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by

D M Egginton

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ABSTRACT

A method which balances data subject to measurement error was initially proposed in the 1940s by Richard Stone and his associates. This technique requires an estimate of the relative reliabilities of the observed data matrix being available. Practical applications have usually relied upon subjective estimates of the normalisation matrix but recently methods to estimate this matrix using residuals from regressions or trends have been proposed. This paper compares the properties of the subjective, regression and trend approaches to balancing a stylized set of accounts using Monte Carlo simulations. It finds that when the measurement errors in the accounts contain both bias and a random component all the methods provide average estimates of the variables which are usually statistically different from the true values. When the observed data contains only a random element the regression and trend methods still produce mean estimates which are statistically different from the true data but the subjective method does not. The paper suggests that the use of either the trend or the regression methods to balance national accounts may result in data which is as misleading to analysts as the observed data itself. Although further work is needed, the results do, tentatively, indicate that in terms of the variance of its estimates the subjective approach is relatively robust to errors in the variance-covariance matrix. However, when bias is present all the methods do equally poorly and, because the resource requirements of the trend approach is smaller than for the other two methods, the trend method is advocated as the preferred method of balancing the accounts.

A Monte Carlo study of alternative approaches to balancing the national accounts

1 Introduction

The collection of national accounts data are subject to a number of sources of measurement error which result in the accounting restrictions only being satisfied by the inclusion of residual errors or balancing items. A technique for balancing data so that it satisfies a set of restrictions was first introduced by Stone, Champernowne and Meade (1942) and the technique has been extended by a number of authors to deal with various error structures. The technique and its extensions all rely on the availability of matrices of reliability for the data. Construction of these matrices has lagged a long way behind other developments in this field and most applied work has relied upon subjective or a priori values supplied by statisticians. Recently, however, Weale (1989) has proposed an asymptotically maximum likelihood method of estimating relative reliabilities from regressions on the observed data and a variant of his technique, which uses trends, has been applied by Dunn and Egginton (1990) to the UK national accounts.

The work reported in this note suggests that using any of these methods, in isolation, is extremely unlikely to result in the equivalence of the balanced and the true data. Nevertheless, the use of objective methods to balance the accounts has a useful qualitative aspect. The reason for this is as follows: In the subjective approach the person conducting the analysis chooses the relative reliabilities to be used in balancing formula. Consequently, the adjustments made to balance the data simply reflect prior beliefs (given the identities and residual errors in the accounts). The objective approaches do not impose prior beliefs (except for the reasonably general assumptions about the structure of the measurement error process) and the adjustments made by these methods do give some indication of the reliabilities of the data. Thus, even if the quantitative adjustments are inaccurate, the methods may give independent qualitative signals about where resources, eg more extensive surveys, could be concentrated to improve the coherence of the national accounts.

In this respect it is interesting to note that, in broad terms, the recent studies of the CSO (1989) and by Dunn and Egginton (1990) suggest that measurement errors are generally located in the financial accounts rather than in the current or capital accounts. Consequently for example, resources to remove the discrepancy in the accounts of the overseas sector may be most effectively used in improving the capital account rather than the current account. There are, however, a large number of areas about which the two studies give conflicting results. It is important, therefore, that the properties of the objective approaches to estimating the reliability matrix is understood.

However, the use of the objective approaches are in their infancy and virtually nothing is known about their small sample properties. If these were to be shown to be poor, then they would not even provide useful qualitative signals let alone quantitative signals. This paper addresses this issue by comparing the properties of the 'regression', 'trend' and 'subjective' methods of compiling the reliability matrix, based upon a modified version of the national accounts used in Dunn and Egginton (1990), when the data contains both random measurement errors and a bias component, by using Monte Carlo simulations.

The Monte Carlo (stochastic) simulation procedure used in this study begins by specifying the true data, which obey the national account identities, a distribution of random errors and bias components. When added together these components give a distribution of observed data. The observed data is used to create the reliability matrix in the trend and regression approaches and the observed data can be balanced using the formula (1) discussed below. The balanced data is then stored. New observed data is then created by using another set of random errors and the procedure is repeated 500 times. The average of the stored (balanced) data is then compared with the (known) true data to analyse the formula's performance in terms of unbiasedness and the distribution of the stored data is analysed to give insights into the efficiency of the estimators. The use of a Monte Carlo procedure in this context is unfamiliar but if the balancing formula is thought of as an estimator and the balanced data as parameter estimates then the procedure used in this paper is similar to that used in numerous other studies.

The paper is set out as follows: section 2 outlines the basic balancing formula and some extensions. It also discusses some of the problems involved when, what is termed, the subjective approach to setting the reliability matrix is used. It should be understood that the term 'subjective' in this context does not necessarily mean that a formal Bayesian approach has been adopted in the construction of the matrix. Nor does it necessarily mean that entirely informal methods have been adopted, it is quite likely that the subjective construction of the reliability matrix has relied upon objective analysis, for example, of the structure of surveys used to construct the data or of the data revision process. What is meant by subjective in this study is that the method of constructing the reliability matrix cannot be modelled in a simple manner. The next two sections set out the regression and trend approaches where, in contrast, the modelling of the construction of the reliability matrix is straight forward being derived from the residuals from regression and trends. Sections 5 and 6 outline the system of accounts and the data used in the study. The next three sections describe, in turn, the information assumed to be available to analysts using the three methods to balance the accounts. The analysts, or their supposed knowledge, do not refer to particular people or institutions, they are simply agents invented for the purposes of the Monte Carlo experiments. Sections 10 to 12 analyse the results of the simulations in terms of average differences from the true data when bias is either present or absent and the variances of the balanced data which is compared both between methods and with the true variances. The final sections provides some conclusions.

2 The balancing formula

The problem is to adjust a vector of observed data items, x, to a vector x^*, which satisfies the linear constraints $Ax^*=0$, where the normalised distance between x and x^* is minimised. The basic solution to this problem is to set

$$x^* = x - VA^T(AVA^T)^{-1}Ax \quad (1)$$

where T is the transpose operator. This solution can be interpreted in terms of least squares and has been given a Bayesian interpretation by van der Ploeg (1984). Byron (1978), on the other hand, describes the problem in terms of a constrained quadratic loss function. Given that the constraints matrix, A, is determined unambiguously from the national account identities, the problem becomes the choice of an appropriate normalisation matrix, V. The choice of V is essentially arbitrary but if the variables in x are observations, recorded with error, of some underlying processes that are not observable then it seems sensible to let V reflect the relative reliabilities of the observed data so that the less reliable data take more of the balancing adjustment. Hence the variance-covariance matrix of the measurement errors may be a suitable choice of V.

This basic balancing rule can be extended in a number of ways: missing observations [Stone (1977), Byron (1978)], multiple prior estimates [Byron (1978)], deterministic and stochastic constraints [van der Ploeg (1982)], intertemporal constraints [Weale (1988)] and error structures which include autocorrelated, trend, systematic and cyclical components [van der Ploeg (1982)]. Each of these methods requires at least one variance-covariance matrix and one each is required for each of the more explicit formulations of the error structures (ie one for the systematic component, one for the trend component etc).

Until Weale (1989) nearly all the estimates of the error variance-covariance matrices were determined subjectively. For example, van der Ploeg (1982) and Barker et al (1984) in their analyses of UK production accounts and the UK social accounts matrix respectively, construct the standard deviation of the measurement error as a percentage of the observed value with the percentage being determined by the row and column reliabilities which, in turn, were subjectively determined from Maurice (1968). Both papers reported balanced accounts which were substantially different from a balanced set of accounts which used a 'neutral' hypothesis that the variance matrix was just proportional to the observed value. Clearly the subjective element plays an important role in the overall balancing of the accounts. (It can be noted that van der Ploeg calculated the variance matrix of the systematic error component using the variance matrix of the residual component divided by the number of time periods considered.) Stone (1982) also used subjective estimates of reliability based on the ranges provided by Maurice (1968) to determine the variance matrix.

There are a number of potential problems with the subjective approach. First and foremost the relative reliabilities may simply be incorrect. This is of particular importance when Maurice's (1968) percentage margins of errors, which are in the form: less than 3%, 3–10% and greater than 10%, are used. For example, Stone (1982) uses these ranges but, Weale (1988) shows that, on the assumption of zero covariances, the rating of the expenditure measure of GDP constructed from its components is inconsistent with the direct estimate using Stone's ratios. It should be noted that CSO (1989) avoided the problem of inconsistencies by asking data compilers for their estimates of the 90% probability range within which the true value would be expected to fall. Nevertheless, the relative measurement errors could still be incorrect simply because some compilers are more pessimistic than others.

