MULTIVARIATE TIME SERIES ECONOMETRIC PERFORMANCE OF DIVISIA MONETARY AGGREGATES FOR THE EURO AREA

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Thesis submitted in partial fulfilment of the requirements of The Nottingham Trent University for the degree of Doctor of Philosophy.

February 2005

ACKNOWLEDGEMENTS

I would like to first of all thank Dr. Jane Binner, Prof. Andrew Mullineux, Dr. Alicia Gazely and Dr. Thomas Elger for their invaluable guidance, discussions and encouragement during the course of my PhD study. I am also grateful to the Nottingham Trent University for providing me the financial support and every facility needed to carry out my PhD study. I am also very grateful to Melanie Mackrell for all her help that have made my study less stressful. The NBS technicians are also heartily acknowledged for keeping my computer running till the end of my PhD. I also wish to say a big thank you to everybody on the fourth floor of NBS and everybody coming to the coffee room on the fourth floor for being so friendly and for encouraging me constantly.

I would also like to thank Dr. Chandradeo Bokhoree, Associate Professor Muddun Bhuruth and Dr. Preetee Gonpot for all their help that have contributed towards me doing this PhD.

I am very grateful to Mr Livio Stracca, Jerome Henry and Alistair Dieppe from the European Central Bank for providing me the Euro area data. I also thank Mr Anindya Banerjee at the European University Institute for his help in directing me towards the data.

Mr Ramdowar, the then Deputy Rector of BASS (now rector of an SSS) is also gratefully acknowledged for all his support towards obtaining a study leave. He as well as the teaching staff of BASSS, particularly B. Patpur, and D. Calchand are also thanked for encouraging me to do the PhD.

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ABSTRACT

Many economists believe that the amount of money in the economy affects either real variables like national output or monetary variables like the price level or both. Developments in monetary aggregates therefore can provide useful information about future price developments. Such a belief has led the European Central Bank to use broad monetary aggregate M3 as a compass for monetary policy strategy, which is aimed at maintaining price stability in the region.

A few decades ago many countries had put similar faith in monetary aggregates to guide their monetary policy strategies. However, a few years later empirical evidence began to emerge showing that monetary aggregates were no longer reliable as a tool for conducting monetary policy and consequently many countries abandoned monetary targeting. A possible reason for the monetary aggregates not being as reliable as previously thought is argued, by researchers such as Barnett, to be the simple summation technique of constructing official monetary aggregates. In this kind of aggregation assets as different as cash and interest bearing time deposits are weighted equally. Clearly one hundred pounds in interest bearing time deposits do not provide the same level of monetary services as the equivalent amount in currency. Therefore, the simple summation aggregation technique produces an unsatisfactory definition of the amount of money in the economy.

Divisia aggregates derived from microeconomic theory, aggregation theory and index number theory are considered to be a viable alternative to Simple Sum aggregates as in their construction assets are given weights according to the level of monetary services they provide. Since the derivation of Divisia aggregates a number of studies from around the world have compared their empirical performance to their Simple Sum counterparts. The results are found to be mixed but leaning slightly in favour of Divisia

aggregates. Since the Euro area has come into existence only recently not many studies exist that compare the relative performance of Simple Sum and Divisia aggregates for the Euro area. Hence it is the main objective in this thesis to provide new empirical evidence on the relative performance of Simple Sum and Divisia aggregates for the Euro area with a view to adding to the literature on the appropriate method of monetary aggregation.

The monetary aggregates are compared in three different frameworks, namely, cointegrated VAR money demand framework, composite leading indicator of inflation turning point framework and inflation forecasting framework. Prior to constructing monetary aggregates, however, weak separability tests are carried out to identify assets that can be reliably included in a monetary aggregate. Weak Separability tests are carried out using the Fleissig and Whitney's Linear Programming test. The evaluation of monetary aggregates in cointegrated VAR money demand framework consists of the following steps. Firstly, graphical analysis and unit root tests are carried out to investigate the stationarity properties of the series entering the VAR models. Secondly, given most of the series were found to be nonstationary, Johansen maximum likelihood tests were used for testing for cointegrating relationships. Finally, the long run stability of the parameters of the different cointegrating vectors was investigated. The evaluation of monetary aggregates in the composite leading indicators of inflation consisted of the following steps. Firstly, the cycles of the inflation series and the indicator series are extracted and their turning points identified. Fourier analysis is then used to model the cycles of the series and lead time of the indicator series over the inflation series are identified for constructing a set of short leading indicators and a set of long indicators. The individual leading indicators series are then aggregated to form composite leading indicators of inflation turning point. Kalman filters are the used to filter out false turning points in the composite leading indicators. Evaluation in the inflation forecasting framework consists of constructing linear and nonlinear forecasting models. Linear models are represented by univariate time series models and multivariate cointegrated VAR models. Nonlinear models are represented by neural networks, so called because their creation was inspired by the functioning of the brain.

To increase the relevance of this study a few other issues of interest to policymakers are also investigated. These additional issues are: (1) whether or not the UK should join the Euro area, (2) whether or not central banks should use nonlinear models for macroeconomic forecasting, and (3) whether or not Divisia aggregates are disadvantaged compared to Simple Sum aggregates when they are tested in a linear framework, given the presence of nonlinear structures in Divisia aggregates.

The main findings of the thesis are as follows: (1) As has been found in many previous studies, findings regarding the relative performance of Divisia and Simple Sum aggregates are mixed, however leaning slightly in favour of weighted Divisia aggregates (2) under present circumstances the UK should not join the Euro area, (3) nonlinear models provide more accurate forecasts of inflation, (4) Divisia aggregates are better modelled in a nonlinear framework. Further work to incorporate the construction of a risk-adjusted Euro Divisia and to optimise the weights of Euro Divisia aggregate using neural networks.

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CHAPTER 1:

INTRODUCTION

The bulk of this thesis deals with constructing monetary aggregates with solid theoretical foundations and analysing their empirical performances against the official monetary aggregates for the Euro area. The interest in working with Euro area monetary aggregates stems directly from their use in the current monetary policy strategy of the European Central Bank (ECB). There is a widely held belief that the amount of money in the economy affects either real variables like national output, unemployment or monetary variables particularly the price level or both (Mullineux, 1996). Developments in monetary aggregates can therefore provide useful information about future price developments. Such a belief has led the ECB to use the broad monetary aggregate M3 as a compass for the conduct of monetary policy, which is aimed at maintaining price stability in the region. The prominent role of monetary aggregates was signalled by the announcement of a reference value for Simple Sum M3 in the first pillar of the ECB's so-called 'two pillar' of monetary policy strategy (see, ECB (1999a, b, 2000)). In the second pillar the ECB analyses a broad range of other economic and financial time series.

Not in a distant past, in the mid 1970s, many countries had put similar faith in monetary aggregates to guide them in their monetary policy strategies. However, a few years later, empirical evidence began to accumulate showing monetary aggregates were no longer reliable tools for the conduct of monetary policy. Consequently many countries abandoned using monetary aggregates for policy purposes. Today, many central banks have relegated the role of money to indicator variables for forecasting future changes in the price level along with an array of other indicators and do not seem to be regarded as more important than others (Drake, Mullineux and Agung, 1997).

A possible reason for the relegation of monetary aggregates was identified by Barnett (1980). He voiced objection against the official monetary aggregates of central banks which are formed by adding together a group of assets that are considered to be likely sources of monetary services. This approach of constructing monetary aggregates is referred to as simple summation and the resulting aggregates as Simple Sum aggregates. In this form of aggregation all the monetary components are assigned a constant and equal (unitary) weight. That is if x_i is the i^{th} monetary component for the aggregate M, then the latter is given by

$$M = \sum_{i=1}^{n} x_i \tag{1.1}$$

This form of aggregation implies perfect substitutability, that is included assets are assumed to provide equal levels of monetary services, whether they are cash or savings deposits. It is clear that all components of the monetary aggregates do not contribute equally to the economy's monetary flow. Obviously, one hundred Euros currency provide greater transactions services than the equivalent value in savings deposits. Thus, this form of aggregation is producing a theoretically unsatisfactory definition of the economy's monetary flow.

The fact that simple summation aggregation is unsatisfactory has long been recognized and there have been attempts at weakening the perfect substitutability assumption by constructing weighted average monetary index (see, for example, Friedman and Swartz (1970)). However, the proposed weighted monetary indices lacked solid theoretical foundations. Two major developments towards the end of the 1970s paved the way for the construction of monetary aggregates with solid theoretical foundations. One was the derivation of the price money, also referred to as the user cost, through rigorous mathematical calculations by Barnett (1978, 1982). With the derivation of the user cost the door was opened for the application of microeconomic theory and aggregation theory in the derivation of theoretically consistent monetary aggregates. The real user cost of the i^{th} asset at time t is calculated as follows

$$\pi_{it} = \frac{(R_t - r_{it})}{(1 + R_t)} \tag{1.2}$$

where r_{it} is the rate of interest on the i^{th} monetary asset and R_t is known as the benchmark rate which should be the rate of return of return on an asset providing no monetary services whatsoever. Obviously no such asset exists on the market and the benchmark rate is normally taken to be a long term interest rate, such as a government bond. The other significant development which led to the construction of theoretically consistent monetary aggregates was the merger of index number theory and aggregation theory by Diewert (1976, 1978). The derivation of a theoretically appropriate monetary index, more specifically the Divisia index, is reviewed in Chapter 2. In doing so, the presentation of Barnett, Fisher and Serlettis (1992) is followed. The theory from which theoretically consistent monetary aggregates are derived from microeconomic theory, aggregation theory and index number theory is known as monetary aggregation theory.

Before any monetary aggregate can be constructed, monetary aggregation theory requires that asset components of the aggregate be weakly separable in the consumer's utility function. Though it is possible to check for weak separability of a group of monetary assets central banks rarely carry out weak separability tests and the common practice is of grouping monetary assets according to subjective judgements about the assets' liquidity (Belongia, 2000). This kind of ad hoc method of aggregation may lead to less stable monetary aggregates (Swofford and Whitney, 1987) and consequently monetary policy in the area may be unstable (Swofford, 2000). Therefore prior to constructing the monetary aggregates in this study weak separability tests are carried out in Chapter 3 to identify groups of monetary assets that can be reliably aggregated.

To carry out weak separability tests an improved version of Varian's (1982, 1983) nonparametric test developed by Fleissig and Whitney (2003) is used. The probability of rejection of weak separability is quite high with Varian's (1982, 1983) test for two reasons. Firstly, rejection could be due to measurement errors and hence nonsignificant. Secondly, rejection could be due to the test procedure returning negative indices which have to be positive. Fleissig and Whitney (2003) reformulate Varian's (1982, 1983) test in terms of a linear programming problem which allows for the aforementioned problems by making small adjustments to the data whenever required and by forcing the indices to be positive.

Since their derivation, a number of studies from around the world have constructed Divisia aggregates and compared their empirical performance in a cointegrated money demand framework against their Simple Sum counterparts (see, for example, Herrmann, Reimers and Toedter (2000) for Germany, Lim and Martin (2000) for Australia, Gaioti (1996) for Italy, Belongia (1996) for the United States, Drake, Chrystal and Binner (2000) for the UK and Chrystal and MacDonald (1994) for a number of countries, including the USA, the UK and Canada). The results from these studies turn out to be mixed but leaning in favour of the Divisia index. Given that the Euro area has come into existence only recently not many studies exist that investigate the usefulness of Divisia monetary aggregates as a policy tool for the Euro area in a money demand framework.

To the best of my knowledge the existing studies are those of Spencer (1997), Drake, Mullineux and Agung (1997), Stracca (2004) and Reimers (2002). Therefore the objective in Chapter 4 of this thesis is to provide new empirical evidence on the relative performances of Divisia and Simple Sum aggregates in a cointegrated money demand framework to supplement the existing ones.

The analysis here will, however, differ from the previous ones in important respects. Drake, Mullineux and Agung (1997) and Spencer (1997) use pre ECB formation data whereas the data in this study is post ECB formation data. Moreover, their data do not encompass data for all the member countries. In this study data are constructed over all member countries apart from Greece which has a very small weight in the Euro area economy. Though the data here are similar to Stracca (2004), the analysis is different. Specifically, weak separability tests are conducted to identify the assets which are weakly separable before constructing the monetary aggregates and the period over which the assets are weakly separable is also identified. Reimers (2002) on the other hand does carry out weak separability tests and investigates the usefulness of Divisia aggregates for policy purposes in the Euro area, but the study does not provide any comparison between Divisia and Simple Sum indices and hence no conclusion can be drawn on whether or not the Divisia aggregates would be better than their Simple Sum counterparts in practice. Moreover, Reimers (2002) conducts weak separability and money demand analysis over different time periods.

As mentioned earlier there exist many non Euro area studies which compare the empirical performances of Simple Sum and Divisia monetary aggregates and the findings are mixed but they do lean slightly in favour of Divisia monetary aggregates. While the slightly better empirical performance of Divisia monetary aggregates over that of Simple Sum aggregates has been able convince some monetary authorities (for example, Bank of England, Federal Reserve Bank) to take an active interest in the construction of Divisia aggregates it has, so far, not been able to persuade them to abandon Simple Sum aggregates and adopt Divisia aggregates for policy purposes. To provide an explanation for why Divisia aggregates do not consistently outperform Simple Sum aggregates despite their theoretical superiority, some researchers have focussed on measurement problems (see, for example, Drake Mullineux and Agung (1997)). However, except Mullineux (1996) none of them have put the validity of the statistical methods used to evaluate them into question. Mullineux (1996) argues that most of the studies tend to find out whether Simple Sum aggregates or Divisia aggregates have a more stable money demand function. This is usually investigated using cointegrated vector autoregressive models. However, it is argued that stability for money demand is a side issue with regard to usefulness of monetary aggregates for policy purposes (Driscoll and Ford, 1982) and issues like indicator properties of the aggregates are of more relevance and should be investigated. Therefore another objective in this study is, apart from using the traditional money demand framework to compare Simple Sum and Divisia aggregates, to use other frameworks to compare the relative indicator properties of the two types of aggregates. The other frameworks used are the composite cyclical leading indicator of inflation framework and inflation forecasting using linear models and nonlinear neural network models. These frameworks have been chosen as, in addition to allowing us to investigate the relative performance of the two types of monetary aggregate, they will also allow us to investigate other issues of relevance to the monetary policy strategy of the ECB. These issues are often overlooked by researchers and therefore such investigations will increase the relevance of this study to policymakers such as the ECB. These additional issues to be investigated are mentioned in the following paragraphs and fuller discussions on them are given in Chapters 5 and 6

In view of the current monetary policy strategy of the ECB, mainly in the second pillar, inflation turning point forecasts can also be very helpful. Despite advances in mathematical and statistical techniques, a reliable method to forecast inflation turning points has continued to evade forecasters. Consequently, interest in the use of composite leading indicators (CLIs) of inflation turning points has been heightened. These are constructed from a group of time series variables that have cycles which resemble the turning points in the inflation cycle but whose turning points precede the turning points in the inflation cycle. To the best of my knowledge there exists no study which develops CLIs of inflation for the Euro area and therefore, one objective in Chapter 5 will be to fill this gap. Monetary variables are often used in the construction of CLIs for inflation as they are considered to be good information carriers for future inflation turning points. Therefore the CLI framework also makes it possible to compare the empirical performance of Simple Sum and Divisia monetary aggregates. Even though the leading indicator approach has been rather successful in providing early information about future turning points, it is widely believed that the way leading indicators are constructed is crude and unsatisfactory on the sort of criteria commonly applied in modern econometrics. Another objective in Chapter 5, therefore, is to develop more sophisticated CLIs by incorporating Fourier analysis and Kalman filters to the prevailing NBER methodology of constructing CLIs.

Also, in Chapter 5, there is an attempt to provide a tentative answer to the issue of whether or not the UK should join the Euro area. One of the effects of the UK joining the Euro area is that the Bank of England will lose complete control of monetary policy for the UK. This would be carried out by policy makers at the ECB. However, measures taken by the ECB to combat inflationary pressures might not have the same corrective effect on the UK economy if the inflation cycle of the UK is not synchronized with the Euro area's inflation cycle. The issue of whether or not the UK should join the Euro area is investigated using graphical analysis and using the CLI framework.

Neural networks (NN) have gained a lot of popularity in recent years, especially in time series forecasting. Their popularity comes from the fact that they are nonlinear models and as opposed to more conventional nonlinear models like threshold autoregressive (TAR) models (Tong, 1990) and the exponential autoregressive model (EXPAR) (Haggan and Ozaki, 1981) they do not require the imposition of assumptions concerning the precise form of nonlinearity. They are data driven and thus capable of producing nonlinear models without prior beliefs about functional forms. Most applications, however, are in areas where data are abundant as NN are very data intensive. In macroeconomics, due to the scarcity of large data samples, there exist only a few studies involving the use of NN. However, there is now growing evidence that macroeconomic series contain nonlinearities (see, for example, Tiao and Tsay (1994) and Stanca (1999) and thus, though linear models have been reasonably successful as a practical tool for analysis and forecasting, they are inherently limited in the presence of nonlinearities in data and consequently forecasts, as well as other conclusions drawn from them could be misleading. In the second pillar of the ECB's monetary policy strategy inflation forecast plays a very important role, as such information allows the policymakers to redo their economic calculations for the forthcoming environment. To the best of my knowledge all inflation forecasting studies for the Euro area use linear models (see, for example, Drake and Mills (2002)). One objective in Chapter 6 therefore is to investigate the usefulness of nonlinear neural network models as forecasting models by comparing their performance against linear forecasting models. Given the ubiquitous relationship between monetary aggregates and inflation, most inflation forecasting studies use monetary variables as a predictor variable. Therefore the inflation forecasting framework can be used for evaluating the relative performance of the two types of monetary aggregate by specifying the forecasting models alternately with Simple Sum and Divisia monetary aggregates.

The above analysis can also be used to provide an insight on a very important issue, often overlooked by researchers working with Divisia monetary aggregates- the issue of whether Divisia aggregates are disadvantaged by comparing them to Simple Sum aggregates in a linear framework. Divisia indices contain nonlinear structures as proved by the evidences provided by Barnett and Chen (1986, 1988a, b), Barnett and Hinich (1992, 1993), Chen (1988), and DeCoster and Mitchell (1991). In spite of this, as mentioned earlier, most of the studies comparing the relative empirical performance of Simple Sum and Divisia monetary aggregates do the comparison using the traditional cointegrated money demand framework. Such a framework, however, is linear and therefore in such circumstances if the empirical performance of a Divisia monetary aggregate relative to its Simple Sum counterpart is poor, one cannot say whether the Divisia index or the linear model, which may not be able to capture the nonlinear behaviour of the Divisia index is responsible for the poor performance. Since the above analysis compares the performance of Divisia aggregates in both a linear and nonlinear framework, it should provide us with an insight on whether or not nonlinear modelling would be more appropriate for the nonlinear structures inherent in Divisia indices.

A summary of the work carried out and the main findings are given in Chapter 7. The findings are drawn together to present an overall conclusion. Suggestions for future research are also given in Chapter 7.

CHAPTER 2:

MONETARY AGGREGATION THEORY

In this chapter the derivation of the theoretically appropriate alternative to Simple Sum aggregates- Divisia monetary aggregates is reviewed.

2.1 Microeconomic Foundations

It is assumed that there is one economy in which there is a representative agent whose utility function, u, is assumed to consist of consumption goods (c), leisure (l) and services of monetary assets (x), that is,

$$u = u(c, l, x) \tag{2.1}$$

The utility in Equation 2.1 can be assumed to be maximised subject to a full income constraint of

$$q'c + \pi'x + wl = y \tag{2.2}$$

where y is full income, q is a vector of the prices of c, π is a vector of the monetary asset user costs (rental prices) and w is the wage rate. In order to focus on the details of monetary services, ignoring other types of goods, a good starting point is the theory of two stage optimisation investigated initially by Strotz (1957, 1959) and Gorman (1959). The theory describes a sequential expenditure allocation in which in the first stage the consumer allocates his expenditures among broad categories (consumption goods, leisure and monetary services) relying on the price indices of these categories and in the second stage allocates expenditure within each category. However, decomposition of the consumer choice problem along these lines is possible only if the individual's utility function (2.1) is weakly separable in the services of monetary assets (Barnett, Fisher and Serlettis, 1992). That is, it must be possible to write the utility function as

$$u = U(c, l, f(x)) \tag{2.3}$$

where f defines the monetary subutility function. Whether or not the utility function is weakly separable in monetary services is an empirical question. This issue is dealt with in greater detail in Chapter 3. Having established that monetary assets are weakly separable one can then proceed further in the framework of the following consumer problem.

$$\text{Max } f(x) \text{ subject to } \pi' x = m \tag{2.4}$$

where m is the total expenditure on monetary services, a total that is determined in the first stage of the two-level optimising problem.

2.2 Aggregation Theory

In the discussion to this point the steps taken to reduce a general consumer choice problem to an asset choice problem have been reviewed. Results from aggregation theory can now be used. In aggregation theory the aggregator function (function that will add together the monetary assets in our case) has been shown to be the subutility function $f(x)$. Thus if $\tilde{x}_t$ is the solution to Equation 2.4, then $M_t = f(\tilde{x}_t)$ is the exact (monetary) aggregate. The problem with using exact aggregates is that the subutility (aggregator) function f is unknown and therefore it must be specified and its parameters estimated. The list of functional forms from which a choice can be made is boundless and each imposes a set of implicit assumptions on the goods to be aggregated. For example, if one chooses to work with a weighted linear aggregator

$$f(x) = \sum_{i=1}^{n} a_i x_i \tag{2.5}$$

this would imply perfect substitutability between the goods. The other problem is that the unknown parameters (for example, in the case of the above functional form the a_i s) have to be estimated and periodically re-estimated. Exact aggregates are therefore specification- and estimation dependent. This kind of dependency is troublesome to governmental agencies which have to justify their procedures to people untrained in economics. However, index number theory provides a means of avoiding specifying functional forms and estimating unknown parameters arising in aggregation theory. This is what is discussed next.

2.3 Index Number Theory

In aggregation theory quantity aggregators depend upon the quantities (prices if price aggregators) of the component goods and upon unknown functions and parameters. In index number theory statistical index numbers do not depend on any unknown functions and parameters but (quantity or price) statistical index numbers depend upon component prices and component quantities. Examples of such statistical index numbers are the Lapesyres, Paasche, Divisia and Tornqvist indices. Until relatively recently the fields of aggregation theory and statistical index number theory had been developing independently. Diewert (1976, 1978) provided the link between these two theories. Diewert (1976, 1978) showed that using a number of well known statistical index numbers is equivalent to using a particular aggregator function. Such statistical indices are termed 'exact'. 'Exactness' occurs when a specific aggregator function is exactly tracked by a particular index number. However, 'exactness' is not enough for accepting the index number when the particular form of the aggregator function is not known a priori. However, in these circumstances it is possible to choose a statistical index number that is exact for a flexible function form – a functional form that can provide a second order approximation to any arbitrary unknown aggregator function. Diewert (1976, 1978) termed such statistical index numbers superlative. Examples are the Fisher ideal index and the Tornqvist discrete time approximation to Divisia index. Following Theil (1967), the latter is usually called the Tornqvist index or just the (discrete time) Divisia index.

2.3.1 The Divisia Index

Barnett (1980) shows that the selection between reputable index numbers (such as the Fisher ideal index or the Tornqvist discrete time approximation to Divisia index) is of little empirical importance since the difference between the growth rates are negligible. However, Barnett and Spindt (1982) suggests the use of the Tornqvist discrete time approximation to Divisia index since its superior properties have been fully explored in more than a half century of extensive research. In addition, its construction and behaviour are easily understood. Therefore the Tornqvist discrete time approximation to Divisia index, henceforth the Divisia index, is the index chosen to work with in this thesis. Let x_{it} be the quantity of the i^{th} asset during period t and π_{it} given by Equation 1.2 be the user cost (rental price) for that good during period t. Then the discrete time Divisia index, Q_t^D, during period t is given by

$$\frac{Q_t^D}{Q_{t-1}^D} = \prod_{i=1}^{n} \left(\frac{x_{it}}{x_{i,t-1}} \right)^{\frac{1}{2}(s_{it}+s_{i,t-1})} \tag{2.6}$$

where

$$s_{it} = \frac{\pi_{it} x_{it}}{\sum_{k=1}^{n} \pi_{kt} x_{kt}} \tag{2.7}$$

Taking the logarithms on both sides of (2.6), we obtain

$$\log Q_t^D - \log Q_{t-1}^D = \sum_{i=1}^{n} s_{it}^* (\log x_{it} - \log x_{i,t-1}) \tag{2.8}$$

where

$$s_{it}^* = \frac{1}{2}\left(s_{it} + s_{i,t-1}\right) \tag{2.9}$$

This index simply defines the single period growth rate of the aggregate as a weighted average of the growth rate of the component quantities. The weights are the corresponding value shares, computed with user cost as prices. Since the value shares represent the contribution of each component to expenditure on the services of all of the components, use of those shares as weights for the growth rates for the corresponding components implies that assets with higher liquidity will have higher weights and assets which are less liquid will have lower weights. As follows this index will produce a better definition of economy's monetary service flow than its Simple Sum counterpart.

Simple Sum aggregates are a special case of Divisia aggregates. If all own rates of return on the all monetary assets are the same, then the growth rate of the Divisia index reduces to the corresponding growth rate of the Simple Sum index. The current official Simple Sum aggregates implicitly assume that all own rates of return are equal. The assumption of equal own rates could be justified if all component monetary assets were perfect substitutes. However, empirical research shows that substitutability among different assets is low (see, for example, Drake (1992)).

2.4 Construction of Monetary Aggregates

Since the proposal for a common currency area first arose, a number of researchers have sought to determine how to measure monetary services flow aggregated over the proposed Euro area in a manner that would be consistent with aggregation theory. Two approaches have been proposed. One has been called the direct approach and the other the indirect approach. Under the direct approach assets of each type are first aggregated by simple summation. Divisia aggregation is then used to aggregate over each internationally aggregated asset type (see, for example, Stracca (2004)). The direct approach however, assumes there is a unilateral representative agent who considers the same goods in different countries regardless of the country of residence of the purchaser or the country within which the good or asset is acquired. Without a homogeneous culture within the Euro area the assumption of a unilateral representative agent will not apply. The alternative indirect approach uses Divisia aggregation within each country and then uses within-in country indexes to aggregate over countries. Aggregation over countries uses weights comprising of exchange rates of individual countries relative to a market basket of currencies, such as the European currency unit (see Barnett (2003)). The indirect approach does not assume there is a unilateral representative agent and hence is based on more reasonable assumptions and therefore is a more ideal way of constructing aggregates. Such an approach requires data on all asset types from every member country of the Euro area. Because we encountered data limitations in this study we use the direct approach to construct our aggregates.

Before aggregating the assets, however, some important issues have to be resolved. Firstly, how does one satisfactorily aggregate each type of assets when pre-Euro area currencies have varying exchange rates? Prior to the monetary union, a considerable amount of work has been carried by EU national central banks of re-denominating individual country data sets into Euro area data. For the period before the monetary union, the figures for the individual countries are aggregated on the basis of the irrevocable exchange rates of January 1999. Since the January 1, 1999 exchange rates among the members of the Eurosystem have been irrevocably fixed. Before that date, exchange rates could change. The ECB (1999) suggests using fixed exchange rates to combine national data for the Euro area data. Volatile movements in exchange rates could potentially affect weak separability tests, as an exchange rate change may look like a change in money holding when it is not. Subsequently the money demand functions of monetary aggregates resulting from weakly separable asset groupings might seem to be unstable when in fact they are not. The use of fixed exchange rates is aimed at avoiding such problems. An alternative method of aggregation is based on real GDP weights at the purchasing power purity (PPP) exchange rates of 1995 (see, Coennen and Vega (2001), Stracca (2003)). Stracca (2004) did not find significant differences between the figures resulting from the use of fixed exchange rates and use of the PPP exchange rates and hence current evidence suggests that the empirical performance of monetary aggregates resulting from these techniques are likely to be similar. The study by Reimers (2002) assumes different exchange rates regimes to calculate aggregates. His settings result in one Divisia aggregate of national monetary components with fixed exchange rates and one aggregate with monetary components with variable exchange rates. He finds none of the aggregates dominates the other. Nevertheless, the aggregate with fixed exchange rate effect seems to have stronger connections with output gap and price changes.

Secondly, there is the question of what assets to aggregate over as different countries possess different types of assets over different historical periods? Because, not all central banks had the same amount of historical series data and type of monetary assets, they firstly had to agree on a minimal set of monetary harmonized assets. Four assets were used in the construction of monetary aggregates, specifically, currency in circulation (CC), overnight deposits (OD), short term deposits other than overnight deposits (SD) and marketable instruments (MI), where existing data could be used to estimate these broad categories of assets over a sufficiently long historical period. The same procedure has been used in calculating the interest rates of the four categories of monetary assets. It has to be acknowledged, however, that due to different institutional, social, tax and legal differences and the range of available alternatives, the deposit and savings instruments being aggregated across countries are almost certainly not strictly comparable and therefore the resulting aggregates can only be considered as approximations to 'true' Euro area aggregates. However, as the Euro area convergence proceeds there could be some evolution towards greater homogeneity in tastes, institutions and laws. Such an evolution would lead to construction of monetary aggregates more representative of 'true' Euro area aggregates.

Thirdly, while different monetary types of monetary assets can be considered to be perfect substitutes, they are not perfect substitutes. Therefore, how much substitution is there between the four categories of assets under consideration? The degree of substitution between the different assets is an empirical issue which can be investigated from, for example, an asymptotically ideal model (AIM) (see, Drake, Fleissig and Mullineux, 1999). However, since it is beyond the scope of this thesis, the degree of substitution will not be investigated here and will be considered for future work. It tends to be the case that only central banks and large firms hold OD, however, in the case of the Euro area, OD are mainly held by households. The decision of an agent to hold a particular type of, say, short-term deposits over another depends mainly on the characteristics of the short-term deposits. The characteristics include (a) checkability, (b) liquidity/term structure, (c) yield, (d) minimum deposit and even possibly risk to a small degree. In the US, for example, demand deposits do not earn interests but have unlimited check writing. Overnight deposits have unlimited check writing and earns minimal interest that depends on minimum balance. Savings deposits have limited checking but higher yields depend on minimal balance. Certificates of deposits (CDs) are non-negotiable time deposits. They do not have check writing, but can be cashed out at a penalty. Negotiable CDs are time deposits over 100, 000 dollars that can be traded on a secondary market. Money market funds essentially earn the Treasury bill rate and may have some check writing. Even though the assets are different in the Euro area, same concepts apply. The decision of an economic agent to hold a particular type of asset over another is affected by many factors such as the economic situation of the person, whether the person is rich or poor; transaction costs over alternative assets. The decision of the agent can also be affected by the general uncertainty in the economy. For example, an increase in interest rate risk, in the form of volatility, also increases the risk of bearing fixed-term interest-paying securities. Economic agents in this environment substitute these securities for monetary assets.

