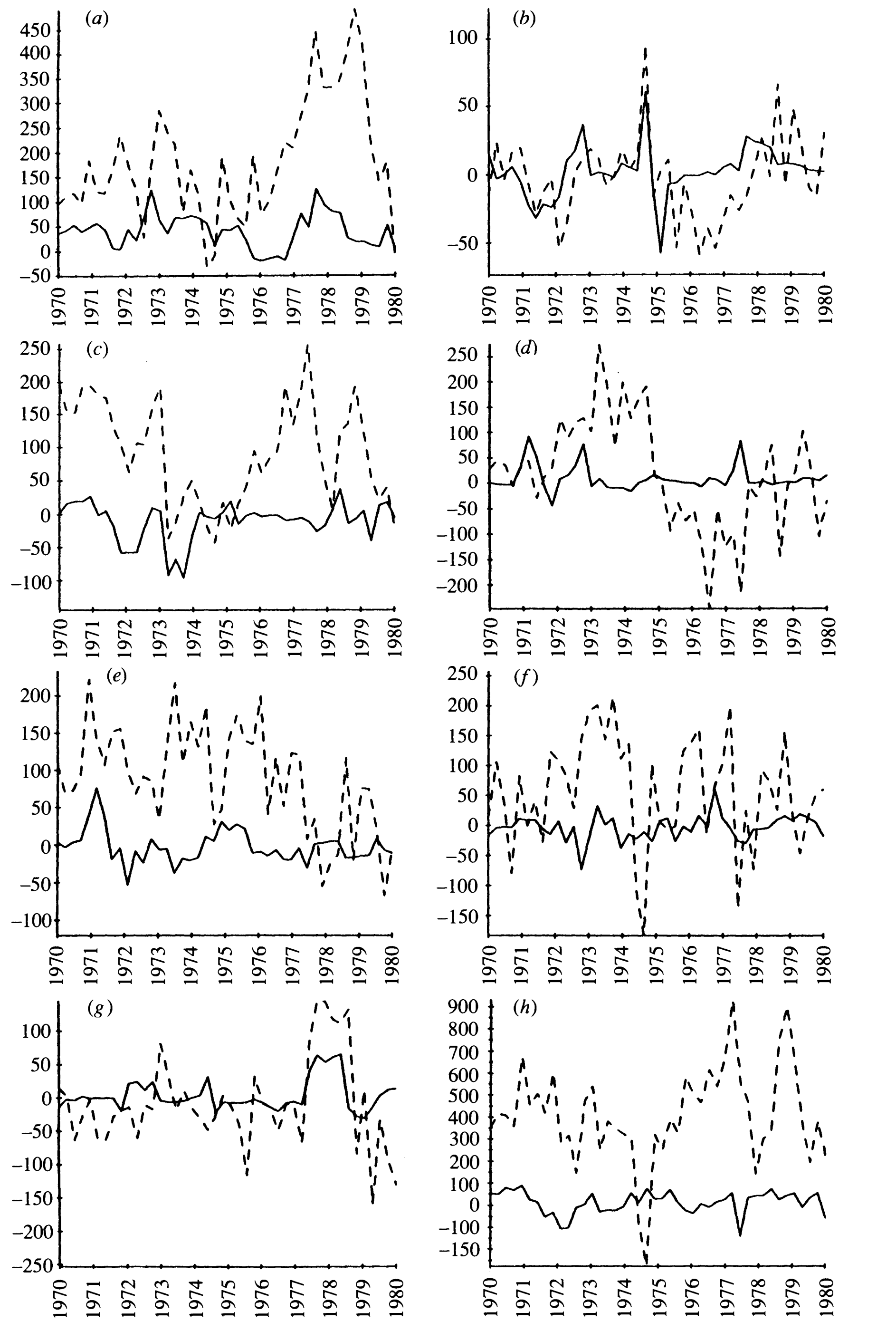

Fig. 1. Revisions to GDPE and its components. ---- Difference between final and initial vintage. —— Difference between final and twenty-first vintage. (*a*) Consumers' expenditure. (*b*) Central government consumption. (*c*) Gross domestic fixed capital formation. (*d*) Import of goods and services. (*e*) Export of goods and services. (*f*) Value of physical increase in stock and work in progress. (*g*) Adjustment to factor cost. (*h*) GDPE.

MacKinnon (1990) which provides finite sample critical values for integration and co-integration testing, as these are more accurate than others published to date.