The second major problem with subjective calculation of the variance matrix is the absence of published estimates of covariances. Clearly appropriate covariances could remove the inconsistencies, noted by Weale, in Stone's ratios. Weale (1982) suggests that redefining the accounts may allow some covariances to be imposed and some covariances, interrelating the price, volume and value of a variable, can be calculated theoretically [Weale (1988)]. Despite this the off-diagonal elements of the variance-covariance matrix are usually assumed to be zero and even if some covariances are calculated the matrix remains sparse. However, Dunn and Egginton (1990) suggest that the presence or absence of covariance terms plays an important role in determining the size and direction of adjustments. On the other hand, van der Ploeg (1984) argues that, in some instances, ignoring covariances may not be too bad an approximation. A final problem is that subjective estimates may not be available. Crossman (1988), for example, used Stone's ratios, which were derived from UK data, to balance the Australian national accounts.

For these reasons the estimation of the variance-covariance matrix by other, more objective, means is to be welcomed not only because they might supply better balanced estimates but also because they can provide a qualitative cross-check on the adjustments made by the use of a subjective variance-covariance matrix. This is not to argue that the subjective and objective settings of the variance-covariance matrix need be mutually exclusive. Indeed, a mixture of the two approaches would appear preferable, *a priori*. An early attempt at an objective setting of the variance-covariance matrix was Weale (1985) who used an analysis of data revisions in his study of the US economy. However, revisions are only one source of measurement error and the relevance of a variance-covariance matrix based on the history of revisions may well decline significantly as the vintage of the data increases. For this reason the setting of the variance-covariance matrix by reference to the revision history of the variables alone does not appear to be a plausible option.[1] Recently, however, Weale (1989) has proposed that the variance-covariance matrix be based on the residuals from regressions on the variables to be balanced. The next section outlines Weale's regression approach in more detail.

3 The regression approach

The Weale approach again employs the balancing formula (1) derived earlier but derives the rule from maximising a likelihood function based on several assumptions about the measurement error; in particular that the errors are normally distributed and are not serially correlated. The variance-covariance matrix, V, of the measurement errors, to be used in the balancing formula, is obtained from the regression residuals and this provides an asymptotic maximum likelihood estimate of the true data.

The essence of the Weale approach is as follows. The measurement error is considered to be made up of two additive components: a bias component which is correlated with the true data and a second random element which is independent of the true data. It is also assumed that neither component of the measurement error obeys the accounting identities. If the bias component was zero throughout then it would be sufficient to set V as the variance-covariance matrix of the actual series to be balanced. At first sight this seems wrong because some series are genuinely more volatile than others and yet may be more reliably measured. However, since genuine volatility in a series must be reflected elsewhere for the accounting identities in the true series to hold, Weale shows that such variance is

(1) Nevertheless, the presence of measurement errors which will later be revised away does suggest that the variance-covariance matrix needs to be allowed to change with respect to data vintage. This is not considered further in this paper.

purged from V on multiplication by the restriction matrix within the balancing formula.

This result means that although variance due to genuine volatility and variance due to measurement error cannot be distinguished for each series, the total variance can be employed in the construction of V. The restrictions matrix then purges that variance which satisfies the accounting identities and the balancing adjustment should reflect only variance due to measurement error.

Problems occur when the assumption that the bias is zero is dropped. Then, because of the correlation of the biases with the true series, the restrictions matrix is no longer able to purge 'genuine' variance from V and the balancing adjustments will reflect genuine noise. Weale overcomes this by using regressions to explain the bias and remove it from the observed data. It does not matter whether the regressions explain, and remove, variance due to genuine volatility or not, providing this is done consistently across series. However, if the regressions also explain part of the true data a two step approach, where the bias is first removed from the data and then the remaining measurement error is allocated across variables, cannot be used. Weale assumes, in the absence of other data, that the variance-covariance matrices of the bias and the random components are the same to a scalar multiple. Thus the bias can be allocated in the same proportions as the random element and the data can be balanced in one step without bias adjustment.

4 The trend approach

Dunn and Egginton (1990) have argued that for practical purposes removal of the bias component can be achieved by the use of trends rather than by regressions. They argue that the choice of available regressors is extremely large and the relevance of any particular variable to the bias component, given that the dependent variable is the observed series not the measurement error, will be hard to determine. Furthermore, in practice the regressor variables may also be measured with error and there is a risk that these errors may be correlated with the random component of the measurement errors. The partitioning between the bias and random components of the measurement error may not, therefore, be achieved in practice.

Dunn and Egginton (1990) note that the assumption that the bias component is correlated with the true data and the random component is independent is essentially arbitrary. They propose the equally arbitrary assumption that the low frequency part of the spectrum of the measurement error is correlated with the true data but the high frequency component is independent. Thus the bias can be removed by the application of a low frequency filter. They also demonstrate that the regression and trend approaches are simply particular choices of a state space representation of the data in terms of a true series and measurement errors. The methods are, however, practical alternatives both to each other and to the subjective approach outlined above.

Each of the three methods; subjective, regression and trend will result in accounts which balance. Even if the variance-covariance matrix is specified correctly, however, the balanced data will not necessarily be the same as the true data and, consequently, the extent to which the balanced and the true data diverge cannot be revealed by analysis of real data. An indication of the relative abilities of the three methods can be gauged from simulations on a constructed set of national accounts. These accounts, the true data and the observed data are described in the next sections.

5 The system of accounts

Tables 1 and 2 present a stylised system of the national accounts which is a highly compact version of that used by Dunn and Egginton (1990). By assumption, each of the variables are measured independently and this implies that the covariances cannot be used to balance the GDP identities as was done by Dunn and Egginton (1990). Without aggregation the number of restrictions, given the

Table 1: Stylized nominal income, expenditure and flow of funds accounts

		1 Person	2 Public	3 Corporations	4 Overseas	5 Not allocated	6 Row Sum
Current net receipts	1	YXJ	YGC				
Current grants	2	YJG	(YJG)				
Transfers overseas	3	EJTA	EGTA		(EJTA+EGTA)		
Stock appreciation	4	YSAJ	YSAG	YSAI			
Debt interest payments	5		EDBT				
Company savings	6			SXI			
Net interest, profits and dividends	7				BIPD		
Expenditure taxes and subsidies	8		ESAB			TE	FCA9
Fixed investment and stock building	9	IXJ9	IXG9	IXI9			IX9
Current expenditure	10	C9	G9		X9-M9		
Flow of Funds							
Net deposits with corporations	11	DXXJ	DXXG	DXXI	DXXO		0
Public sector borrowing	12	BXGJ	BXGG	BXXI			0
Miscellaneous transactions	13	PEXX	PUXX	ICXX	OUXX		0
Column Sum		0	0	0	0		

Note
GDPY9 = Sum rows 1 to 7 minus expenditure taxes.
GDPE9 = Sum rows 8, 9 and 10
GDPY9 = GDPE9

Both X9 and M9 are measured independently but are included in the same row for compactness.
Variables in brackets have no independent estimates thereby avoiding the need for restrictions.

number of stimulations performed, would have provided too large a burden on computer resources to be justified. Consequently, the accounts were aggregated, in particular by removing the distinction between the industrial and financial sectors. Table 1 provides the nominal income and expenditure accounts and the flow of funds for 4 sectors of the economy. It can also be seen that for some items, for example receipts of transfers by the overseas sector, there are no explicit measures. On the other hand, some measures are identified in slightly more detail than the accounts suggest. For example, public sector current receipts (YGC) includes taxes on expenditure (TE). Thus the accounts implicitly identify total other current receipts even though they are not separated out in the accounts.

Each of the sectoral columns in table 1 sum to zero, that is each sector's current income minus current expenditure equals investment in fixed assets plus net purchases of financial assets.

Each of the rows numbered 11 to 13 in table 1 also sum to zero; that is, an increase in assets must result in an increase in the liabilities of another sector. The sum of row 9 gives total fixed investment, IX9, whilst the sum of row 8, taxes on expenditure plus subsidies gives the factor cost adjustment, FCA9. The sum of the rows 1 to 7 minus taxes on expenditure gives the income measure of GDP, GDPY9, and the sum of rows 8, 9 and 10 gives the expenditure measure of GDP, GDP9, both of which are equivalent. Thus there are 35 variables, all of which are measured independently and 12 restrictions, of which only 11 need be imposed since if any eleven are satisfied then the twelth will automatically hold. (The corporations column is balanced by residual.)