Fourth, regards the choice of the benchmark rate – how should this instrument or basket of instruments be selected. As discussed in Chapter 1 the benchmark rate has should be the rate of return on an asset providing no monetary services whatsoever but no such asset exists on the market. It was also mentioned that a long term rate of return is usually used as the benchmark rate. However, it is often the case that capital certain assets in some periods have a higher return than long term interest rates. An alternative, therefore, is to use an envelope method which amounts to searching across the range of assets to find the highest rate of return in each period. The highest return, usually with a small increment to avoid negative user costs, then becomes the benchmark rate. In this thesis, a long term interest rate is used as the benchmark rate over the period of study (1980 -2000) as in general the rates of return on capital certain assets are lower than the long term interest rate. Different assets within each category of assets bear different rates of return. However, the difference between the rates of return is likely to be small.

For example, the Bank of England uses a single interest rate for the different categories of assets within a particular asset-type. Therefore an average of the different rates of return could be used as an estimate for the rate of return for the category as whole. An alternative would be to construct a weighted interest rate where the highest rate of return gets the highest weight.

Previous research (see, for example, Belongia and Chrystal (1991), Drake and Chrystal (1994)) has indicated that there may be significant differences between the demand for money across sectors. Drake and Chrystal (1994), for example, indicate that the money demand function estimated for the corporate sector differed markedly from the money demand functions estimated from official monetary data. The differences are likely to emerge from the fact that official monetary aggregates have no economic interpretation in the sense that they attempt to combine two entirely sets of demands. This would suggest that disaggregated studies on sectoral demands for various categories of monetary aggregates would be more insightful than the more usual aggregate studies. In this study we are unable to test weak separability and estimate money demand functions for the two different sectors due to the lack of availability of breakdown data.

In testing for weak separability of asset groupings, data on consumption and leisure which enter the consumer's utility function are also required as illustrated by Equation 2.3. However, given that the euro area has only recently come into existence such data are not available and hence we are forced to assume that the monetary data is weakly separable from consumption and leisure in the consumer's utility function and we focus on testing for weakly separable asset subgroupings. Also, given the increase in liquidity of risky assets like bonds and equities, if such data were available we would have subjected them to weak separability tests along with capital certain assets. If groups of assets consisting of both capital certain and risky assets were found to be weakly separable, these groups would have been used to construct monetary aggregates (see, for example, Elger and Binner (2004)).

The monetary data for the Euro area data have been provided to us by Mr Livio Stracca at the ECB. The data are harmonized data from 1980Q1 to 2000Q4 and as mentioned earlier, consist of currency in circulation, overnight deposits, short term deposits other than overnight deposits and marketable instruments. In October 2004, currency in circulation was 446 Euro billion, overnight deposits 2434 Euro billion, other short term deposits 2644 Euro billion and marketable instruments 940 Euro billion for a total of 6464 M3 Euro billion. In this current study we are forced to employ Mr Stracca's data set as data over individual member countries over a sufficiently long historical period are not available on Datastream. I had even contacted some central banks such as Bank de France and Deutsche Bundesbank but was not provided with sufficient data for the analysis. Individual member countries have provided their data to the European Central Bank only a confidential basis and are not disseminated to the general public.

CHAPTER 3:

WEAK SEPARABILITY

In this chapter weak separability tests are carried out to identify groups of monetary assets that can be reliably aggregated to form monetary aggregates. Nonparametric tests of weak separability derived by Fleissig and Whitney (2003) are used for that purpose. These tests are an improved version of the traditionally used weak separability tests derived by Varian (1982, 1983).

3.1 Introduction

As discussed in Chapter 2, in monetary aggregation theory, monetary assets enter as a component in the utility function of the consumer. In order to construct a monetary aggregate over a group of assets, the group must be weakly separable from all other assets, goods and leisure in the consumer's utility function. Swofford (2000) less formally argues that the weak seperability criterion for aggregation is a way to identify what people view as money, that is, to identify what assets have to be included in a monetary aggregate. This issue has received even less attention than the one on the appropriate aggregation formula. Though it is possible to check for weak separability of a group of monetary assets, central banks rarely carry out weak separability tests and the common practice is of grouping monetary assets according to subjective judgements about the assets' liquidity (Belongia, 2000).

In this chapter, therefore, the objective is to carry out tests to identify groups of monetary assets which are weakly separable for the Euro area. Studies on the issue of weak separability involving the search for admissible monetary aggregates include that of Swofford and Whitney (1987, 1988) for the US, Belongia and Chrystal (1991), Drake and Chrystal (1994, 1997), Drake (1996, 1997), Patterson (1991) for the UK, Belongia (2000) for US, Germany and Japan. Weak separability studies for the Euro area also have been carried out by Spencer (1997), Swofford (2000) and Reimers (2002). Spencer (1997) uses monthly data for the period 1985 to 1990. For the pre German Monetary Union (GMU) period (January 1985- June 1990) no weakly separable group of monetary assets was found, however for the post GMU period (July 1990- January 1995) one group of monetary asset (non interest bearing assets) was found to be weakly separable. Swofford (2000) using annual data for the period 1987 to 1997 found that the monetary assets for the Euro area were not weakly separable. Reimers (2002) uses post ECB formation data for the period 1997 to 2000 and finds the whole data, that is, all the components of official Simple Sum M3, and the components of M1 to be weakly separable. The present analysis differs in a significant manner from the previous Euro area studies in that an improved version of Varian's (1982, 1983) nonparametric weak separability tests derived by Fleissig and Whitney (2003) is used.

3.2 Weak Separability Tests for the Identification of Admissible Groups of Monetary Assets

Two types of test that can be used to check for weak separability are parametric and nonparametric tests. The parametric test requires the specification and estimation of a particular functional form for the utility function. However, as Varian (1983) points out such a parametric test is necessarily a joint test of consumer theory and the particular functional form chosen. Thus, when the collection of assets fails the weak separability test, one cannot say whether it is consumer theory or the particular functional form of the model being rejected. In contrast the nonparametric test (Varian, 1982, 1983) is not dependent on a particular form of the utility function. This feature makes it more attractive among researchers (Swofford and Whitney (1987, 1988), Patterson (1991), Belongia and Chrystal (1991), Drake (1994), Drake and Chrystal (1994, 1997), Elger, Binner and Jones (2003)) and therefore is the preferred choice in this thesis. However, the nonparametric test also has some shortcomings. The chief one is that the probability of rejecting weak separability is high. Two distinct reasons can be given for this. The first one is theoretical and lies in the fact that the test is nonstochastic, meaning that a single violation of the test leads to rejection of the hypothesis. But violations of the test may be due to purely stochastic causes such as measurement error and are therefore should be ignored. The second reason is related to the test procedure itself which may return negative indices (also called Afriat numbers, discussed in Section 3.3) instead of positive indices when there are large fluctuations in the data, leading to the rejection of weak separability. In view of these problems Fleissig and Whitney (2003) have developed an improved version of Varian's (1982, 1983) test which allows for the above mentioned problems.

3.3 Nonparametric Weak Separability Tests

While testing for weak separability using Varian's (1982, 1983) nonparametric approach one checks if the necessary and sufficient conditions for weak separability are satisfied. Before looking at these conditions a theorem and some conditions on which the weak separability conditions are based are reviewed.

Afriat's Theorem (Afriat, 1967)

This theorem allows us to verify whether the prices and quantities of a particular data set are consistent with the maximisation of a well-behaved nontrivial utility function. That is it allows us to check if the data are consistent with a nontrivial utility function that is nonsatiated, continuous, concave and monotonic. If we let $x^i = (x_1^i, \cdots, x_k^i)$ be a $k \times 1$ vector of goods quantities and $p^i = (p_1^i, \cdots, p_k^i)$ be the associated prices and $D = \{x^i, p^i) \in R^{2k}$ $i = 1 \cdots n$ be the data set containing n observations of x^i and p^i, then the Afriat conditions are given as follows

The following conditions are equivalent:

(1) There exists a nonsatiated utility function that rationalises the data.

(2) The data satisfy the "cyclical consistency"; that is,

$$p^r x^r \geq p^r x^s, \quad p^s x^s \geq p^s x^t, \quad \cdots, \qquad p^q x^q \geq p^q x^r \tag{3.1}$$

implies

$$p^r x^r = p^r x^s, \quad p^s x^s = p^s x^t, \quad \cdots, \qquad p^q x^q = p^q x^r \tag{3.2}$$

(3) There exist numbers $U^i, \lambda^i > 0$, $i = 1, \cdots, n$ such that satisfy:

$$U^i \leq U^j + \lambda^j p^j (x^i - x^j) \text{ for } i, j = 1, \cdots, n. \tag{3.3}$$

(4) There exists a nonsatiated, continuous, concave, monotonic utility function that rationalizes the data.

The implication of the above theorem is that if the data set satisfies any of the first three conditions then the fourth condition would automatically hold, i.e., there will exist a well behaved function that is nonsatiated, continuous, concave, monotonic utility function that rationalizes the data. Despite the fact that conditions (2) and (3) offer a more sympathetic approach to testing for the existence of a well behaved utility function that rationalizes the data, they are still very burdensome computationally. However, Varian (1982) developed an equivalent formulation of condition (2) which is easier to test. He called his condition the generalised axiom of revealed preference (GARP). In order to describe this formulation (GARP) the following definitions adapted from Varian (1982, pg 947) must first be considered.

Definitions: For a given observation x^i and a bundle x:

(1) x^i is directly revealed preferred to x, written $x^i R^0 x$, if $p^i x^i \geq p^i x$.

(2) x^i is strictly directly revealed preferred to x, written $x^i P^0 x$, if $p^i x^i > p^i x$.

(3) x^i is revealed preferred to x, written $x^i Rx$, if $p^i x^i \geq p^i x^j, p^j x^j \geq p^j x^l, \cdots,$

$p^m x^m \geq p^m x$ for some sequence of observations $(x^i, x^j, \cdots, x^m)$.

Definition:

A set of data satisfies the General Axiom of Revealed Preference (GARP) if $x^i R x^j$ implies not $x^j P^0 x^i$.

Varian (1982) proves that a set of data satisfies cyclical consistency if and only if it satisfies GARP. Thus if some data satisfy GARP, the data are consistent with the maximisation of a well-behaved nontrivial utility function. If the data contain a violation of GARP, then there does not exist a nonsatiated utility function that will rationalize the data. Checking for consistency with GARP becomes straight forward if, using the above definitions, GARP is reformulated as: if $x^i R x^j$ then $p^j x^j \leq p^j x^i$ for $i, j = 1, \cdots, n$. Hence verifying that some data satisfy GARP is quite easy once the relation R-the transitive closure of the direct revealed preference relation R^0 is known.

The relation R can be constructed using the following steps: First an n by n matrix M is constructed, whose ij^{th} entry is given by:

$$m_{ij} = \begin{cases} 1 & \text{if } p^i x^i \geq p^i x^j, \text{that is}, x^i R^0 x^j \\ 0 & \text{otherwise} \end{cases} \tag{3.4}$$

The matrix M summarise the relation R^0. Appling Warshall's algorithm (see Varian 1982, p. 972) to M creates a matrix MT which represents the relation R, where

$$mt_{ij} = \begin{cases} 1 & \text{if } x^i R x^j \\ 0 & \text{otherwise} \end{cases} \tag{3.5}$$

If $mt_{ij} = 1$ and $p^j x^j > p^j x^i$ for some i and j, there is a violation of GARP.

With these definitions and the ability to check for GARP violations it is now possible to look at the conditions for weak separability. If a data set is partitioned into two sets of goods and associated prices $(p^i, x^i), (q^i, z^i)$ $i = 1, \cdots, n$, where x and z are goods and p and q are the corresponding prices then as discussed in section 2.1 of Chapter 2 a utility function U is weakly separable in z goods, if the utility function $U(x,z)$ can be written as

$$U(x,z) = \tilde{U}(x, V(z)) \tag{3.6}$$

where $V(z)$ is the subutility function (Blackorby, Primont and Russel, 1978). In this vein Varian (1983) showed that the following conditions are equivalent:

(1) There exists a weakly separable concave, monotonic, continous nonsatiated utility funtion that rationalises the data.

(2) There exist numbers $U^i, V^i, \lambda^i > 0, \mu^i > 0$ $i = 1, \cdots, n$ that satisfy the following Afriat inequalities:

$$U^i \leq U^j + \lambda^j p^j(x^i - x^j) + (\lambda^j / \mu^j)(V^i - V^j) \quad (3.7)$$

$$V^i \leq V^j + \mu^j q^j(z^i - z^j) \quad (3.8)$$

for $i, j = 1, \cdots, n$;

(3) The data (q^i, z^i) and $(p^i, (\mu^i)^{-1}; x^i, V^i)$ satisfy GARP for some choice of (μ^i, V^i), called Afriat numbers, that satisfy the Afriat inequalities.

To check for weak separability the one type of condition that can be tested is Condition 3, which calculates indices that satisfy the inequality constraint (3.8). To meet Condition 3 the entire data set and the hypothesized weakly separable subgroup (z in this case) must satisfy GARP. These are the necessary conditions for weak separability. The sufficient condition of weak separability is that aggregate of the hypothesized weakly separable subgroup (the Afriat numbers) together with the remainder of goods, that is, $(p^i, (\mu^i)^{-1}; x^i, V^i)$ satisfy GARP for some choice of (μ^i, V^i). The program to test for the necessary and sufficient conditions of weak separabiliry is given in Appendix A. It involves calculating the Afriat numbers and checking the different groups for consistency with GARP. The program is written in GAUSS mathematical software.

3.3.1 Fleissig and Whitney Test

Varian's (1982, 1983) algorithm for calculating the Afriat numbers μ^i and V^i places no other constraints than μ^i and V^i should be positive. However, it is not unusual to obtain negative values for V^i, implying rejection of weak separability for the group being tested. Given that that V^i can be interpreted as a utility function, Fleissig and Whitney

(2003) use this property to calculate μ^i and V^i alternately. As discussed in Section 2.3 of Chapter 2, using a statistical index number is equivalent to using a particular aggregator function (utility function) and an index number can be considered superlative if it can provide a second order approximation to the unknown aggregator function (Diewert, 1976, 1978). Fleissig and Whitney (2003) use this property to obtain estimates for V^i, using a superlative index number (the Tornqvist discrete time approximation to Divisia index) and a corresponding range of values of μ^i. Let the superlative index number be $QV^i = f(q,z)$ which is a function of the goods and prices of z, be an estimate for V^i in Equation 3.8. If the estimates give positive values for μ^i the superlative index number solves the Afriat inequalities. The superlative index number may fail to give a range of μ^i that satisfies the Afriat inequalities because of the possibility of third or higher order approximation errors to the unknown aggregator function. Moreover, factors such as measurement error may result in the superlative index number QV^i failing to give a solution to Afriat inequalities. A small adjustment to QV^i may be required to obtain a solution. Thus by adding a positive number $(Q_p^i \geq 0)$ or a negative amount $(-Q_n^i \leq 0)$ to QV^i, the superlative index number with error QV^{*i}

$$QV^{*i} = QV^i + Q_p^i - Q_p^n \tag{3.9}$$

will provide a solution if one exists. If $Q_p^i = 0$ and $Q_n^i = 0$ for $i = 1,\cdots,n,$ then the superlative index without error provides a solution. Assuming that the superlative index number with error QV^{*i} gives a solution to the separability inequalities, Equation 3.8 can be written as

$$QV^{*i} \leq QV^{*j} + \mu^j q^j (z^i - z^j) \tag{3.10}$$

Substituting Equation 3.9 in 3.10 gives

$$QV^i + Q_p^i - Q_p^n \le QV^j + Q_p^j - Q_p^j + \mu^j q^j (z^i - z^j) \qquad (3.11)$$

μ^i can be obtained from the following equation

$$\mu^i = QV^i / inc^{iy} \qquad (3.12)$$

where inc^{iy} is the expenditure on *y* goods in period *i*. Let a positive number $(\mu_p^i \ge 0)$ or a negative amount $(-\mu_n^i \le 0)$ be adjustments that may be required to make μ^i satisfy the Afriat inequalities. μ^i can then be written as

$$\mu^i = QV^i / inc^{iy} + \mu_p^i - \mu_n^i \qquad (3.13)$$

If $\mu_p^i = 0$ or $\mu_n^i = 0$ then μ^i without adjustment provides a solution to the Afriat inequalities. To preserve the economic interpretation of the solution other constraints are

$$\mu^i > 0 \qquad (3.14)$$

$$QV^{*i} > 0 \qquad (3.15)$$

$$QV^i + Q_p^i - Q_n^i > 0 \qquad (3.16)$$

The goal is to minimise the adjustments $Q_p^i, Q_n^i, \mu_p^i, \mu_n^i$ subject to the constraints 3.11, 3.13, 3.14, 3.15 and 3.16. This problem can be formulated as a linear programming (LP) problem as follows

Minimise $Z = \sum_{i=1}^{n} Q_p^i + \sum_{i=1}^{n} Q_n^i + \sum_{i=1}^{n} \mu_p^i + \sum_{i=1}^{n} \mu_n^i$

Subject to

$$QV^i + Q_p^i - Q_p^n \le QV^j + Q_p^j - Q_p^j + \mu^j q^j (z^i - z^j) \qquad (3.11)$$

$$\mu^i = QV^i / inc^{iy} + \mu_p^i - \mu_n^i \tag{3.13}$$

$$\mu^i > \varepsilon_u^i \tag{3.17}$$

$$QV^i + Q_p^i - Q_n^i > \varepsilon_{QV}^i \tag{3.18}$$

$$Q_p^i \geq 0$$

$$Q_n^i \geq 0$$

$$\mu_p^i \geq 0$$

$$\mu_n^i \geq 0$$

where the constraints (3.14) and (3.15) have been transformed to weak inequalities as required by LP problems and which are as follows

$$\mu^i > \varepsilon_u^i$$

$$QV^i + Q_p^i - Q_n^i > \varepsilon_{QV}^i$$

The above problem is a linear programming (LP) problem but is in nonstandard form. The standard form of an LP model is

$$\min\{c'x \mid Ax \leq b, x \geq 0\}$$

Substituting Equation 3.13 into equations 3.11 and 3.17 will transform the nonstandard LP problem into a standard one.

3.4 Data for Weak Separability Testing

The data on monetary assets and their corresponding rates of return have been provided by Mr Livio Stracca at the ECB, taken from his study (see, Stracca (2004)). The data are quarterly harmonised from 1980Q1 to 2000Q4 for the Euro-11, that is, Euro area excluding Greece. Due to the small weight of Greece in the Euro area economy, the exclusion of Greece is unlikely to affect the main results of this thesis in a significant manner. In this thesis the Euro -11 area will be referred to as the Euro area. The four components of the official monetary aggregate (Simple Sum) M3 are taken into consideration and which are given in Table 3.1 below with the definition of Simple Sum aggregates that can be constructed using them

Table 3.1: Definition of the asset components of M3 and the monetary aggregates that can be constructed from them.

		Monetary Aggregates		
Monetary Assets		M1	M2	M3
Currency in circulation	(CC)	x	x	x
Overnight deposits	(OD)	x	x	x
Short term deposits other than overnight deposits	(SD)		x	x
Marketable instruments	(MI)			x

Note: x means the corresponding monetary asset is included in the construction of the monetary aggregate.

The asset components are in levels and have been seasonally adjusted using the X-12 ARIMA procedure. Let r_{CC}, r_{OD}, r_{SD} and r_{MI} be the rate of return on CC, OD, SD and MI respectively. Obviously $r_{CC} = 0$, Stracca (2004) has derived r_{OD} and r_{SD} using estimates of the own rate of return of M1 (r_{M1}^{own}) and the own rate of return of M3 (r_{M3}^{own})

which have been respectively derived by Stracca (2003) and Calza, Gerdesmeier and Levy (2001). r_{OD} is derived on the basis of the following formula

$$r_{CC}\frac{CC}{M1}+r_{OD}\frac{OD}{M1}=r_{M1}^{own} \tag{3.19}$$

and hence

$$r_{OD}=r_{M1}^{own}\frac{M1}{OD} \tag{3.20}$$

since $r_{CC}=0$. Regarding r_{SD}, this can be obtained by means of a similar procedure to derive r_{OD} by extending Equation 3.19 above to include the SD and using a combination of the own rate of M1 and M3 to obtain an estimate of the own rate of M2. Finally r_{MI} is proxied with a short term interest rate.

Data on the population of the Euro area is required to transform the quantities to a per capita scale. The population data for the Euro area are only collected on an annual basis on DataStream and therefore a spline technique has been used to transform the data to a quarterly basis. The GDP deflator for the Euro area, also provided by Stracca (2004), is used to deflate the quantities. The prices of the monetary assets are also required to carry out weak separability tests and following Elger and Binner (2004) these are taken to be the nominal user costs of monetary assets, that is, the nominal user cost multiplied by a price index which is taken to be the GDP deflator in this study. The nominal user cost of an asset *i* at time *t* can be represented as follows

$$\pi_{it}=p_t\frac{(R_t-r_{it})}{(1+R_t)} \tag{3.21}$$

where *p* is the price level. Data on nondurable goods and services are required to carry out weak separability tests (see, for example, Swofford and Whitney (1987)). However, given that the Euro area has recently come into existence it is very difficult to obtain such data over long historical periods. Therefore, following the common practice in such circumstances (see, for example, Barnett (1980), Spencer (1997) and Belongia (2000)), it is assumed that the monetary assets used in this study are weakly separable from the nondurable goods and services. Also, ideally, given that financial innovation has increased the liquidity of risky assets, such as equities, bonds and mutual funds (see, for example, Elger, Binner and Jones (2003)), they should have also been included in the analysis to determine whether they could be incorporated along with the capital certain assets, that is CC, OD, SD and MI, to construct monetary aggregates for guiding the monetary policy strategy in the Euro area. However, due to data limitations, it was not possible to do so.

3.5 Results for Weak Separability Tests

On testing for consistency of the full data set with GARP, two violations are noted. While testing for weak separability of asset components for the Euro area, Spencer (1997) splits his data set to allow for the German monetary union (GMU) which had caused high fluctuations in the German data. The fact that Germany has a big weight in the Euro area economy makes it highly likely it would affect the weak separability results. Following Spencer's (1997) procedure the data set is divided into two sub-samples. One of the sub-samples, 1980Q1-1991Q1, contains the GMU and the second one, 1991Q2-2000Q4, is post a GMU period sample. On testing for consistency with GARP for the different samples, two violations are noted for the first sub-sample but no violations are observed for the second sub-sample, as shown in Table 3.2

Table 3.2: Consistency of full data set with GARP

Time Period	1980Q1-2000Q4	1980Q1-1991Q1	1991Q2-2000Q4
No. of Violations	2	2	0

Given that the full data set is consistent with GARP for the period 1991Q2-2000Q4, identification of weakly separable groups of monetary assets is confined to that data period. Weak separability results, given in Table 3.3, suggest all asset groups considered are weakly separable and can be used to form meaningful monetary aggregates.

Table 3.3: Weak separability tests (1991Q2-2000Q4)

Subsets of monetary assets	GARP	Weak Separability
CC	Y	Not applicable
(CC, OD)	Y	Y
(CC, OD, SD)	Y	Y
(CC, OD, SD, MI)	Y	Y by assumption

Notes: Y indicates consistency with GARP and weak separability, respectively whereas N indicates inconsistency.

It should be noted that apart from the incremental groups of monetary assets, other groups of assets could be formed and subjected to weak separability. However, since it is generally held that any economically meaningful aggregate cannot be constructed without the inclusion of assets with high liquidity, the analysis has been confined to the groups of assets given in Table 3.3.

Small adjustments were required for the superlative index and μ, for the groups of assets that were found to be weakly separable. The superlative index used here is the Divisia index. In line with Fleissig and Whitney (2003) the PRMSE, given below, is used to measure by how much the adjusted superlative index and adjusted μ differ from the corresponding values calculated from the data.

$$\text{PRMSE}\,(.) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{adjusted\ data - data}{data}\right)^2} \qquad (3.22)$$

where n is the number of data points. Table 3.4 shows how large the adjustments are for the different weakly separable groups.

Table 3.4: Magnitudes of adjustments required to make asset groups weakly separable.

Weakly separable Groups	PRMSE (TV)	PRMSE (MU)
(CC, OD)	0.00157741	0.04836028
(CC, OD, SD)	0.00175990	0.06968298

Note: TV = superlative index and MU= μ

Adjustment of similar magnitudes were required in Fleissig and Whitney (2003) to make the superlative index and μ satisfy weak separability and have been considered to be very small. Hence, in line with Fleissig and Whitney (2003), the adjustments here can also be considered to be very small and hence the groups of assets in Table 3.3 are weakly separable.

3.6 Summary and Conclusions

In this chapter weak separability tests are carried out to identify groups of monetary assets that can be reliably used to construct monetary aggregates for monetary policy purposes in the Euro area. The tests used are those developed by Fleissig and Whitney (2003) which are an improved version of Varian's (1982, 1983) nonparametric tests. More specifically, the probability of rejection of weak separability using Varian's (1982, 1983) procedure is quite high for two reasons. Firstly, Varian's (1982, 1983) procedure is nonstochastic and hence a single violation will lead to rejection of weak separability. But violations can be purely due to measurement errors and hence not significant. Secondly, Varian's (1982, 1983) procedure sometimes produces negative Afriat indices which should be positive and hence leading to rejection of weak separability. Fleissig and Whitney (2003) allow for these problems by reformulating Varian's (1982, 1983) procedure into a linear programming problem where the constraints force the Afriat indices to be positive and small adjustments are made wherever required.

On subjecting the data set in this study to the weak separability test, the whole data set was not found to be consistent with GARP, possibly due to GMU. Hence the data were divided into two sub-samples- one consisting of the GMU and the other a post GMU sample. As expected two violations were obtained for the first sample and no GARP violations for the second sample. Therefore, identification of weakly separable subgroups was confined to the post GMU period. All the groups of assets considered were found to be weakly separable. This result is slightly different to previous such Euro area studies in the sense that previous studies do not find many weakly separable asset groups (see, for example, Spencer (1997)). One of the reasons could be that a slightly different data set over a different time period has been considered. However, the main reason for such discrepancies could be due to the fact that a slightly different weak separability test has been used. As expected the rejection rate of weak separability is higher in the other studies which use the traditional Varian (1982, 1983) approach. Whereas by accounting for problems like measurement error and negative Afriat indices the Fleissig and Whitney (2003) approach used in this chapter reduces the chances of wrongly rejecting weak separability and hence it is strongly recommended that further weak separability studies use the improved version of Varian's (1982, 1983) nonparametric tests.

CHAPTER 4:

MONEY DEMAND ANALYSIS

In this chapter the weakly separable groups of monetary assets are used for constructing Simple Sum and Divisia monetary aggregates. However, given that at low levels of aggregation the behaviour of Simple Sum and Divisia aggregates tend to be very similar, only the broader groups of weakly separable assets, that is, (CC, OD, SD) and (CC, OD, SD and MI), are considered to construct the monetary aggregates. The relative empirical performances of the monetary aggregates are then compared in a cointegration money demand framework with a view to advising the ECB on the use of the appropriate monetary aggregate for policy purposes.

4.1 Introduction

Money demand studies that compare Simple Sum and Divisia monetary aggregates for the Euro area are very limited. Therefore the main objective of this chapter is to provide new empirical evidence on the relative performances of Divisia and Simple Sum aggregates to supplement the existing ones. Among the very few existing studies are those of by Drake, Mullineux and Agung (1997), Spencer (1997), Stracca (2004) and Reimers (2002). All these studies differ from the present one in important respects. Drake, Mullineux and Agung (1997) and Spencer (1997) use pre ECB formation data whereas the data in this study are post ECB formation data. Moreover, the data in these studies are not constructed over all the member countries, whereas the data here apart from Greece, which has a very small weight in the Euro area economy, are constructed over all member countries. Though the data here are similar to Stracca (2004), the analysis has been carried out differently. Specifically, weak separability tests are conducted (carried out in the previous chapter) to identify the assets which are weakly separable before constructing monetary aggregates and the period over which the assets are weakly separable is also identified. Reimers (2002) on the other hand does carry out weak separability tests and investigates the usefulness of Divisia aggregates for policy purposes in the Euro area, but the study does not provide any comparison between Divisia and Simple Sum indices and hence no conclusion can be drawn on whether the Divisia aggregates would be better than their Simple Sum counterparts in practice. Moreover, Reimers (2002) conducts weak separability and money demand analysis over different time periods.

The overwhelming majority of studies involving evaluation of monetary aggregates carry out the evaluation in a money demand framework (see for example, Lutkephol and Wolters (1998) for Germany, Belongia and Chystal (1991) for the UK). The studies often focus on establishing whether there exists a stable relationship in terms of parameter stability between monetary aggregates and a set of economic variables usually consisting of GDP, inflation and interest rate. There is no general agreement, however, that a stable money demand is an important prerequisite for usefulness of monetary aggregates for policy purposes. For example Lutkephol and Wolters (1998, pg 371) note, "A stable money demand is an important prerequisite for such a policy [monetary policy]." On the other hand Driscoll and Ford (1982) take the view that a stable money demand is a side issue with regards to usefulness of monetary aggregates for policy purposes. The latter opinion is supported by Mullineux (1996) who suggests that issues like indicator properties of the aggregates are of more relevance and should be investigated. The debate on whether or not stability of money demand is an important issue with respect to usefulness of monetary aggregates for monetary policy purposes is beyond the scope of this thesis. The approach here is to consider both views and therefore the empirical performance of the monetary aggregates is evaluated using a money demand framework as well as using other frameworks, considered in later chapters, that enable us to evaluate the indicator properties of the monetary aggregates.

4.2 Money Demand Theory

Most theories of money demand lead to a long run specification of the following form for cointegration analysis (Hendry and Ericsson, 1991)

$$\frac{M_t}{P_t} = g(S_t, \widetilde{R}_t) \tag{4.1}$$

where M_t is the nominal quantity of money demanded, P_t is some price variable, S_t is some scale variable such as GDP and $\widetilde{R}_t$ represents the opportunity cost of holding money. The opportunity cost variable may be represented in the form of a vector of interest rates (see, for example, Elger and Binner (2004)) or dual user cost indices (see, for example, Stracca (2004)). Many economists have suggested including inflation in (4.1) (see, for example, Goldfeld and Sichel (1987)) as it may represent partial adjustment or it may be viewed as on opportunity cost variable. In applied work it is common to use the following log-linear specification of (4.1)

$$\ln(M_t / P_t) = \delta_0 + \delta_1 \ln(S_t) + \delta_2 \Delta p_t + \delta_3 \ln(\widetilde{R}_t) + \varepsilon_t \tag{4.2}$$

where g has been extended to include the quarterly inflation rate and ε_t is the equilibrium error at time t. In this thesis the opportunity cost variables are taken to be dual user cost indices as they have been argued to be the appropriate opportunity cost variables (Mullineux, 1996). For Simple Sum indices the procedure of Lutkepohl and Wolters (1998) is followed in calculating the dual user cost as

$$R_t^L - R_t^{own} \tag{4.3}$$

where R_t^L is a long term interest rate and R_t^{own} a weighted average of the interest rates calculated as

$$R_t^{own} = \sum r_{it} \frac{x_{it}}{M_t} \tag{4.4}$$

where x_{it} is the i^{th} monetary asset at time *t* and r_{it} is the corresponding rate of return and M_t is the sum of all monetary assets. For the Divisia indices the dual user cost, P_t^D, is calculated as (see, for example, Stracca (2004))

$$\log P_t^D - \log P_{t-1}^D = \sum_{i=1}^{n} s_{it}^* (\log \pi_{it} - \log \pi_{i,t-1}) \tag{4.5}$$

where $s_{it}^* = \frac{1}{2}\left(s_{it} + s_{i,t-1}\right)$ and $s_{it} = \dfrac{\pi_{it} x_{it}}{\sum_{k=1}^{n} \pi_{kt} x_{kt}}$ and $\pi_t = \dfrac{(R_t^L - r_{it})}{(1 + R_t^L)}$

Economic theory suggests that $\delta_1 > 0$ (=1 if the relationship is to be interpreted as a velocity relationship), $\delta_3 < 0$ (Doornik, Nielsen and Hendry, 1998). There is, however, some ambiguity concerning the expected sign of δ_2. Partial adjustment models suggest that it should be positive while if inflation is viewed as an opportunity cost variable it should be negative.