III.1 Unit root tests

The first stage in testing for co-integration is to assess whether the components of GDP are integrated of order 1, I(1). In Table 4 we report the augmented

Table 4
Unit Root Tests for First and Final Vintages

	C	*I*	*G*	*X*	*M*	*FCA*	*SWIP*	*GDPE*
$v = 1$	−2·31	−2·31	−1·86	−4·99*	−2·33	−1·87	−2·99	−3·32
	−2·24	*−3·63**	*−1·58*	*−4·97**	*−3·20*	*−3·65**	*−3·13*	*−3·31*
$v = 25$	−2·06	−2·76	−2·09	−4·39*	−1·88	−2·54	−2·65	−3·28
	−2·04	*−3·34*	*−2·01*	*−4·35**	*−2·16*	*−2·66*	*−2·76*	*−3·32*

The DF/ADF test statistic is in roman type, $Z(t_\alpha)$ in italics; $p = 0$ for *C*, *G*, *X*, *SWIP* and *GDPE*; $p = 1$ for *I*; $p = 3$ for *FCA*; $r = 1$ except for *I* where $r = 2$. * indicates significance at the 5% level. 5% critical value from MacKinnon (1990) = −3·52.

Dickey–Fuller, ADF, test statistic with p denoting the number of difference terms in the regression, which includes drift and a time trend – failure to include both of these terms can seriously distort the results of integration testing, see Perron (1988). In most cases $p = 0$, which corresponds to the standard Dickey–Fuller, DF, test, suffices with the regression passing an LM test for autocorrelation at conventional significance levels. Where this is not the case we increase p until there is no evidence of autocorrelation. We also report the Phillips and Perron extension of the DF test, referred to as $Z(t_\alpha)$, see Perron (1988), which allows an innovation sequence permitting many weakly dependent and heterogeneously distributed time series. This test involves the choice of a truncation parameter, r, which determines the number of lagged residuals involved in the test; in practice sample values of $Z(t_\alpha)$ stabilised at low values of r ($r = 1$, except for I where $r = 2$). A wider range of test statistics is reported in Patterson and Heravi (1989).

In general we find that the null hypothesis of a unit root is not rejected at the 5% significance level for all of the components of *GDPE* except *X*. In this case we find stationarity about a significant deterministic time trend. A further application of these tests to see if the series were I(2) resulted in a uniform rejection of the null hypothesis.

III.2 Co-integration tests

The co-integration test statistics for particular vintages are reported in Table 5. For $v = 1$ and $\alpha = 0{\cdot}05$, the null hypothesis is rejected for *I*, *X*, *SWIP* and *GDPE*; *G* is a borderline case with conflicting test statistics. We do not reject the null for *C*, *M* and *FCA*. These non-rejections are generally not marginal and, except for *FCA*, are firm enough not to be affected by a change in the size of the tests. By vintage 21 we would expect all of the series to be *strongly*

Table 5

Co-integration Test Statistics for Particular Vintages

	C	I	G	X	M	FCA	$SWIP$	$GDPE$
$v = 1$	−2·55 (0)	−3·99* (1)	−2·08 (2)	−4·87* (0)	−2·11 (0)	−2·18 (1)	−5·24* (0)	−3·63* (0)
	−2·62	*−3·66**	*−4·83**	*−4·85**	*−2·91*	*−3·48+*	*−5·24**	*−3·66**
$v = 13$	−3·87* (2)	−4·98* (1)	−3·24+(3)	−3·47+(1)	−4·89* (0)	−4·71* (1)	−5·31* (0)	−4·60* (3)
	*−4·10**	*−4·77**	*−3·40+*	*−3·59**	*−4·89**	*−4·89**	*−5·29**	*−4·72**
$v = 21$	−3·17+(0)	−4·21* (0)	−4·69* (0)	−4·33* (2)	−4·32* (3)	−4·56* (3)	−5·34* (0)	−4·55* (0)
	−3·17+	*−4·28**	*−4·78**	*−3·85**	*−3·56*	*−3·56**	*−5·33**	*−4·50**

The DF/ADF test statistic is in roman type with the order of p following in parentheses, $Z(t_\alpha)$ is in italics; 10% and 5% critical values are −3·14 and −3·48 respectively. A + and a * indicate rejection of the null of non-co-integration at the 10% and 5% significance levels (α), respectively. The test statistics for the vintages of X, which were found to have deterministic trends, should be interpreted as giving a broad indication as to whether the trends cancel.