Table 1 could, if so desired, be balanced separately from the real variables but this may imply implausible price deflators. However, the restrictions between real and nominal variables, given by restrictions 1 to 7 in table 2, are non-linear and cannot be directly dealt with by the balancing formula outlined above. One method which circumvents this problem is to take logs of each of these variables (including the price deflators) and enter these, together with the corresponding real and nominal variables into the variable set and the constraints matrix. The logarithmic identities (1 to 7 from table 2) are contained within the constraint matrix but the logarithmic data are not linked to the natural variables by any linear constraints, rather the covariances are used to ensure that the balanced natural variables and the exponent of the balanced value of the logarithmic variables are approximately equal. Thus, even if there were no covariances between the measurement errors, the variance covariance matrix will not be diagonal using this method. The use of logarithms is, however, only an approximation and the Monte Carlo simulations provide a test of whether or not this approximation is good enough or whether other methods need to be sought. Restriction 8 and 9 in table 2, which define the real expenditure measure of GDP and the equality of the real income and expenditure measures of GDP, are imposed in the restrictions matrix, A. The addition of the national accounts of the real side of the economy adds a further 8 variables (the price deflators are not added in an unlogged form) which are measured independently and 21 variables in logs to bring the total to 64. The total number of restrictions is raised to 14. In matrix terms the observed variables, x, are a vector of dimension 64x1, the restrictions matrix A is of dimension 13x64 and the variance-covariance matrix, V, is of dimension 64x64.

Table 2: Real GDP and prices identities

1	Consumers' expenditure	C9	=	PC*CONS
2	Public sector current expenditure	G9	=	PG*G
3	Fixed investment	IX9	=	PIX*IX
4	Exports	X9	=	PX*X
5	Imports	M9	=	PM*M
6	Factor cost adjustment	FCA9	=	PFCA*FCA
7	GDP expenditure	GDP9	=	PGDP*GDPE
8	Real GDP expenditure components	GDPE	=	CONS+G+IX+X-M-FCA
9	GDP Income	GDPE	=	GDPY

6 The observed data

This section describes the construction of the observed data, x. Initially seasonally adjusted data consistent with the November 1989 Economic Trends and the November 1989 Bank of England Quarterly Bulletin was balanced for the period from the second quarter of 1979 to the fourth quarter of 1988 using the same 3 term moving average method (see equation 10 below) and variables as in Dunn and Egginton (1990). This balanced data was aggregated to form the 'true' data which obeys the accounts given in tables 1 and 2. To each of these variables measurement errors were added which are comprised of 2 components: an independent random component, e_t, which has a mean of zero and a standard deviation equal to 5% of the mean value of the true data (see appendix 1 for these values), and a bias component which is determined by:

$$\beta_1 z_{1t} + \beta_2 z_{2t} + \text{constant} \qquad (2)$$

where β_1 and β_2 are parameters which are different for each variable (see appendix 2) and z_1 and z_2 are variables which determine the bias (see appendix 3). The observed data is therefore equal to:

$$x_t^* + \beta_1 z_{1t} + \beta_2 z_{2t} + e_t + \text{constant} \qquad (3)$$

where x_t^* is the true data. The bias component has a mean of zero over the sample period (ensured by the presence of the constant terms) but there is no reason to suppose that the variance-covariance matrices of the bias and the random components are equivalent up to a scalar multiple. The presence of the measurement errors results in the restrictions given in tables 1 and 2 not holding, ie $Ax \neq 0$ and the problem faced by analysts is to estimate the variance-covariance matrix which will ensure that the balanced data is identical to the true data. The subjective, regression and trend approaches are used, in turn, to estimate the variance-covariance matrix and the problem facing each approach is set out below.

7 Balancing using the subjective approach

In this experiment it is assumed that the analysts have the following information. They are aware that there are random measurement errors on each of the series which are independently measured and, for the purposes of the Monte Carlo simulations, it is assumed that they know the variances which underlie these error processes. This is highly unlikely to occur in practice, but these assumptions do not mean that the analyst possesses the actual variance-covariance matrix which determines the random errors. This is because with only 250 independent replications being used it is unlikely that the true underlying process will be established. Thus, the analysts do not possess the operationally relevant variance-covariance matrix which may, for example, contain significant covariance terms even though these are not present (except for logarithmic linking purposes) in the true variance-covariance matrix. It is also assumed that the analysts know that there is a mean zero bias component to the measurement error. However, they do not know the magnitude of the bias in any given period. They therefore expect that the bias is zero and they make no prior adjustments to the data. The analysts' final problem is to calculate elements of the variance-covariance matrix corresponding to the logs of variables and the covariances between the variables for which linear constraints cannot be imposed. All other covariances are assumed to be zero by the analysts both because of their expectation that the bias term is zero and because they know this is true for the underlying random error processes.

Weale (1988) provides the formulae for the calculation of these elements and these can be slightly simplified because the analysts know that all real and nominal variables have been constructed independently by the data compilers. Consequently, the covariances of the random component between nominal and real variables; logs of nominal and real variables; and the logs of real variables and nominal variables and vice versa are all zero. The remaining covariances are given by:

$$\text{Cov}(\log w, \log P_w) = -\text{var}(w)/w^2$$

$$\text{Cov}(\log W, \log P_w) = \text{var}(W)/W^2$$

$$\text{Cov}(W, \log P_w) = \text{var}(W)/W$$

$$\text{Cov}(w, \log P_w) = -\text{var}(w)/w$$

$$\text{Cov}(W, \log W) = \text{var}(W)/W$$

$$\text{Cov}(w, \log w) = \text{var}(w)/w$$

The variance terms are calculated as:

$Var(\log W) = var(W)/W^2$

$Var(\log w) = var(w)/w^2$

$Var(\log P_w) = var(W)/W^2 + var(w)/w^2$

Where: var (.) are the variances of the random component of measurement errors, W is the nominal variable, w is the corresponding real variable and P_w is the price deflator (defined as W/w). The accounts analysed in this paper require the calculation of 21 variance terms and 84 covariance terms.

As both Var (W) and Var (w) are known by the data compilers to be constant, the variance-covariance matrix only alters in the simulations because the observed values of the variables change with each simulation. Nevertheless, the non-constancy of the matrix has potentially important consequences for the performance of the balancing procedure. With a constant variance-covariance matrix and measurement errors which have a mean of zero for a given time period, an asymptotically consistent estimate of the true data can be found with any variance-covariance matrix. As would be expected, the balancing formula, (1) above, can be replaced by the mean of the observed replications.

This can be shown as follows:

$$\text{Let } x_t = x^* + e_t \qquad (4)$$

using the balancing formula (1), substituting in (4) above and using the fact that $Ax^* = 0$.

$$x_n = x^* + e_{nt} - VA^T(AVA^T)^{-1}A(e_{nt}) \qquad (5)$$

where x_n is the balanced data in replication n for time period t.

e_{nt} is the measurement error for replication n for time period t.

As e_{nt} is assumed to be mean zero, then its sum over the N replications is also zero. Thus

$$\sum x_n = Nx^* \qquad (6)$$

where N is the total number of replications. Hence, provided the number of replications is large enough, the mean of the balanced data will equal the true data, x^*, irrespective of the choice of V (provided it is constant between replications). In fact V in (5) above could be set so that the final term becomes zero and in this case an estimator of the true data simply becomes the mean of the observed value from each replication. In the case of antithetic random errors only a matched pair of observations would be required to achieve an unbiased estimate of the true data. The intuition of this is clear, a large error on one side of the variable will be offset by another equally large error on the other side so that on average the balanced data equals the true value. This result does not follow if bias is present, ie the mean of the measurement error is not zero, in which case the bias is only removed if the variance-covariance matrix exactly corresponds with the distribution of the bias.

However, if the variance-covariance matrix changes between replications, as it will do as the calculated covariances depend upon the observed data, then the final term of equation (5) above will not cancel for antithetic pairs and, in general, the number of replications required before the mean estimate of the balanced data is equivalent to the true data will be larger than with a constant variance-covariance matrix. There is, therefore, no guarantee that the use of the subjective approach will necessarily result in data which is on average statistically equivalent to the true data.

Although, as demonstrated above, any fixed variance-covariance matrix will on average balance the data correctly, the penalty for specifying an incorrect matrix (but not one which is simply a scalar multiple of the true variance-covariance matrix) is that the variance of the balanced data will, in general, be increased. This follows from an application of the Rao-Blackwell theorem by which it can be shown that the balancing formula is the minimum variance unbiased estimator of the true data, if the observed data is distributed normally [van der Ploeg (1984)]. It should be noted in passing that the balanced variances need not increase as the degree of error in the variance-covariance matrix rises (in the sense that all but one element of the variance-covariance matrix increases in magnitude).