4.3 Cointegration Analysis

Regression analysis is very likely to produce reliable results when the variables are stationary, that is, when the mean, variance and covariance of the variables are constant over time and the value of the covariance depends only on the distance or lag between the two time periods and not on the actual time at which the covariance is computed.

When this is not the case, that is, when the variables are nonstationary, the results are very likely to be spurious (Granger and Newbold, 1974). That is regression results will look good in the sense of having high R^2 values and significant t statistics, but which in fact have no real meaning. A good example is provided by Hendry (1980) who shows the strong but spurious relationship between rainfall and the UK inflation rate. Granger (1981) identifies a situation when regression between nonstationary variables produces results which are not spurious. This occurs when the nonstationary variables are cointegrated. Cointegration occurs when a linear combination of nonstationary variables results in a stationary process. A number of methods for estimating cointegration relations have been proposed; see for example, Engle and Granger (1987), Stock and Watson (1998), Bossaert (1988), Johansen (1988, 1992, 1995), Johanssen and Juselius (1990). In this study, the maximum likelihood procedure developed by Johansen and Juselius (1990) will be used as it is the most commonly used technique in empirical studies. Consider the vector $z_t = (m_{1t}, m_{2t}, \cdots, m_{pt})$ consisting of p variables. The vector z_t can be formulated as vector autoregressive (VAR) model of order k:

$$z_t = \Pi_1 z_{t-1} + \Pi_2 z_{t-2} + \cdots + \Pi_k z_{t-k} + \mu + \delta t + \phi D_t + \varepsilon_t \tag{4.6}$$

where μ is a constant and the error term, ε_t, is independently and normally distributed and $\Pi_1, \Pi_2, \cdots, \Pi_{t-k}$ are coefficient matrices. The variables D_t are dummy variables. The variables of z_t have to be at most I(1)[1] as the statistical procedures derived by Johansen and Juselius (1990) are based on that assumption. Expressing the VAR in first differences leads to the following short run vector error correction model (VECM):

$$\Delta z_t = \Gamma_1 \Delta z_{t-1} + \cdots + \Gamma_{k-1} \Delta z_{t-(k-1)} + \Pi z_{t-k} + \mu + \delta t + \phi D_t + \varepsilon_t \tag{4.7}$$

where Δz_t is stationary and the coefficient matrices are defined as

[1] An I(d) variable, where d>0, is a nonstationary variable that has to be differenced d times to become stationary.

$$\Gamma_i = -I + \Pi_1 + \cdots + \Pi_i \text{ and } \Pi = -I + \Pi_1 + \cdots + \Pi_k \tag{4.8}$$

where I is the identity matrix and the matrix Π contains information about long-run relationships between the variables in the data vector z_t. Equation 4.7 shows that the matrix Π determines how the levels of the process z_t enter the system. If $\Pi = 0$, the dynamic evolution does not depend on the levels. This indicates the importance of the rank of Π in the analysis. If the rank $(\Pi) = p$, then the process z_t is stationary. Whereas if $\operatorname{rank}(\Pi) = r$, where $0 < r < p$, implies existence of $p \times r$ matrices α and β such that $\Pi = \alpha\beta'$ and $\beta' z_t$ is I(0) (Johansen and Juselius, 1990). r is the number of cointegrating relationships and each column of β is the cointegrating vector. The order of the rank can be determined by the use of the trace test (see, Johansen (1995)).

In testing for cointegration, the question of whether a constant and trend should enter the long run relationship also arises. There are in general 5 possible ways of incorporating these deterministic components into the analysis (see Johansen 1992, Hansen and Juselius, 1995). Following Hansen and Juselius (1995) δ and μ from Equation 4.7 are decomposed into:

$$\delta = \alpha\delta_1 + \alpha_\perp\delta_2 \tag{4.9}$$

$$\mu = \alpha\mu_1 + \alpha_\perp\mu_2 \tag{4.10}$$

where

$\delta_2 = \left(\alpha_\perp^{\mathrm{T}}\alpha_\perp\right)^{-1}\alpha_\perp^{\mathrm{T}}\delta$ is a p-r-dimensional vector of quadratic trend coefficients in the data;

$\delta_1 = (\alpha^{\mathrm{T}}\alpha)^{-1}\alpha^{\mathrm{T}}\delta$ is an r-dimensional vector of linear trend coefficients in the cointegration space;

$\mu_2 = (\alpha_\perp^{\mathrm{T}}\alpha_\perp)^{-1}\alpha_\perp^{\mathrm{T}}\mu$ is a p-r-dimensional vector of linear trend slopes in the data

$\mu_1 = (\alpha^{\mathrm{T}}\alpha)^{-1}\alpha^{\mathrm{T}}\mu$ is an r dimensional vector of intercepts in the cointegrating relations.

And using the above decompositions, (4.7) can now be reformulated as

$$\Delta Z_t = \Gamma_1 \Delta Z_{t-1} + \ldots + \Gamma_{k-1}\Delta Z_{t-k+1} + \alpha\begin{pmatrix}\beta \\ \mu_1 \\ \delta_1\end{pmatrix}\widetilde{Z}_{t-1} + \alpha_\perp\mu_2 + \alpha_\perp\delta_2 t + \phi D_t + \varepsilon_t \qquad (4.11)$$

where $\widetilde{Z}_t = [Z_t, 1, t]$.

The five different models that arise when the deterministic components in (4.11) are restricted are now discussed.

Model 1

$\delta = 0,\ \mu = 0$. This model corresponds to the case where there are no deterministic components in the data and all intercepts in the cointegration relations equal zero.

Model 2

$\delta = 0,\ \mu_2 = 0,\ \mu_1$ unrestricted. In this case the model does not allow for linear trends in the data. The only deterministic components in the model are the intercepts in the cointegration relations.

Model 3

$\delta = 0$, μ_1, μ_2 unrestricted. If $\delta = 0$ but $\mu_2 \neq 0$, the model allows for linear trends in the data through μ_2, but it is assumed that there are no trends in the cointegration relations. The effect of having $\mu_1 \neq 0$ is that the cointegration relations have a non-zero intercept.

Model 4

$\delta_2 = 0$, δ_1, μ_1, μ_2 unrestricted. When δ_2 is restricted to 0 in Equation 4.11 the model is restricted to exclude quadratic trends. But having $\delta_1 \neq 0$ means that the cointegration space has a linear trend.

Model 5

No restrictions on δ, μ. The parameters being unrestricted imply the model allows for linear trends in the differenced series Δz_t thus allowing for quadratic trends in z_t.

In empirical analysis the first and the last models are generally ruled out (see for example, Drake (1996)). This is because the first is too restrictive in the sense that it does not even allow for an intercept, which is generally needed in such relationships and the last model is too unrestricted in the sense that it allows for a nonlinear trend in the levels of the data. Economists usually reject nonlinear trends in money demand relationships because they can improve in sample fit but provide very poor out of sample forecasts (Hansen and Juselius, 1995). In order to determine which of the different possible deterministic specifications is the most appropriate in the cointegration, Johansen (1992) suggests applying the Pantula (1989) principle. In so doing, the rank order and the presence of the deterministic components are jointly determined. In practice this involves estimating all the three models of interest outlined above (Model 2 – Model 4) and conducting the trace test to determine the cointegration rank sequentially from the most restrictive to the least restrictive specification. The first time the null hypothesis of r cointegrating vectors is not rejected indicates both the cointegration rank and the appropriate specification for the deterministic components.

4.4 Unit Root Testing

Prior to testing for cointegrating relationships it is important to check the order of integration of the variables, since, as mentioned earlier in the preceding section, the cointegration analysis is valid for at most I(1) variables. To check the stationarity properties of the series the most commonly used Augmented Dickey Fuller (1979) unit root test is used. To perform a unit root test on a variable y_t we employ the following model

$$\Delta y_t = \beta_1 + \beta_2 t + \delta y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta y_{t-i} + \mu_t \tag{4.12}$$

where β_1 and β_2 are constants and t is the trend variable. When the series does not seem to exhibit any trend and it is fluctuating around a zero mean, then β_1 and β_2 are restricted to 0. If the series does not contain any trend but has a non zero mean then β_2 is set to 0. If the series contains a trend then no restrictions are imposed on β_1 and β_2. The appropriate lag order m of the Dickey Fuller (1979) test is chosen in such a way to ensure that the errors are serially uncorrelated. The process is stationary if $\delta < 0$ and if $\delta = 0$, y_t is nonstationary. Thus the Dickey Fuller test considers the null hypothesis H_0: $\delta = 0$ against the one sided alternative H_1: $\delta < 0$.

4.5 Data and Preliminary Analysis

Given that the monetary assets were found to be weakly separable for period the 1991Q2 to 2000Q4, money demand analysis is also confined to that period and the definitions of the monetary aggregates constructed are as follows:

Monetary Assets	Simple Sum Aggregates	Divisia Aggregates
CC, OD, SD	SM2	DM2
CC, OD, SD, MI	SM3	DM3

The GDP deflator is used as the price variable, the scale variable is the real GDP as this variable is used in the very large majority of money demand studies (for the Euro area, see, for example, Calza, Gerdesmeier and Levy (2001), Stracca (2004)). The long term interest rate is a 10 year government bond yield. These data are also taken from the study of Stracca (2004). The definitions of the variables used are as follows:

$sm2_t$ is the log of real SM2

$sm3_t$ is the log of real SM3,

$dm2_t$ is the log of real DM2

$dm3_t$ is the log of real DM3

y_t is the log of real GDP

$dualsm2_t$ is the log of the opportunity cost variable of real SM2

$dualsm3_t$ is the log of the opportunity cost variable of real SM3

$dualdm2_t$ is log of the opportunity cost variable of real DM2

$dualdm3_t$ is the log of the opportunity cost variable of real DM3

$sm2_t$ is contrasted to $dm2_t$ and $sm3_t$ is contrasted to $dm3_t$ in Figure 4.1a and Figure 4.1b respectively . $sm2_t$ and $dm2_t$ are almost identical up to 1997 and the difference afterwards is also minuscule. However, $sm3_t$ begins to increase faster than $dm3_t$ and diverges afterwards. As expected larger differences between the two measures of the money stock arise when the monetary aggregates are broadened. The other series are plotted in Figure 4.2.

Figure 4.1a : log real Simple Sum M2 and log real Divisia M2

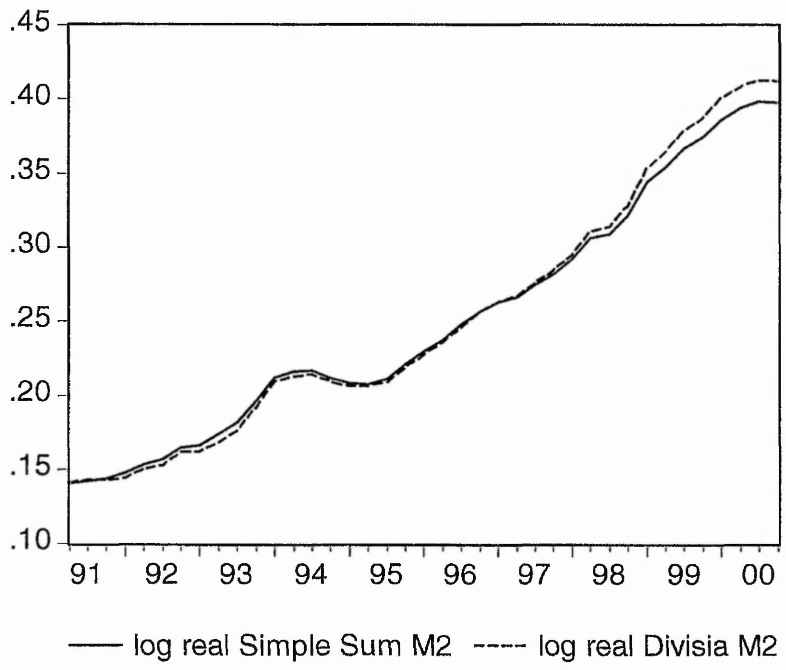
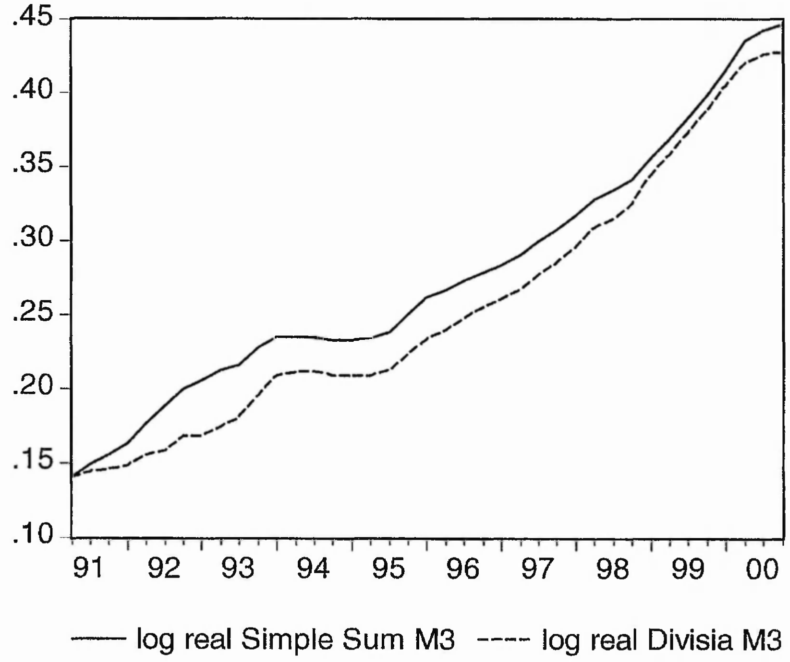


Figure 4.1b : log real Simple Sum M3 and log real Divisia M3



The stationarity properties of the series based on the Augmented Dickey and Fuller (1979) unit root test are reported in Table 4.1. Except for inflation which seems to be marginally stationary at the 10% significance level, results from the unit root test suggest that the remaining variables are not stationary. The first difference of the series appear to be I(0) at the 5% level but at the 1% level they appear to indicate the presence of nonstationarity, with $\Delta sm3_t$ not even stationary at the 10% level. An inspection of the graphs of $sm3_t$, however, reveals that there appears to be a structural break around 1993. Perron (1989) shows that in the presence of such breaks, conventional unit root tests have low power and tend to indicate nonstationarity instead of stationarity. The first difference of $sm3_t$ and the other series, presented in Figures 4.3a and 4.3b, in fact, appear to be stationary and hence for further analysis it is assumed that the variables are I(1).

Figure 4.2: Other time series used

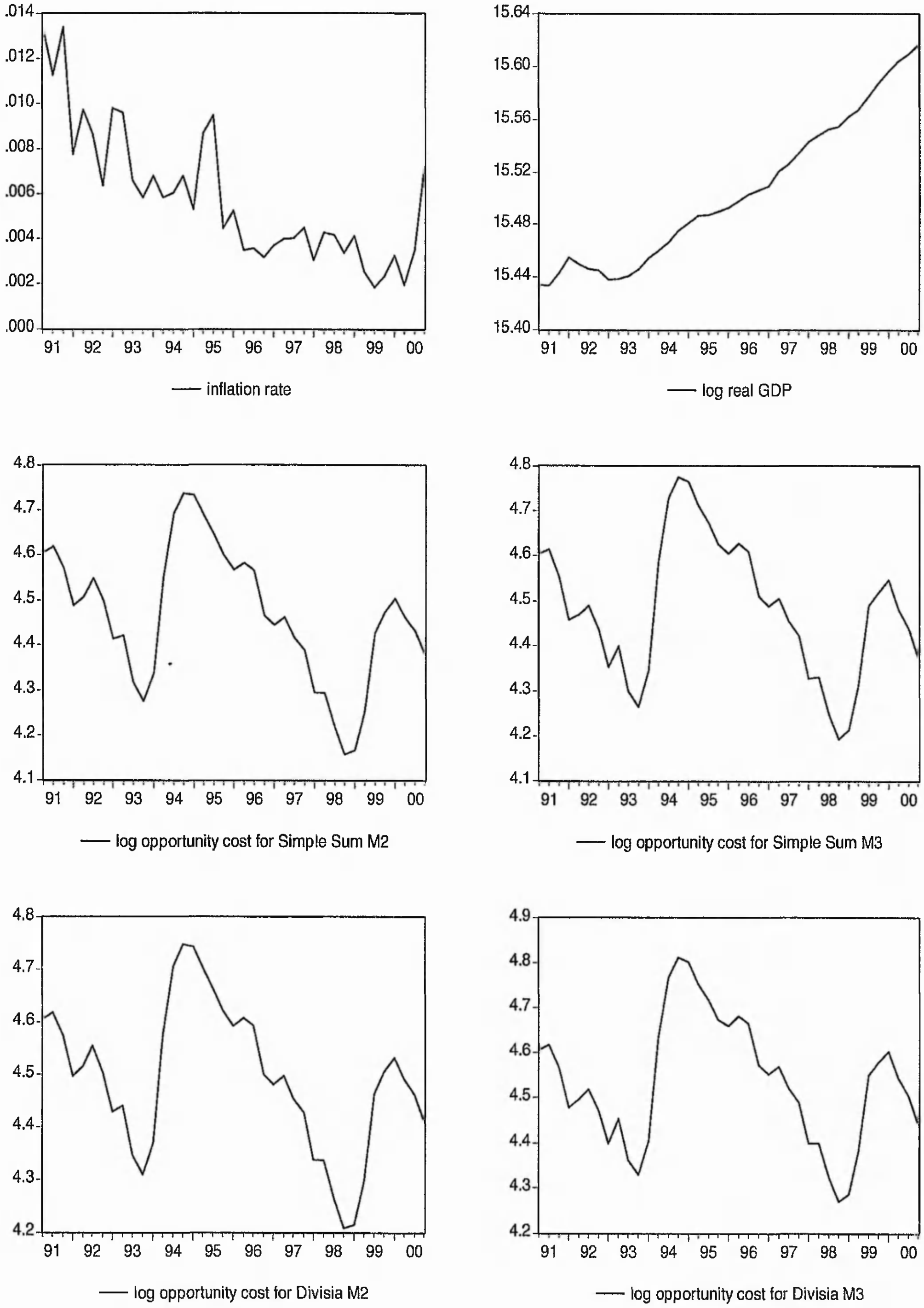


Table 4.1: ADF unit root tests (1991:2-2000:4)

Variable	ADF test statistics	Specification
$sm2_t$	-1.997	[T, 1]
$\Delta sm2_t$	-3.262**	[C, 0]
$sm3_t$	-1.720	[T, 1]
$\Delta sm3_t$	-2.568	[C, 0]
$\Delta^2 sm3_t$	-6.189***	[C, 0]
$dm2_t$	-1.951	[T, 1]
$\Delta dm2_t$	-3.307**	[C, 0]
$dm3_t$	-1.550	[T, 1]
$\Delta dm3_t$	-2.872*	[C, 1]
$dualsm2_t$	-3.134	[T, 1]
$\Delta dualsm2_t$	-3.352**	[C, 0]
$dualsm3_t$	-2.937	[T, 1]
$\Delta dualsm3_t$	-3.438**	[C, 0]
$dualdm2_t$	-3.077	[T, 1]
$\Delta dualdm2_t$	-3.371**	[C, 0]
$dualdm3_t$	-2.803	[T, 1]
$\Delta dualdm3_t$	-3.509**	[C, 0]
y_t	-1.364	[T, 1]
Δy_t	-3.841***	[C, 0]
Δpr_t	-3.758*	[T, 0]
$\Delta^2 pr_t$	-5.872***	[C, 1]

Notes:

T: constant and trend, C: represents constant

[, n], n: the number of lags used

***: significant at 1%, **: significant at 5%, *: significant at 10%

Critical values are from MacKinnon (1991)

Figure 4.3a : First difference of time series

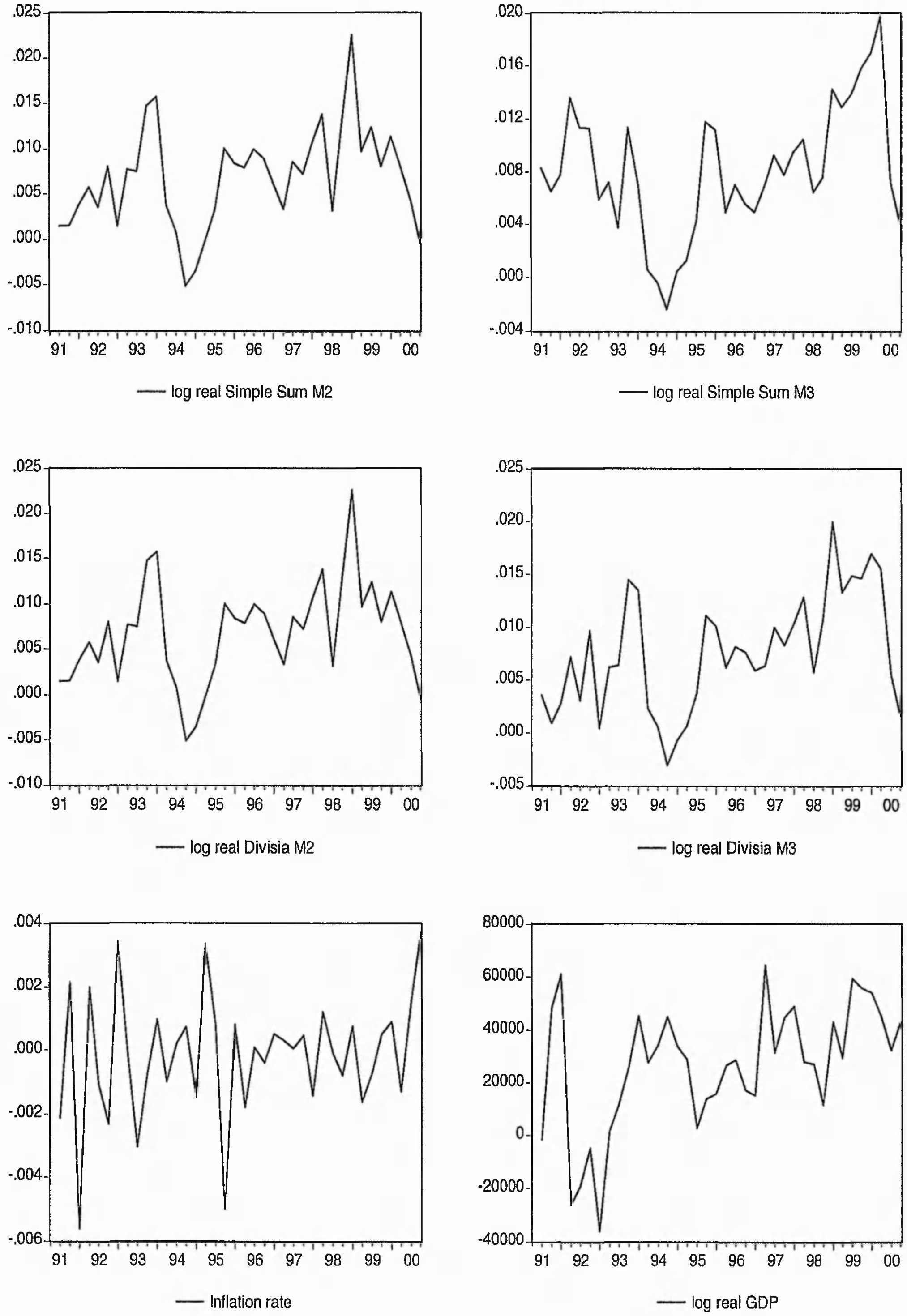
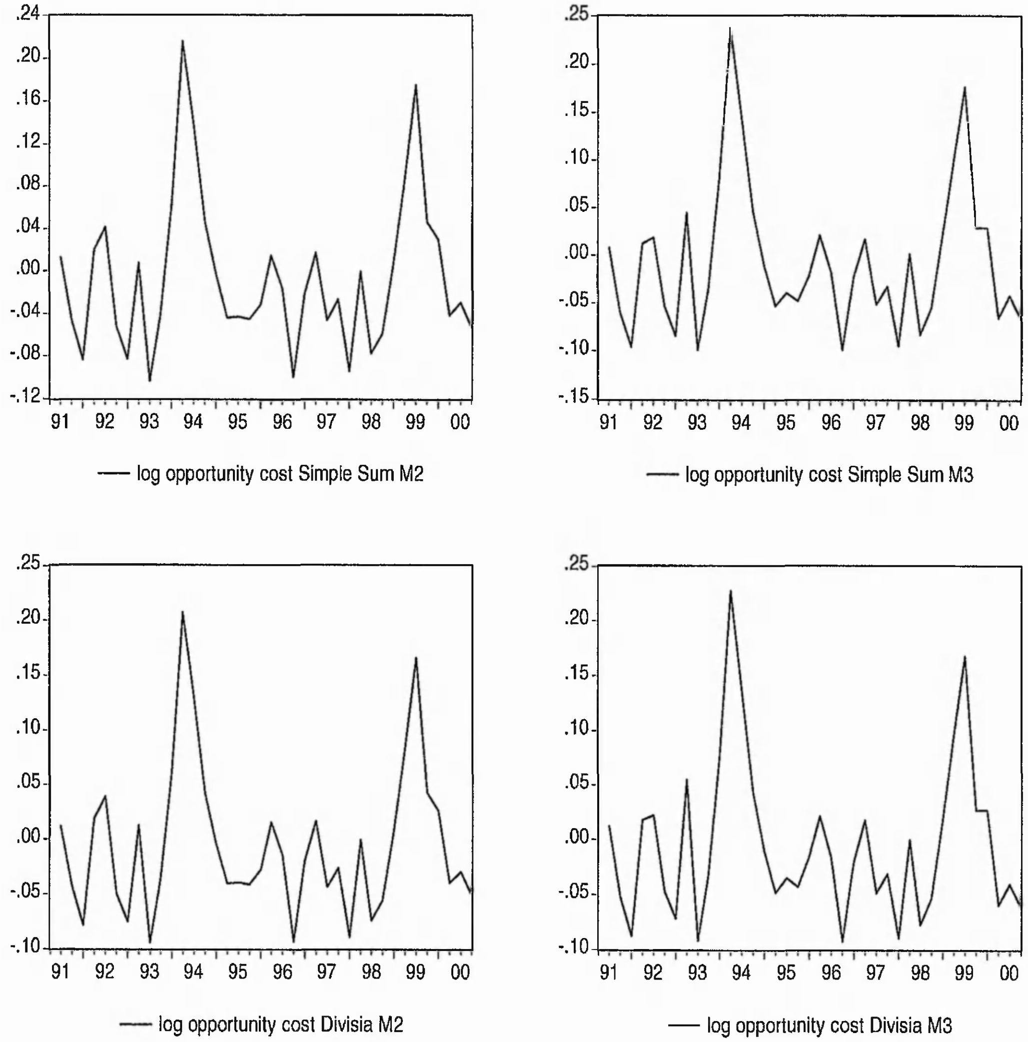


Figure 4.3b: First difference of time series



4.6 Further Empirical Analysis

4.6.1 Model Specification

Hall (1991) points out that the Johansen maximum likelihood test for the number of cointegrating relationships is sensitive to the VAR lag length. The lag length can be determined by some of the many information criteria procedures, such as Akaike Information Criterion (Akaike, 1973) and the Schwarz Criterion (Schwarz, 1978).

However, different criteria often suggest different orders. A more appropriate method is to combine this with misspecification tests by choosing the lag length to ensure that the underlying assumptions of the VAR model are satisfied (Johansen, 1995). More specifically, one checks whether the residuals in the Johansen VAR are free from serial correlation and the distribution of the residuals is normal. On this basis, a VAR of lag length 4 has been used for each system. Results from the multivariate Lagrange multiplier, LM(k), representing the test for autocorrelation of order k and Jarque-Bera (JB), representing the test for normality conducted on the above VAR systems are reported in Table 4.2. The tests do not suggest any major misspecification as the models seem to be well specified.

Table 4.2: Multivariate autocorrelation and normality tests (1991:2-2000:4)

	$sm2_t$	$sm3_t$	$dm2_t$	$dm3_t$
Autocorrelation test:				
LM(1)	16.02	16.11	15.78	14.49
	(0.45)	(0.45)	(0.47)	(0.56)
LM(4)	19.24	22.58	15.28	18.34
	(0.26)	(0.13)	(0.50)	(0.30)
JB normality test	4.92	5.04	4.47	7.69
	(0.77)	(0.75)	(0.81)	(0.46)

Note: Values in parenthesis are p-values. The LM-tests are asymptotically distributed $\chi^2(16)$*, whilst the normality test is asymptotically distributed* $\chi^2(8)$*.*

In this chapter instead of applying the Pantula (1989) principle for identifying the appropriate deterministic components for cointegration analysis, following Elger and Binner (2004) the same deterministic components for every system are consistently used. More specifically Model 4 described in Section 4.3 is adopted. Such an approach can be justified on two grounds, firstly to treat all the systems on an equal footing and secondly it is very common to find that that the Pantula (1989) principle suggests using Model 3 or 4. Doornik, Nielsen and Hendry (1998) show that Model 4 can be used instead Model 3 at a low cost.

Based on the aforementioned specifications the trace test statistics for the null hypothesis that $r \leq 0,1,2,3$ for each system are given in Table 4.3. The trace test suggests that the rank, that is the number of cointegrating vectors, is three for the Simple Sum M2 system. The rank is found to be four for the Simple Sum M3 system, which implies that the variables in its cointegrating vectors, that is, $sm3_t$, $dualsm3_t$, y_t and Δp_t, are all stationary. However, from the unit root tests in Section 4.4, the variables are clearly nonstationary and therefore it can be concluded that cointegration analysis will not provide sensible results for the Simple Sum M3 system and hence no further analysis is carried out in this chapter for it. For the Divisia M2 and M3 systems the rank is found to be borderline two and three. However, to maintain consistency with the Simple Sum M2 system their ranks are set at 3.