Table 6

Fractional Differencing Parameters for Consumption*

	C^1	C^{13}	C^{21}	C^{25}	$C^{25}–C^1$	$C^{25}–C^{13}$	$C^{25}–C^{21}$
$\hat{d}$	1·36	1·33	1·33	1·32	1·20	0·52	0·35

* Estimation method due to Geweke and Porter-Hudak (1983); estimated standard error = 0·353

co-integrated, as we are now very close to the final revision. In general this is the case but we need to investigate C further. (Incidentally, using logs rather than levels did not alter these conclusions.)

First, we note that the non-co-integration null hypothesis is an example of what Leamer (1988) has called a 'sharp null hypothesis', with non-rejection (implying non-stationarity) carrying markedly different implications compared to rejection (implying stationarity). It seems prudent, therefore, to examine somewhat further the revisions to the consumption series, in particular the overall revision, $C^{25}–C^1$, and the last (annual) revision, $C^{25}–C^{21}$. Both appear to have a long-memory characteristic where shocks have a persistent, though not necessarily infinitely lived, effect. It is this class of long-memory models which led Granger and Joyeux (1980) to introduce the idea of fractional differencing, with parameter d, of a time series to achieve stationarity. The unit root literature has concentrated on integer differencing with $d = 1$ or $d = 2$, corresponding to one and two unit roots, respectively; thus overlooking the possibility that, at least in principle, a more precise estimate of d may be available. To explore this possibility further we used Geweke and Porter-Hudak's (1983) method of estimating d for the levels of, and revisions to, the consumption series. Their method is based on estimating the log of the spectral density function and assumes that $d \in (-\frac{1}{2}, \frac{1}{2})$. Where it is suspected, as here for some cases, that $d \geqslant \frac{1}{2}$ Geweke and Porter-Hudak (1983, p. 228) recommended prior integer or fractional differencing to ensure that this condition is met for the transformed series. This we do; thus in Table 6, which summarises the results, where the reported values of $\hat{d} \notin (-\frac{1}{2}, \frac{1}{2})$ estimation was based on a transformed (first-differenced) series to ensure a consistent method.

Note that the estimate of d for the levels data comes out fairly constant for the different vintages – at just over 1·3 and about 1 standard error away from the simple unit root hypothesis. Considering the revisions, we see that the estimate of d is around 1·2 for the overall revision, which tends to confirm the earlier conventional co-integration approach, but that the estimate of d for the final (annual) revision is consistent with a stationary series; indeed, in this latter case, as the differencing parameter is about 1 less than the corresponding parameter for the levels series, the final revision would satisfy the definition of co-integration given in Eagle and Granger (1987).

IV. ORTHOGONALITY TESTS

Harvey *et al.* (1983) and Mankiw *et al.* (1984), amongst others, have noted that preliminary vintages of data can be viewed as forecasts of the final vintage or as a preliminary measurement of the final vintage subject to a measurement error. Mork (1987) combines both of these elements in his view of how the data might be generated. If a preliminary vintage is a forecast of the final vintage, and Z summarises the information available at the time of the forecast, then if the forecast is efficient it should fully incorporate the information in Z. This implies the following orthogonality condition if the preliminary vintages are efficient forecasts of the final vintage,

$$Y_t^m - Y_t^v = \mu + \mathbf{Z}_s \boldsymbol{\beta} + u_s \quad \text{for } v = 1, \ldots, m-1 \tag{3 a}$$

$$\text{orthogonality condition: } \mu = 0 \text{ and } \boldsymbol{\beta} = \mathbf{0} \tag{3 b}$$

where μ is a constant, $\boldsymbol{\beta}$ is a $k \times 1$ vector of coefficients on the variables in the information set at time s, and s is the time at which $Y_t^{(v)}$ is compiled. If $\mu = 0$ and $\boldsymbol{\beta} = \mathbf{0}$ the preliminary vintage can be viewed as measuring the final vintage with error u_s. Note that following Brown and Maital (1981), Hansen and Hodrick (1980) and Mork (1987), u_s might well be serially correlated, and these authors adopt low order moving average processes for the disturbance terms in 'orthogonality' regressions. We follow this approach and use Hansen and Hodrick's estimation method. Note that there is a difference of approach between the tests for orthogonality and those for co-integration. The former assume stationary variables and moving average disturbances, whereas the latter assume non-stationary variables and autoregressive disturbances in the case of the Dickey–Fuller tests (the Phillips and Perron test leaves the form of serial correlation unspecified). This difference does not appear to have been resolved yet in the literature.