8 Balancing using the regression method

In this case the analysts are assumed to be aware of the bias component and to know that it is determined by the variables z_1 and z_2 which are known with certainty. The analysts do not know the parameters (β_1, β_2) or the constant which determines the bias, but they do know that it has a zero mean. Nor do they know the variance-covariance matrix of the random component of the measurement errors and they assume that the variance-covariance matrices of both the bias and random components of the measurement error are equivalent up to a scalar multiple. The statisticians choose to construct the variance-covariance matrix from the regression residuals of z_1 and z_2 on the observed data for the period second quarter of 1979 to the fourth quarter of 1988. They calculate the residuals for the logarithmic data by taking the log of the fitted value from the regression on the natural variables and subtracting this from the log of the natural variable (a log of a residual cannot be taken because the residual can be negative).

The residuals for the price deflators are calculated as the logarithm of the price deflator minus the log of the ratio of the fitted values for the respective value and volume variables. However, the use of this technique to construct the covariances for the logarithmic variables implies an inconsistent error structure between the natural variables and their logarithmic counterparts because the residual calculated for the logarithmic variables are (approximately) in percentage not level terms. An alternative method would be to use the formulae given by Weale (1988) for the calculation of the variances and covariances but this has the disadvantage that other covariances are not defined. Thus, if the analysts believe covariances are potentially important, they may be reluctant to set them to zero and would prefer to use the approximation.

Again it should be noted that the assumption that the determinants of the bias are known with certainty is optimistic. It is also highly unlikely that the components of the measurement errors will have similar variance-covariance matrices up to a scalar multiple. Indeed it is not true in the data which is investigated in this study. Recognising this last point, the analysts may use an alternative procedure which removes the bias from the data, and then balance the accounts. The estimate of the bias is constructed from the knowledge that the mean of the bias term is zero together with the estimated parameters $\hat{\beta}_1$ and $\hat{\beta}_2$. This allows an estimate of the constant term in the bias equation to be constructed using:

$$-(\hat{\beta}_1 \bar{z}_1 + \hat{\beta}_2 \bar{z}_2) = \text{constant} \tag{7}$$

where $\bar{z}_1$ and $\bar{z}_2$ are the means of z_1 and z_2 respectively. Using the estimated parameters and the constant, the bias for each quarter can be estimated and subtracted from the observed data and this adjusted data can be balanced. The variance-covariance matrix is still formed from the regression residuals as in the one step method. The two step procedure does, however, provide inconsistent estimates of the parameters. The reason is that the regressions have measurement errors in the dependent variables and these errors are correlated with the dependent variables (the biases), ie the model which the analysts would wish to know is:

$$b_t = \beta_1 z_{1t} + \beta_2 z_{2t} + c \tag{8}$$

whereas they actually estimate:

$$b_t + x_t^* + e_t = \beta_1 z_{1t} + \beta_2 z_{2t} + c + v_t \tag{9}$$

where b_t = bias, x_t^* = true data, e_t = random measurement error, cov $(x_t^*, b_t) \neq 0$, c = constant, v_t = random error

Moreover, the expectation of the left hand side of equation (9) is not zero because it contains the true value of actual data (x_t^*). This is why the constant from the regression is replaced by that calculated using equation (7). It is not, therefore, even possible to conclude that the parameters will be underestimated.

9 Balancing using the trend approach

The analysts are aware that the data contains a bias component which is likely to be correlated with the true data. They are unaware of the determinants of the bias and they do not know the variance-covariance matrix of the random component. Thus they have the least prior information available and indeed the trend approaches prior data requirement is less than either of the other methods. In the absence of this knowledge they assume that the bias and the random measurement errors have the same variance-covariance matrix up to a scalar multiple ie the same assumption made by the analysts using the regression approach. In the present case however they choose to remove the bias component by running the data through a low frequency filter given by:

$$0.25\, w_{t+1} + 0.5\, w_t + 0.25 w_{t-1} \tag{10}$$

The residuals from the filtering process are used to construct the variance-covariance matrix. The choice of this filter is entirely arbitary but the use of methods such as variate difference to determine the trend to fit also contain a subjective element [see Kendal (1973)] and as such it was decided to retain the same simple moving average process for each variable. Of course, allowing differing moving average processes also increases the complexity of the trend method and hence reduces its attractiveness when compared with the other methods. The filter can be used directly on logarithmic variables and, as the analysts are unware of the functional form of the bias, they arbitrarily construct the residual for logarithmic variables from:

$$\log w_t - (0.25 \log w_{t+1} + 0.5 \log w_t + 0.25 \log w_{t-1})$$

rather than from, say:

$$\log w_t - \log (0.25\, w_{t+1} + 0.5\, w_t + 0.25\, w_{t-1})$$

10 The simulation results including bias

For each of the 3 methods there are two simulations: one with bias added and one without. A further simulation is run for the regression approach where the data is adjusted to remove the estimated bias prior to balancing. In total there are 7 simulations each consisting of 250 antithetic pairs of random measurement errors (ie 500 replications). The bias remains the same in each replication and the random errors are identical across simulations. The number of replications per simulation is the same as that used by Hall and Stephenson (1990).

The simulations provide direct estimates of 64 variables and a further 7 price deflators are implicit. However, the two GDP estimates are not independent and, consequently, 69 estimates can be evaluated. The evaluation is simply a test of the difference between the mean value of each variable from the replications and the true value using a t-test. The results are given in table 3. Table 4 allows the evaluation of the appropriateness of the logarithmic approximations. The difference of the estimated means of the 21 logged and natural variables are tested using a t-test.

The results of the simulations containing the biases are given in columns 1, 3 and 5 of table 3. As can be seen, the hypothesis that the average of the balanced data and the true data are the same can be rejected for virtually all of the variables no matter which method was used to balance the data. The subjective, trend and regression methods managed to pass the t-tests, 9, 8 and 5 times respectively at the 5% level of significance. There is also little coherence in which variables pass and which fail the t-test, although all 3 methods produce balanced data for the log of G (real government expenditure) and unlogged G which are close to its true value. However, as table 4 indicates, the logarithmic approximation which links real and nominal variables produces estimates which are statistically similar. Hence given that one of these variables passes a t-test in table 3 it might be expected that its logarithmic counterpart would also pass the t-test (the exception to this being nominal imports (M9) which just passes in its log form but fails in its unlogged form using the trend method). Making an allowance for this, the results are worse than they appear and they clearly suggest that none of the methods can deal with data which contains both random and bias components.

Of course, simply because the average balanced estimate and the true data are statistically different it does not follow that the differences are necessarily numerically large. However, as table 5 (columns 1, 3 and 5) shows, the average percentage error can be large and the use of any of these methods to balance the accounts is likely to produce accounts which are as misleading to the analyst as the measured data itself. As these methods all produce results which are equally poor this suggests that should balanced accounts be required the use of the trend method would be preferable because its information and resource requirements are so much smaller than the other methods.

A comparison of the difference between the average estimate of the balanced data and the true data with the bias reveals a strong positive correlation of between 0.85 (for the subjective approach) and 0.81 (for the trend approach) for these methods. Regressions of the average balancing error on the bias reveal that a £1 million increase in the bias results in between £0.97 and £1.03 million increase in the average error. We cannot reject the hypothesis that the average error for each variable for each method rises one for one with the bias. Hence, because the mean of the random measurement error is zero, the balancing exercises have been, on average, unable to improve upon the unbalanced accounts. Whilst the presence of bias in the observed data is not the whole reason for the failure of the methods to correctly balance the data, these results suggest that removing the bias would result in an improvement in the number of variables which pass their respective t-tests.

Column 6 of table 3 reports the results for the two stage regression method discussed above. The removal of the bias results in slightly more variables passing t-tests (12 compared with 5 for the one step approach). However, this can hardly be described as a vast improvement. Clearly, the problem of inconsistent parameter estimates is a serious one for this data set. For example, the average of the estimated parameters for GDP9 (the nominal expenditure measure of GDP) are 94.5 and 1440.0 respectively and this gives an estimate of the constant term as 6226.6. For the first quarter of 1984 these parameters give a bias estimate of -2390.9 whereas the true bias is only -760.0. Thus, in this example, the correlation between the bias and the true value of GDP9 is sufficient to cause an overadjustment of the data prior to balancing which in turn contributes to the failure of the balancing procedure to determine the true value of GDP9. In passing it can also be noted that, with the exception of the real government expenditure variable, G, the variables which pass the t-tests using the one-step approach are not those which pass the t-tests using the two-step approach.

The poor results reported when the observed data contains bias may, however, be due to insufficient numbers of simulations. This can be evaluated by forming a 95% confidence interval around the estimate of the standard deviation of the mean of the balanced data. By taking the upper bound to this confidence interval and using it as the estimate of the standard deviation we can derive a lower bound to the number of variables failing the t-tests. Thus the t-test is replaced by the following test:

$$\frac{(\bar{x} - x)}{\left(\dfrac{\sigma}{\sqrt{n}} + \dfrac{1.96\sigma}{\frac{n}{2} \cdot \sqrt{2}}\right)}$$

where $\bar{x}$ is the estimated mean of variable x derived from the replication.

x is the true value.