Table 4.3 : Number of cointegrating vectors (r)

	$sm2_t$	$sm3_t$	$dm2_t$	$dm3_t$	
r		Trace Statistics			90% quartile of Trace distribution
0	99.41	104.48	101.01	92.85	*58.96*
1	49.84	51.50	49.71	46.99	*39.08*
2	23.16	28.31	22.89	22.05	*22.95*
3	9.66	12.34	8.80	8.87	*10.56*

As it is usually the case the number of cointegrating vectors is found to be greater than one for the different models. In such circumstances there are two common approaches to proceed further with the cointegration analysis. The first and the most common approach is to select from the cointegrating vectors the one which is consistent with economic theory in terms of correct signs and magnitudes of the coefficients of the variables in the cointegrating vectors (see, for example, Drake, Chrystal and Binner (2000)). The second approach is to impose identifying restrictions to the different cointegrating vectors (see, for example, Johanssen and Juselius (1994), Elger and Binner (2004)), that search for stationary relationships supported by the data by imposing restrictions on the parameters of the cointegrating vectors. In this chapter, the second approach is adopted.

4.6.2 Identification of Stationary Relationships

In this section stationary relationships supported by the data are searched for from a variety of economic hypotheses. These are formulated by imposing restrictions on the parameters of the cointegrating vectors. For cointegration vectors of the following form

(monetary variable, opportunity cost variable, scale variable, inflation, trend)

the hypotheses that are tested are given in Table 4.4.

Table 4.4: Economic hypotheses tested

	Null Hypothesis
H_1^0	(1, 0, -1, 0, *)
H_2^0	(0, 0, 1, *, *)
H_3^0	(0, *, 1, 0, *)

Note: Using these restrictions 1 forces the coefficient to be 1, while 1 and -1 forces the coefficients to be equal to 1 but of different signs. 0 forces the coefficient to be 0 while * means the coefficient is unrestricted.

The strategy here is to model money demand in terms of as few variables as possible and hence the first hypothesis can be interpreted as a money demand function from which the inflation and opportunity cost variables have been excluded. As noted earlier the inclusion of inflation in the money demand relationships is not unequivocal and hence is among the first ones to be removed. We also try to exclude the opportunity cost variable. The second hypothesis relates GDP to inflation and opportunity cost and the third equation relates GDP to opportunity cost and the trend.

For the Simple Sum M2 system the above restrictions are supported by the data as indicated by standard errors of the coefficients of the cointegrating vectors and the likelihood ratio (LR) test and its corresponding p-value in the $\chi^2(1)$ distribution.

$$\begin{gathered} sm2_t - y_t - \underset{(0.001)}{0.003T} = \varepsilon_{1t} \end{gathered} \tag{4.13}$$

$$y_t - \underset{(2.789)}{21.795}\Delta p_t - \underset{+(0.001)}{0.006T} = \varepsilon_{2t} \tag{4.14}$$

$$y_t + \underset{(0.015)}{0.058}dualsm2_t - \underset{(0.001)}{0.007T} = \varepsilon_{3t} \tag{4.15}$$

LR = 3.64 $\qquad$ p-value = 0.06

The loading coefficient associated with Equation 4.13 in the short run money demand function is equal to -0.092 [-1.158]. Though it carries the correct sign, it is not statistically significant as indicated by the t-statistics in the square brackets.

For the Divisia M2 system, the p-value of the LR test is only marginally not significant and hence the hypotheses can be considered to be largely supported by the data.

$$dm2_t - y_t - 0.004T = \varepsilon_{1t} \qquad (4.16)$$
$$(0.001)$$

$$y_t - 28.901\Delta p_t - 0.007T = \varepsilon_{2t} \qquad (4.17)$$
$$(3.485) \qquad + (0.001)$$

$$y_t + 0.058dualdm2_t - 0.007T = \varepsilon_{3t} \qquad (4.18)$$
$$(0.012) \qquad (0.000)$$

LR = 4.65 p-value = 0.03

The loading coefficient associated with Equation 4.16 in the short run money function is equal to -0.049 [-0.624]. Similar to its Simple Sum counterpart though it carries the correct sign it is not statistically significant.

The economic hypotheses are also supported by the data in the case of the Divisia M3 system.

$$dm3_t - y_t - 0.009T = \varepsilon_{1t} \qquad (4.19)$$
$$(0.002)$$

$$y_t + 17.836\Delta p_t - 0.018T = \varepsilon_{2t} \qquad (4.20)$$
$$(2.507) \qquad + (0.005)$$

$$y_t + 0.026dualdm3_t - 0.010T = \varepsilon_{3t} \qquad (4.21)$$
$$(0.008) \qquad (0.001)$$

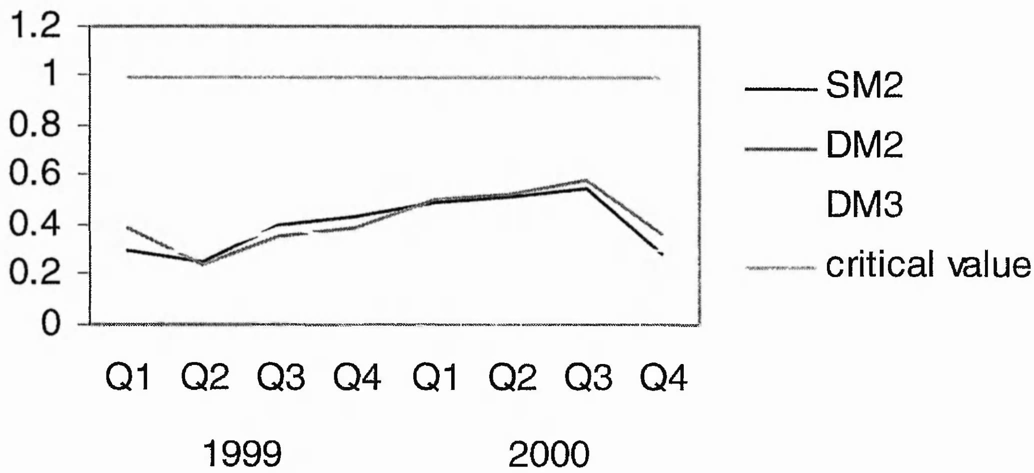
LR = 3.69 p-value = 0.05

The loading coefficient associated with Equation 4.19 in the short run money demand function is -0.160 [-2.769]. In addition to carrying the correct sign it is also statistically significant.

4.6.3 Constancy of the Parameters of the Cointegrating Vectors

In this section further analysis is carried out to investigate the suitability of the cointegration results after imposing the restrictions on them. Specifically, the constancy of the parameters of the cointegration vectors for the period 1999Q1 to 2000Q4 (see, Hansen and Juselius, 1995) is investigated. The LR statistics obtained are shown in Figure 4.4 for the different systems. They are all asymptotically distributed as χ^2. The test statistic has been scaled by the 95% quantile in the χ^2 distribution such that unity corresponds to a test with 5% significance level. As evident from Figure 4.4 the null of constancy cannot be rejected as the test statistics are all below one.

Figure 4.4: Test of constancy of cointegration vector parameters



4.7 Summary and Conclusions

In this chapter monetary aggregates are constructed from the two broadest groups of assets that were found to be weakly separable in the previous chapter. The monetary aggregates constructed are SM2, DM2, SM3 and DM3. SM2 and DM2 consist of the same assets. SM3 and DM3 consist of the same assets. SM2 and SM3 are constructed using Simple Sum aggregation whereas DM2 and DM3 are constructed using Divisia aggregation. The empirical performances of the different monetary aggregates are evaluated in a cointegrated money demand framework. Given that the number of cointegrating vectors is found be greater than one for every system, restrictions are imposed on the parameters of the cointegrating vectors to identify stationary economic relationships.

The empirical performance of Simple Sum and Divisia M2 are almost similar and hence it is very difficult to differentiate between them. This result, however, is not surprising as graphical comparison of SM2 and DM2 suggests that their behaviour is very similar. This is because at low levels of aggregation Simple Sum and Divisia monetary aggregates tend to move closely.

The empirical performance of Divisia M3 is found to be very sensible and stable. In contrast to SM2 and DM2 the loading coefficient associated with its short run money demand function is found to be both negative and significant. On the other hand, the money demand relationship of Simple Sum M3 is not modelled as in its case the number of cointegrating vectors is found to be four, which implies that the variables in its system are all stationary. This implication however is contradictory to the unit root tests which suggest otherwise. Such an observation suggests that cointegration analysis will not yield sensible results for Simple Sum M3 and therefore no further analysis is carried out for SM3 in this chapter.

In sum the results in this chapter suggest there is little difference between Simple Sum and Divisia aggregates in the Euro area at low levels of aggregation. On the other hand at higher levels of aggregation Divisia aggregates clearly outperform their Simple Sum counterparts and therefore should be considered more by policymakers and academics. Such a result is consistent with earlier evidence on the performance of Simple Sum and Divisia aggregates for the Euro area (see, for example, Drake, Mullineux and Agung (1997)).

CHAPTER 5:

SIMPLE SUM AND DIVISIA MONETARY AGGREGATES IN COMPOSITE LEADING INDICATOR OF INFLATION

In this chapter the empirical performances of Euro area Simple Sum and Divisia monetary aggregates are compared in a composite leading indicator of inflation turning point framework. Additional aims are to construct sophisticated composite leading indicators using the techniques of Fourier analysis and Kalman filters and to provide a tentative answer to the issue of whether or not the UK should join the Euro area.

Given that in the previous chapter not much difference was found between Simple Sum M2 and its Divisia M2 counterpart, in this chapter and the following one, only the broadest monetary aggregates, that is, SM3 and DM3, will be considered. Also, given that present analysis and the one in the following chapter require data over long historical periods to yield sensible results the whole data sample, that is, from 1980Q1 to 2000Q4, will be considered.

5.1 Introduction

Financial market participants and policymakers such as the European Central Bank (ECB) are heavily dependent on forecasts of the rate of inflation and its turning points as such information allows them to adjust their calculations of the future economic environment. In this chapter the focus will be on inflation turning point forecasts for the

Euro area; inflation forecasts are looked at in the following chapter. Despite advances in mathematical and statistical techniques, a reliable method to forecast inflation turning points has continued to evade forecasters. Consequently, interest in the use of composite leading indicators (CLIs) of inflation turning points has been heightened. These are constructed from a group of time series variables which have cycles which resemble the turning points in the inflation cycle but whose turning points precede the turning points in the inflation cycle.

The leading indicator approach was developed by the National Bureau of Economic Research (NBER) and was popularised by the work of Burns and Mitchell (1946) in the US. This approach has since been utilised in a number of studies, but mostly applied to business cycles. Application to the inflation cycle is relatively new and much of the literature is related to the US (see, for example, Roth (1991), Boughton and Branson (1991)). A few European studies exist (see, for example, Artis, *et al.*, (1995) and Binner, Fielding and Mullineux (1999) for the UK and Bikker and Kennedy (1999) for seven EU countries) but to the best of my knowledge no study has been carried out to develop CLIs of inflation for the Euro area. One of the objectives of this chapter, therefore, is to develop CLIs of inflation for the Euro area and to assess their forecasting performance.

Even though the leading indicator approach has been rather successful in providing early information about future turning points, it is widely believed that the way leading indicators are constructed is crude and does not look rigorous in terms of criteria commonly applied in modern econometrics. For example in the UK, a recent research project supported jointly by the Central Statistics Office and HM treasury was designed to investigate possible alternatives to the existing methods of constructing leading indicators which form the basis of most official published leading indicators (Salazar *et al.*, 1995). Recently, time series techniques of Fourier analysis and Kalman filters have been used in the construction of CLIs and the resulting CLIs were found to offer considerable improvement over the traditionally constructed indicators (see, (Binner and Wattam (2003)). Therefore, following the seminal work of Binner and Wattam (2003), Fourier analysis and Kalman filters are used to develop more sophisticated CLIs of inflation turning points for the Euro area.

There are two additional aims in the chapter. The first one is the comparison of the performances of Euro area Simple Sum and Divisia monetary aggregates in a CLI of inflation framework. A few Euro studies exist which compare the empirical performances of the Simple Sum and Divisia aggregates, (see, for example, Drake, Mullineux and Agung (1997) and Stracca (2004)), but in most cases the monetary indices are compared in a money demand framework. It has however been argued that stability of money demand is a side issue with regards to usefulness of monetary aggregates for policy purposes and of more relevance is the comparison of the indicator properties of the aggregates (Mullineux, 1996). The CLI of inflation framework provides us with an opportune way of investigating the indicator properties of the monetary aggregates, given that the latter are considered as good information carriers of future inflation and are often included in the construction of CLIs of inflation. To the best of my knowledge, no study exists for the Euro area which compares the Simple Sum and Divisia indices in a CLI of inflation turning points framework. Hence, the motivation to perform such a comparison. The second additional aim is to provide a tentative answer to the issue of whether or not the UK should join the Euro area. This investigation is based on graphical analysis and the CLI of inflation framework. For the CLI framework, first, UK CLIs are constructed with economic series considered to have ample information for future UK inflation turning points. Then Euro-based UK CLIs, are constructed, that is, indicators constructed with Euro area inflation cycle turning point CLI as a component, in addition to component series of UK CLIs. Graphical analysis and comparison of the correlations of the aforementioned CLIS with the UK inflation cycle will be used to provide a tentative answer to the issue of whether or not the UK should join the Euro area.

5.2 Methodology and Data

The prevailing methodology used in constructing leading indicators for economic activity is still very similar to that established by the NBER in the 1930s and 1940s. Applied to inflation cycles it consists of the following major steps:

(1) Firstly the turning points of the inflation cycle are identified.

(2) Secondly appropriate economic and financial variables which contain information about future inflation turning points are selected. This is normally done in two stages. In the first stage, a large number of series are chosen which are thought to have a theoretical leading relationship with the inflation series[2]. In the second step, only those series are chosen whose turning points predate those of the inflation series.

(3) Thirdly composite leading indicators are constructed and their performances evaluated.

For the construction of Euro CLIs of inflation it is, however, not possible to proceed exactly in the above described traditional manner. More specifically, instead of choosing the component series of the CLI as described in step 2, a more subjective

[2] Other criteria in selecting component series are that they should also be quickly and regularly available and not be subject to major revisions (Neftci, 1991)

technique is used. This is because the Euro area has come into existence only recently and therefore the set of component series from which a selection can be made is very limited. Moreover, some of the series that do exist are available for a limited historical period. Therefore, instead, the series that are used are those that are both available and that have been very successfully used in previous studies for constructing CLIs of inflation for European countries (see for example, Bikker and Kennedy (1999), Binner and Wattam (2003), Artis *et al.*, (1995)). For the UK, the series are those used by Binner and Wattam (2003), most of which have been previously identified as leading indicators of inflation turning point by Artis *et al.*, (1995) using the criteria described in step 2 above. Tables 5.1 and 5.2 contain the list of series used in the construction of CLIs, for the period 1980 to 1998, for the Euro area and the UK respectively. The starting and ending periods of the data sample are constrained by the availability of Euro area data taken from the Euro area studies of Stracca (2004) and Fagan, Henry and Mestre (2001). Monthly data are preferred in the construction of CLIs and this is often a criterion for selecting component series of CLIs. This is because the more data points are observed, the closer the cycle can be captured and the better the possibilities of dating the turning points. However, some of the data are only available as quarterly series and the Euro area data made available to me were quarterly data. In these cases, the quarterly data are converted into monthly data using linear interpolation following the Organisation for Economic Co-operation and Development (OECD) which does so while constructing leading indicators of business cycles for its member countries. For the construction of the inflation series[3], the GDP deflator is used for the Euro area while RPI is used for the UK.

[3] Following Artis *et al.* (1995) we use 'headline inflation' which is the annual percentage change in the seasonally unadjusted Retail Price index for the UK or GDP deflator for the Euro Area.

In addition to the slightly different approach for constructing CLIs, value is added to NBER methodology by using Fourier analysis and Kalman filters. Fourier analysis is used for modelling the cyclical components of the series under investigation while the Kalman filter algorithm is used to extract the inflation turning point signal from 'crude' forms of CLIs which are constructed by aggregating the modelled individual cyclical components. These techniques have been previously used in constructing CLIs by Binner and Wattam (2003) and the resulting CLIs were found considerably to outperform traditionally constructed CLIs.

Table 5.1: Data definitions and sources for the Euro Area

Variable	Original Series	Frequency	Seasonally adjusted at source	Source
DM3	Real Divisia M3	Quarterly	Yes	Stracca (2004) ECB working paper no. 79
SM3	Real Simple Sum M3	Quarterly	Yes	Stracca (2004) ECB working paper no. 79
GDPDEF	GDP deflator	Quarterly	Yes	Stracca (2004) ECB Working paper no. 79
ENN	Effective Exchange Rate	Quarterly	Yes	Fagan, Henry and Mestre (2001) ECB Working Paper no. 42
UNN	Unemployment	Quarterly	Yes	Fagan Henry and Mestre (2001) ECB Working Paper no. 42
ULC	Unit Labour Costs	Quarterly	Yes	Fagan Henry and Mestre (2001) ECB Working Paper no.42
COMPR	Commodity Prices	Quarterly	Yes	Fagan Henry and Mestre (2001) ECB Working Paper no.42

Table 5.2: Data definitions and sources for the UK

Variable	Original Series	Frequency	Seasonally adjusted at source	Source
DM4[4]	Real Divisia M4	Quarterly	No	Bank of England
SM4	Real Simple Sum M4	Quarterly	No	Bank of England
RPI	Retail Price Index	Monthly	No	Datastream
IUV	Import Unit Value Index	Monthly	No	Datastream
UNE	Adult Unemployment	Monthly	No	Employment Gazette/Labour Market Trends
VAC	Vacancies at Job Centres	Monthly	Yes	Datastream
RSI	Retail Sales Index	Monthly	No	Datastream
IIP	Index of Industrial Production	Monthly	Yes	Datastream
GCP	Global Commodity Price Index	Monthly	No	Datastream

5.2.1 Derivation of Cycles

Cycles are an abstract concept and are not observable in reality. Therefore, to measure cycles, they must first be defined. In general, cycles are defined in two ways- classical cycles and deviation from trend cycles. Classical cycles refer to declines and rebounds in the level of economic series, whereas deviation cycles refer to deseasonalized, smoothed series expressed as the deviation from its long term trend. Most leading indicators are based on deviation cycles, as classical cycles are sometimes very difficult to identify because the fluctuations in many economic series appear to be dominated by strong trends. Therefore, in this study deviation cycles are used to construct the leading indicators.

[4] For the UK SM4 and DM4 monetary aggregates the asset components and their corresponding rates are obtained from the Bank of England website (http://www.bankofengland.co.uk/Links/setframe.html). The asset components are notes and coins, non-interest-bearing deposits, interest-bearing bank sight deposits, interest-bearing bank time deposits and building society deposits. The benchmark rate used in the construction of the Divisia index is a three month local government deposit rate to which 2% points have been added to avoid obtaining negative user costs.

Generally, it may be assumed that an observed univariate additive[5] time series y_t is the sum of four unobserved components, namely the cycle (C_t), seasonal (S_t), trend (T_t), and irregular components (I_t), i.e, can be represented as

$$y_t = C_t + S_t + T_t + I_t \qquad \text{for } t = 1, \cdots, n \tag{5.1}$$

Adopting the deviation cycle approach, the cyclical components can be obtained by subtracting the seasonal, trend and irregular components from y_t.

The seasonal and irregular components do not permit a clear vision of the cyclical behaviour and are normally filtered out first. The very commonly used Census X-12 procedure, developed by the US Bureau of Census, is used to capture these components[6]. The Census X-12 procedure is essentially a combination of moving averages. Many detrending techniques exist to remove the trend, however, it is very difficult to know which one is the most appropriate. Each one is relevant in certain circumstances and has its own implications. Canova (1999) examines the sensitivity of the turning points classification to different detrending methods and the ability of each to replicate the NBER dating of business cycles. The Hodrick-Prescott filter (HP) (Hodrick and Prescott (1997)) and the frequency domain filters (see,for example, Baxter and King (1999)) methods are found to be the most reliable methods to reproduce closely the NBER classifications. However, empirically, HP is the most extensively used technique and hence it is opted for use. Our description of the HP filter follows the exposition of Hodrick and Precott (1997). Let $\hat{y}_t$ be the series resulting from removing the irregular and seasonal component of y_t, that is, $\hat{y}_t = y_t - (S_t + I_t)$. This means that $\hat{y}_t$ is the sum of the trend and cyclical components, that is,

[5] A multiplicative model is essentially the same as (5.1) on taking logs.

[6] In cases where the series have been seasonally adjusted at source only the irregular components are captured using the Census X-12 program.

$$\hat{y}_t = C_t + T_t \quad \text{for } t = 1, \cdots, n \tag{5.2}$$

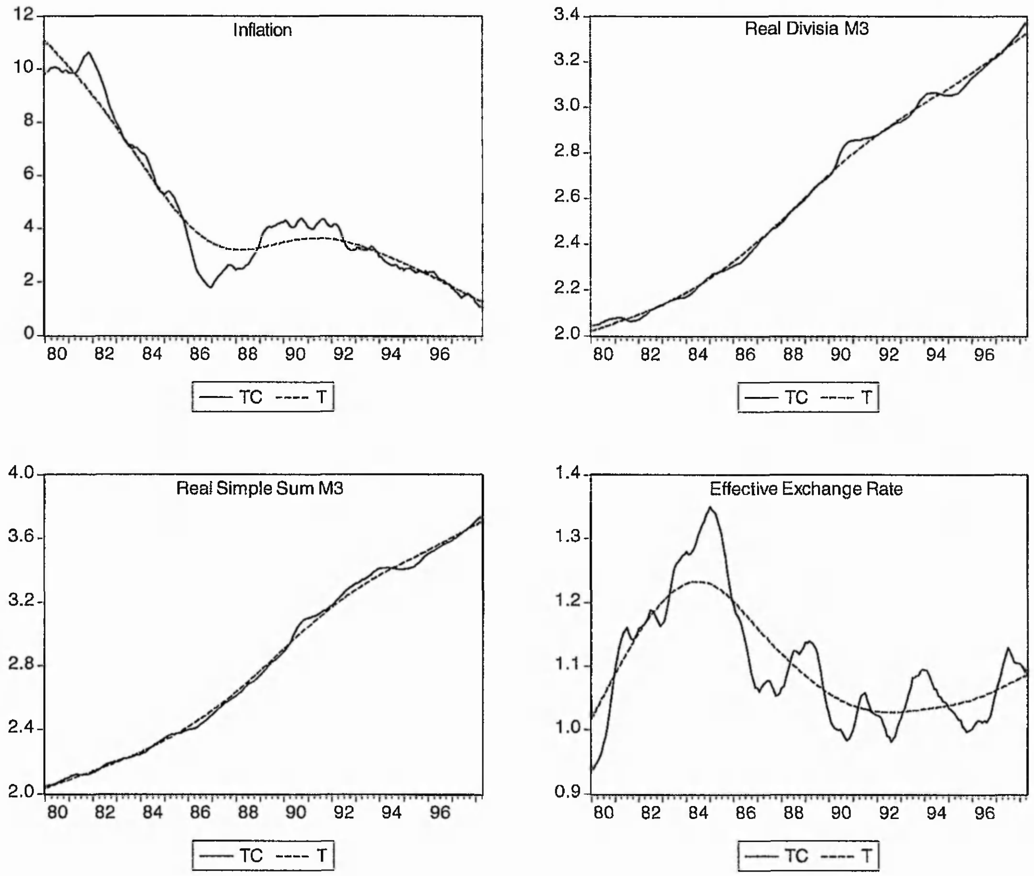
The measure of smoothness of the trend component T_t is the sum of squares of its second difference. The cyclical components C_t are deviations from the trend and it is assumed that over long periods their average mean is near zero. These considerations lead to the following programming problem for determining the components of T_t

$$\min_{\{T_t\}_{t=-1}^{n}} \left\{ \sum_{t=1}^{n} C_t^2 + \lambda \sum_{t=1}^{n} \Delta^2 T_t \right\} \tag{5.3}$$

where $C_t = \hat{y}_t - T_t$. The parameter λ is a positive number which controls the variability of the trend component. The larger the value of λ the smoother is the solution series. In the extreme case as $\lambda \to \infty$, the trend approaches a linear time trend. The optimal value of λ depends on the time series and may be derived by means of a 'signal extraction-prediction error decomposition' technique (see, den Butter, Coenen and van de Gervel (1985) for more information on this technique). Most empirical work, however, simply assume a particular value for λ equal for all series under consideration. For quarterly data λ is usually set to 1600 and for monthly data to 14400. However, following a suggestion of Serletis and Kraus (1996) λ is set to 129600 in this study as this value approximately averages to the quarterly components defined by $\lambda = 1600$ which is commonly used to define business cycle fluctuations in the research literature. According to the derivation of Ravn and Uhlig (2002) the HP parameter λ should be adjusted to with the fourth power of the frequency change that is $\lambda_N = \frac{1}{N^4} \lambda_O$ where N represents new frequency and O represents old frequency. Thus for a frequency change from quarterly, where $\lambda = 1600$, to monthly, the new λ is calculated as $1600/(1/3)^4 =$ 129600. It can be noticed from Figures 5.1a,b and Figures 5.2a,b, for the Euro area and

UK respectively, that the application of the HP filter results in nonlinear trends for all series under investigation.

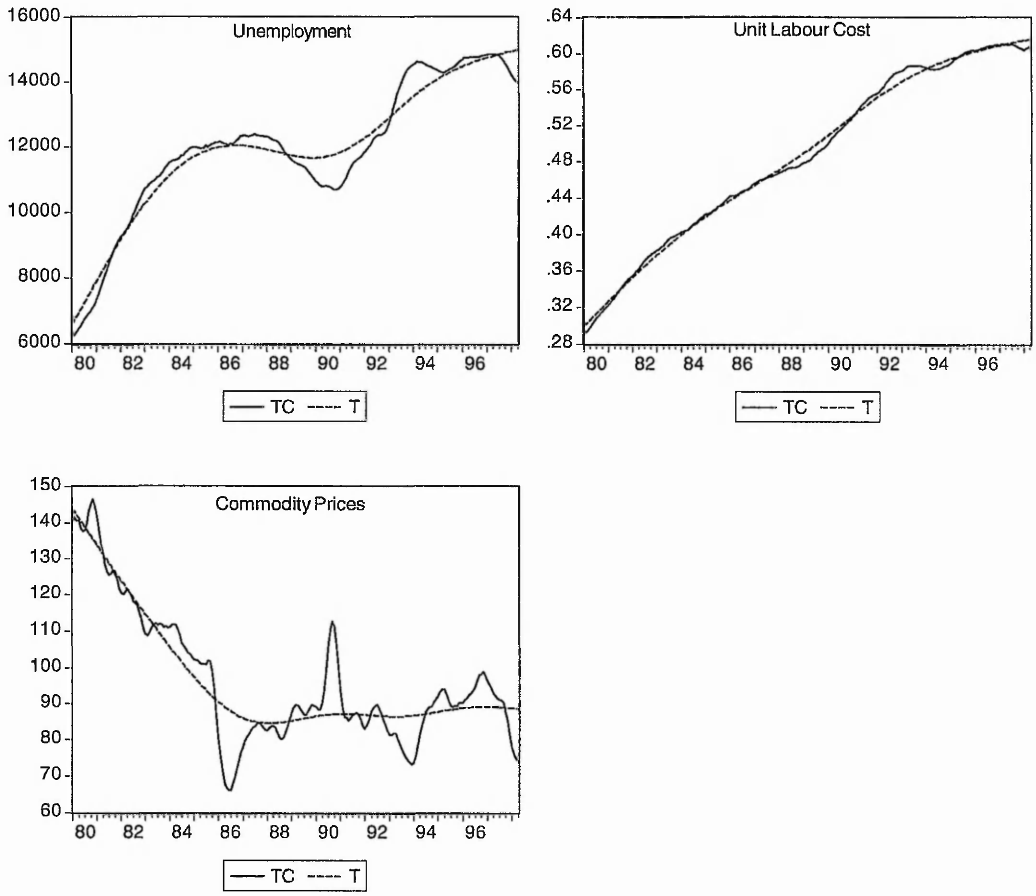
Figure 5.1a: Graphs of sum of trend and cyclical components and trend components for the Euro area



TC represents the sum of trend and cyclical components

T represents the trend component obtained using the HP filter

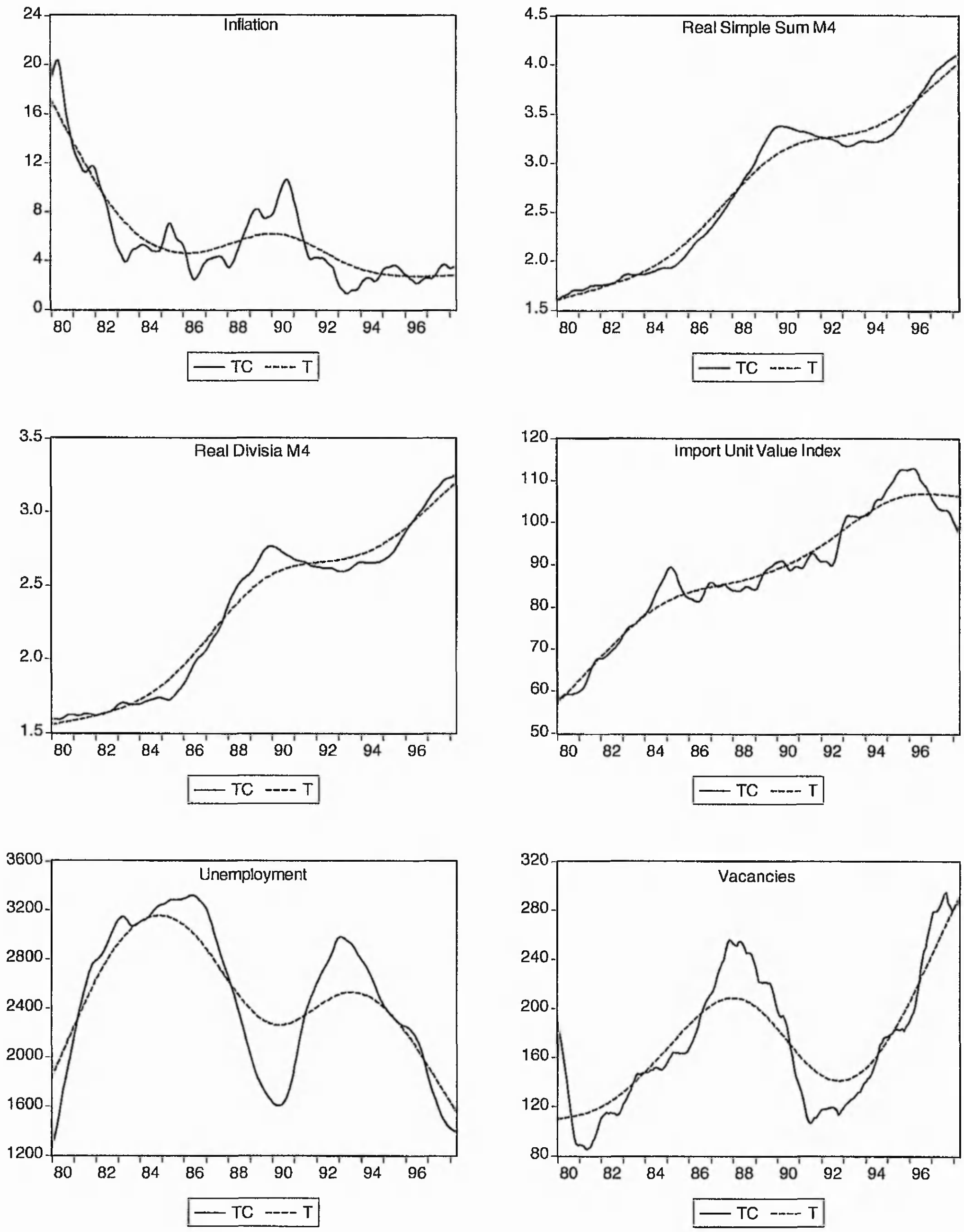
Figure 5.1b: Graphs of sum of trend and cyclical components and trend components for the Euro area