To implement the test in (3 *a*) we need to consider possible components of the information set, Z. One aspect likely to be of importance here is the history of revisions. For example, potential candidates for the last (annual) revision $Y_t^{25} - Y_t^{21}$ are $Y_t^{21} - Y_t^{17}$, $Y_t^{17} - Y_t^{13}$ and so on back to the first annual revision. Also available is the history of the same vintage, for example Y_{t-i}^{21} for $i = 1, \ldots, n$. Outside of these two kinds of autoregressive processes Kenny (1987) has suggested that revisions might be related to the rate of inflation. To capture this aspect we also include the percentage rate of change of the retail price index – an index which is not revised over time. The results of applying the orthogonality tests with this information set for the components of GDPE are summarised, for selected vintages, in Table 7. The first two rows for each

Table 7
Orthogonality Tests†

	C	*I*	*G*	*X*	*M*	*SWIP*	*FCA*
$v = 1$							
$\mu = 0$	11·15*	6·49*	−0·59	−0·24	−0·10	2·33*	1·76
$\boldsymbol{\beta} = \mathbf{0}$	92·20*	23·69*	4·48	85·83*	10·47*	6·77	6·85
DF test‡	−4·91*	−5·02*	−5·61*	−5·84*	−3·62+	−5·72*	−4·88*
$v = 21$							
$\mu = 0$	5·88*	0·11	0·51	−1·94	0·78	1·91	1·29
$\boldsymbol{\beta} = \mathbf{0}$	63·75*	16·77	15·46	18·63*	15·32	13·93	31·73*
DF test†	−7·10*	−5·37*	−5·35*	−4·71*	−5·23*	−5·87*	−4·82*

† The entry for $\mu = 0$ is the t statistic for testing that null hypothesis. The entry for $\boldsymbol{\beta} = \mathbf{0}$ is the appropriate χ^2 statistic; for $v = 1$ note that $\chi^2(4)_{0·05} = 9·49$; and for $v = 21$, $\chi^2(10)_{0·05} = 18·30$. Values which are significant at the 5% level are indicated by a *. This table is a summary from applying these tests to all vintages one annual period apart. For $v = 21$ we used an MA(5) error process, for $v = 17$ an MA(4) error process and so on. Lagged values of the v-th vintage up to 4 were included and all possible annual revisions, in addition to the inflation variable.

‡ DF test is the Dickey–Fuller 't' test for a unit root in the residuals from the orthogonality regressions. $p = 0$ was sufficient in all cases except I for $v = 1$, where we used $p = 1$. A + and a * indicate rejection of the null of non-co-integration at the 10% and 5% significance levels, respectively.

vintage give the orthogonality test statistics. For $v = 1$ we can reject the null hypothesis of orthogonality for *C*, *I*, *X* and *M*; in addition the constant is significant for *SWIP*. For $v = 21$ we can reject the orthogonality conditions for *C*, *X* (just) and *FCA*. The inflation variable is significant in the regressions for *C* and *I* when $v = 1$, and *C* and *X* for $v = 21$. The evidence from these tests suggests there is information which has predictive ability for the final vintage, implying that it is not fully incorporated into the preliminary vintage. The third row for each vintage gives the relevant Dickey–Fuller test statistic for the null of non-co-integration for the residuals from the orthogonality regressions. Here we see that the general effect of introducing the information in *Z* is to reduce the residuals to stationarity. This is particularly marked for the problematic case of consumption, where there is now a very firm rejection of the null of non-co-integration.

V. CONCLUDING REMARKS

We have suggested and applied a method to construct the real, or constant price, expenditure components of GDP which avoids a confusion between the base change and vintage effects. Once this rebased data had been obtained we were able to assess the characteristics of the preliminary vintages compared to the final vintage. We found, for example, a systematic tendency for a number of the expenditure components to be revised up. We were also able to assess whether the preliminary vintages of data embodied information available at the time of their construction. For some series we found that this was not the case, and that it was possible to find information with predictive ability for the final vintage. Regressions of the revisions on such information resulted in residuals which led to rejection of the null hypothesis of non-co-integration, whereas this was not always the case for the revisions themselves. We hope in future research to assess the impact of data revisions on particular areas of applied work.

It is important for researchers to bear in mind that published data are a mixture of vintages, with potentially different properties, corresponding to different stages of the revisions process. For example, a run of data published in *Economic Trends* corresponds to a *diagonal* from the kind of data matrix illustrated in Table 1 until a 'final' vintage is reached. At the least it would seem prudent for researchers using series subject to revision to assess the sensitivity of their results to a different choice of vintages of data on what is ostensibly the same variable.

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Date of receipt of final typescript: September 1990

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