σ is the estimated standard deviation of the variable x.

n is the number of replications (500).

$n/2$ is used in place of n because antithetic errors were used in the replications which can be thought of as halving the sample size.

The original t-test was

$$\frac{(\bar{x} - x)}{\dfrac{\sigma}{\sqrt{n}}} = T$$

Thus

$$\frac{(\bar{x} - x)}{\sigma} = \frac{T}{\sqrt{n}}$$

Hence the adjusted test can be written as:

$$T \Big/ \left(1 + \frac{1.96\sqrt{2}}{\sqrt{n}}\right)$$

The term in brackets (with n=500) is equal to 1.124 and consequently the adjustment reduces the value of the t-tests by 12.4%. In other words, only those variables with t-statistics, reported in table 3, which are below 2.20 would pass the adjusted t-tests at the 5% level of significance. However, the number of t-tests with values of between 1.96 and 2.20 are small, with at most 3 extra variables passing the adjusted t-test (for the trend method when no bias is present). These results strongly suggest that the large number of rejections recorded when bias is present in the measured data are not due to insufficient replications but are due to the inability of the model to deal with biases which do not possess a similar variance-covariance matrix to the random error component.

11 The simulation results excluding bias

As none of the above approaches appear capable of dealing with measurement errors which include a bias term, this raises the question of what the small sample properties of the methods are when dealing with a random error term alone. Columns 2, 4 and 7 of table 3 report the t-tests for the subjective, trend and 'regression' methods respectively.

Table 3: T-Tests on differences between the variables and the estimated mean

	Subjective		Trend		Regression		
	with bias	without bias	with bias	without bias	with bias	with bias adjust-ment	without bias
GDP9	-24.97	0.00	-24.20	-1.57	-27.91	23.36	1.63
GDPE	-12.69	0.00	-13.30	-3.69	-17.03	21.80	2.27
G9	-7.69	0.00	-6.22	0.52	-6.58	-2.23	0.72
IX9	-1.30	0.01	-4.16	-4.07	-10.88	56.73	2.87
IXG9	-10.25	-0.00	-1.17	7.32	-10.08	-27.56	-9.97
IXJ9	-14.99	-0.00	-21.97	-13.90	-27.80	8.13	-2.63
IXI9	14.93	0.01	6.35	-0.83	3.51	69.42	6.20
C9	-20.98	0.01	-16.22	2.09	-20.34	26.80	2.61
X9	-5.93	0.00	-6.50	-2.81	-3.82	-12.99	-1.04
M9	-0.93	0.00	2.09	2.60	-0.42	12.87	1.52
FCA9	0.69	-0.00	2.45	0.28	3.25	21.17	2.75
TE	2.01	-0.00	2.95	-0.58	4.99	9.80	1.85
ESAB	7.51	-0.00	1.94	-3.83	6.35	-46.25	-9.92
YGC	-24.35	0.00	-19.45	0.17	-20.68	-13.80	-0.34
YXJ	-9.20	0.01	-8.80	-0.76	-11.32	24.41	2.30
SXI	-27.56	-0.01	-14.32	-4.67	-16.22	41.18	3.39
YSAG	-34.97	0.00	-12.51	-13.16	-23.06	3.70	-13.78
YSAJ	-9.33	0.00	3.02	8.03	-5.01	48.18	9.51
YSAI	-8.10	0.00	2.66	5.75	2.27	40.64	11.63
YJG	-14.55	0.00	-11.98	0.14	-13.78	-22.35	-1.23
EDBT	-5.09	0.00	-8.02	-5.20	-7.66	-26.81	-4.76
BIPD	-7.59	-0.00	-3.30	-1.79	-13.44	11.69	-2.96
EJTA	-12.44	-0.00	-8.72	-5.47	9.45	146.12	22.12
EGTA	6.22	0.00	-1.77	-3.29	-13.75	-23.95	-19.43
CONS	-11.83	0.00	-8.23	1.51	-11.63	23.45	5.03
IX	-15.03	0.00	-13.93	-4.55	-21.51	29.44	0.93
G	-0.94	0.00	0.91	1.35	0.18	-0.40	1.00
X	-6.57	0.00	-6.79	-2.22	-6.25	14.49	3.34
M	-10.70	0.00	-6.26	2.74	-11.64	32.77	5.06
FCA	-8.03	0.00	-3.24	3.71	-3.97	15.72	6.93
BXGJ	71.85	-0.00	5.88	2.73	14.25	-19.37	0.19
BXXI	-0.92	0.00	3.17	4.07	-6.10	34.40	-11.90
BXGG	-66.65	-0.00	-5.78	-4.59	-3.52	-30.72	8.25
DXXO	111.85	-0.00	12.91	0.40	10.78	30.42	8.31
DXXG	-124.63	-0.00	2.08	7.81	-4.00	22.68	8.12
DXXJ	76.58	-0.00	6.46	2.48	7.60	0.66	-0.19
DXXI	-73.14	0.00	-7.10	-3.53	-7.99	-5.28	-1.08
PUXX	-59.36	-0.00	1.27	4.43	-0.04	-8.89	-0.14
OUXX	96.83	0.00	20.03	13.00	8.70	51.45	10.10
PEXX	73.31	-0.00	0.67	-5.47	2.49	-17.41	-10.34
ICXX	-95.30	0.00	-8.96	-3.80	-6.05	-1.25	0.85
Log GDP9	-24.00	0.87	-22.06	-2.12	-26.43	21.95	0.74
Log GDPE	-12.02	0.69	-13.54	-4.43	-17.97	20.80	1.55
Log G9	-7.51	0.13	-5.46	0.67	-5.11	-2.54	0.17
Log IX9	-0.11	1.18	-3.81	-4.06	-11.28	49.22	1.83
Log C9	-20.40	0.55	-15.06	1.76	-18.88	25.24	1.78
Log X9	-5.52	0.40	-6.56	-2.80	-5.11	-13.70	-1.64
Log M9	-0.49	0.43	1.96	2.36	-1.18	12.33	0.69
Log FCA9	1.00	0.31	2.25	-0.18	4.46	20.55	1.84
Log CONS	-11.49	0.32	-8.32	1.39	-12.12	22.75	4.65
Log IX	-15.01	0.02	-13.38	-4.23	-21.83	27.26	0.33
Log G	-0.91	0.03	1.08	1.38	0.01	-0.68	0.70
Log X	-6.51	0.05	-6.82	-2.28	-6.90	14.20	2.96
Log M	-6.70	0.87	-6.04	2.90	-11.78	32.24	4.62
Log FCA	-8.02	0.01	-3.17	3.67	-4.23	15.45	6.58
Log PGDP	-6.38	0.55	-5.80	2.35	-5.15	0.00	-0.25
Log PG	-3.44	0.94	-3.95	0.32	-3.15	-0.64	0.00
Log PC	-3.49	0.33	-2.68	0.78	-2.37	0.52	-0.80
Log PIX	14.23	1.49	11.58	2.95	16.94	11.39	2.20
Log PX	3.12	1.07	2.99	1.21	2.55	-22.37	-4.47
Log PM	8.92	1.06	7.14	0.29	9.67	-18.10	-3.94
Log PFCA	7.70	1.11	5.02	-2.17	6.94	1.65	-1.20
PG	-3.54	0.88	-4.28	0.21	-4.22	-0.63	0.46
PC	-3.41	0.68	-2.72	0.85	-3.60	-0.24	-0.05
PIX	13.74	0.98	11.94	2.95	15.83	10.96	3.10
PX	2.93	0.88	3.22	1.21	3.22	-22.00	-4.22
PM	8.72	0.85	7.57	0.29	10.51	-18.04	-3.58
PFCA	7.53	0.93	5.22	-1.90	5.97	1.89	-0.42
PGDP	-6.52	0.48	-5.95	2.37	-5.56	-0.07	0.52
Total number passing t-test at 5% level	9	69	8	26	5	12	32
Critical values		10%	5%	1%			
		1.645	1.960	2.576			

It should be noted that the results reported in column 7 were derived without the use of any regressions by using the variance-covariances of the observed data. Column 4 on the other hand, still sets the variance-covariance matrix by using the residuals from the filtered data. The rationale for this is that the analysts who were assumed to know both the variables which determine the bias and their magnitude would also know that these variables now do not determine the bias and would no longer use them to construct the variance-covariance matrix. The analysts using the trend approach are, however, unaware of the source of biases and simply assume that some is present even when it is not. Hence the analysts using the trend approach continue to form the variance-covariance matrix from filter residuals.