TC represents the sum of trend and cyclical components

T represents the trend component obtained using the HP filter

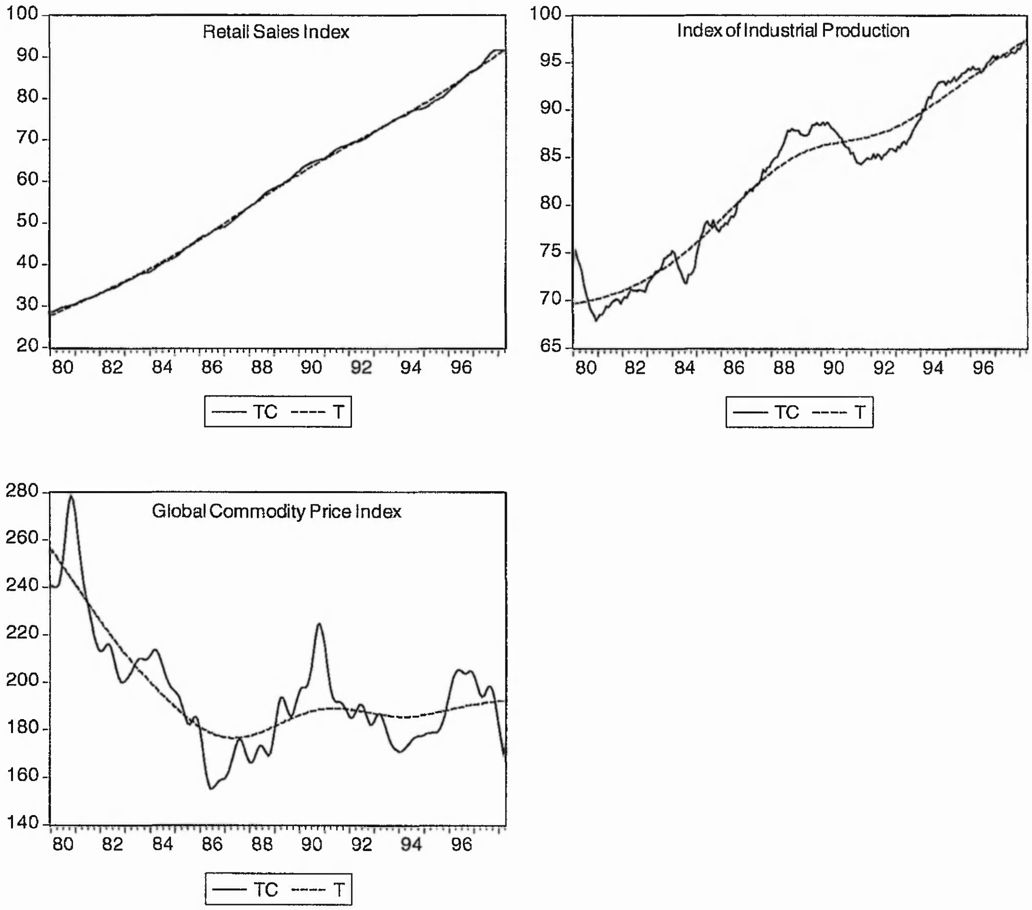
Figure 5.2a: Graphs of sum of trend and cyclical components and trend components for the UK



TC represents the sum of trend and cyclical components

T represents the trend component obtained using the HP filter

Figure 5.2b: Graphs of sum of trend and cyclical components and trend components for the UK



TC represents the sum of trend and cyclical components

T represents the trend component obtained using the HP filter

5.2.2 Dating Cyclical Turning Points

The next issue is what criteria to use to date the turning points of the cyclical components. Bodies like the NBER and the Central Statistics Office provide reference chronologies for business cycles but no reference chronologies exist for inflation cycles. Artis *et al.* (1995), however, have devised some ground rules for dating inflation turning points and despite their simplicity, they seem to capture well the turning points of inflation in studies where they have been used (see, for example, Binner, Fielding and Mullineux (1999)). Therefore in this study also the rules devised by Artis *et al.*, (1995) are used which are as follows. First is the obvious requirement that peaks will always follow troughs and vice versa. Second, the duration of an upswing or downswing regime should be at least nine months in order to capture satisfactorily medium term movements in inflation. Third, a turning point is the most extreme value between two adjacent regimes and fourth, if there are two or more equal values satisfying the first three requirements, the most recent one is chosen as the turning point of the regime. The same rules are applied in dating the turning points in the cycles of the inflation series and each of the indicator series. The number of cycles identified in each case is given in Tables 5.3 and 5.4 for the Euro area and the UK respectively.

Table 5.3: Number of cycles found in Euro Area data

Series	Number of Cycles
Real Simple Sum M3	4.5
Real Divisia M3	4.5
Inflation	4.5
Effective Exchange Rate	5
Unemployment	3.5
Unit Labour Costs	3.5
Commodity Prices	4

Table 5.4: Number of cycles found in UK data

Series	Number of Cycles
Real Simple Sum M4	2
Real Divisia M4	2
Inflation	3.5
Import Unit Value Index	2.5
Adult Unemployment	4
Vacancies at Job Centres	3.5
Retail Sales Index	4.5
Index of Industrial Production	3
Global Commodity Price Index	3

5.2.3 Fourier Analysis of Cyclical Components and Timing Classification of Indicators

In this section the cyclical components are modelled using Fourier analysis. The mathematical Fourier Theorem states that periodic data, like cyclical components of time series, can be expressed as the sum of a series of sine or cosine terms. If it is assumed that the periodic data consist of a single cosine wave, like in Binner and Wattam (2003), then they can be represented as

$$C_t = \mu + R\cos(\omega t + \phi) + \varepsilon_t, \qquad t = 0,1,\cdots,n-1, \tag{5.4}$$

where n is the number of observation, μ is a constant, R the amplitude, $\omega = 2\pi p/n$, is the frequency, where p is the number of cycles and ϕ is the phase of the wave and ε_t is the t^{th} residual. The unknown parameters here are μ, R, and ϕ and their estimation becomes less cumbersome if Equation 5.4 is reformulated as

$$C_t = \mu + A\cos\omega t + B\sin\omega t + \varepsilon_t \tag{5.5}$$

where $A = R\cos\phi$ and $B = -R\cos\phi$. Estimates of μ, A, and B can be obtained from the following equations (Bloomfield, 1976).

$$\begin{aligned} \tilde{\mu} &= \tilde{C} = (1/n)\sum C_t \\ \tilde{A} &= (2/n)\sum (C_t - \tilde{C})\cos\omega t \\ \tilde{B} &= (2/n)\sum (C_t - \tilde{C})\sin\omega t \end{aligned} \tag{5.6}$$

Given the estimates of A and B, R and ϕ may be solved for. The basic equation for ϕ is $\tan\phi = -B/A$. However, the solution $\phi = \tan^{-1} -B/A$ is incorrect as it gives the same values for $-A$ and $-B$ as for A and B. The full solution is obtained from the solution set (Bloomfield, 1976) given in Appendix B1. The estimates of μ, ϕ, A, B and R for the different series are given in Tables B2.1and B2.2, for the Euro area and the UK respectively, in Appendix B2.

After the cyclical components of the different series have been modelled using Fourier analysis, the modelled cycles are normalized to make them comparable and to avoid the series with the greatest amplitudes in their cycles exerting too much influence on the composite indicator. Normalization involves setting the means of the Fourier generated cycles to zero and their standard deviations to one. The series are then expressed in the index-number form by adding 100 to them. The graphs of these series are given in Figures 5.3 and 5.4 for the Euro area and the UK respectively.

Figure 5.3: Normalised Euro area series

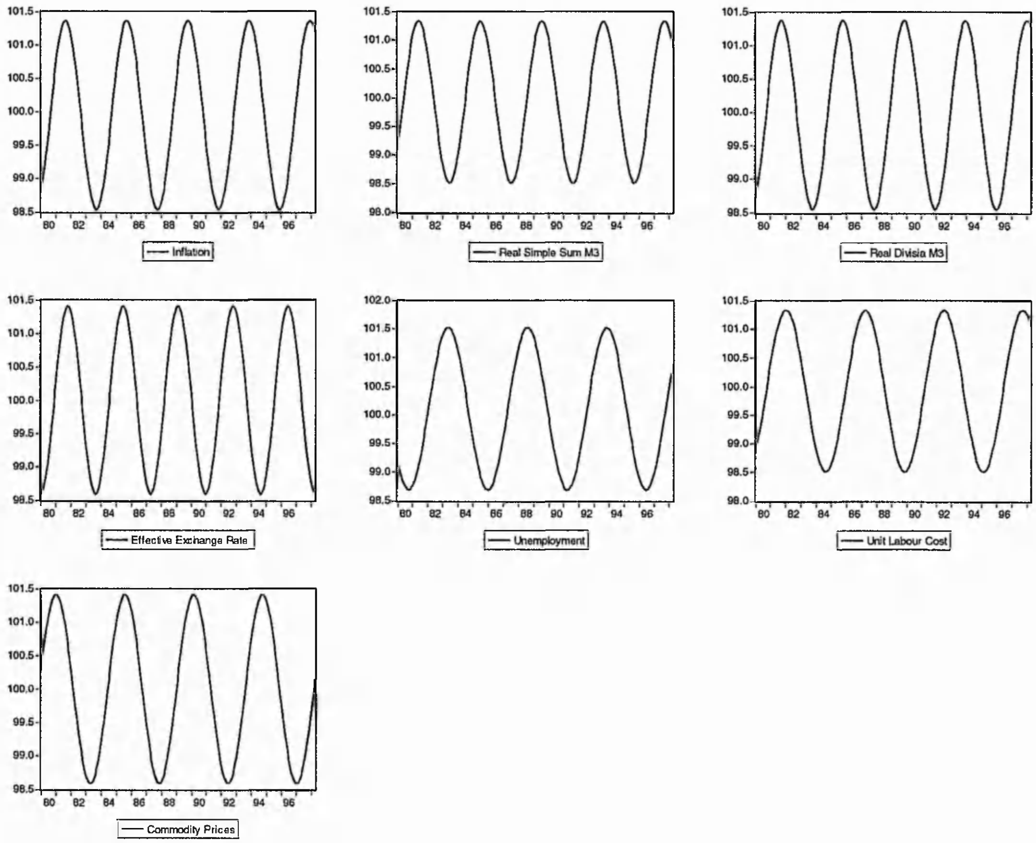
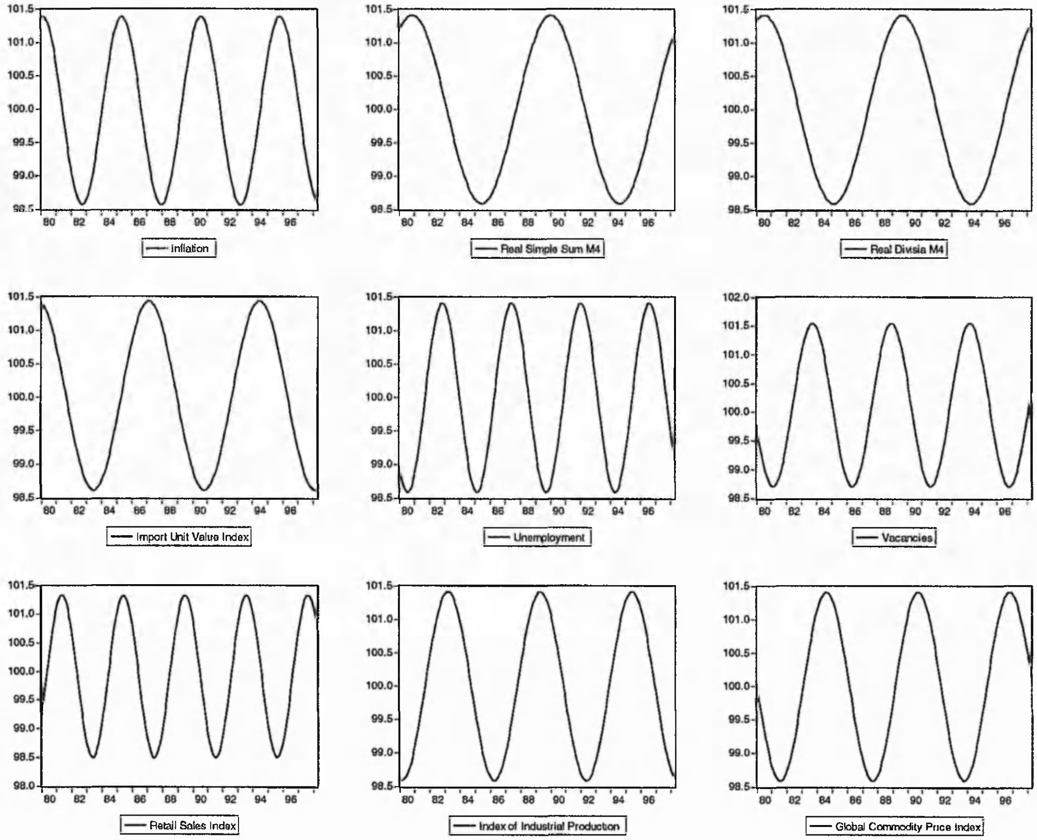


Figure 5.4: Normalised UK series



The modelled cycles of the indicator series are then compared to that of the inflation series. The resulting lead times in months were calculated by visual inspection and subsequently the standard deviations were also calculated. These values are given in Tables 5.5 and 5.6 for the Euro area and the UK respectively. For example, Real Simple Sum M3, in Table 5.5, gives a three months warning of the next turning point (either peak or trough) in the inflation series; the standard deviation around this mean is 0.4 months. From Tables 5.5 and 5.6 it can be seen that 20 months is a natural borderline between the various lead times achieved. Hence 20 months and below were chosen to represent short leading indicators, whilst leads above 20 months were assumed to be longer leading indicators.

Table 5.5: Average lead times for the leading indicators versus inflation reference series for the Euro Area

Series	Lead Months	Standard Deviation	Indicator Classification
Real Simple Sum M3	3	0.387	Both
Real Divisia M3	48	0.354	Both
Effective Exchange Rate	10	0.268	Short
Unemployment	21	2.40	Long
Unit Labour Costs	24	3.51	Long
Commodity Prices	27	1.57	Long

Table 5.6: Average lead times for the leading indicators versus inflation reference series for the UK

Series	Lead Months	Standard Deviation	Indicator Classification
Real Simple Sum M4	31	23.5	Both
Real Divisia M4	35	23.5	Both
Import Unit Value Index	35	0.5	Long
Adult Unemployment	36	0.35	Long
Vacancies at Job Centres	20	0	Short
Retail Sales Index	17	0	Short
Index of Industrial Production	18	0	Short
Global Commodity Price Index	9	5	Short

From the tables above the average lead for composite short term and long term indicators were set at 15 and 29 months respectively, whilst Divisia and Simple Sum indices were classified as both short and long term indicators for experimental purposes. Before constructing composite leading indicators the individual leading indicators are lagged according to the average lead times.

There are various ways of combining the leading indicator series into a composite leading indicator. One of the simplest techniques, as used in, for example, Artis *et al.*

(1995) is by simple averaging. It has been argued that such a method, however, is essentially arbitrary as it is neither data driven nor theory driven (Binner, Fielding and Mullineux, 1999). For this reason, Binner, Fielding and Mullineux (1999) have derived the appropriate weight for each component using the principal components method, which assumes that the first principal component of the leading indicator series, which explains as much as possible of the variation of the leading indicator series, may be taken to represent the inflation series (see, for example, Bikker and Kennedy (1999)). In this study for every CLI, the component series are aggregated using both simple averaging (that is giving equal weights (of unity) to each of the component series) and weights derived from principal component analysis. However, only the CLIs resulting from whichever aggregation technique showing a closer relationship with the inflation cycles are presented.

When the individual leading indicator series are combined, the CLIs do not closely resemble the inflation cycle and in some cases there are false signals of turning points. The different CLIs are plotted against the inflation cycle of the Euro area and the UK in Figures 5.5a,b and 5.6a,b respectively. The disagreement between the CLIs and the inflation cycle is due to the undue influences of some turning points from some of the individual leading indicator series. Therefore, the 'true' signal for inflation turning points has to be separated from unwanted information. For this purpose State Space models and Kalman filters can be used (see, for example, Harvey, (1989), Chatfield (1996)), to which attention is turned to in the next section. These techniques have been very successfully applied in extracting the inflation cycle turning points from the 'crude' form of CLIs by Binner and Wattam (2003).

Figure 5.5a: Crude form of Euro short CLIs

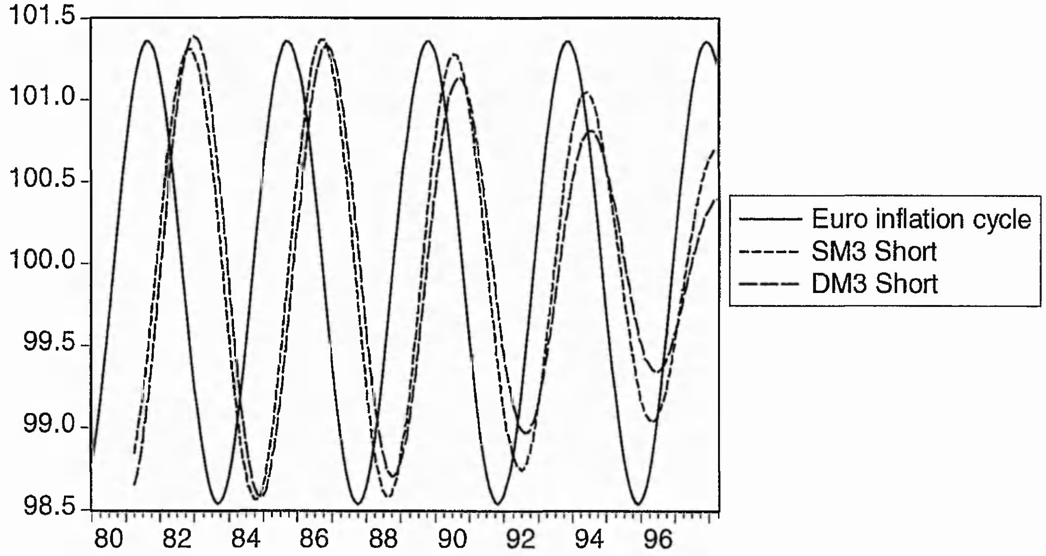


Figure 5.5b: Crude form of Euro long CLIs

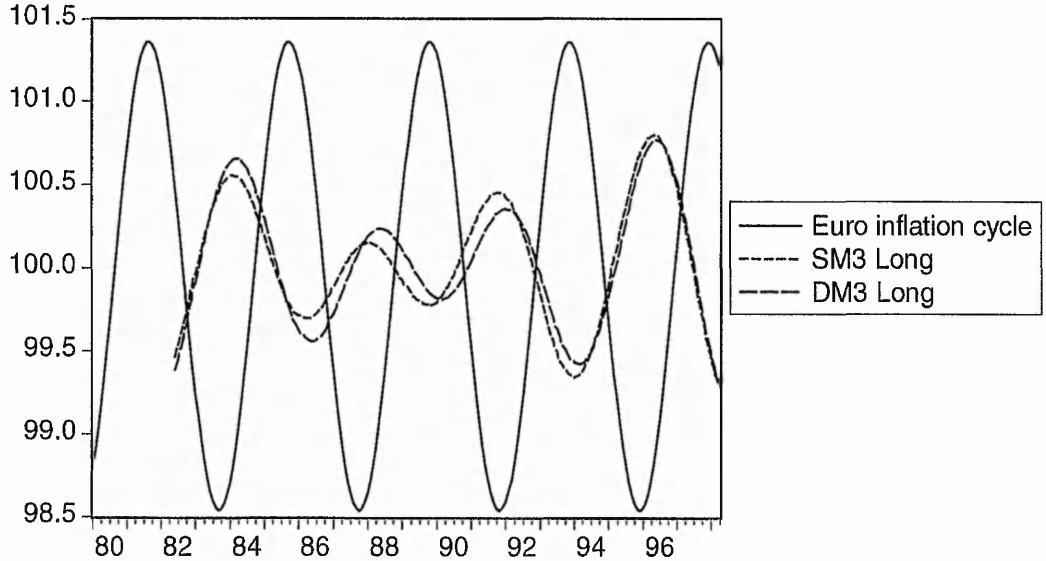


Figure 5.6a: Crude form of UK short CLIs

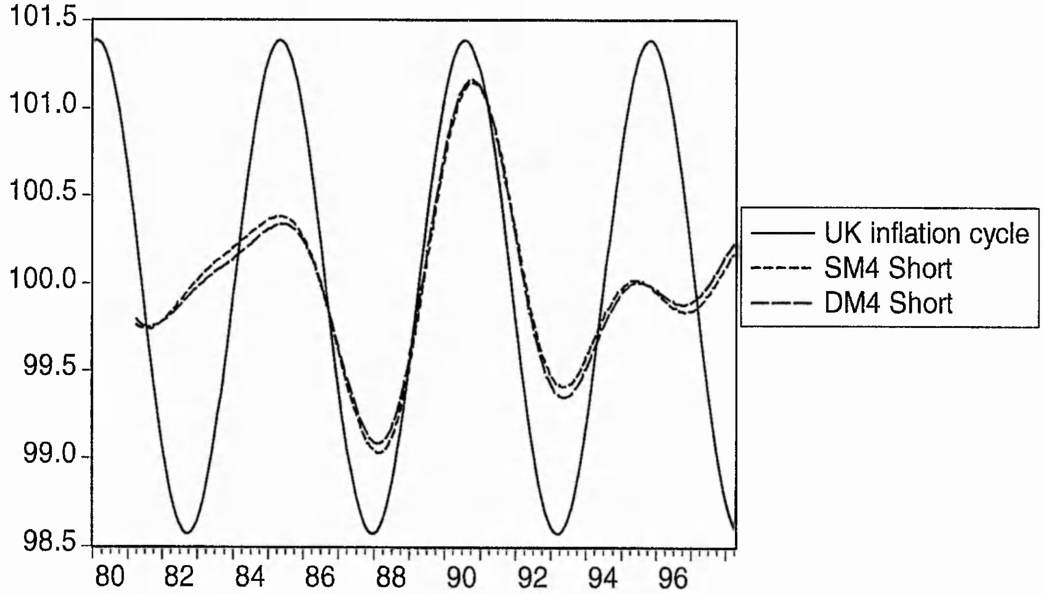
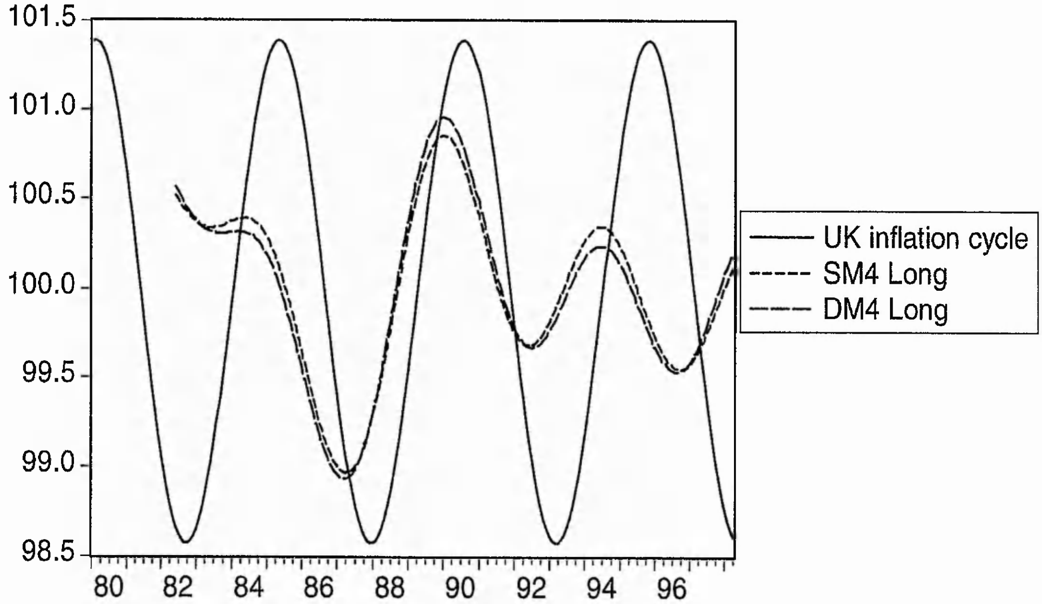


Figure 5.6b: Crude form of UK long CLIs



5.2.4 State Space Models

Generally when scientists try to measure any sort of signal it is contaminated by noise, so that the actual observation x_t is given by

$$\text{Observation} = \text{signal} + \text{noise} \tag{5.7}$$

In state space models the signal is taken to be a linear combination of a set of variables, called state variables, which constitute what is called the state vector at time *t*. This vector describes the state of the system at time *t*. Denoting the $(m \times 1)$ state vector by $\boldsymbol{\theta}_t$, Equation 5.7 can be written as

$$x_t = \mathbf{h}_t^T \boldsymbol{\theta}_t + \eta_t \tag{5.8}$$

where $\mathbf{h}_t$ is an $(m \times 1)$ vector assumed to be known and η_t denotes the observation error. The state vector $\boldsymbol{\theta}_t$ which is of prime importance cannot be observed (i.e., is unobservable) and so we wish to use the observations on x_t to make inferences about $\boldsymbol{\theta}_t$. Although not directly observable, it can be assumed that how $\boldsymbol{\theta}_t$ changes through time is known (see, for example, Chatfield (1996)), and the updating equation can be denoted by

$$\boldsymbol{\theta}_t = \mathbf{G}_t \boldsymbol{\theta}_{t-1} + \mathbf{w}_t \tag{5.9}$$

where the $(m \times m)$ matrix $\mathbf{G}_t$ is assumed known and $\mathbf{w}_t$ is a vector of residuals. The two equations constitute the general form of the state space model. Equation 5.8 is called the observation (or measurement) equation, while Equation 5.9 is called the transition equation.

The errors in the observation and transition equations are generally assumed to be uncorrelated with each other at all time periods, and also to be serially uncorrelated. It may further be assumed that that η_t is $\mathrm{N}(0,\sigma_\eta^2)$ while $\mathbf{w}_t$ can be assumed multivariate normal with zero mean vector and known variance-covariance matrix denoted by $\mathbf{W}_t$.

5.2.5 Kalman Filters

In state space modelling, the prime objective is to estimate the signal in the presence of noise, that is, we want to estimate $\boldsymbol{\theta}_t$. The Kalman filter can be used for this purpose. It consists of a set of equations which updates the estimate of $\boldsymbol{\theta}_t$ when a new observation becomes available. The updating procedure has two stages, called the prediction stage and updating stage.

Suppose a time series is observed up to time $t-1$ and $\hat{\boldsymbol{\theta}}_{t-1}$ is the 'best'[7] estimator for $\boldsymbol{\theta}_{t-1}$ based on the information up to this time. Further suppose that the variance-covariance matrix of $\hat{\boldsymbol{\theta}}_{t-1}$ which we denote by $\mathbf{P}_{t-1}$ may have been evaluated. The first stage, the prediction stage, is concerned with forecasting $\boldsymbol{\theta}_t$ from time $t-1$, and the resulting estimator is denoted by $\hat{\boldsymbol{\theta}}_{t|t-1}$. Considering Equation 5.9 where $\mathbf{w}_t$ is still unknown at time $t-1$, the estimator for $\boldsymbol{\theta}_t$ is given by

$$\hat{\boldsymbol{\theta}}_{t|t-1} = \mathbf{G}_t \hat{\boldsymbol{\theta}}_{t-1} \tag{5.10}$$

with the variance-covariance matrix

$$\mathbf{P}_{t|t-1} = \mathbf{G}_t \mathbf{P}_{t-1} \mathbf{G}_t^T + \mathbf{W}_t \tag{5.11}$$

Equations 5.10 and 5.11 are the prediction equations. When new observations become available, the estimator of $\boldsymbol{\theta}_t$ can be modified to take into account this extra information. The prediction error is then given by

[7] By best we mean that it is the minimum mean square error estimator

$$e_t = x_t - \mathbf{h}_t^T \hat{\boldsymbol{\theta}}_{t|t-1} \tag{5.12}$$

and the updating equations are given by

$$\hat{\boldsymbol{\theta}}_t = \hat{\boldsymbol{\theta}}_{t|t-1} + K_t e_t \tag{5.13}$$

and

$$\mathbf{P}_t = \mathbf{P}_{t|t-1} - K_t \mathbf{h}_t^T P_{t|t-1} \tag{5.14}$$

where

$$K_t = \mathbf{P}_{t|t-1}\mathbf{h}_t / [\mathbf{h}_t^T \mathbf{P}_{t|t-1}\mathbf{h}_t + \sigma]_n^2 \tag{5.15}$$

K_t is called the Kalman gain matrix and Equations 5.13 and 5.14 constitute the second stage of the Kalman filter and are the updating equations.

5.3 Performance of Composite Leading Indicators and Discussions

The correlations of the Kalman generated Euro CLIs against the inflation reference cycle are given in Table 5.7. It can be seen from these results that on the whole the cyclical patterns of the different CLIs are rather similar and closely reflect the cycles in the inflation series. These findings demonstrate that CLI are a useful and powerful alternative to statistical methods for forecasting turning points of inflation. Implicit in the findings is the fact that techniques like Fourier analysis and Kalman filters can be used for constructing very sophisticated CLIs of inflation.

When the results are examined in greater detail, firstly, the longer CLIs are found to be more closely related to the inflation cycle. Secondly, CLIs that incorporate Divisia monetary indices show a stronger relationship to the inflation cycle than CLIs based on Simple Sum monetary indices. This result suggests that Divisia monetary indices would provide earlier warning of impending inflation than their Simple Sum counterparts. It may also be concluded that the simple summation way of constructing aggregates is flawed and therefore the Divisia aggregates should be taken more seriously by policy makers and academics.