Column 2 of table 3 gives the results of the t-tests for the subjective approach and, as might be expected, given that the true variance-covariance matrix is almost constant, the method passes the t-tests for all of the variables. For the logarithmic variables, where the corresponding elements of the variance-covariance matrix are constructed, and as a consequence are non-constant, the t-statistics are relatively larger. Nevertheless, from table 5, column 2, it can be seen that the average percentage errors for both the logarithmic variables and for the price deflators are relatively small, being, at most, 0.4% in the case of the logarithmic price deflator for investment and stockbuilding (PIX). This result gives further support to the use of logarithmic approximations to simultaneously balance value and volume data.

Table 4: T-Tests on logarithmic approximation

	Subjective		Trend		Regression		
	with bias	without bias	with bias	without bias	with bias	with bias adjustment	without bias
GDP9	-0.69	-0.62	0.34	0.51	0.41	0.72	0.62
G9	-0.13	-0.09	-0.30	-0.13	-0.78	0.21	0.37
IX9	-0.84	-0.83	-0.10	0.11	-0.20	0.21	0.87
C9	-0.40	-0.39	-0.04	0.14	-0.45	0.19	0.58
X9	-0.27	-0.29	0.21	0.12	0.98	0.65	0.48
M9	-0.31	-0.30	-0.06	0.02	0.57	0.21	0.57
FCA9	-0.22	-0.22	-0.01	0.32	-1.14	0.56	0.62
GDPE	-0.48	-0.47	0.17	0.54	0.57	0.73	0.52
G	-0.02	-0.02	-0.12	-0.03	0.12	0.20	0.21
IX	-0.01	-0.01	-0.30	-0.20	0.09	0.77	0.43
CONS	-0.24	-0.22	-0.03	0.09	0.27	0.43	0.38
X	-0.04	-0.04	-0.09	0.03	0.36	0.26	0.29
M	-1.09	-0.70	-0.18	-0.11	0.06	0.23	0.45
FCA	-0.01	-0.01	-0.10	0.06	0.15	0.23	0.31
PDGP	-0.10	-0.06	0.13	-0.05	-0.14	-0.05	0.54
PG	-0.07	-0.05	-0.14	-0.08	-0.66	0.01	0.31
PIX	-0.36	-0.36	0.24	0.25	-0.22	-0.69	0.76
PC	0.54	0.17	0.01	0.03	-0.81	-0.54	0.54
PX	-0.13	-0.14	0.24	0.07	0.47	0.28	0.44
PM	-0.15	-0.15	0.13	0.11	0.44	0.14	0.48
PFCA	-0.12	-0.13	0.13	0.18	-0.88	0.18	0.57
Number passing t-tests at 5% level	21	21	21	21	21	21	21
Critical values		10%	5%	1%			
		1.645	1.960	2.576			

Table 5:Percentage error of the average balanced data from the true data 1984 Q1

	Subjective		Trend		Regression		
	with bias	without bias	with bias	without bias	with bias	with bias adjustment	without bias
GDP9	-2.8	-0.0	-3.2	-0.2	-3.1	2.2	0.8
GDPE	-1.6	0.0	-2.0	-0.5	-2.1	2.3	0.4
GDPY	-1.6	0.0	-2.0	-0.5	-2.1	2.3	0.4
GDPY9	-2.8	-0.0	-3.2	-0.2	-3.1	2.2	0.8
G9	-1.6	0.0	-1.7	0.1	-1.4	-0.4	0.4
IX9	-0.1	0.0	-0.8	-0.7	-2.3	9.6	2.0
IXG9	-2.2	-0.0	-0.4	-2.1	-3.0	-6.4	-2.6
IXJ9	-3.2	-0.0	-6.8	-3.6	-7.5	1.9	-1.8
IXI9	2.9	0.0	2.7	-0.3	1.4	22.6	6.7
C9	-3.0	0.0	-2.8	0.3	-2.8	3.3	1.5
X9	-0.9	0.0	-1.3	-0.5	-0.7	-2.0	0.5
M9	-0.1	0.0	0.4	0.5	-0.1	2.2	0.9
FCA9	0.1	0.0	0.5	0.0	-0.6	3.3	1.7
TE	0.3	0.0	0.5	-0.1	0.8	1.3	1.0
ESAB	1.5	0.0	0.6	-1.0	2.0	-11.7	-3.4
YGC	-2.8	0.0	-2.9	0.0	-2.7	-1.5	-0.2
YXJ	-1.5	0.0	-1.7	-0.1	-1.8	3.3	1.1
SXI	-4.1	-0.0	-5.7	-1.5	-6.1	11.8	2.8
YSAG	-6.1	0.0	-37.2	-31.3	-51.9	6.3	-27.1
YSAJ	-2.5	0.0	2.5	5.1	-5.1	34.9	10.2
YSAI	-3.0	0.0	4.5	7.8	3.9	50.2	20.8
YJG	-3.2	0.0	-3.1	0.0	-2.7	-3.7	-0.7
EDBT	-1.1	0.0	-2.4	-1.3	-1.7	-5.0	-1.9
BIPD	-1.5	0.0	-2.9	-1.3	-15.0	9.5	-5.0
EJTA	1.4	0.0	3.2	1.6	-7.0	-74.6	-29.8
EGTA	1.0	0.0	-2.1	-3.1	-12.5	-16.8	-14.0
CONS	-2.1	0.0	-1.9	0.3	-1.9	3.4	1.2
IX	-3.3	0.0	-4.3	-1.2	-6.4	7.2	0.4
G	-0.2	0.0	0.2	0.3	0.0	-0.1	0.2
X	-1.4	0.0	-1.9	-0.5	-1.4	2.7	0.9
M	-2.3	0.0	-1.8	0.7	-2.6	6.1	1.9
FCA	-1.9	0.0	-0.9	0.9	-0.9	3.1	1.7
BXGJ	23.6	0.0	38.3	14.3	56.4	-57.5	0.7
BXXI	-0.0	0.0	6.4	6.4	-8.3	-30.0	-15.4
BXGG	4.8	0.0	12.9	8.0	5.0	-35.6	-12.1
DXXO	-74308.3	0.0	-76399.3	-1910.5	-96426.1	-202674.9	83520.9
DXXG	2542.8	0.0	-1285.1	-3845.8	1573.9	-6652.0	-2873.7
DXXJ	-13.9	0.0	-19.9	-6.0	-14.8	-1.0	0.4
DXXI	-13.1	0.0	-21.6	-8.4	-14.8	-7.4	-2.3
PUXX	159.5	0.0	-91.4	-251.6	1.7	319.5	5.8
OUXX	-19.2	0.0	-39.9	-20.6	-17.7	-80.0	-25.6
PEXX	9.1	-0.0	1.3	-8.0	2.7	-13.9	-8.4
ICXX	15.5	-0.0	23.8	8.0	11.9	1.8	-1.2
Log GDP9	-2.7	0.1	-3.2	-0.3	-3.1	2.1	0.4
Log GDPE	-1.6	0.1	-2.0	-0.6	-2.2	2.2	0.3
Log G9	-1.6	0.0	-1.6	0.2	-1.1	-0.5	0.1
Log IX9	-0.0	0.1	-0.8	-0.7	-2.2	9.5	1.2
Log C9	-3.0	0.1	-2.8	0.3	-2.7	3.2	1.0
Log X9	-0.8	0.1	-1.3	-0.5	-1.0	-2.1	-0.8
Log M9	-0.1	0.1	0.5	0.5	-0.3	2.1	0.4
Log FCA9	0.2	0.1	0.5	-0.0	1.0	3.2	1.1
Log CONS	-2.0	0.1	-1.8	0.3	-2.0	3.3	1.1
Log IX	-3.3	0.0	-4.2	-1.1	-6.4	7.0	0.1
Log G	-0.2	0.0	0.3	0.3	0.0	-0.1	0.1
Log X	-1.4	0.0	-1.9	-0.5	-1.5	2.6	0.8
Log M	-1.9	0.2	-1.7	0.7	-2.6	6.0	1.7
Log FCA	-1.9	0.0	-0.9	0.9	-0.9	3.1	1.7
Log PGDP	-1.1	0.1	-1.1	0.4	-0.9	0.0	-0.1
Log PG	-1.1	0.3	-1.5	0.1	-0.9	-0.2	0.0
Log PC	-1.0	0.1	-0.7	0.2	-0.5	0.1	-0.3
Log PIX	3.7	0.4	4.0	0.7	4.8	2.6	0.8
Log PX	0.8	0.3	0.9	0.3	0.7	-4.5	-1.6
Log PM	2.5	0.3	2.6	0.0	2.6	-3.6	-1.4
Log PFCA	2.4	0.3	1.8	-0.6	2.2	0.4	-0.6
PG	-1.1	0.3	-1.6	0.1	-1.2	-0.2	0.2
PC	-0.8	0.2	-0.7	0.2	-0.7	-0.0	-0.0
PIX	3.5	0.2	4.1	0.8	4.7	2.3	1.3
PX	0.8	0.2	1.1	0.3	0.8	-4.4	-1.4
PM	2.4	0.2	2.7	0.1	2.8	-3.6	-1.2
PFCA	2.3	0.3	1.9	-0.6	1.8	0.5	-0.2
PGDP	-1.1	0.1	-1.1	0.4	-0.9	-0.0	0.2
Average absolute % error (excluding DXXO and DXXG)	5.33	0.06	5.98	5.95	4.96	13.48	3.43

Note: The large percentage errors on DXXO (net deposits with corporations made by the overseas sector) and DXXG (net deposits with corporations made by the public sector) result from the true values of these variables being small (-0.0171 and -0.9732 respectively) in the first quarter of 1984. The actual average errors corresponding to the columns above are (in £'s millions).

DXXO	12.71	0.0	13.07	0.32	16.50	34.68	14.29
DXXG	-24.75	0.0	12.51	37.43	-15.32	64.74	27.97

The trend (see column 4 of table 3) and 'regression' approaches (see column 7 of table 3) pass the t-tests for 26 and 32 cases respectively and for both methods the t-statistics have been reduced, in absolute terms, in around 75% of the cases. Nevertheless, as these methods result in less than half of the variables passing the t-tests they strongly suggest that the small sample properties of the estimators underlying these methods are rather poor, especially when any variance-covariance matrix will produce unbiased estimates of the true variables when the measurement error is mean zero.

It should be borne in mind that the asymptotic properties of the regression approach would be improved by regressing the observed data on variables which explain the true data. If all of the true data was explained by the regressors the variance-covariance matrix formed from the residuals would not change between antithetic pairs of errors. Hence, errors in balancing the accounts would cancel between the pairs and the mean estimate of the balanced data would be equivalent to the true data. Thus the properties of the regression approach could be improved by removing at least some of the true data from the observed data prior to the forming of the variance-covariance matrix. For the trend approach a similar result could be obtained by increasing the period from which the variance-covariance matrix was calculated which would reduce the probability of spurious correlation between the true data and the measurement error. A risk associated with this procedure is however, that process underlying the measurement error may not be constant over time and this would need to be taken into account when balancing the observed data. However, as argued above, any constant variance-covariance matrix will correctly balance the data and so these avenues of research are not explored in this paper. Moreover, the arbitrary nature of assuming how much of the true data is explained in the regression approach would also make it difficult to examine the benefits, in terms of reduced variance, of this procedure. In the remaining section we have, therefore, only examined the sensitivity of the variance of the balanced estimates to changes to the variace-covariance matrix used in the subjective approach.

12 Variances of the balanced data

As observed above, the assumption that the analysts using the subjective approach know the true variance-covariance matrix is highly unlikely. This raises the question of what size of errors can be made in setting the variance-covariance matrix before the performance of the subjective approach, in terms of the variance of its estimates, significantly deteriorates. There are numerous methods by which the variance-covariance matrix can be changed and in this paper the effects are analysed by increasing the measurement error corresponding to the nominal income measure of GDP (GDPY9) by 10% and by 100%. The results of these changes are given in table 6.

Table 6: Standard Deviations of Balanced Data

	Percentage errors 0%	10%	100%	Trend	Regression
GDP9	1730.1	1729.5	1751.5	2001.0	1681.8
GDPE	2137.1	2137.1	2137.1	2500.0	2052.3
GDPY	2137.1	2137.1	2137.1	2500.0	2052.3
GDPY9	1730.1	1729.5	1751.5	2001.0	1681.8
G9	795.5	795.8	798.6	1017.9	786.6
IX9	327.0	327.0	327.5	600.8	630.0
IXG9	154.7	154.7	154.8	249.5	219.4
IXJ9	191.8	191.8	191.7	273.0	238.6
IXI9	270.4	270.4	270.7	596.9	566.9
C9	1555.7	1552.7	1555.1	1857.3	1481.3
X9	741.8	741.8	741.6	946.1	946.1
M9	739.9	739.9	740.0	982.6	1017.3
FCA9	451.1	451.3	452.6	512.6	490.5
TE	450.0	450.1	451.3	504.0	475.5
ESAB	78.7	78.7	78.7	119.7	123.0
YGC	893.5	894.4	900.1	1158.8	1025.4
YXJ	1589.0	1585.8	1585.7	1892.5	1512.1
SXI	284.9	285.0	285.3	754.2	714.3
YSAG	4.6	4.6	4.6	78.0	59.0
YSAJ	6.1	6.1	6.1	18.7	23.1
YSAI	52.9	52.9	53.0	244.7	249.2
YJG	508.8	508.9	509.0	610.7	451.9
EDBT	196.6	196.7	196.7	278.0	204.3
BIPD	38.3	38.3	38.3	166.3	212.4
EJTA	2.4	2.4	2.4	7.4	15.1
EGTA	28.2	28.2	28.2	213.2	165.3
CONS	2052.0	2052.0	2052.0	2599.3	1935.1
IX	718.8	718.8	718.8	1018.1	970.8
G	952.4	952.4	952.4	1110.0	847.6
X	1161.0	1161.0	1161.0	1512.9	1168.2
M	1084.2	1084.2	1084.2	1459.5	1143.6
FCA	608.8	608.0	608.8	750.2	455.9
PGDP	3.5	3.5	3.6	3.8	3.4
BXGJ	37.8	37.8	37.8	750.2	455.9
BXXI	14.4	14.4	14.4	894.7	605.7
BXGG	40.6	40.6	40.6	1254.4	796.3
DXXO	2.5	2.5	2.5	22.6	34.2
DXXG	4.4	4.4	4.4	134.6	85.7
DXXJ	63.0	63.0	63.0	1069.4	672.9
DXXI	62.3	62.3	62.3	1053.7	643.6
PUXX	50.6	50.6	50.6	1357.1	895.4
OUXX	39.9	39.9	39.9	400.3	409.4
PEXX	82.2	82.3	82.2	1259.2	711.4
ICXX	72.3	72.3	72.3	1182.0	876.1
Log GDP9	1731.5	1730.7	1752.0	2241.7	1815.0
Log GDPE	2136.2	2136.2	2136.2	2499.4	2035.9
Log G9	795.3	795.6	798.5	1076.8	838.5
Log IX9	327.4	327.5	327.9	633.8	592.5
Log C9	1555.6	1552.8	1554.9	1993.1	1544.1
Log X9	741.6	741.6	741.6	980.4	967.3
Log M9	739.8	739.8	739.8	1091.3	1068.4
Log FCA9	450.7	451.0	452.2	559.0	542.4
Log CONS	2051.6	2051.6	2051.6	2559.0	1917.0
Log IX	718.8	718.8	718.8	1026.9	962.0
Log G	952.4	952.4	952.4	1111.0	850.1
Log X	1160.8	1160.8	1160.8	1478.2	1143.3
Log M	1430.6	1426.9	1412.5	1451.2	1138.5
Log FCA	608.8	608.8	608.8	734.5	567.9
Log PGDP	3.5	3.5	3.6	4.0	3.5
Log PG	6.6	6.6	6.7	7.9	6.1
Log PC	5.8	5.8	5.8	5.7	4.4
Log PIX	5.0	5.0	5.0	7.1	5.9
Log PX	5.3	5.3	5.3	6.7	5.3
Log PM	5.5	5.5	5.5	7.5	5.5
Log PFCA	6.4	6.4	6.5	7.7	6.6
PG	6.6	6.6	6.7	7.6	5.9
PC	4.7	4.7	4.7	5.6	4.3
PIX	5.0	5.0	5.0	7.1	6.2
PX	5.3	5.3	5.3	6.8	5.3
PM	5.5	5.5	5.5	7.3	5.4
PFCA	6.4	6.4	6.5	7.7	6.4

Note: all the standard deviations of the price deflators and logged price deflators

The first point to note is the marginal decline in the balanced standard deviation of GDPY9 as its variance is increased by 10%. This is because, as noted above, the analysts are assumed to know the true distribution of the errors but the true distribution is not established by the use of 500 replications. The true standard deviation (see appendix 1) is 3468.7778 but the actual standard deviation is 3553.6718. Thus multiplying the initial variance of GDPY9 by 10% produces a smaller balanced variance of GDPY9 because the initial variance is closer to the variance of the observed data. This also, explains why some of the balanced variances, for example public sector nominal investment IXG9, exceed the true variances reported in appendix 1. The main point is that for deviations around the original variance-covariance matrix, the changes in the variances of the balanced data are, on the whole, minor or non-existent even when the error on GDPY9 is 100%. An error of this magnitude seems likely to be at the upper end of the error range made by analysts and we tentatively conclude that, for the model under examination, at least, the subjective approach appears to be robust to errors in specifying the variance-covariance matrix. Obviously, further work on this area needs to be undertaken particularly on models in which covariances play an important role.