Table 5.7: Correlations of CLIs with inflation reference cycle for the Euro Area

CLIs	Correlation with Inflation Cycle	Weight[8]
SM3 Short	0.99997636	P
DM3 Short	0.99997902	P
SM3 Long	0.99999548	P
DM3 Long	0.99999567	P

Under the heading 'Weight', P indicates the component series of the CLI were aggregated using principal components weights, while E indicates equal (unity) weights were used in the aggregation.

The difference between the Kalman generated Euro CLIs and the inflation reference cycle was compared and checked for residual autocorrelation, results are presented in Table 5.8. The Durbin Watson test appears to indicate that autocorrelation is present in the residuals, which suggests that observed time series have more periodic features in them than can be detected by the dating rules employed here and the equation used to model them in this study. It might also suggest that the phase of the CLIs are out of synchronisation with the inflation reference cycle. However, graphical inspection of the CLIs plotted against the inflation reference cycle, in Figures 5.7a-5.7d suggests that the cycles are very closely synchronised[9]. Moreover, the prediction error covariance, of every model decreases asymptotically rapidly, as exemplified by that of the SM3 Short model in Figure 5.8. This is indicative of the adequacy of Kalman generated CLIs.

[8] The weights obtained from principal component analysis are given in Appendix B3

[9] The long and short term leading indicators are lagged by their average lag and plotted against inflation

Figure 5.7a Simple Sum as Short Leading Indicator

Inflation reference cycle against Simple Sum short

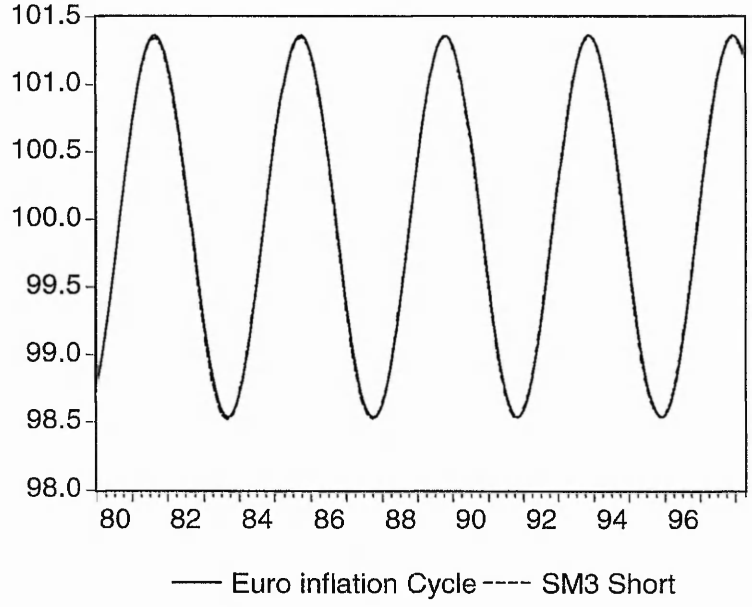


Figure 5.7b Divisia as Short Leading Indicator

Inflation reference cycle against Divisia short

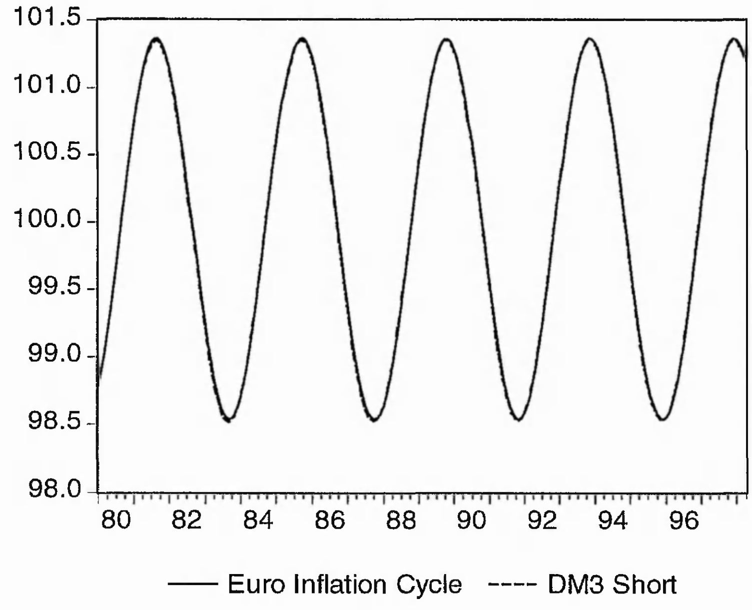


Figure 5.7c Simple Sum as Long Leading Indicator

Inflation reference cycle against Simple Sum Long

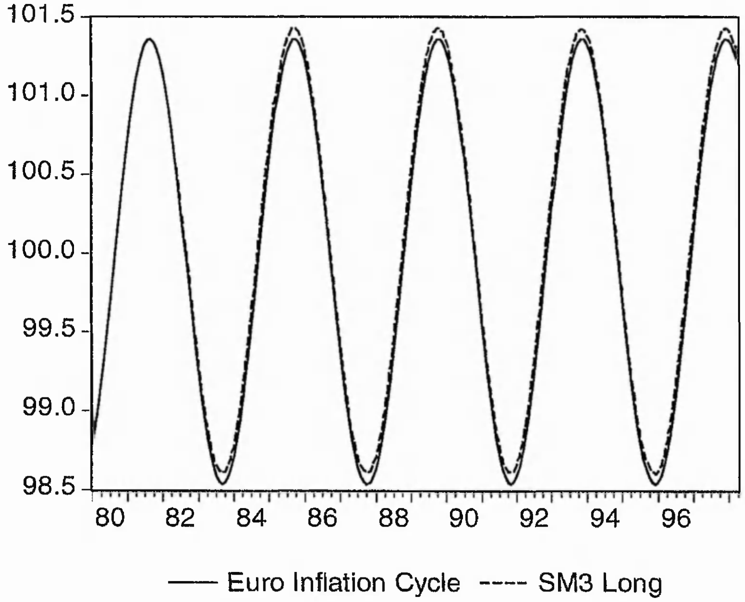


Figure 5.7d Divisia as Long Leading Indicator

Inflation reference cycle against Divisia long

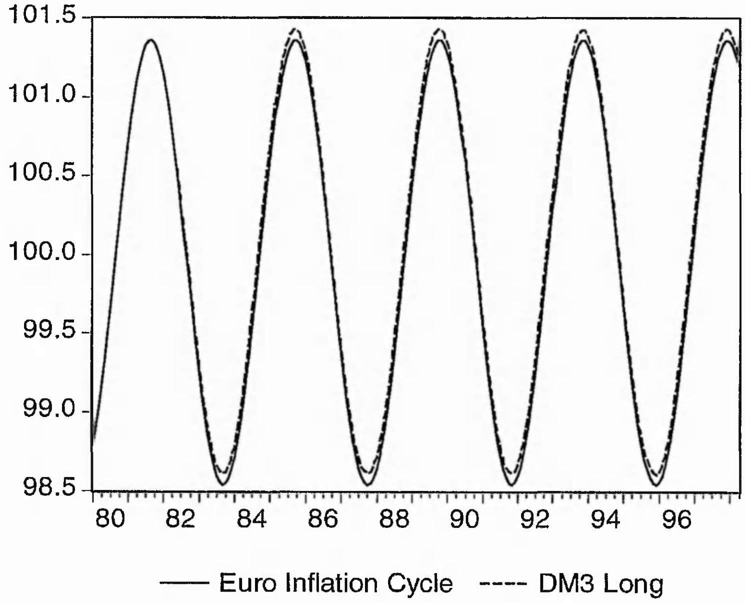


Figure 5.8: Prediction error covariance for SM3 Short

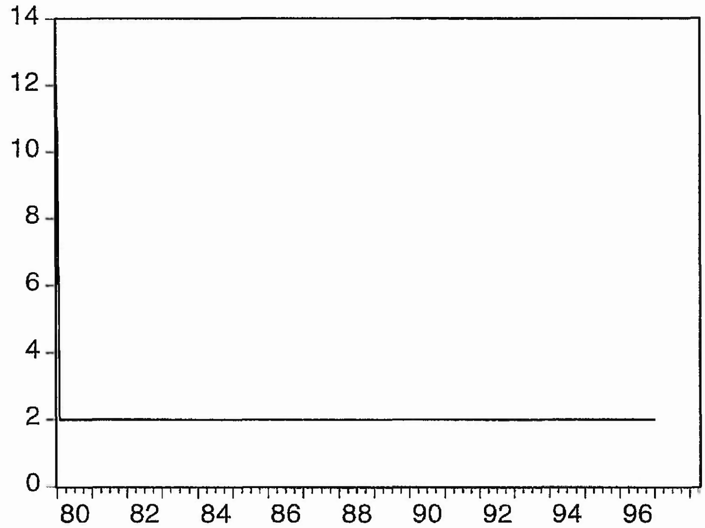


Table 5.8: Residual analysis between inflation reference cycle and CLIs for the Euro Area

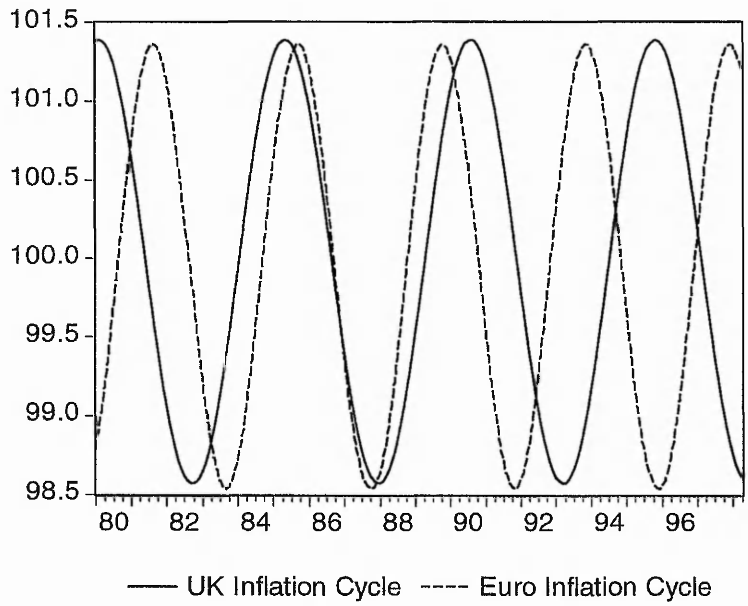
	SM3 Short	DM3 Short	SM3 Long	DM3 Long
Durbin Watson	0.025392	0.016368	0.000085	0.000087

5.3.1 Whether or not the UK should join the Euro Area

There is an ongoing debate on whether or not the UK should join the Euro area. The opinions of the public, businesses and professional economists are divided on this issue. However, at present it seems that joining the Euro area does not seem to be a very popular action. From an economist's perspective, one of the major concerns is membership to the Euro area would most probably deprive the UK of an independent monetary policy, that is, the Bank of England will have almost no say in the monetary policy, which will be carried out by policymakers at the ECB. The problem for many economists is the lack of credibility of the ECB. In contrast to the Bank of England which has become very credible because of its record on inflation, the procedures of the ECB are much less transparent and its objective less clear and the ECB is felt not to have performed so well. This results in a lack of confidence in the Euro in comparison with Sterling. Many economists also allude to the experience of Britain in the Exchange Rate Mechanism (ERM). During its ERM membership, October 1990 to September 1992, when Britain had contracted out its monetary policy to Europe, it suffered its worst recession, as measured by total output lost, in sixty years, unemployment doubled, three-quarter million homes were thrown into negative equity and 100,000 businesses went bankrupt. But once the UK left the ERM, its economy recovered immediately. Leaving the ERM proved to be a blessing for the UK, however, Euro membership is irrevocable and there is no guarantee of success. Therefore the UK, which is the world's fifth largest economy, has to be extremely cautious for every step it takes towards the Euro. It seems to be the case at the moment, given that the UK has not joined the Euro area yet as four of the five tests, introduced by the Chancellor of the Exchequer of Britain to analyse the possibility of Britain joining the Euro, have failed. In this chapter some further tentative evidence on whether or not the UK should join the Euro area is provided.

Firstly on comparing the number of cycles in Tables 5.3 and 5.4, it can be noticed that in the majority of cases, the number of cycles in the Euro area series is higher than in their UK counterparts, implying that the UK economic cycles will be out of phase with those of the Euro area. This finding is consistent with those of studies like Artis and Zhang (1999), Artis, Krolzig and Toro (1999) and Barrios, Brulhart and Elliot (2002). The UK inflation series being out of phase with the Euro area inflation series, as shown in Figure 5.9, is of even greater interest from a monetary-policy viewpoint. It can be seen that there are times when the UK economy enters recession the Euro area economy enters recovery and vice versa. If the UK unites with the Euro area and such divergences were to occur in the future, the UK would have to endure interest rates that are quite inappropriate to the phase of the UK economic cycle. More specifically, if for example the UK is still in recession but the Euro area economy is growing, the ECB would certainly want to raise interest rates, to slow down the Euro area boom. Such an action could bring the UK economy further down. On the other hand if the UK economy is growing fast while the Euro area economy is in recession, the ECB might want to cut interest rates. Such an action could have a disastrous effect on the British economy- for example this could fuel a house price explosion. Therefore, the initial conclusion is that the UK should not join the Euro area. However, the diverging behaviour of UK and Euro inflation cycles could be due to different macroeconomic policies. Membership of the UK to the Euro area might force the cycles to converge.

Figure 5.9: UK and Euro inflation Cycle



The CLIs in Table 5.9 consists of economic series which are considered to have UK inflation information content and will be referred to as UK CLIs. The CLIs in Table 5.10, in addition to containing the component series of their UK CLIs counterparts, also consist of appropriate CLIs of the inflation turning point for the Euro area[10], these CLIs will be referred to as Euro-based UK CLIs. The residual tests are given in Table 5.11 and 5.12 based on residuals obtained from models in Tables 5.9 and 5.10 respectively. Here also the residual tests indicate the presence of autocorrelation, but a graphical inspection suggests that the cycles of the indicators and that of inflation are not out of synchronisation, as exemplified by that SM4 Long in Figure 5.10, and the prediction error covariance of each model decreases asymptotically, as exemplified by the prediction error covariance of SM4 Long in Figure 5.11. On comparing the corresponding CLIs (for example, SM4 Short from Table 5.9 is compared to SM4 Short in Table 5.10), it is found that all the CLIs from Table 5.9 show a closer relationship to

[10] The component CLI of, for example, UK SM4 Short CLI is Euro SM3 Short CLI and so on.

the inflation cycle than those in Table 5.10. Such a finding suggests that Euro area series with information content about the Euro area inflation do not help in constructing superior CLIs for UK inflation. Therefore the conclusion that can be drawn from this finding is that, if the UK unites with the Euro area, ECB measures to combat inflationary pressures might not have the same corrective effect on the UK as would measures taken based on future UK inflation information. Therefore it can be tentatively concluded that the UK would be better off on its own as long as it pursues a sensible monetary policy strategy. This reinforces the initial conclusion based on graphical inspection.

Figure 5.10 UK inflation and SM4 Long indicator

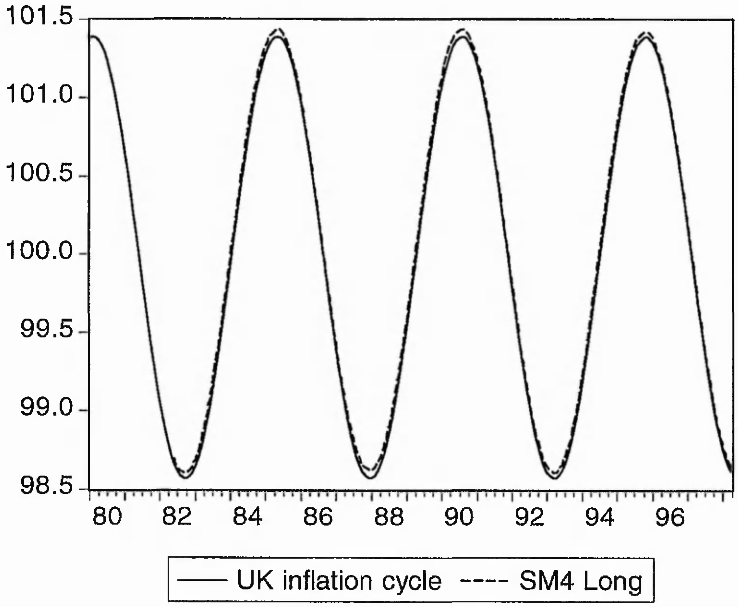


Figure 5.11: Prediction error covariance of SM4 Long

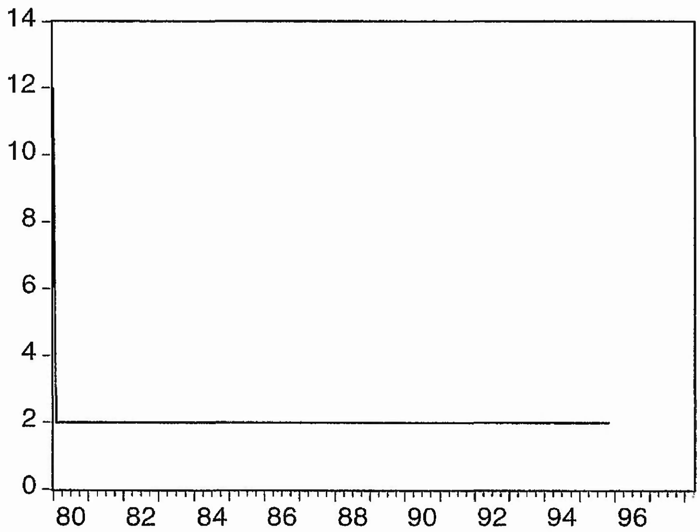


Table 5.9: Correlations of UK CLIs with inflation reference cycle for the UK

CLIs	Correlation with Inflation Cycle	Weights
SM4 Short	0.99998924	E
DM4 Short	0.99998926	E
SM4 Long	0.99999046	E
DM4 Long	0.99998906	E

Under the heading 'Weight', P indicates the component series of the CLI were aggregated using principal components weights, while E indicates equal (unity) weights were used in the aggregation.

Table 5.10: Correlations of Euro-based UK CLIs with inflation reference cycle for the UK

CLIs	Correlation with Inflation Cycle	Weights
SM4 Short	0.99998879	E
DM4 Short	0.99998890	E
SM4 Long	0.99998754	E
DM4 Long	0.99998674	E

Under the heading 'Weight', P indicates the component series of the CLI were aggregated using principal components weights, while E indicates equal (unity) weights were used in the aggregation.

Table 5.11: Residual analysis between UK inflation reference cycle and UK CLIs

	SM4 Short	DM4 Short	SM4 Long	DM4 Long
Durbin Watson	0.000066	0.000066	0.000260	0.000280

Table 12: Residual analysis between UK inflation reference cycle and Euro-based UK CLIs

	SM4 Short	DM4 Short	SM4 Long	DM4 Long
Durbin Watson	0.000063	0.000062	0.000357	0.000370

5.4 Summary and Conclusions

In this chapter short and long composite leading indicators of the inflation turning points for the Euro Area are constructed using Fourier analysis and Kalman filters. Empirical performances of Simple Sum and Divisia aggregates are also compared in the composite leading indicator framework. The same framework and graphical analysis are also used to provide a tentative answer to the issue of whether or not the UK should join the Euro area.

On the whole the cyclical patterns of the different CLIs are rather similar and closely reflect the cycles of the inflation series. Such a finding demonstrates that CLIs are a useful and powerful alternative to statistical methods for forecasting turning points of inflation. It also suggests that Fourier analysis and Kalman filters can be combined with the traditional NBER methodology to construct sophisticated CLIs. The finding also lends support to the similar seminal study for the UK carried out by Binner and Wattam (2003). It is also of some significance to policymakers and should form the basis of future research for constructing leading indicators of inflation cycle or business cycles.

Regarding the relative performance of Divisia and Simple Sum monetary aggregates in the Euro area, the results suggest that the Divisia indices appear to offer advantages over simple sum indices as macroeconomic indicators. The Divisia based CLIs are found to be more closely related to the inflation cycle than Simple Sum based CLIs. This finding is consistent with earlier evidence provided by Binner, Fielding and Mullineux (1999) and Binner and Wattam (2003). These findings therefore suggest that the behaviour of the Divisia monetary aggregate should be taken more seriously by both policymakers and academics. It may be concluded that a money stock mismeasurement problem exists and that the technique of simply summing assets in the formation of monetary aggregates is inherently flawed.

Based on findings from graphical analysis and CLI analysis it might also be concluded that the UK is better out of the Euro area as the monetary policy strategy of the ECB to maintain price stability in the Euro area might not be stabilising for the UK. However, UK membership of the Euro area might lead to converging behaviour of inflation cycles and economic cycles and hence ECB's monetary policy strategy would have the desired effect on the UK economy.

CHAPTER 6:

NEURAL NETWORKS VERSUS ECONOMETRIC MODELLING IN INFLATION FORECASTING[11]

In line with the argument in the previous chapter the focus in this chapter will be on comparing the indicator properties of Simple Sum and Divisia indices. The monetary indices are compared in an inflation forecasting framework. Additional aims in this chapter are to investigate, firstly, whether the ECB is justified in using linear models for forecasting inflation and, secondly, whether Divisia aggregates are disadvantaged with respect to Simple Sum aggregates when comparison between them is made using a linear framework.

6.1 Introduction

In the second pillar of the ECB's monetary policy strategy inflation forecasts play a very important role. In order to enable the monetary authorities to tackle appropriately inflationary pressures that may arise in the future it is necessary and crucial to produce accurate and reliable forecasts of inflation. A large body of research is devoted to inflation forecasting (see, for example, De Brouwer and Ericsson (1998) for Australia, Stock and Watson (1999) for the US, Drake and Mills (2002) for the Euro area). One question that lies in the heart of every forecasting exercise is which forecasting method to use? The overwhelming majority of studies on inflation forecasting divide forecasts into two main categories:

(1) forecasts from time series models such as ARIMA models and

[11] Part of this chapter has been published as a journal paper entitled A Comparison of Linear Forecasting Models and Neural Networks: An Application to Euro inflation and Euro Divisia and is forthcoming in Applied Economics.

(2) forecasts from econometric models such as VAR models.

However, such models are based on the assumption of linearity in the data and there is now growing evidence that macroeconomic series contain nonlinearities (see, for example, Tiao and Tsay (1994) and Stanca (1999)) and thus, though linear models have been reasonably successful as a practical tool for analysis and forecasting, they are inherently limited in the presence of nonlinearities in data and consequently forecasts, as well as other conclusions drawn from them, could be misleading. In view of the limitations of linear models, nonlinear time series have gained much attention in the recent decades. Several nonlinear models, such as the threshold autoregressive (TAR) models (Tong, 1990) and the exponential autoregressive model (EXPAR) (Haggan and Ozaki, 1981), have been developed. However, an immediate problem encountered while opting for such nonlinear models in preference to linear models is that there exists no unified theory that can be applied to all such nonlinear models as they require the imposition of assumptions concerning the precise form of nonlinearity. But there are too many possible nonlinear patterns in a particular data set and the prespecified nonlinear model may not be broad enough to capture all essential characteristics. An alternative way to deal with nonlinearities in data is to use neural networks (NN). In contrast to the above model-based nonlinear methods, NN are data driven and are thus capable of producing nonlinear models without prior beliefs about the functional forms. NN are also highly flexible as they can approximate any continuous function to any degree of accuracy (Hornik, Stinchcombe and White, 1989). Thus from a statistical viewpoint the nonlinear NN would be expected to perform better than the linear models in inflation forecasting and since no such work has been carried out for the Euro area one of the main objectives of this chapter is to investigate the performance of NN vis a vis linear models in forecasting Euro inflation.

As it is the case while constructing CLIs, monetary variables are considered to be good information carriers for future inflation and hence are often used as predictor variables in inflation forecasting models. This feature makes it possible to use the inflation forecasting framework to compare the indicator properties of the two monetary variables. More specifically, every multivariate inflation forecasting model is specified in turn with Simple Sum and Divisia monetary aggregates as monetary variables and ultimately their inflation forecasting ability are compared.

As mentioned in the introductory chapter there have been numerous studies comparing the empirical performance of Simple Sum and Divisia monetary aggregates. And the results have been mixed but leaning in favour of Divisia monetary aggregates. While such results have been strong enough to satisfy those already persuaded of the practical usefulness of the Divisia monetary aggregates and convince some central banks (Bank of England, Federal Reserve Bank, USA) to take an active interest in the construction of Divisia monetary aggregates, they have not been successful in persuading central banks to abandon Simple Sum monetary aggregates. This leads us to asking the question why Divisia aggregates do not always outperform their Simple Sum counterparts given their theoretical superiority. Some researchers argue that some measurement problems (such as choice of appropriate benchmark rate) have to be overcome before the true Divisia index can be calculated (see, for example, Drake, Mullineux and Agung (1997)) for a more detailed description of measurement problems). However, one important issue has been overlooked by researchers working with monetary aggregates. The issue of the presence of nonlinear structures in Divisia aggregates, as evidenced by Barnett and Chen (1986, 1988a, b), Barnett and Hinich (1992, 1993), Chen (1988), and DeCoster and Mitchell (1991). In the overwhelming majority of cases the comparison of Simple Sum to Divisia aggregates is done using linear models. In the event that Divisia perform poorly with respect to Simple Sum aggregates when compared using linear models, one cannot conclude that the Divisia aggregates are not suitable for monetary policy as it may well be that the linear techniques used may not be able to capture the nonlinear behaviour of Divisia aggregates, thus undermining their empirical performance. To shed some light on this issue the analysis to be carried out, described above, can be very readily used. More specifically, by analysing the performance of Divisia aggregates relative to Simple Sum aggregates in both linear and nonlinear frameworks it is possible to get an idea on whether future research on Divisia aggregates should be conducted in a nonlinear framework.

6.2 Literature Comparing Forecasting Method Effectiveness

This section provides a brief review of recent research on comparing linear models, like ARIMA and VAR models to nonlinear NN, but makes no attempt to be exhaustive.

NN have gained enormous popularity in the recent years, especially in time series forecasting. Most applications, however, are in areas where data are abundant as NN are very data intensive. In macroeconomics, due to the scarcity of large data samples, there exist only a few studies involving the use of NN that can be used to gauge their usefulness in the field. Recent studies include that of Johnes (2000) and Moshiri and Cameron (2000). Johnes (2000) contrasts models of the UK economy constructed using NN and a variety of econometric models. Moshiri and Cameron (2000) use NN to forecast Canadian inflation and compare the results to those from time series and econometric models. The results in these studies, based on out-of-sample forecasts, do not permit a demarcation between the linear models and NN as the latter are able to justify their theoretical superiority in only some of the cases. In fact, these observations reflect the results of quite a large number of such comparative studies across different fields. This has led to questions being raised on whether studies implement NN in such a way that they stand a reasonable chance of performing well (Adya and Callopy, 1998). Indeed, the risks of making bad decisions are extremely high while building NN as there are no established procedures available to decide on the choices of the parameters of the NN, which basically are problem dependent. Although there have been attempts in several studies to develop guidelines in making these choices (see, for example, Balkin and Ord (2000), Gorr, Nagin and Szcypula (1994)), so far this matter is still subject to trial and error. Thus, despite the many satisfactory characteristics of NN, building NN for forecasting a particular problem is a nontrivial task. Consequently, tedious experiments and time-consuming trial and error procedures are inevitable. However, this has not been the case in most of the comparative studies as, in the absence of any a priori information about the parameters of the NN, their choice has involved a lot of subjectivity (Nag and Mitra, 2002). Such an approach considerably reduces the possibilities of exploiting the true potential of the NN and ultimately leads to results from a large number of studies being dubious. For example, Moshiri and Cameron (2000) perform some experimentation in finding the optimum number of hidden units, however their choice for the amount of training required, another equally critical parameter, is rather subjective, thereby limiting the power of the NN. In this study, it is endeavoured to keep the level of subjectivity to a minimum and appropriately deal with other issues prone to affect the performance of NN in an attempt to obtain the best possible NN models. Since it is beyond the reach of this chapter to evaluate the performance of NN against the entire class of linear models, the well-established and extensively used ARIMA and VAR models are chosen as representatives for linear models in recognition of their ability to produce reliable forecasts.

6.3 Data and Preliminary Analysis

Many economic indicators help predict inflation. For example Stock and Watson (1999) show 168 variables can be used to forecast US inflation. In this study, instead of using so many variables, the list is limited to those that are more closely linked to inflation by economic theory or that have been regularly used in previous empirical studies. Thus, in keeping with previous studies such as Hendry and Doornik (1994), the variables required for multivariate forecasting are: inflation, monetary aggregates- Simple Sum M3 and Divisia M3, GDP, GDP deflator and the opportunity cost variables of the corresponding Simple Sum and Divisia aggregates. These are quarterly seasonally adjusted data for the period 1980Q1 to 2000Q4, defined by the availability of the Euro area data. Data on monetary assets, their respective rates of return, GDP and GDP deflator have been obtained from Stracca (2004). After allowing for lags and transformations estimation is conducted using data from 1981Q2 to 1998Q2, while the remaining 10 observations (1998Q3 to 2000Q4) are kept for forecast evaluation (testing). The log of all variables has been taken and thus

$sm3_t$ is the log of real Simple Sum M3,

$dm3_t$ is log of real real Divisia M3,

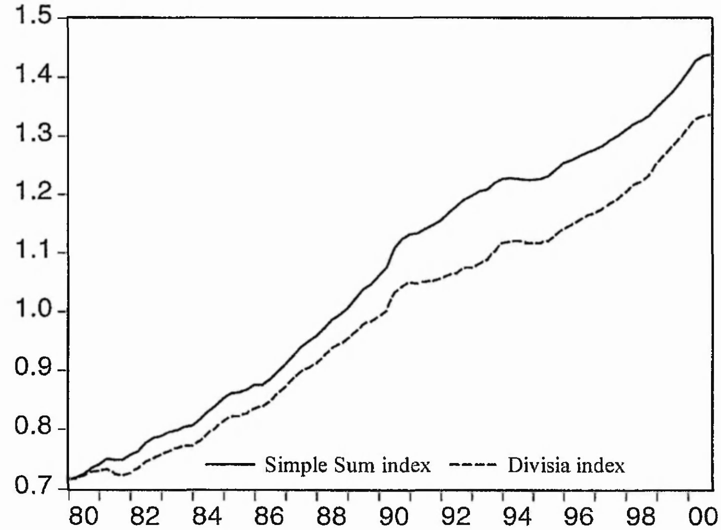
y_t is the log of real GDP,

$dualsm3_t$ is the log of the opportunity cost variable for Simple Sum M3 and

$dualdm3_t$ is the log of the opportunity cost variable for Divisia M3.

p_t is the logarithm of the GDP deflator and $\Delta p_t = p_t - p_{t-1}$ is the quarterly inflation rate.