Table 6 can also be used to compare balanced variances using the subjective trend and 'regression' approaches. In only one case (log PC) is the variance smaller for the trend method and for 24 cases the variance is smaller for the regression method than the subjective approach. Thus the subjective approach is clearly more efficient than the trend method in small samples and it is on the whole slightly more efficient than the regression method. A comparison of table 6 and appendix 1 reveals that the standard deviation of the variables are reduced compared with the theoretical standard deviations by balancing in 35 of the 43 comparisons (81%) when the subjective approach is used. For the instances where the standard deviation is increased the rise is always marginal. On the other hand, 56% and 70% of the variables have their standard deviations increased when the regression and trend methods respectively are used to balance the data. Had the correct variance-covariance matrix been used the standard deviations would have been reduced or left unchanged by balancing.

13 Conclusions

The results of the Monte Carlo simulations on the three approaches of deriving the variance-covariance matrix lead to the following conclusions. The logarithmic approximation which allows both volume and value data to be balanced simultaneously appears to be highly robust. None of the approaches can deal with measurement errors which include a bias term. Virtually all the mean estimates of the balanced variables are statistically and numerically different from their true values. A two step regression approach in which an estimate of the bias is removed from the data prior to balancing also failed to significantly improve this performance. When the measurement error contained only a random component, the success rate of the trend and regression approaches increased, but the results suggest that the small sample properties of the estimators are poor. These results indicate that data derived from these two methods may be as misleading to the analyst as the measured data itself. Although further work is needed in this area the results do, tentatively, suggest that in terms of the variance of its estimates the subjective approach is relatively robust to errors in the variance-covariance matrix. In the Monte Carlo simulations presented in this paper the subjective approach clearly outperforms both the trend and regression approaches when bias is absent and is not clearly inferior when bias is present. However, in the more likely situation when bias is present all the methods do equally poorly and, because the information and resource requirements of the trend approach are so much smaller than for the other two methods, the trend method is advocated as the preferred method of balancing the accounts.

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Appendix 1

Standard deviations of the random components of the measurement errors

Variable	Standard Deviation	Variable	Standard Deviation
GDP9	3468.7778	EGTA	26.6661
GDPE	3739.3932	CONS	2676.0534
GDPY	3739.3932	IX	739.1898
GDPY9	3468.7778	G	917.5454
G9	846.9406	X	1225.1317
IX9	708.8022	M	1207.4579
IXG9	150.4732	FCA	611.0691
IXJ9	187.4732	BXGJ	43.3336
IXI9	370.8288	BXXI	14.3237
C9	2497.9362	BXGG	105.8790
X9	1070.6291	DXXG	4.3420
M9	1075.6245	DXXO	2.6009
FCA9	579.9014	DXXJ	95.8571
TE	675.8948	DXXI	90.2434
ESAB	77.9934	PUXX	56.1517
YGC	1717.3826	OUXX	40.1088
YXJ	2243.2427	PEXX	111.9247
SXI	457.1675	ICXX	92.6422
YSAG	4.3552		
YSAJ	6.4827		
YSAI	53.3258		
YJG	508.1446		
EDBT	192.9501		
BIPD	40.7196		
EJTA	2.5185		

The standard deviation of the measurement error is constructed as 5% of the mean of the absolute value of the true data over the period from the second quarter of 1979 to the fourth quarter of 1988.

See Tables 1 and 2 for a guide to the notation.

Appendix 2

Parameters used to calculate the bias component of the measurement errors

	Bias Parameters			Bias in 1984 Q1 level	Percentage
	β_1	β_2	Constant		
GDP9	30	175	565.0000	-760.0000	-1.1
GDPE	22	175	646.6667	-558.3333	-1.0
GDPY	50	150	233.3333	-1266.6667	-1.7
GDPY9	60	150	130.0000	-1520.0000	-2.2
G9	19	8	-156.333	-481.3333	-2.9
IX9	2	27	114.3333	-50.6667	-0.4
IXG9	3	3	-16.0000	-76.0000	-2.3
IXJ9	5	-2	-61.6667	-126.6667	-3.2
IXI9	5	1	-46.6667	-126.6667	-2.0
C9	60	-100	-1120.0000	-1520.0000	-3.2
X9	5	-60	-351.6667	-126.6667	-0.6
M9	4	30	108.6667	-101.3333	-0.5
FCA9	-2	37	205.6667	50.6667	0.5
TE	-2	-40	-179.3333	50.6667	0.4
ESAB	-1	5	35.3333	25.3333	0.2
YGC	20	10	-156.6667	-506.6667	-1.5
YXJ	50	-10	-566.6667	-1256.6667	-2.9
SXI	-4	-10	-8.6667	101.3333	1.2
YSAG	0.2	-0.5	-6.6333	-7.1333	-6.1
YSAJ	0.1	0.1	-0.5333	-2.5333	-2.5
YSAI	1	-1	-15.3333	-25.3333	-3.9
YJG	10	-15	-178.3333	-253.3333	-2.4
EDBT	2	3	-5.6667	-50.6667	-1.2
BIPD	0.5	2	4.8333	-12.6667	-1.5
EJTA	0.05	0.1	-0.0617	-1.8670	2.1
EGTA	-0.3	1.0	8.1000	7.6000	0.9
CONS	55	-90	-1018.3333	-1393.3333	-2.7
IX	20	-10	-256.6667	-506.6667	-3.5
G	3	-80	-431.0000	-76.0000	-0.4
X	16	-70	-515.3333	405.3333	-1.7
M	18	30	-36.0000	-456.0000	-2.0
FCA	8	7	-47.6667	-202.6667	1.7
BXGJ	-5	7	86.6667	126.6667	24.6
BXXI	0.02	2	9.7933	-0.5067	0.03
BXGG	3.7	11	16.7667	-93.7333	3.7
DXXO	-0.5	-0.01	5.1167	-12.6667	-74037.2
DXXG	1	-0.1	-10.3833	-24.8833	2556.8
DXXJ	-6	-20	-38.0000	152.0000	-9.8
DXXI	11	-4	-133.6667	-278.6667	-18.0
PUXX	-5	6	-21.6667	23.3333	-27.7
OUXX	-7	3	87.3333	177.3333	-19.8
PEXX	-12	7	159.0000	304.0000	10.2
ICXX	12	-11	-179.0000	-304.0000	15.3

The bias component is calculated as $\beta_1 z_1 + \beta_2 z_2 +$ constant. See appendix 3 for the values of z_1 and z_2.

See Tables 1 and 2 for a guide to the notation.

Appendix 3

Constructed values of the bias variables

Period		z_1	z_2
1979	Q2	0.2	-24.0
	Q3	-4.2	-23.0
	Q4	-8.2	-22.0
1980	Q1	-11.8	-21.0
	Q2	-15.0	-20.0
	Q3	-17.8	-19.0
	Q4	-20.2	-18.0
1981	Q1	-22.2	-17.0
	Q2	-23.8	-16.0
	Q3	-25.0	-15.0
	Q4	-25.8	-14.0
1982	Q1	-26.2	-13.0
	Q2	-26.2	-12.0
	Q3	-25.8	-11.0
	Q4	-25.0	-10.0
1983	Q1	-23.8	-9.0
	Q2	-22.2	-8.0
	Q3	-20.2	-7.0
	Q4	-17.8	-6.0
1984	Q1	-15.0	-5.0
	Q2	-11.8	-4.0
	Q3	-8.2	-3.0
	Q4	-4.2	-2.0
1985	Q1	0.2	-1.0
	Q2	5.0	0.0
	Q3	10.2	1.0
	Q4	15.8	2.0
1986	Q1	21.8	3.0
	Q2	28.2	4.0
	Q3	35.0	5.0
	Q4	42.2	6.0
1987	Q1	49.8	7.0
	Q2	57.8	8.0
	Q3	66.2	9.0
	Q4	75.0	10.0
1988	Q1	84.2	11.0
	Q2	93.8	12.0
	Q3	103.8	13.0
	Q4	114.2	14.0

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(a) These papers are no longer available from the Bank, but photocopies can be obtained from University Microfilms International, at White Swan House, Godstone, Surrey RH9 8LW.