Figure 6.1: Simple Sum M3 index versus Divisia M3 index



$sm3_t$ and $dm3_t$ are contrasted in Figure 6.1. The Simple Sum aggregate begins to increase faster than its Divisia counterpart in 1980 and diverges significantly afterwards. To check the stationarity properties of the series the Augmented Dickey and Fuller (1979) unit root test, described in Section 4.4 Chapter 4, is used. The results reported in Table 6.1 show that for the majority of the variables the null hypothesis of unit root and hence nonstationarity in the levels cannot be rejected i.e., most variables are not I(0). The variables $dualsm3_t$ and $dualdm3_t$ are marginally stationary, as the hypothesis of stationarity in levels is not rejected at 5% level but rejected at the 1% level. Unit root tests on the first differences of the variable reveal that all of them are stationary. Hence all variables appear to be I(1) with the exception of $dualsm3_t$ and $dualdm3_t$ which may be borderline I(0)/I(1) variables .

Table 6.1: ADF unit root tests (1980:1-1998:2)

Variable	ADF Test Statistics	Specification
$sm\ 3$	-1.503	[T, 1]
$\Delta sm3_t$	-4.834***	[C, 0]
$dm3_t$	-2.288	[T, 1]
$\Delta dm3_t$	-5.151***	[C, 0]
y_t	-2.280	[T, 4]
Δy_t	-6.932***	[C, 0]
p_t	-2.451	[T, 2]
Δp_t	-2.785	[T, 1]
$\Delta^2 p_t$	-14.316	[C, 0]
$dualsm3_t$	-3.825**	[T, 1]
$\Delta dualsm3_t$	-5.680***	[C, 1]
$dualdm3_t$	-3.781**	[T, 1]
$\Delta dualdm3_t$	-5.760***	[C, 1]

Notes:

T: constant and trend, C: represents constant

[, n], n: the number of lags used

***: significant at 1%, **: significant at 5%

Critical values are from MacKinnon (1991)

6.4 Model Specification and Estimation

In this section the main decisions regarding the specification and estimation of the three classes of model (univariate ARIMA, multivariate VAR and NN) are presented. While the ARIMA and VAR methods are widely used, the NN method is a relatively new method in Economics. Thus, only brief accounts for the ARIMA and VAR methods are presented and a more detailed account for the NN method is given.

6.4.1 Univariate Time Series Model

The ARIMA is a general class of univariate time series models which represents current values of a time series by past values of itself (autoregressive term (AR)) and past values of stochastic errors (moving average terms (MA)). The acronym I refers to the number of times (d) the time series has to be differenced to render it stationary. A nonseasonal[12] ARIMA(p,d,q) process can be represented as

$$\phi(L)(1-L)^d x_t = \theta(L)\varepsilon_{at} \tag{6.1}$$

where ε_{at} is independently and normally distributed with zero mean and constant variance. $\phi(L)$ and $\theta(L)$ are the AR and MA polynomials, respectively with orders p and q such that $\phi(L)=1-\phi_1 L-\cdots-\phi_p L^p$ and $\theta(L)=1-\theta_1 L-\cdots-\theta_q L^q$, where L represents the backshift operator such that $L^s y_t = y_{t-s}$. A slightly modified Box and Jenkins approach (Box and Jenkins, 1970) is used for identifying the best model for ARIMA forecasting. Thus, instead of inspecting the autocorrelation function (ACF) and partial ACF (PACF) in the identification stage a range of models, represented in Table 6.2, is estimated with $d=2$ (for p_t from Section 6.3 and since $\Delta x_t = (1-L)x_t$, $(1-L)^2 p_t = \Delta^2 p_t$) and values of p and q varying from 0 to 3 in a first step and retain the models which pass the diagnostic tests (such as, no autocorrelation and conditional heteroscedasticity, significance of parameters). In a second step the best ARIMA model is chosen to be the one which provides the best out-of-sample forecasts. An ARIMA model with the orders of p and q equal to 6 is also estimated. We then use Hendry's (1993) general-to-specific methodology to obtain a more parsimonious model.

[12] The reason for using nonseasonal ARIMA models is that the data provided to me had already been seasonally adjusted.

Table 6.2: ARIMA models considered. Y represents Yes and N represents N (1980:1-1998:2)

Models	Retained
ARIMA(0,2,1)	**Y**
ARIMA(0,2,2)	N
ARIMA(0,2,3)	N
ARIMA(1,2,0)	**Y**
ARIMA(1,2,1)	N
ARIMA(1,2,2)	**Y**
ARIMA(1,2,3)	N
ARIMA(2,2,0)	N
ARIMA(2,2,1)	N
ARIMA(2,2,2)	N
ARIMA(2,2,3)	N
ARIMA(3,2,0)	N
ARIMA(3,2,1)	N
ARIMA(3,2,2)	N
ARIMA(3,2,3)	N
ARIMA(6,2,6)	**Y**

After the first step only 4 ARIMA models were retained as the others exhibit insignificant parameters and out of the 4 remaining models the ARIMA(0,2,1) is the preferred ARIMA specification because it outperforms the others in terms of out-of-sample forecasting accuracy. Such an approach is adopted in choosing the ARIMA for forecasting so as to ensure that the performance of NN is not overstated. The estimated model is given below and the test statistics given are computed from the residuals of the estimated models. JB represents the Jarque-Bera test for normality, LM(k), represents the test for autocorrelation of order k, and ARCH(k) represents the test for conditional heteroscedasticity of order k (for more details on this tests, see for example, Hendry (1995)). None of the diagnostic tests is significant at conventional levels and, hence, the residuals appear to be normally distributed and free from autocorrelation and autoregressive conditional heteroscedasticity.

$$\Delta^2 p_t = \varepsilon_{1t} - \underset{(0.102)}{0.510}\varepsilon_{1t-1} \tag{6.2}$$

Sample: 1981Q2-1998Q2

$R^2 = 0.23$ $J.B = 0.16[0.92]$ S.E. of regression = 0.002525

LM (1) = 0.00 [1.00] LM (4) = 1.61 [0.81] LM (8) = 4.91[0.77]

ARCH (1) = 0.40 [0.52] ARCH (4) = 7.28 [0.12] ARCH (8) = 10.81[0.21]

Values in parentheses under the estimated coefficients are standard errors and values in square brackets after the values of the test statistics are the corresponding p-values.

6.4.2 Multivariate Vector Autoregressive (VAR) Models

The advantage of VAR models over ARIMA models is that they can incorporate more information in terms of other time series instead of just past observations and errors of the series to be forecast. Having established in Section 6.3 that the variables entering the VAR are I(1), investigation is carried out to determine whether they are cointegrated, that is, verify whether some linear combination of these nonstationary variables is stationary. In the absence of cointegration between the variables a common forecasting procedure would be to conduct a VAR on the first differences. However, if cointegrating relationships can be established between the variables, the VAR should also include the lagged cointegrating error term (vector error correction models (VECM)) (Granger, 1981). This prevents neglecting long run information contained in the levels of the variables and it has been shown that such an approach leads to improved forecasting accuracy (Lesage(1990), Shoesmith (1992, 1995)).

6.4.2.1 Testing for Cointegration

To check for cointegration, the Johansen and Juselius (1990) procedure, described in Section 4.3 of Chapter 4, is used. Here $z_t = (M_t, y_t, R_t^{opp}, \Delta p_t)^T$ where

$M_t = sm3_t$ and $dm3_t$ and $R_t^{opp} = dualsm3_t$ and $dualdm3_t$. As mentioned earlier cointegration results are sensitive to the choice of the lag length *(k)* of the VAR model. Therefore, in line with the discussion on this issue in chapter 4, the choice of the appropriate lag length is combined with misspecification tests to ensure that the underlying assumptions of the VAR model are satisfied (Johansen, 1995). The experimentation uses VAR lag lengths of 1 to 8 and for VARs of order 6 for each system, the LM and JB tests, represented in Table 6.3, do not suggest any misspecification and hence is the preferred lag length.

Table 6.3: Multivariate Autocorrelation and Normality Tests (1980:1-1998:2)

	Simple Sum	Divisia
Autocorrelation test:		
LM (1)	15.04	21.92
	(0.52)	(0.15)
LM (4)	22.09	17.80
	(0.14)	(0.34)
Jarque Bera Normality test	7.47	11.22
	(0.49)	(0.19)

Note: Values in parenthesis are p-values. The LM-tests are asymptotically distributed $\chi^2(16)$, whilst the normality test is asymptotically distributed $\chi^2(8)$.

To determine the appropriate deterministic components for the VAR models, the Pantula (1989) principle is applied to Model 2, Model 3 and Model 4 described in Section 4.3 of Chapter 4. Results from the application of the Pantula (1989) principle, reported in Table 6.4, suggest that Model 3 should be used for the Simple Sum system and the rank is two whereas Model 3 should be used and the rank is three for the Divisia system.

Table 6.4: Simultaneous choice of rank and deterministic components (1980:1-1998:2)

		Simple Sum			Divisia		
p-r	*r*	Model 2	Model 3	Model 4	Model 2	Model 3	Model 4
		80.30	58.65	65.81	81.13	56.86	66.78
4	0	*49.92*	*43.84*	*58.96*	*49.92*	*43.84*	*58.96*
		49.19	33.46	39.26	48.05	33.56	43.38
3	1	*31.88*	*26.70*	*39.08*	*31.88*	*26.70*	*39.08*
		24.00	9.96	14.08	28.49	16.42	24.34
2	2	*17.79*	*13.31*	*22.95*	*17.79*	*13.31*	*22.95*
		7.41	2.34	3.57	11.88	0.36	7.82
1	3	*7.50*	*2.71*	*10.56*	*7.50*	2.71	*10.56*

Note: Numbers in italics are 90 percent quantiles of the trace test tabulated in Johansen (1995)

Here also the number of cointegrating vectors is found to be greater than one in each case. The cointegrating vectors for both systems are presented in Table 6.5. However for further analysis, in this chapter, the most common approach of selecting the one cointegrating vector which is consistent with economic theory in terms of the signs and magnitude of the coefficients of its parameters is chosen (see, for example, Drake, Chrystal and Binner (2000)). On this basis the second cointegrating vector in each case is selected.

Table 6.5: Cointegration vectors (1980:1-1998:2)

	Money	GDP	Inflation	Opp. cost	Trend
Simple Sum	-1	1.181	-40.345	0.633	-
	-1	1.451	-1.809	-0.055	-
Divisia	-1	2.596	45.946	-0.232	-
	-1	1.220	-2.054	-0.032	-
	-1	1.304	-3.186	0.111	-

6.4.2.2 Short-run Equations for Inflation

In this section estimation results for single error correction equations of inflation are presented. For both Simple Sum and Divisia, the corresponding second cointegrating vector is used for specifying their short-run equations of the form of Equation 4.7 for inflation. Money affects prices with long lags, approximately two years and hence 7 lags of each of the independent variables have been used.[13] Following the general to specific methodology (Hendry, 1993), parameters insignificant at the 5% significance level are deleted and the equations rerun, using the ordinary least squares method, until just significant parameters remain. The error correction terms are kept in the equations at all times and eliminated in the final stage if they were not significant. This strategy eventually results in the equations given by Equations 6.4 and 6.5 for the Simple Sum M3 and Divisia M3 respectively. Here also the diagnostic tests do not show any signs of misspecification.

Simple Sum

$$\underset{}{\Delta^2 p_t} = \underset{(0.054)}{0.121\Delta sm3_{t-2}} - \underset{(0.102)}{0.533\Delta^2 p_{t-1}} + \underset{(0.000026)}{0.000062\,\mathrm{Res1}_{t-1}} + \varepsilon_{2t} \tag{6.4}$$

Res1 are the residuals from 2nd cointegrating vector of Simple Sum M3 system

Sample: 1981Q2-1998Q2

$R^2 = 0.30$	$J.B = 0.41[0.81]$	S.E. of regression = 0.002454
LM (1) = 0.38 [0.54]	LM (4) = 1.61 [0.81]	LM (8) = 8.61 [0.38]
ARCH (1) = 1.70 [0.19]	ARCH (4) = 1.61 [0.81]	ARCH (8) = 2.22 [0.97]

Values in parentheses under the estimated coefficients are standard errors and values in square brackets after the values of the test statistics are the corresponding p-values.

[13] The computations reported in this section were carried out on Eviews 4.0

Divisia

$$\Delta^2 p_t = \underset{(0.054)}{0.141\Delta dm3_{t-3}} - \underset{(0.102)}{0.537\Delta^2 p_{t-1}} + \underset{(0.000027)}{0.000070\text{Res}2_{t-1}} + \varepsilon_{3t} \tag{6.5}$$

Res2 are the residuals from 2nd cointegrating vector of Divisia M3 system

Sample: 1981Q2-1998Q2

$R^2 = 0.32$ $J.B = 0.24\,(0.88)$ S.E. of regression = 0.002908

LM (1) = 1.34 (0.25) LM (4) = 3.18 (0.53) LM (8) = 5.94(0.65)

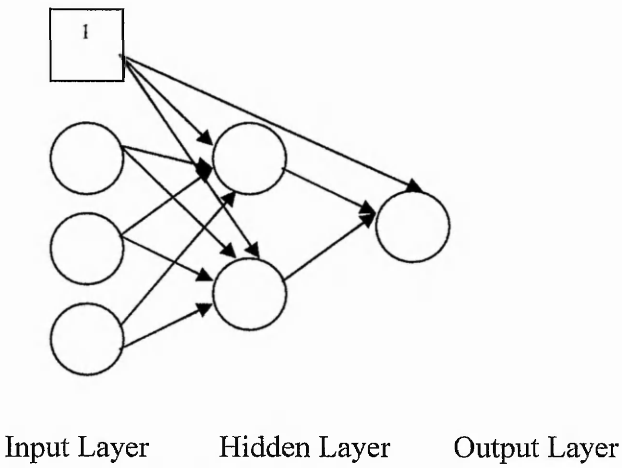
ARCH (1) = 0.05 (0.83) ARCH (4) = 5.64 (0.23) ARCH (8) = 8.81 (0.36)

Values in parentheses under the estimated coefficients are standard errors and values in square brackets after the values of the test statistics are the corresponding p-values.

6.4.3 Nonlinear Models: Neural Networks (NN)

Neural networks are composed of highly interconnected processing elements (nodes) that work simultaneously to solve specific problems. In time series analysis they are used as nonlinear function approximators. They take in a set of inputs and produce a set of outputs according to some mapping rules predetermined in their structure.

Figure 6.2: NN model



In this chapter the most popular form of NN called the feedforward network is considered. Figure 6.2 depicts such a network that consists of layers of nodes. The input layer and output layer represent the input and output variables of the model. Between them lie one or more hidden layers that progressively transform the original input stimuli to final output and hold the networks ability to learn nonlinear relationships. For a feedforward NN with one hidden layer, the general prediction equation, given by Faraway and Chatfield (1998), for computing a forecast of y_t using an input vector $(x_1, x_2, \cdots, x_m)$ may be written in the form

$$\hat{y}_t = f(w_{co} + \sum_h w_{ho} g(w_{ch} + \sum_i w_{ih} x_i)) \tag{6.6}$$

where w_{ch} denote the weights for the connections between a constant input, usually taken as 1, and the hidden nodes and w_{co} denotes the weight of the direct connection between the constant input and the output. The weights w_{ih} and w_{ho} denote the weights for the other connections between the input and hidden nodes and between hidden and the output nodes respectively. The two functions f and g denote the activation functions used in the hidden layer and the output layer respectively.

NN have to be trained in order to be able to use them to perform certain tasks like predicting a response corresponding to a new input pattern. The training procedure involves iteratively modifying the randomly initialised weights of the NN to minimise some kind of error function usually the mean square error (MSE), $\sum (y_t - \hat{y}_t)^2 / n$. Various standard optimisation techniques such as the conjugate gradient and quasi-Newton methods exist for minimising the error function, however, in application studies, the backpropagation algorithm (Rumelhart, Hinton and Williams, 1986) developed by the neural network community is the most popular training algorithm used. Standard optimisation techniques tend to converge faster than the backpropagation algorithm but this advantage is overshadowed by the fact that the latter is computationally more efficient (Monterola *et al.*, 2002). Moreover, the backpropagation algorithm generally has better generalisation (performs well on unseen data) than standard optimisation techniques (Cubiles-de-la-Vega *et al.*, 2002), hence is the preferred algorithm despite the greater time required for convergence.

However, it is well known that the backpropagation algorithm used for training suffers from local minimum problem (see for example, Faraway and Chatfield (1998)). Randomly selecting initial weights for training is a common approach, however, if these initial weights are located close to local minima, the algorithm is likely to converge to a local minimum. Some researchers have tried to overcome this problem by, for example, using genetic algorithms (Shazly and Shazly, 1999) or simulated annealing (Masters, 1993). Even then there is no assurance that such measures will help the optimisation algorithm to converge to a global minimum. The most commonly used method to find the best local minimum or even the global minimum is followed, more specifically, training is restarted with different weights. The actual number of restarts employed in practice is generally limited by the computing time required to train a NN (Plasmans, Verkooijen and Daniels, 1998).Therefore in this work 10 restarts are used.

6.4.3.1 Designing the Neural Networks

Apart from the weights of the NN, there are many other parameters, like the number of input variables, the combination of input variables, the number of hidden layers and hidden nodes, the types of activation functions in the hidden and output layers, the value of the learning rate and the momentum rate and the amount of training which are also unknown. As mentioned earlier there are no established rules that can be used to choose the appropriate values of these parameters and trial and error has to be used to obtain their appropriate values. Clearly, experimenting over the whole parameter space of the parameters is beyond the scope of this chapter. In this study, therefore, the focus will be on experimenting with different values of key parameters like initial weights, the number of hidden nodes, amount of training required, different sets of input variables and we attention is drawn to the other issues that need to be considered while making the choices for the remaining parameters of the NN.

The common practice has been to construct NN using the same input variables as in VAR models to allow direct comparison between them. However, such a procedure is biased towards the linear model as the regressors from the linear equation tell us about linear correlation and this is not appropriate for nonlinear relationships modelled by the NN (Zhang, Patuwo and Hu, 1998). For these reasons, in this chapter the 'best' set of input variables for the NN is used. A modified version of the preferred model of the relationship between inflation and money of Binner, Gazely and Chen, (2002) adapted originally from Dorsey (2000, pp.34) given by Equation 6.7 below is used. However, for comparative purposes NN are constructed using the set of input variables of the VAR models and using the set of input variables of the VAR models from which the error correction term has been excluded.

$$\Delta^2 p_t = f(\Delta M_{t-1}, \Delta M_{t-2}, \Delta M_{t-3}, \Delta M_{t-4}, \Delta^2 p_{t-1}) + \varepsilon_{ct} \tag{6.7}$$

Hidden layers play a very important role for the successful applications of the NN as they allow NN to perform nonlinear mapping between the input and the output. Without hidden nodes, NN are equivalent to linear statistical models (see, for example, Warner and Misra (1996)). It has been shown that a 3 layer NN, i.e., a NN with only one hidden layer can approximate any function to any degree of accuracy (Hornik, Stinchcombe and White, 1989). Two hidden layer NN could be more beneficial to certain problems (Barron, 1994), however, given the relatively small sample and the fact that the number of parameters increases rapidly with each layer (Tkacz, 2001), the focus is on 3 layer NN in the present study.

The choice of the number of hidden nodes is more complicated. Usually few hidden nodes are preferred as there is less likelihood of overfitting, i.e. encountering problems of drawing too many characteristics from the data used for training, and a higher tendency to yield better generalisation. But NN with too few hidden nodes may not have enough power to model and learn the richness of the data (Church and Curram, 1996). Similar problems are encountered if NN are not trained to the right degree. Inadequately training NN will lead to missing patterns in the data while excessive training will result in overfitting. A grid search is used to jointly determine the appropriate number of hidden nodes and the amount of training required (Gorr, Nagin and Szcypula, 1994). Five networks with hidden units between 1 and the number of input variables (Balkin and Ord, 2000) that is five here are considered. Preliminary investigation over the amount of training ranging from 10,000 to 50,000, suggested that better results are obtained in the range 15000 to 20000 for the Simple Sum NN models and in the range 10000 to 15000 for the Divisia NN models. Therefore, extensive experimentation is constrained to these ranges with increments of 1000. Since 10 restarts were performed for each point in our grid, this means that 300 NN for each set of input variables and monetary aggregate are investigated, i.e. a total of 1800 NN are run in this investigation.

The logistic function $f(x) = 1/(1+e^{-x})$ is the most popular activation function among researchers for the hidden layer. However, the hyperbolic tangent (*tanh*) function, $f(x) = (e^{x} - e^{-x})/(e^{x} + e^{-x})$ is used as it has been used very successfully in inflation forecasting experiments (see, for example, Binner, Gazely and Chen, (2002)). It is also generally held that *tanh* gives rise to faster convergence of training algorithms than logistic functions (Bishop, 1995). For the output layer, the recommendation of Rumelhart *et al.* (1995) is followed who suggest the use of the linear function $f(x) = x$ for time series prediction with continuous output. The remaining parameters for the NN, the learning and momentum rates for the backpropagation algorithm are set as the default values of Matlab 6.0, i.e. 0.01 and 0.9 respectively (see, for example, Bishop (1995), for more details on these parameters).

In addition to the parameters of the NN, there are some other factors such as the data normalisation and performance measures that affect the performance of NN (Zhang, Patuwo and Hu, 1998). In practice NN training can be made more efficient by preprocessing the data as this enables the network to extract valuable information (Gately, 1996) and to significantly reduce the time necessary to complete training (Krunic, Krcmar and Rajakovic., 2000). In this chapter one of the most common forms of preprocessing which consists of rescaling the data in the range [-1, 1] so that they have similar values is used. This choice is motivated by the fact that the input variables used for NN modelling differ by several orders of magnitude and the sizes of variables do not necessarily reflect their relative importance in finding out the required outputs (Bishop, 1995). Another issue of concern is related to performance measures. There are several measures of accuracy but each of them has advantages and limitations (Makridakis, Wheelright and McGee, 1983). For this reason none of them is universally accepted as the best measure of accuracy and hence in this study a number of performance measures will be used.

6.5 Predictive Performance Assessment

NN should be tested on a validation set after they have been trained. The NN leading to the minimum forecast error in the validation set should provide the best generalisation and are normally retained to evaluate their forecasting performance on a test sample. However, one of the main disadvantages of NN, as mentioned above, is that they require an enormous amount of data, if the series are short or not representative of the process being modelled NN might not perform well (Balkin and Ord, 2000). Thus in studies with small data sets it is common to use the test set for both validation and testing purposes (Zhang, Patuwo and Hu, 1998). That is the route followed in this chapter given that the data set available to me is quite modest by the standards of NN analysis.

Three traditional performance measures are first used to compare the fit and forecasting accuracy of alternative models: root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Before calculating these measures the NN forecasts are backtransformed to the same units as their actual values to make them comparable.

Figures 6.3a, 6.3b and 6.3c show the within-sample RMSE, MAE and MAPE performances respectively and Figures 6.3d, 6.3e and 6.3f show the corresponding out-of-sample performances of the Simple Sum NN constructed with the set of input variables as in Equation 6.7. The corresponding patterns shown by the RMSE, MAE and MAPE, within-sample and out-of sample, for different number of hidden nodes and amount of training across different sets of input variables are in general similar. A comparison of the within-sample RMSE to that of the out-of-sample RMSE reveals that as the number of hidden nodes and amount of training are increased the within-sample forecast error decreases but, as expected, the reversed pattern is observed with the out-of-sample forecasts. This clearly demonstrates that with too many hidden nodes and excessive training, poor generalisation will occur and hence the need to appropriately choose these parameters. The MAE shows a similar pattern to that of the RMSE, however, the movement across both surfaces is not always in congruence. The discrepancies in the performance measures become more apparent as the RMSE and MAE are compared to the MAPE. The differences are apparently due to the inherent limitations in each of the performance measures. Therefore, these observations show that choosing the best model on the basis of just one performance measure would be misleading and thus in the current study the best model is chosen to be the one which consistently shows small forecast errors across each of the three performance measures and which also provides the best trade-offs between within-sample and out-of-sample forecast errors. On this basis, the amount of training and hidden nodes chosen are reported in Table 6.6 for each set of input variables (sets A, B and C also defined Table in 6.6) for each monetary aggregate. One noticeable pattern in these values is that the amount of training or number of hidden nodes or both increase as the number of input variables increases. This could be due to the fact that the higher the number of input variables, the higher the level of complexity of the NN and hence more hidden nodes or/and training are required to learn the relationship between input and output variables. The static forecasting performance of the ARIMA and VAR models are reported in Tables 6.7 and 6.8 respectively, while those of the NN based on the three different sets of input variables are reported in Tables 6.9, 6.10 and 6.11.

Figure 6.3a: Within-sample RMSE performance of NN for the Simple Sum M3

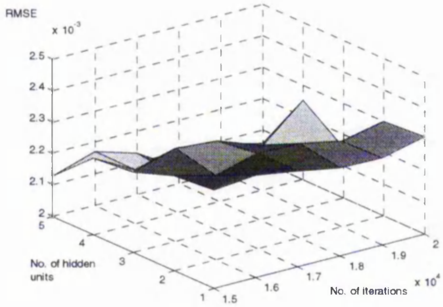


Figure 6.3d: Out-of-sample RMSE performance of NN for the Simple Sum M3

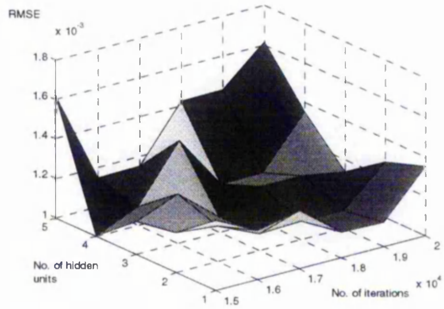


Figure 6.3b: Within-sample MAE performance of NN for the Simple Sum M3

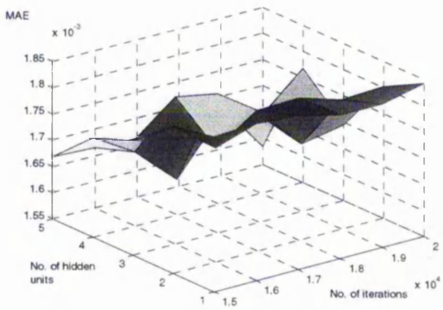


Figure 6. 3e: Out-of-sample MAE performance of NN for the Simple Sum M3

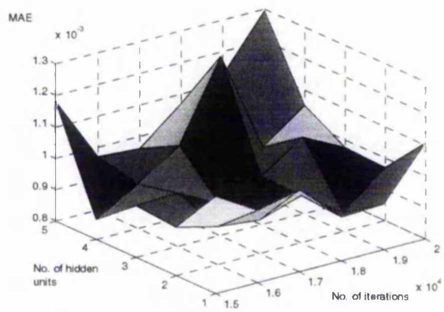


Figure 6.3c: Within-sample MAPE performance of NN for the Simple Sum M3

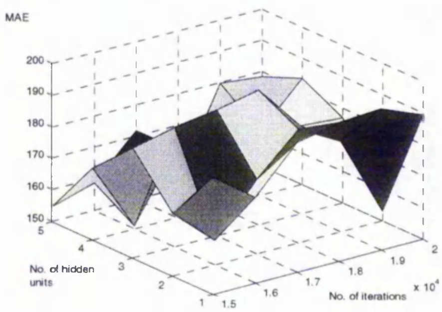


Figure 6.3f: Out-of-sample MAPE performance of NN for the Simple Sum M3

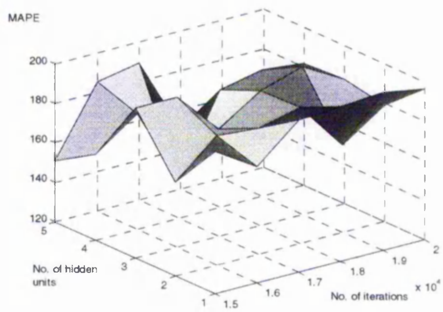


Table 6.6: Amount of training and hidden nodes used for the different networks

	Simple Sum		Divisia	
Input Variables	Amount of training	No. of hidden nodes	Amount of training	No. of hidden nodes
Set A: $\Delta m3_{t-2}$ / $\Delta d3_{t-3}$, $\Delta^2 p_{t-1}$	15000	2	10000	2
Set B: $\Delta m3_{t-2}$ / $\Delta d3_{t-3}$, $\Delta^2 p_{t-1}$, Res_{t-1}	16000	4	10000	4
Set C: ΔM_{t-1}, ΔM_{t-2}, ΔM_{t-3}, ΔM_{t-4}, $\Delta^2 p_{t-1}$	18000	5	12000	2

Table 6.7: Within-sample and out-of-sample fit measures using the best ARIMA model for inflation

	Within-Sample	Out-of-Sample
RMSE	0.002502	0.001601
MAE	0.002070	0.001145
MAPE	139.7463	103.6850

Table 6.8: Within-sample and out-of-sample fit measures using VAR model

Simple Sum			**Divisia**		
	Within-sample	Out-of-sample		Within-sample	Out-of-sample
RMSE	0.002383	0.001456	RMSE	0.002334	0.001495
MAE	0.001906	0.001113	MAE	0.001814	0.001164
MAPE	168.24%	157.34%	MAPE	166.48%	166.62%

Table 6.9: Within-sample and out-of-sample fit measures using NN constructed using the variables in set A

Simple Sum			Divisia		
	Within-sample	Out-of-sample		Within-sample	Out-of-sample
RMSE	0.002381	0.001455	RMSE	0.002383	0.001466
MAE	0.001935	0.001112	MAE	0.001854	0.001147
MAPE	166.04%	153.69%	MAPE	164.56%	144.46%

Table 6.10: Within-sample and out-of-sample fit measures using NN constructed using the variables in set B

Simple Sum			Divisia		
	Within-sample	Out-of-sample		Within-sample	Out-of-sample
RMSE	0.002412	0.001179	RMSE	0.002416	0.001807
MAE	0.001924	0.000983	MAE	0.001865	0.001324
MAPE	157.06%	153.84%	MAPE	154.53%	161.21%

Table 6.11: Within-sample and out-of-sample fit measures using NN constructed using the variables in set C

Simple Sum			Divisia		
	Within-sample	Out-of-sample		Within-sample	Out-of-sample
RMSE	0.002050	0.001345	RMSE	0.002192	0.001316
MAE	0.001585	0.001071	MAE	0.001689	0.000999
MAPE	152.41%	150.62%	MAPE	142.19%	111.61%

A comparison of the results from the ARIMA and VAR forecasts suggest the multivariate models provide more accurate forecasts of Euro inflation. Looking at RMSE for example, the out-of-sample forecasting accuracy increases by about 9% with VAR models when compared to ARIMA models and hence the VAR models are retained as representatives for linear models for comparison with nonlinear NN. On comparing the results from VAR modelling and NN constructed with the same input variables as in the VAR models (set B), it is not possible to discriminate between them as both of perform equally well in twelve comparisons of the within-sample and out-of-sample forecasts of the two monetary indices. NN constructed with the input variables from set A show a better performance but are still outperformed by the linear models in a few cases. However, a comparison of the results from the VAR modelling to those from NN constructed input variables from set C, reveals that superior inflation forecasts are achieved using NN, both within-sample and out-of-sample, in every case examined. Looking again at the RMSE, for example, out-of-sample forecasting accuracy increases by approximately 10% with NN over VAR models. These results demonstrate the sensitivity of the NN to the choice of input variables and reveal that input variables used for building the linear models are not necessarily the most appropriate ones for the nonlinear models.

The relative forecasting potential of the VAR and NN models are also evaluated using a simple encompassing test (Fair and Shiller, 1990). Such a test has some advantages over the other performance measures (RMSE, MAE, MAPE) to compare the forecasts. Firstly, it can differentiate between competing forecasting models even if there are no big differences in the performance measures. Secondly, it helps to discriminate between models in cases where the performance measures are in favour of a particular model while despite having larger performance measures other competing models might contain vital information unique to them. Thirdly, such a test gives some statistical meaning to the forecasts of the NN relative to those of the linear models. The test is carried out by regressing the actual values of the changes in inflation on a constant, linear model forecasts (f^L) and NN forecasts (f^N). If the t tests show that the coefficients of the forecasts of both models are significantly different from zero, then both models contain independent information that have power in forecasting the changes in inflation. If one of the coefficients of the forecasting models is significantly different from zero and the other one is not then the latter is just a subset of the former. In addition, the model with the significant coefficient contains further relevant information. Finally, if none of the coefficients are significantly different from zero then neither model is useful in forecasting the changes in inflation. The best NN forecasts obtained by using the input variables in C, are evaluated against the VAR forecasts. The results from the encompassing tests carried out for within-sample and out-of-sample forecasts are given below. The JB, LM and ARCH tests do not show any signs of misspecification. The results reveal that in every case only the coefficient of the NN forecast is significant at the conventional 5% significance level which implies that that NN forecasts are statistically superior to the linear models forecasts and hence VAR forecasts are simply a subset of the NN. These results further confirm that better macroeconomic forecasts can be achieved with the use of nonlinear NN.

Simple Sum

Within-sample

$$\Delta^2 p_t = 0.0000007 - 0.165 f^L + 1.128 f^N + \varepsilon_{4t} \tag{6.8}$$
$$\qquad (0.000253) \qquad (0.287) \qquad (0.232)$$

Sample: 1981Q2-1998Q2

$R^2 = 0.49$ $\quad J.B = 2.40[0.30]$ $\quad$ S.E. of regression = 0.002090

LM (1) = 2.47 [0.12] $\quad$ LM (4) = 5.35 [0.25] $\quad$ LM (8) = 12.30 [0.14]

ARCH (1) = 0.26 [0.62] $\quad$ ARCH (4) = 0.63 [0.96] $\quad$ ARCH (8) = 3.80 [0.88]

Values in parentheses under the estimated coefficients are standard errors and values in square brackets after the values of the test statistics are the corresponding p-values.

Out-of-sample

$$\Delta^2 p_t = -0.000615 - 0.0933 f^L + 1.349 f^N + \varepsilon_{5t} \tag{6.9}$$
$$\qquad (0.0006) \qquad (1.005) \qquad (0.689)$$

Sample: 1998Q3-2000Q4

$R^2 = 0.41$ $\quad J.B = 0.67[0.72]$ $\quad$ S.E. of regression = 0.001375

LM (1) = 0.25 [0.62] $\quad$ LM(2) = 0.53 [0.77] $\quad$ LM (4) = 3.60 [0.46]

ARCH (1) = 1.46 [0.23] $\quad$ ARCH(2) = 2.84 [0.24] $\quad$ ARCH (4) = 5.82 [0.21]

Values in parentheses under the estimated coefficients are standard errors and values in square brackets after the values of the test statistics are the corresponding p-values.

Divisia

Within-sample

$$\Delta^2 p_t = \underset{(0.000272)}{0.00000268} + \underset{(0.361)}{0.0647} f^L + \underset{(0.323)}{0.960} f^N + \varepsilon_{6t} \tag{6.10}$$

Sample: 1981Q2-1998Q2

$R^2 = 0.42$ $J.B = 0.40[0.82]$ S.E. of regression = 0.002241

LM (1) = 3.80 [0.15] LM (4) = 3.83 [0.43] LM (8) = 10.39 [0.24]

ARCH (1) = 0.14 [0.71] ARCH (4) = 3.69 [0.45] ARCH (8) = 7.87 [0.45]

Values in parentheses under the estimated coefficients are standard errors and values in square brackets after the values of the test statistics are the corresponding p-values.

Out-of-sample

$$\Delta^2 p_t = \underset{(0.000551)}{-0.000411} - \underset{(0.925)}{0.969} f^L + \underset{(0.830)}{1.633} f^N + \varepsilon_{7t} \tag{6.11}$$

Sample: 1998Q3-2000Q4

$R^2 = 0.42$ $J.B = 0.16[0.92]$ S.E. of regression = 0.001365

LM (1) = 0.74 [0.39] LM(2) = 0.77 [0.68] LM (4) = 6.26 [0.18]

ARCH (1) = 0.47 [0.49] ARCH(2) = 1.79 [0.41] ARCH (4) = 5.93 [0.20]

Values in parentheses under the estimated coefficients are standard errors and values in square brackets after the values of the test statistics are the corresponding p-values.

Finally, on comparing the inflation forecasting performance of the two monetary indices firstly within a linear framework, it is found that Divisia M3 has better within-sample convergence than its Simple Sum counterpart. However, the main property sought here is better generalisation, i.e. better out-of-sample performance that apparently Divisia fails to provide. When the impact of the two monetary indices on the prediction accuracy is evaluated in a nonlinear framework, overall the Simple Sum index has better within-sample convergence, however, the Divisia index clearly outperforms it in terms of out-of-sample convergence. These results do seem to suggest that one of the reasons for the poor historical performance of the Divisia index against the Simple Sum index could be attributed to incorrectly choosing linear models to evaluate the two monetary indices. These results corroborate the findings of Binner and Gazely (1999), Binner, Gazely and Chen (2002), Binner et *al*., (2003) and Gazely and Binner (1998, 2000) who have consistently found that the Divisia index outperforms its Simple Sum counterpart when evaluated using NN.

6.6 Summary and Conclusions

There is growing evidence that macroeconomic series contain nonlinearities but linear models such as ARIMA and VAR models are widely used for forecasting such series, despite the inability of linear models to cope with nonlinearities. In this chapter new empirical evidence on the relative Euro inflation forecasting performance of linear ARIMA and VAR models and the nonlinear NN is provided. Also investigated is the relative empirical performance of Simple Sum and Divisia indices and whether the historically poor performance of the theoretically superior measure of monetary services, Divisia, relative to its Simple Sum counterpart could be attributed partly to the incorrect choice of linear models used to evaluate them.

A considerable amount of research has been carried out in the recent years on NN. However, despite their ability to capture nonlinear relationships, findings generally do not allow any discrimination between conventional linear statistical techniques and NN. One of the main reasons for this is that there are no well defined guidelines to build NN for solving a particular task and their construction has involved a lot of subjectivity on the part of researchers, thereby considerably restricting the power of NN and ultimately leading to the results of many studies being dubious. In this study it has been tried to keep the level of subjectivity to a minimum in order to obtain the best possible NN forecasting models and some other issues likely to affect the performance of NN are also considered. The best NN models in this study outperform the traditionally used linear ARIMA and VAR models in macroeconomic forecasting and are also statistically superior to them. The gain in forecasting accuracy in the NN is very likely to have emerged from the capability of NN to capture nonlinear relationships between macroeconomic variables. The first conclusion to be drawn from this result is that despite being constrained by the lack of large data samples in macroeconomics, NN can be successfully applied in the field, provided extreme care is taken in designing the NN. However, at this stage policymakers, such as the ECB who require inflation forecasts, would not be recommended to abandon the use of conventional statistical techniques in favour of NN. The latter still have some very serious limitations, e.g., particularly time consuming trial and error procedures and the lack of available statistical techniques for analyzing the relationship between input and output variables. However, until such problems are overcome, it is macroeconomic forecasters can use NN as a complementary tool for forecasting.

It is widely accepted that the Simple Sum procedure is inappropriate and the weighted Divisia index is a superior measure of monetary services flow. However, the Divisia index does not always outperform its Simple Sum counterpart in empirical studies, explaining the reluctance of the ECB to use the weighted monetary aggregate instead of Simple Sum M3. The results of this study suggest that the poor performance of the Divisia index can be attributed to a certain extent to the incorrect choice of linear statistical methods used to evaluate its performance relative to the Simple Sum index, as the Divisia clearly outperforms the Simple Sum index when evaluated in a nonlinear framework but not in a linear framework. Thus the recommendation to the ECB would be to at least pay more serious attention to the behaviour of the Divisia monetary aggregate.

CHAPTER 7:

SUMMARY, CONCLUSIONS AND FUTURE WORK

7.1 Summary and Conclusions

The thesis focuses mainly on comparing the empirical performances of Simple Sum and Divisia monetary aggregates for the Euro area. The motivation to work with monetary aggregates comes from the fact that they have been given a prominent role in the current monetary policy strategy of the ECB, which is aimed at maintaining price stability in the Euro area. Simple Sum monetary aggregates have long been recognised to be incorrect as in their construction assets as different as cash and interest bearing time deposits are weighted linearly and equally. Divisia aggregates, on the other hand, are based on more solid theoretical foundations. As reviewed in Chapter 2, Divisia monetary aggregates are derived from microeconomic theory, aggregation theory and statistical index number theory and they are considered to be a viable alternative to Simple Sum aggregates for the conduct of monetary policy at central banks where monetary aggregates are used for such purposes. Since the derivation of Divisia aggregates a number of studies from all over the world have compared the empirical performance of Simple Sum and Divisia monetary aggregates. Though the results are found to be mixed, there is a general consensus that the results lean in favour of Divisia monetary aggregates. Studies comparing Simple Sum and Divisia aggregates for the Euro area are very limited and half or more of them are pre-ECB formation studies and can be only considered as indicative. Hence, the principal aim in this thesis is to provide new empirical evidence on the performance of Simple Sum and Divisia monetary aggregates for the Euro area, with a view of supplementing the small existing literature.

Before any monetary aggregate can be constructed monetary aggregation theory requires that the asset components of the aggregate be weakly separable, as discussed in Chapter 2. Therefore, weakly separable groups of monetary assets that can be reliably aggregated are first identified in Chapter 3. The tests used are nonparametric weak separability tests, originally derived by Varian (1982, 1983) and recently improved by Fleissig and Whitney (2003). The rate of rejection of weak separability is usually very high using the original Varian (1982, 1983) test. Firstly, because of the fact that the test is nonstochastic, a single violation of the test would lead to rejection of weak separability. However, sometimes, violations of the test can be due to measurement errors in the data and are therefore not significant. Secondly, because of the test procedure itself, which sometimes return negative indices that should be positive. Fleissig and Whitney (2003) reformulate Varian's (1982, 1983) test in terms of a linear programming problem which forces the indices to be positive and makes small adjustments to the data to allow for measurement errors.

In the first stage of testing for weak separability, consistency of the whole data set with GARP was checked. Two violations were noted and hence the data set was divided into two subsamples to allow for GMU, which is thought to be the possible cause of the violations. As expected two violations were noted for the first subsample which consists of the GMU and no violations were noted for the post GMU subsample. Therefore the tests in the later stages for testing for weak separability were confined to the post GMU period. All the groups of assets considered were found to be weakly separable. However, small adjustments were required, due to measurement errors in the data, to make the different groups pass the weak separability test. The fact that all groups we subjected to weak separability tests passed the tests and that most previous weak separability studies find very few weakly separable groups, suggest that a large number of weakly separable groups have wrongly failed weak separability because of deficiency in the original Varian (1982, 1983) test. The Fleissig and Whitney (2003) improved version of the test is a more reliable alternative.

Given that at low levels of aggregation there tends to be very little difference in the behaviour of Simple Sum and Divisia monetary aggregates, the broadest two groups of assets from the three that were found to be weakly separable are used to construct monetary aggregates for cointegrated money demand analysis for the period the assets were found to be weakly separable (post GMU period) in Chapter 4. The performances of Simple Sum and Divisia aggregates from the less broad of the two groups are almost similar which is not surprising because as mentioned earlier the behaviour of the two types of monetary aggregates tend to be similar at low levels of aggregation. However, considerable differences emerge between Simple Sum and Divisia aggregates constructed from the broader group of assets. The money demand relationship of Divisia was found to be very stable and sensible. On the other hand, the number of cointegrating vectors of the Simple Sum system is found to be equal to the number of variables in its system. This implies that all the variables in its system are stationary. However, the unit root tests clearly show that none of the variables is stationary. Such a contradiction in the results, especially the cointegration result, suggests that cointegration analysis will not yield sensible results for Simple Sum M3 and hence no further money demand modelling was carried for it. In sum the results corroborate the findings of a large number of previous studies from around the world on these aggregates. At low levels of aggregation there is not much difference between Simple Sum and Divisia aggregates, however, at higher levels of aggregation Divisia aggregates outperform their Simple Sum counterparts.

It has been argued that stability of money demand functions is a side issue with regards to usefulness of monetary aggregates for monetary purposes and of more relevance is the comparison of the indicator properties of monetary aggregates. Therefore, such properties of the Simple Sum and Divisia aggregates are also investigated using the CLI of inflation turning point framework and inflation forecasting framework. Given that the abovementioned frameworks require large data samples, that is, data over a long historical period, to yield sensible results, the full data sample, that is, from 1980Q1 to 2000Q4, is considered. Moreover, given very little difference was found between SM2 and DM2, only SM3 and DM3 which are constructed from the broadest group of weakly separable assets are considered for further analysis analyses.

In chapter 5, CLIs of inflation turning point for the Euro area are developed to compare the relative performance of the Simple Sum and Divisia monetary aggregates. CLIs of inflation turning points themselves could be of some interest to policymakers as they would allow them to adjust their economic calculations for the forthcoming economic environment. A great deal of interest is being shown in CLIs as traditional statistical forecasting models have not proved to be very successful in forecasting turning points. To the best of my knowledge no CLI of inflation turning point for the Euro area has been developed and hence the incentive to work with such a framework. It is acknowledged that the way leading indicators are constructed does not look rigorous in terms of criteria commonly used in econometrics and there have been incentives to develop more sophisticated CLIs. To this end, time series techniques of Fourier analysis and Kalman filters have been used in this study. CLIs constructed with these techniques have been shown to considerably outperform traditionally constructed CLIs. Comparison of Simple Sum and Divisia monetary aggregates in such a framework is possible because monetary aggregates are considered to be good information carriers of future inflation and hence are often used in the construction of CLIs of inflation turning points. A further aim in the chapter is to provide a tentative answer to the issue of whether or not the UK should join the Euro area. For this purpose graphical analysis and the CLI of inflation turning point framework are used.

The CLIs developed appear to be very closely related to the inflation cycle, as indicated by the correlations between the variables, and hence are a powerful alternative to traditional statistical methods for forecasting turning points. Implicit in this finding is the fact that time series techniques such as Fourier analysis and Kalman filters can be used to construct sophisticated CLIs. A comparison of the Simple Sum and Divisia aggregates in the CLI framework suggests that Divisia aggregates are more closely related to Euro area inflation cycle over the time period considered. On the issue of whether or not the UK should join the Euro area, the UK and Euro area inflation cycles are found to be out of synchronisation, which suggests that measures taken by the ECB would not have the same stabilising effect on the UK economy as would measures taken by the Bank of England. A similar conclusion emerges on using the CLI of inflation turning point framework.

In Chapter 6, the Euro area inflation forecasting framework is used to compare the relative empirical performance of the Simple Sum and Divisia indices. Inflation forecasts play an important role in the second pillar of the ECB's monetary policy strategy. However, most inflation forecasting models used are linear, but now there is growing evidence of nonlinearity in macroeconomic data. Therefore, linear models might not be able to capture all nonlinear characteristics in the data and not be able to produce reliable forecasts. In view of such limitations of linear models, nonlinear statistical models have been developed but these models require the imposition of assumptions regarding the precise form of nonlinearity in the data. However, there might be too many nonlinear patterns in the data and the prespecified nonlinear model may not be able to capture all the nonlinear characteristics.

An alternative nonlinear model is neural networks model. Neural networks do not require the imposition of any assumption as they are data driven. From a mathematical point of view neural networks would be expected to forecast inflation more accurately than linear models and since these models have not been compared in Euro area inflation forecasting, such an investigation is carried out. Again, it is possible to compare Simple Sum and Divisia monetary aggregates in such a framework as monetary aggregates are considered to be good information carriers for future inflation and hence are often used in constructing inflation forecasting models. It has been shown that Divisia aggregates consist of nonlinear structures and despite this they continue to be modelled and compared to their Simple Sum counterparts in linear frameworks. In the event that Divisia aggregates perform poorly relative to their Simple Sum counterparts one cannot say Divisia aggregates are inferior to Simple Sum aggregates as indicator variables. As it is highly likely that linear models are not able to capture all essential characteristics, more specifically nonlinear structures, in Divisia aggregates and therefore undermining the performance of Divisia aggregates. However, only rarely have the limitations of linear models been questioned in such circumstances.

The analysis in Chapter 6 can be very conveniently used to shed some light on the issue of whether Divisia aggregates are disadvantaged to their Simple Sum counterparts when compared in linear frameworks. More specifically, the inflation forecasting performance of the Euro Divisia aggregate is compared to its Simple Sum counterpart in both linear and nonlinear frameworks.

The main results in Chapter 6 are as follows. Firstly, nonlinear neural networks are found to perform better than linear ARIMA and VAR models in forecasting Euro inflation. Such a result confirms the hypothesis that macroeconomic data which are being shown to consist of nonlinearity are better modelled using nonlinear models like neural networks. However for such models to be successful they have to be very carefully designed. Based on the findings in this thesis it is suggested that the ECB uses neural networks as a complementary tool for inflation forecasting. Secondly, the

Simple Sum aggregate is found to perform better than the Divisia aggregate in forecasting Euro inflation in a linear framework. However, in a nonlinear framework the converse is observed, that is, Divisia performs better than Simple Sum. Based on these observations, it can therefore be concluded that in certain cases where Divisia aggregates have underperformed relative to Simple Sum aggregates, the poor performance may be attributed to using linear models for the comparison, which are not able to capture all essential characteristics in the Divisia aggregates.

Findings regarding the relative performance of Divisia and Simple Sum aggregates are found to be mixed; however lean slightly in favour of weighted Divisia aggregates. It may be concluded that a money stock mismeasurement problem exists and that the technique of simply summing assets in the formation of monetary aggregates is inherently flawed. Divisia aggregates should, therefore, be taken more seriously by the policymakers at the ECB and academics around the world.

7.2 Future Work

Although noncapital certain risky assets such as mutual funds and bonds have existed since a long time now, their growth has been quite recent. For example, in the United States, in the early 1970s, there were about 400 bond and mutual funds; today this figure has increased by ten times. The growth of such risky assets may be attributed, in part, to declining transaction costs when investing in such assets. Another innovation that may have contributed to the growth is that the balances held in such assets can be used more readily as a means of payment in the purchase of goods and services (Orphanides, Reid and Small, 1994). The increased liquidity of such funds leads us to ask whether risky assets are substitutes for capital certain monetary assets. If the answer is yes, then these risky assets should be included in the monetary aggregates used as indicators for guiding the conduct of monetary policy. Such analysis has already been conducted in the US in response to the breakdown of stable relationship between money, interest rates, prices and a few other variables in the early 1990s, the so called 'missing M2 episode', (see for example Duca (1995), Orphanides, Reid and Small (1994)) and recently in the UK by Drake, Flessig and Mullineux (1999) and Elger and Binner (2004).

Whether or not risky assets should be included in the monetary aggregates is an empirical question. When the data on risky assets for the Euro area becomes available an interesting avenue for research would be to use monetary aggregation theory to determine whether risky assets can be incorporated with the capital certain assets of the Euro area for monetary policy purposes. More specifically, weak separability tests should be conducted to determine whether or not risky assets can be added to capital certain assets. If it is found that risky assets are substitutes for capital certain assets then these assets can be aggregated together using Divisia aggregation and ultimately the empirical performance of such aggregates can be evaluated against the official aggregates. Barnett (2004) has recently found and improved way of deriving risk adjusted user costs for the construction of Divisia aggregates which could be used in the construction the aggregates.

It is argued that the weights of Divisia monetary aggregates have not been fully optimised yet and once this problem is overcome, Divisia aggregates would be far superior to Simple Sum aggregates. Recently neural networks have been used in finding the ‘optimal’ weights for Divisia type aggregates and their inflation forecasting performance has been found to be superior to conventional Divisia aggregates (see Gazely and Binner (2000)). Such a technique could be applied to construct Divisia type monetary aggregates which can be subsequently used for building more accurate inflation forecasting models.

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APPENDICES

APPENDIX A

This program verifies the necessary and sufficient condition for weak separability (Varian, 1982, 1983).

```
#include maxelm2;

#include min;
#include vecmul;
#include viol;
proc(4)=afriatmo(&maxelm2,&min,&vecmul,p,q);
local                    maxelm2:proc,min:proc,vecmul:proc,n,k,k1,count,i,U,B,II,E,
mx,Lamda,qd,pqd,temp1,temp2,ud,pq,qd1,umx,lm,mt,tv;
{mt,tv}=viol(&garp1,&garp2,&garp3,&garp4,q,p);
n=rows(mt);
B=zeros(n,1);
U=zeros(n,1);
Lamda=zeros(n,1);
II=ones(n,1);
count=0;
k=sumc(ii);
k1=sumc(B);

do while k>0;
count=count+1;
mx=maxelm2(&min,mt,II);  /* maxelm2 is a subroutine that computes the maximal
element of the set indexed by II*/

E=zeros(n,1);
for i (1,n,1);
          if II[i]==1;
                if mt[i,mx]==1;
                    E[i]=1;
                endif;
          endif;
endfor;


if k1==0;
       U[mx]=vecmul(q[mx,.],p[mx,.]);
       Lamda[mx]=1;
   endif;
if k1/=0;
   umx=1000000000;
      for j (1,n,1);
             if B[j]==1;
```

```
                if U[j]<umx;
                    umx=U[j];
                endif;
            endif;
    endfor;
     for i (1,n,1);
            for j (1,n,1);
                if E[i]==1 and B[j]==1;
                qd=q[i,.]-q[j,.];
                pqd=vecmul(p[j,.],qd);       /*vecmul is a subroutine which computes
the dot product of 2 rows*/


                temp1=U[j]+(Lamda[j]*pqd);
                        if temp1<umx;
                        umx=temp1;
                        endif;
                  endif;
              endfor;
           endfor;
U[mx]=umx;

lm=1;
             for i(1,n,1);
                    for j(1,n,1);
                       if E[i]==1 and B[j]==1;
                           ud=U[j]-U[mx];
                           qd1=q[j,.]-q[i,.];
                            pq=vecmul(p[i,.],qd1);
                             temp2=ud/pq;
                                   if temp2>lm and temp2>1;
                                          lm=temp2;
                                   endif;
                       endif;
                   endfor;
              endfor;

Lamda[mx]=lm;

endif;



for i (1,n,1);
      if E[i]==1;
        U[i]=U[mx];
        Lamda[i]=Lamda[mx];
      endif;
endfor;
for i (1,n,1);
```

```
if E[i]==1;
II[i]=0;
B[i]=1;
endif;
endfor;

k=sumc(ii);
k1=sumc(B);

endo;

retp(U,Lamda,tv,count);
endp;
```

Subroutines for the above program

Subroutine 1

```
#include tes5;
proc(1)=maxelm2(&min,mt,II);
local i,j,n,mx,min:proc;

n=rows(mt);
j=min(II);

mx=j;

for i (1,n,1);


if ii[i]==1;
if mt[i,j]==1;
j=i;
mx=i;
endif;
endif;
endfor;
retp(mx);
endp;
```

Subroutine 2

```
/*this program finds the minimum index */
proc(1)=min(e);
local i,counter;
i=1;
counter=0;
do while e[i]<1;
counter=i;
i=i+1;
endo;
counter=counter+1;
```

```
retp(counter);
endp;
```

Subroutine 3

```
/*this program multiplies any two rows of a matrix (x'y) */

proc(1) =vecmul(x,y);
local k,nn,xy;
nn=cols(x);
xy=0;
for k(1,nn,1);
xy=xy+x[k]*y[k];
endfor;
retp(xy);
endp;
```

Subroutine 4

```
#include garp1
#include garp2
#include garp3
#include garp4
proc(2)=viol(&garp1,&garp2,&garp3,&garp4,q1,p1);
local garp1:proc,garp2:proc,garp3:proc,garp4:proc,m1,mt1,pq1,v1,tv1;
m1=garp1(q1,p1);
mt1=garp2(m1);
pq1=garp3(q1,p1);
v1=garp4(mt1,pq1);
tv1=sumc(sumc(v1));
retp(mt1,tv1);
endp;
```

Subroutine 5

```
/*This program constructs the matrix m of varian's algorithm-pg 949*/
/*the columns of matrix q are the quantities of the monetary assets*/
/*the columns of matrix p are the prices corresponding quantities of monetary assets*/
proc (1) = garp1(q,p);
local pxii,pxij,sum,sum1,n,m,nn,i,j,k;
n=rows(q);
nn=cols(q);
m=zeros(n,n);
for i (1,n,1);
sum=0;
        for k (1,nn,1);
        sum=sum+p[i,k]*q[i,k];
```

```
endfor;
pxii=sum;

for j (1,n,1);
sum1=0;
for k(1,nn,1);
sum1=sum1+p[i,k]*q[j,k];
endfor;
pxij=sum1;
if pxii >= pxij;

m[i,j]=1;
else;
m[i,j]=0;
endif;

endfor;
endfor;

retp(m);
endp;
```

Subroutine 6

```
/*This program computes the matrix MT of varian's algorithm- pg 949*/
/* The matrix M computed in a previous step (GARP1) will be also used*/
proc(1)=garp2(m);

local i,j,k,n;

n=rows(m);
for k (1,n,1);
for i (1,n,1);
for j (1,n,1);

if m[i,k]==0 or m[k,j]==0;
m[i,j]=m[i,j];
```

```
else;

          m[i,j]=1;
endif;

endfor;
endfor;

endfor;

retp(m);
endp;
```

Subroutine 7

```
/*This program computes the matrix PQ*/
/*Results from garp1 and garp2 will be used*/

proc(1)=garp3(q,p);
local i,j,k, pq,n,nn;
n=rows(p);
nn=cols(p);
pq=zeros(n,n);
for i (1,n,1);
for j (1,n,1);
pq[i,j]=0;
for k (1,nn,1);
pq[i,j]=pq[i,j]+p[i,k]*q[j,k];
endfor;
endfor;
endfor;
retp(pq);
endp;
```

Subroutine 8

```
/* this prog tests for GARP and returns the number of violations*/
/*this prog  uses value from garp1,garp2 and garp3*/

proc(1)=garp4(mt, pq);
local i,j,n,v;
n=rows(mt);
v=zeros(n,n);
for i (1,n,1);
for j (1,n,1);
if mt[i,j]==1 and (pq[j,j]>pq[j,i]);
v[i,j]=1;
else;
v[i,j]=v[i,j];
endif;
```

```
endfor;
endfor;
retp(v);
endp;
```

APPENDIX B1

$\phi = \Bigg\{$	$\tan^{-1}(-B/A),$	$A > 0,$
	$\tan^{-1}(-B/A) - \pi,$	$A < 0, B > 0,$
	$\tan - 1(-B/A) + \pi,$	$A < 0, B \leq 0,$
	$-\pi/2,$	$A = 0, B > 0,$
	$\pi/2,$	$A = 0, B < 0,$
	arbitrary,	$A = 0, B = 0.$

APPENDIX B2

Table B2.1 Approximate values of μ, ϕ, A, B and R for the Euro Area

	DM3	SM3	INF	ENN	UNN	ULC	COMPR
μ e^-7	0.0001	0.0001	0.0001	0.0000	0.4476	0.0000	0.0032
A	-0.0047	-0.0048	-0.1548	-0.0206	-214.63	-0.0025	0.2832
B	0.0025	0.0067	0.1075	0.0016	-268.48	0.0022	1.2752
R	0.0054	0.0082	0.1885	0.0206	343.72	0.0033	1.3062
ϕ	-2.6526	-2.1876	-2.5346	-3.0619	2.2452	-2.4164	-1.3522

Table B2.2 Approximate values of μ, ϕ, A, B and R phi for the UK

	DM4	SM4	INF	IUV	UNE	VAC	RSI	IIP	GCP
μ e^-8	0.0009	0.0009	0.0016	0.0274	0.6667	0.0635	0.0208	0.0311	0.0636
A	0.0916	0.1083	1.4139	0.8346	-111.94	-2.4487	-0.1450	-1.0180	0.2445
B	0.0354	0.0727	0.1746	-0.1464	-104.16	-9.4506	0.2589	-0.1524	-9.5480
R	0.0982	0.1304	1.4246	0.8473	152.91	9.7626	0.2968	1.0294	9.5511
ϕ	-0.3693	-0.5908	-0.1228	0.1736	2.3922	1.8243	-2.0812	2.9929	1.5452

APPENDIX B3

Tables B3.1 – B3.4 show the factor loadings of the first principal component of the leading indicator series. The weights are directly proportional to the size of the factor loadings. For example in table B3.1, given that the sum of the factor loadings is 1.56, the weight of Real Simple Sum M3 is calculated as 0.78/(1.56)=0.5.

Table B3.1 Factor loadings derived from principal component analysis and weights of leading indicators for the Euro Area for short CLI for Simple Sum

Leading indicators	Factor loadings	Weights in leading indicators
Real Simple Sum M3	0.780	0.5
Effective Exchange Rate	0.780	0.5

Table B3.2 Factor loadings derived from principal component analysis and weights of leading indicators for the Euro Area for short CLI for Divisia

Leading indicators	Factor loadings	Weights in leading indicators
Real Divisia M3	0.663	0.5
Effective Exchange Rate	0.663	0.5

Table B3.3 Factor loadings derived from principal component analysis and weights of leading indicators for the Euro Area for long CLI for Simple Sum

Leading indicators	Factor loadings	Weights in leading indicators
Real Simple Sum M3	0.498	0.163
Unemployment	0.958	0.313
Unit Labour Costs	0.656	0.214
Commodity Prices	0.950	0.310

Table B3.4 Factor loadings derived from principal component analysis and weights of leading indicators for the Euro Area for long CLI for Divisia

Leading indicators	Factor loadings	Weights in leading indicators
Real Divisia M3	0.534	0.171
Unemployment	0.844	0.271
Unit Labour Costs	0.769	0.246
Commodity Prices	0.973	0.312